Research article

Sensitivity analysis of cultivar parameters to simulate wheat crop growth and yield under moisture and temperature stress conditions

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A B S T R A C T

Sensitivity of cultivar input parameters were characterised on the outputs of yield and growth variables using a web based crop simulation model Web InfoCrop Wheat. The crop model was assessed for each combination of seventeen input cultivar parameters tested under moisture and temperatures stress conditions in four different ecological regions. Three model outputs, total dry matter at harvest, grain yield at harvest and duration of the crop were chosen for subsequent evaluation. The most dominant cultivar parameters were identified to be TPOPT (Optimum Temp), TTVG (Thermal time for germination to 50% Flowering), KDFMAX (Extinction coefficient of leaves at flowering), GNOCF (Slope of storage organ number/m^2 to dry matter during storage organ formation), POTGWT (Potential storage organ weight) and PHOTOSENS (Photoperiod sensitivity) which were associated with growth, thermal time accumulation, leaf area index, grain number and photosensitivity. Comparison of crop simulations with all the cultivar parameters incorporated from the experimental observations and those with only the most sensitive cultivar parameters incorporated was performed. Outputs of the crop simulation were significantly correlated with results from the field experiments. The present study could save time and effort in generating all the cultivar parameters required to perform the crop simulation under moisture and temperature stress conditions. The most significant cultivar parameters (TPOPT, TTVG, KDFMAX, GNOCF, POTGWT and PHOTOSENS) identified through the sensitivity analysis conducted in this study could significantly simulate the crop growth and yield of wheat.

1. Introduction

Computer based agronomic crop models are useful tools for the quantitative examination of the growth and yield of crops (Dzotsi et al., 2013; Krishnan and Aggarwal 2017; Krishnan et al., 2016). The execution of crop models usually involves huge data sets. Crop growth models include a number of model parameters as input data, the measurement of which is a great difficult task as they are not identified with certainty (Jin et al., 2018; Jones et al., 2012). These parameters are challenging to measure mainly because of the erraticism and inconsistency in natural phenomenon, price and time required in measuring, or mistakes in their determinations (Jabloun et al., 2018; Richter et al., 2010). Another way out is to generate the parameters from related reports and findings, however the discrepancy of these parameters owing to cultivars, weather changes, agro-ecological region variations etc. are not considered (Liu et al., 2019; DeJonge et al., 2012). Ultimately the model estimates using these imprecise parameter values are unreliable and are not regarded. It is principally difficult to measure all the unknown parameters of a model

instantaneously (Wang et al., 2013). Therefore, having a greater number of parameters in an intricate model offers a tough decision. Thus, an operative technique to decrease the number of input parameter is obligatory. In fact, a limited number of model parameters might be appropriate for the maximum variability in the model outputs, even though several of the parameters could have least effect on the outputs (He et al., 2011).

The parameter sensitivity analysis (SA) technique can have a crucial role to identify sensitive parameters, and users can concentrate more efforts on calibrating the sensitive parameters (Krishnan and Aggarwal 2017; Saltelli and Annoni, 2010). Input parameters which have less influence on the output variables can be given a default value. In addition to this, sensitivity analysis is beneficial to understand, improve and employ models for several applications (Dzotsi et al., 2013). Similarly, based on the SA, the performance and weakness of the model can be scrutinized for the evolution and improvement (Krishnan and Aggarwal 2017; Richter et al., 2010). It has been recognized that identifying the probabilities of outputs with a quantifiable uncertainty analysis and

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evaluating their likelihood can assist decision makers with more important proof to generate or evaluate simulation judgements (Haan and Skaggs, 2003; Ogle et al., 2003). Further several modelling groups agree with the fact that having an extensive choice of cultivar parameters in generic models would upsurge the use of the models, nevertheless add to establishing a mutual understanding among these cultivar parameters (Saltelli and Annoni, 2010). Therefore, sensitivity analysis can assist in scrutinizing the main causes of model prediction uncertainty.

The main aim of this investigation is to determine the performance of the Web InfoCrop - wheat model outputs to cultivar parameter uncertainty in different moisture and temperature stress conditions. The objectives of the present study were (i) to characterize the influence of variations in cultivar parameters within their choices of uncertainty, on total dry matter at harvest, grain yield and duration of wheat crop; (ii) to identify with utmost accuracy the cultivar parameters in Web InfoCrop - wheat that have the maximum significant effect on model outputs, (iii) to examine the variations in the effects of cultivar parameter uncertainty on model outputs simulated in different agro-ecological conditions and at potential, moistures stress, high temperature and combined moisture and high temperature stress conditions.

2. Materials and methods

2.1. Web based InfoCrop – wheat model: Web InfoCrop - wheat

In this study we have employed the crop model Web InfoCrop - wheat implemented into a web-based system by means of ASP.net (version 4.5) platform. We have used the integrated development Environment (IDE) provided by visual studios (Express) (Krishnan et al., 2016). In general, this web model had C# in the front-end language and SQL at the backend language. InfoCrop-Wheat is a dynamic crop growth model developed by Aggarwal et al. (2006). It is less complicated in its parameterization. It offers a collective assessment of the effect of weather, soil, pests, management and cultivar on crop growth processes and yield. The model incorporates essential processes like impacts of water, frost and temperature stress, flood, crop-pest interrelation, nitrogen management, soil water and nitrogen balance and soil carbon dynamics on crop growth. The InfoCrop -Wheat crop model is established on the modelling methodologies adopted by SUCROS - abbreviated for Simple and Universal Crop growth Simulator, sequences. Dry matter is considered on the basis of canopy photosynthesis. The crop development is calculated from photoperiod vernalisation and temperature. Dry matter partitioning and specific leaf area are exercised to estimate the alterations in leaf area.

InfoCrop first considers the influence of weather, followed by soil factors, and pests, respectively. InfoCrop has inbuilt checks on carbon, water and nitrogen balance. These checks verify each day that the integral of all fluxes into and out of the systems agree to the changes since the start of simulation. InfoCrop is widely used to assess the impact of climate change (Haris et al., 2013), characterise the moisture stress effects on yield (Aggarwal et al., 2008) and comparative studies of crop yield models (Kang et al., 2009; Krishnan et al., 2007).

2.2. Model description

Web InfoCrop-wheat model ponders to the following processes of crop growth and development, soil water, nitrogen, carbon, and crop–pest interactions (Aggarwal et al., 2006; Krishnan et al., 2016) (i) Crop growth and development: phenology, photosynthesis, partitioning, leaf area growth, number of storage organs, source: sink balance, transpiration, and uptake, allocation and redistribution of nitrogen (ii) Effects of moisture, nitrogen, temperature, flooding and frost stresses on crop growth and development (iii) Crop–pest interactions: damage mechanisms of insects and disease. (iv) Soil water balance: root water uptake, inter-layer movement, drainage, evaporation, runoff, ponding (v) Soil nitrogen balance: mineralisation, uptake, nitrification, volatilization, interlayer movement, denitrification, leaching (vi) Soil organic carbon dynamics: mineralisation and immobilization. (vii) Emissions of greenhouse gases: carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O).

The plant growth model in Web InfoCrop -Wheat is capable of simulating wheat cultivar, with each one having unique values for the model parameters, e.g., harvest index (HI), Thermal time based on Growing Degree days (GDD), and optimum and maximum temperature for plant growth, photoperiod sensitivity, Root growth rate, Radiation use efficiency, specific and relative growth rate of leaf area etc. (Table 1). Plant growth is simulated by a Thermal unit scheme. Plant growth and development is simulated by model on the basis of accumulated degree days, which is based on the daily maximum and minimum temperature. Potential crop growth and yield are usually not achieved because of constraints imposed by the plant environment, such as moisture, nitrogen or temperature stresses. Crop yield may be reduced through moisture-stress-induced reductions in the harvest index. InfoCrop - Wheat requires the user to input information on weather, soil, field management, and agro-ecological region. The daily on-site weather data consists of precipitation, maximum and minimum temperature, solar radiation, relative humidity, and wind speed. The soil profile is divided into three layers. InfoCrop - Wheat requires layer depth, bulk density (BD), wilting

Table 1. List of Web InfoCrop - wheat model cultivar parameters and definitions.

No.	Parameters	Unit	Definition	Min	Max
1	TTGERM	°C days	Thermal time for germination	60	70
2	TTVG	°C days	Thermal time for germination to 50% Flowering	750	1085
3	TTGF	°C days	Thermal time for 50% Flowering to Maturity	373	393
4	TPOPT	°C	Optimum Temp	20	30
5	TPMAXD	°C	Maximum Temp	35	50
6	PHOTOSENS	0.5–1.5	Photoperiod sensitivity	0.5	1.5
7	ZRTPOT	mm/day	Root Growth Rate	25	30
8	RUE	g/MJ/day	Radiation Use efficiency	2.75	2.8
9	SLA	dm^2/mg	Specific leaf area	0.0017	0.0022
10	RGRPOT	°C/d	Relative growth rate of leaf area	0.005	0.008
11	IndexGreen	0.8–1.2	Index of greenness of leaves	0.8	1.2
12	KDFMAX	ha soil/ha leaf fraction	Extinction coefficient of leaves at flowering	0.4	0.8
13	SensLowTemp	0–1.5	Sensitivity of storage organ setting to low temp	0	1.5
14	SensHighTemp	0–1.5	Sensitivity of storage organ setting to high temp	0	1.5
15	POTGWT	mg/grain	Potential storage organ weight	41.9	54.5
16	GNOCF	storage organ/kg/day	Slope of storage organ number/m^2 to dry matter during storage organ formation	13300	30000
17	NMAXGR	fraction	Nitrogen content of storage organ	0.01	0.03

Table 2. Detailed attributes of the locations used in the present study.

Latitude	Longitude	Altitude (m)	Agro ecological sub region	Agro climatic region (Planning commission)	Agro climatic zone (NARP)	Soil-type	Avg solar radiation (MJ m^{-2})	Avg max temp (°C)	Avg min temp (°C)	Total annual rainfall (mm)
(A) Delhi										
28.38	77.12	238	hot, dry, semi-arid ecological sub region (4.1)	Trans Gangetic Plain region (VI)	Western Zone (HR-2)	Sandy Loam	16697	30.95	17.83	634.41
(B) Dharwad										
15.43	75.11	678	hot dry sub humid (6.4)	Southern Plateau and Hills Region (X)	Northern Transitional Zone (KA-8)	clay	21837	31.77	19.72	683.23
(C) Indore										
22.61	75.83	557	Semi-arid ecological sub region (5.2)	Central plateau (IX)	Malawa plateau Agro climatic Zone (MP-10)	clay	19051	32.10	18.48	900.49
(D) Ranchi										
23.35	85.33	629	Hot Sub humid ecological sub region (12.3)	Eastern Plateau And Hills Region (VII)	Central And North Eastern Plateau Zone (BI-4)	clay loam	18806	29.42	16.43	1467.28

point (WP), field capacity (FC), percentage of sand, silt and clay, pH, and percentage of organic C content.

2.3. Uncertainty and sensitivity analysis

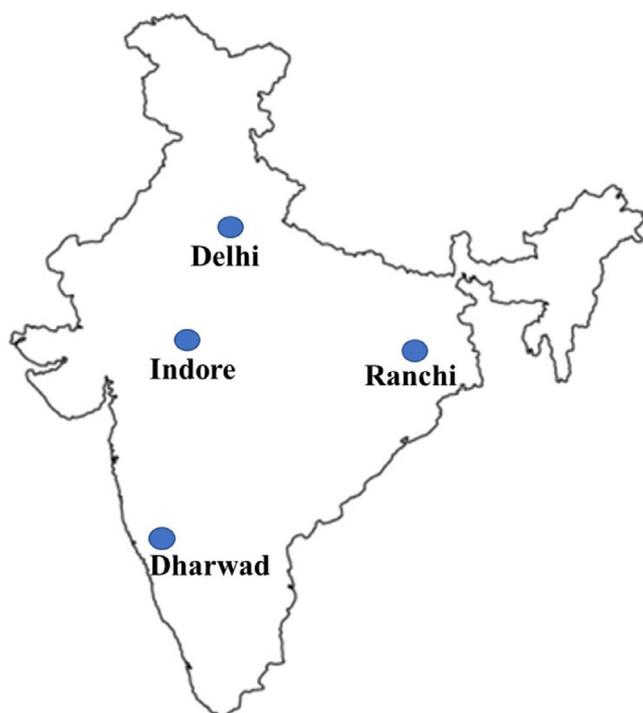#### 2.3.1. Agro- ecological region and analysis settings

Uncertainty and sensitivity analysis of the wheat crop characterised in the present study encompassed a sum of 1440 treatments due to four different ecological regions (Table 2), four production conditions (i) Potential, (ii) moisture stress – one irrigation at CRI stage; (iii) high temperatures stress – normal +3 °C and (iv) high temperature and moisture stress with 10 years of weather data at each agro-ecological region, three planting dates and three seed rates. The investigation was done for wheat (*Triticum Aestivum* L.) crop. Exact weather and soil conditions at the four different agro-ecological regions are given in Figure 1 and Table 2, which reveals a pattern of decrease in maximum and

Figure 1. Map showing the locations used in this study.

minimum temperatures with decrease in latitude. The planting dates were adopted from Indian Institute of Wheat and Barley Research (IIWBR, India) publication on usual planting dates in India (Anonymous, 2013). Planting densities were 120, 240 and 360 plants m^{-2}, respectively corresponding to a seed rate of 50, 100 and 150 kg/ha (Ram et al. 2013). Soil characteristics and daily weather data were taken from the individual research station for all the four locations (Delhi, Dharwad, Indore and Ranchi) in different agro-ecological regions. Soil survey information from the National Bureau of Soil Survey and Land Use Planning (NBSS&LUP) and data from individual research station on properties of soil profiles was used in the simulation model, for all the four agro-ecological regions. Weather data were collected from the observed meteorological weather station located in these agro-ecological regions.

2.3.2. Steps involved in uncertainty and sensitivity analysis

The uncertainty and sensitivity analysis focused on the influence of cultivar parameter uncertainty on the ranking of cultivar parameters and the variability in model outputs. This was executed by means of a Monte Carlo method comprising four steps, reiterated for every treatment and cultivar. The foremost step comprised of describing a probability distribution for individual cultivar parameter. The triangular distribution was assumed for all the seventeen cultivar parameters based on expert judgment, due to the following reasons (Wang et al., 2005): (1) it is challenging to define the authentic form of the probability distribution function (PDF) since it is largely not possible to gather a huge, random sample to test several PDFs for their capability to define the uncertainty in parameters; (2) understanding the means and variances of the input parameters is very much required than understanding the precise PDFs (Haan et al., 1998). The succeeding section describes the approach for creating synthetic data, using the probability distributions and ranges of some of the cultivar parameters. In the next step, depending on the statistical distributions and the correlation construct outlined in the previous step, we acquired, a Latin Hypercube (LH) sample of the cultivar parameters (McKay et al., 1979). For interrelated cultivar parameters (Stein, 1987), a Stein's approach for attaining a LH sample for dependent variables was adopted. In the succeeding step, the model was gauged for every combination of cultivar parameter. For subsequent investigation eight final outputs of the model were chosen namely, final total dry matter (TDM), final grain yield (YIELD), crop duration (DAS), maximum leaf area index (MAXLAI), crop growth rate (GCROP), grain number (G No.), grain weight (WGRAIN), root weight (WRT). At the end, the uncertainty in model outputs was measured, along with the sensitivity of the model outputs to individual cultivar parameter (Figure 2).

Variances along with the means of the resultant distributions besides the cumulative distribution functions (CDFs), were generally used to categorize uncertainty in model outputs (Krishnan and Aggarwal 2017;
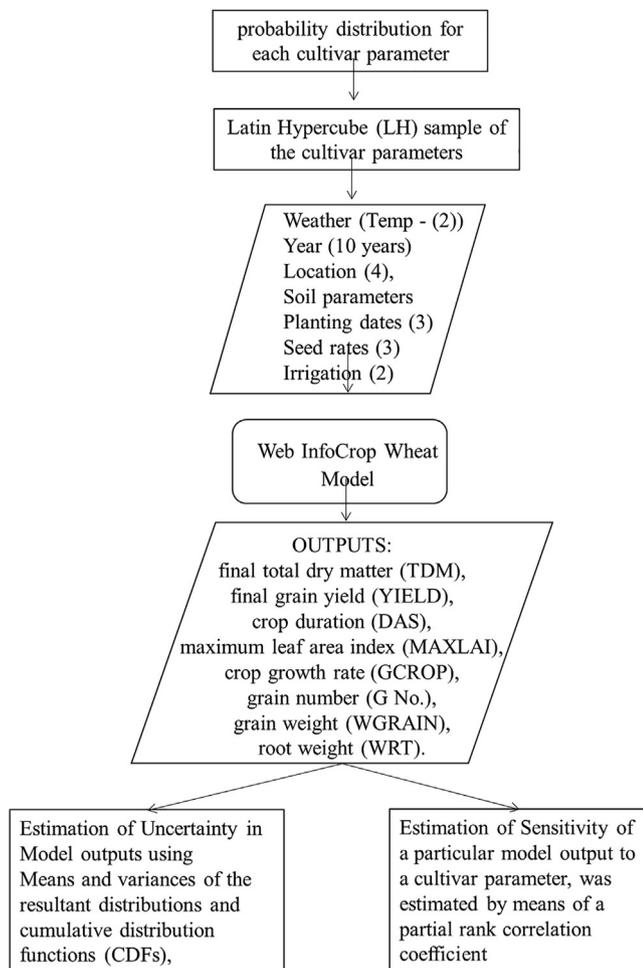
Figure 2. Steps involved in the uncertainty and sensitivity analysis.

top-down concordance coefficient (TDCC) (Savage, 1956; Iman and Conover, 1987; Marino et al., 2008). When the p-value ensuing from the top-down concordance coefficient (TDCC) test was lesser than a primary level of 0.05, then rankings were taken in a top-down sense. Changes in PRCC due to cultivar parameter rankings within two treatments were examined by means of TDCC.

The total number of model runs was decided by executing the model for wheat crop at one agro-ecological region (IARI, Delhi) for numerous sample dimensions within 100 and 10,000 executions and characterising the stability of model outcomes. For determining any statistically important changes in rankings obtained at diverse sample sizes from the TDCC investigation, the 10,000 model executions were considered as a reference. In this study, it was observed that within 100 and 500 executions, the sample size-caused increase in mean total dry matter of up to 7%. At the end to assure stability in the investigation a sample size of 1,000 model executions was selected that provided a sum of 1,440,000 model estimations (for the entire 1440 treatments) for wheat crop.

2.3.3. Cultivar data

Computer based test was generated to understand the interactions within the cultivar parameters: TTGERM, TTVG, TTGF, TPOPT, TPMAXD, PHOTOSENS, ZRTPOT, RUE, SLA, RGRPOT, IndexGreen, KDFMAX, SensLowTemp, SensHighTemp, POTGWT, GNOCF and NMAXGR. The computer experiment considered inputs such as cultivar, agro-ecological regions, and plant population as experimental factors (Table 3). The crop simulations were planting date, performed at potential production condition using web InfoCrop - Wheat model. The InfoCrop database (these are not model generated but created by researchers as a database, from different field observations) was used to get the extents for the genetic coefficients of the cultivars given in Table 1. DAS, YIELD, TDM, MAXLAI, ZRT, GCROP, GNO, WGRAIN and WRT were computed directly from the outputs given by the computer test. Normality from the kutisis and skewness of data was evaluated using the D'Agostino-Pearson's chi-square test (Zar, 1999). Later it was used to examine the hypothesis of normality in the cultivar parameters obtained from synthetic data. When the p-value from the test was greater than 0.05, the parameters or their transformed versions were considered as normal.

2.4. Application of sensitivity analysis to simulate wheat yield with the most sensitive cultivar parameters

2.4.1. Field experiment

Results from the sensitivity analysis were used to simulate the wheat yield with the most sensitive cultivar parameters among all the cultivar parameters listed in Table 1. Out of the seventeen cultivar parameters used in the web based InfoCrop model six parameters namely TPOPT,

Helton et al., 2005). Sensitivity of a particular model output to a cultivar parameter was estimated by means of a partial rank correlation coefficient (Marino et al., 2008). Greater the definite value of the Partial Rank Correlation Coefficient (PRCC) the greater sensitive is the model output to the parameter characterised. The PRCC was considered significantly different from 0, when the p-value from the PRCC test was lesser than a primary level of 0.01. Changes in PRCC due to cultivar parameter rankings between any two treatments were determined by means of the

Table 3. Treatments considered for generating the synthetic data.

| Treatments	Details			
Locations (India, 4 levels)	Semi-arid region -Delhi (A), Hot dry sub humid region -Dharwad (B), Semi-arid region-Indore (C) and Hot sub humid region -Ranchi (D)			
Planting dates (3 levels)		**Early**	**Med**	**Late**
	Delhi	18-Oct	08-Nov	29-Nov
	Dharwad	18-Oct	08-Nov	29-Nov
	Indore	25-Oct	15-Nov	06-Dec
	Ranchi	25-Oct	21-Nov	18-Dec
Seed rate (kg/ha) (3)	87.5, 100, 125			
Year (10 levels)	2008 to 2017			
Irrigation (2 levels)	Potential, Moisture stress (Irrigation at CRI stage only)			
Temperature stress (2 levels) stress	Normal, +2 °C			
Total number of treatments (4 × 3 × 10 × 2 × 2)	1440			
Total runs (1440 × 1000)	1440000			
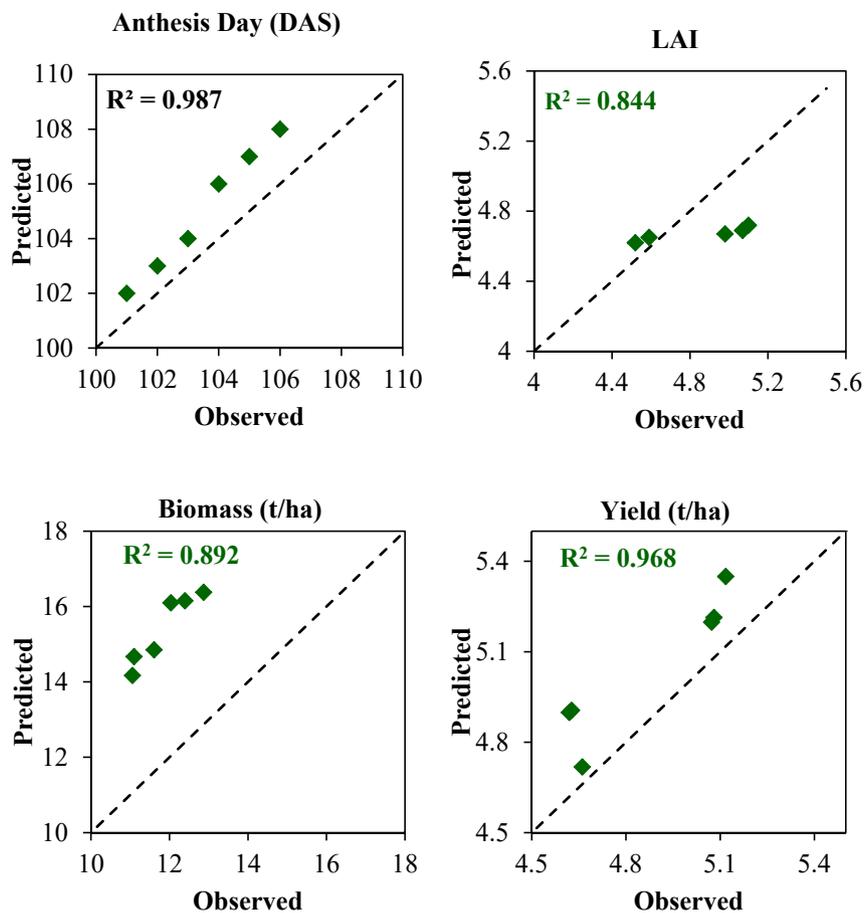
Figure 3. Calibration of Web-InfoCrop for (a) anthesis date, (b) LAI, (c) biomass and (d) yield.

TTVG, KDFMAX, GNOCF, POTGWT and PHOTOSENS were concluded as the most sensitive parameters. The web based InfoCrop model was then run with ten wheat cultivars (HD-2987, HD-77, PBW-343, PBW-175, HD-2967, HD-2781, HD-2985, HD-3043, C-306, PBW-502) grown under irrigated condition (with five irrigations at CRI, Tillering, Jointing, Boot leaf stage, Flowering and grain filling stages) and with recommended dose of nitrogen (150 kg/ha equal split at sowing, CRI and Booting stages). Field experiments were conducted during 2014–17 (for three years) to characterise the grain yield for wheat crop, in the experimental farm of Indian Agricultural Research Institute, New Delhi located at 28°35 N latitude, 77°12 E longitude and at an altitude of 228.16 m above mean sea level.

2.4.2. Calibration and validation

The model was calibrated (Figure 3) with the most sensitive cultivar parameters namely TPOPT, TTVG, KDFMAX, GNOCF, POTGWT and PHOTOSENS from the experiment conducted during 2014–15 for these cultivars. Other cultivar parameters were taken as default with slight adjustments within the range. The cultivar parameters used in the model are as given in Table 4. The calibrated model was then validated (Figure 4) for grain yield using the observed wheat yield (2015–16 and 2016–17). During calibration all the parameters other than LAI were over simulated, but during validation yield was better simulated than anthesis and biomass, this is because we have considered the calibration and validation for ten different

Table 4. Parameters for the most sensitive cultivar parameters.

	Parameters	TTVG ºC days	TPOPT ºC	KDFMAX ha soil/ha leaf fraction	POTGWT (mg/grain)	GNOCF storage organ/kg/day	PHOTOSENS
1	HD-2987	1012	25	0.52	46.8	17100	1
2	HD-77	957	26	0.49	47.5	13500	1
3	PBW-343	1067	26	0.55	45	22400	1
4	PBW-175	883	26	0.45	47	14500	1
5	HD-2967	975	26	0.5	46	24000	1
6	HD-2781	1159	25	0.6	48	12000	1
7	HD-2985	1030	26	0.53	45	20000	1
8	HD-3043	883	26	0.45	47	13700	1
9	C-306	1122	25	0.58	46.5	18500	1
10	PBW-502	1178	26	0.61	47	22000	1

wheat cultivars which differ considerably in their duration and biomass.

3. Results

3.1. Uncertainty analysis

3.1.1. General influence of cultivar parameter uncertainty

Cultivar parameter uncertainty caused potential model output ranges to vary: for total dry matter 0.5 t ha^{-1} to 20.327 t ha^{-1}, for grain yield 0.012 t ha^{-1} to 10.31 t ha^{-1} and crop duration 59–171 days, when all agro-ecological regions and years were considered. Under moisture stress condition maximum total dry matter reached 14.48 t ha^{-1}, 14.29 t ha^{-1}, 13.44 t ha^{-1} and 17.266 t ha^{-1} respectively in Delhi, Dharwad, Indore and Ranchi respectively. Under High moisture stress conditions, limited total dry matter values were simulated in Ranchi due to the high mean annual rainfall at this agro-ecological region (Table 2), which implied that the soils besides the distribution of rainfall possibly supported more influence on the effects of moisture stress. In general, uncertainty in cultivar parameters alone resulted in the inconsistency in model outputs. In the subsequent sections, we have explained the variations in the influence of cultivar parameter uncertainty as determined by cultivar and treatments.

3.1.2. Evaluation at potential level among years

Depending on the agro-ecological region, the means of potential total dry matter distributions ranged within 15.42 t ha^{-1} (Indore) and 20.327 t ha^{-1} (Delhi) (Table 5). This variation was within 3.5 t ha^{-1} and 8.85 t ha^{-1} at the similar respective agro-ecological regions, for the standard deviations of the distributions of total dry matter. Dissimilarities among the years were more distinct in agro-ecological regions at higher latitudes. The variation, (with increasing latitude) between the mean potential total dry matter in the maximum and minimum productive year

was observed to be 1.5 t ha^{-1}, 1.8 t ha^{-1}, 2.4 t ha^{-1} and 2.8 t ha^{-1} in Delhi, Ranchi, Indore and Dharwad respectively. Uncertainties in the allocations of total dry matter, as quantified by the standard deviations, related with parameter uncertainty were also greater at higher latitudes. This shows that, total dry matter levels were actually stable, in spite of being low in Dharwad. The standard deviation of potential total dry matter for the year with maximum variability contrasted from the most stable year was 1.4 t ha^{-1}, 1.9 t ha^{-1}, 2.1 t ha^{-1}, and 2.3 t ha^{-1}, in Dharwad, Indore, Ranchi and Delhi respectively. Although inter-annual changes in the standard deviations and means of the distributions of potential total dry matter were obviously dependent on latitude, their distributions were least influenced by agro-ecological region (Figure 5). Irrespective of the year under consideration, the coefficient of variation (CV) of potential total dry matter was nearly 42% in Dharwad, Indore and Ranchi. Delhi showed the highest CV range, 31–45% (subjected to the year).

3.1.3. Effect of growth conditions

As anticipated, the simulation of temperature stress, moisture stress and combination of both (moisture and temperature stress) lead to a significant decrease in the total dry matter and greater variability within the different years (Figure 5C and D). At all agro-ecological regions, potential cumulative distribution functions (CDFs) were more similar than moisture stress or high temperature stress and their combination of both moisture and high temperature CDFs, recommending that in the occurrence of stress whether moisture or temperature stress, final total dry matter uncertainty was much related to the year of study. Similarly, for potential production, among the years considered in this study, the mean total dry matter gap increased with the increase in latitude. This indicate that throughout the years of study, total dry matter under moisture stress was correspondingly more stable in Dharwad but highly variable in Delhi. Dissimilarities in mean total dry matter between the years with minimum and maximum rainfall were
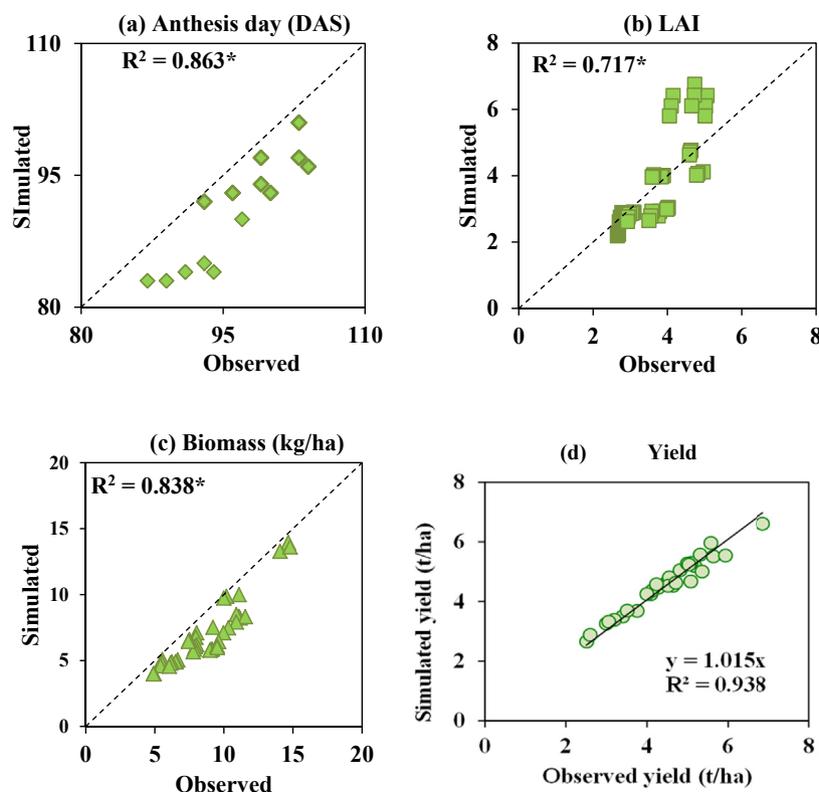

Figure 4. Validation of Web-InfoCrop model for (a) anthesis date (b) LAI (c) biomass and (d) yield.

Table 5. Values of grain yield, total dry matter and crop duration, based on 1440000 simulations (over 10 years of the study) for wheat.

	Delhi		Dharwad		Indore		Ranchi	
	Max	Min	Max	Min	Max	Min	Max	Min
DAS (days)								
P	171	70	140	63	147	67	155	80
W	163	66	135	59	132	66	153	81
PT	163	65	153	62	149	63	150	71
WT	156	63	146	59	136	62	148	72
Yield (kg/ha)								
P	10310.2	395.39	6640.7	335.95	7747.2	451.02	9148.1	117.43
W	6950.7	42.41	6089.3	182.65	6405.4	238.04	8930.6	169.91
PT	9184.4	311.46	3604.7	7.49	6600.4	181.80	8226.0	147.75
WT	6545.9	80.23	3462.1	12.00	5675.6	86.31	7956.1	317.37
TDM (kg/ha)								
P	20327.6	3090	15921.1	1212.9	15420.3	2445.0	18140.3	4814.8
W	14484.4	2562.3	14291.6	1058.7	13440.1	2006.3	17266.9	6023.1
PT	18600.8	991.71	10698.4	500.07	14438.9	819.7	16644.2	4581.6
WT	13436	776.19	10901.4	505.28	12647.2	731.39	16208.7	5224.7

about 3.6 times more than at potential production. Similarly, greater variability was observed in every individual distribution (Fig. 5C and D), Dharwad, had a high (82%) Coefficients of variations. Under moisture-stress conditions most CVs in total dry matter were higher than the observed (42%) at potential production. Inconsistency in rainfall at each agro-ecological region and soil variability within agro-ecological regions might be the main cause for the interactions between growth condition and agro-ecological region. In general, wheat grain yield at all agro-ecological regions showed parallel changes in uncertainty outcomes (Figure 5).
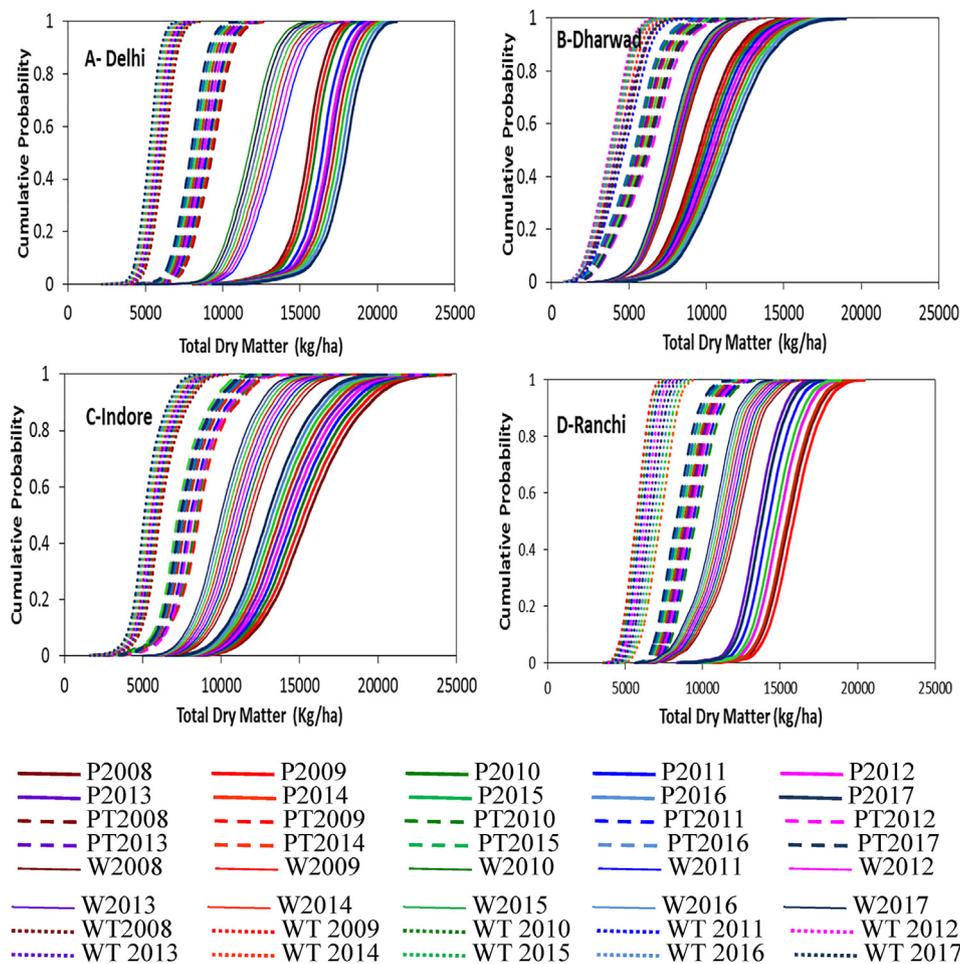
Figure 5. Cumulative distribution functions of wheat total dry matter over the 10 years of the study in hot, dry, semi-arid region -Delhi (A), hot dry sub humid region-Dharwad (B), Semi-arid region-Indore (C) and Hot Sub humid region -Ranchi (D). The influence of crop parameter uncertainty is represented by each line (which signifies one of the 10 years). P = Potential, W = water-limited, T = high temperature WT = combined water and high temperature stress conditions.
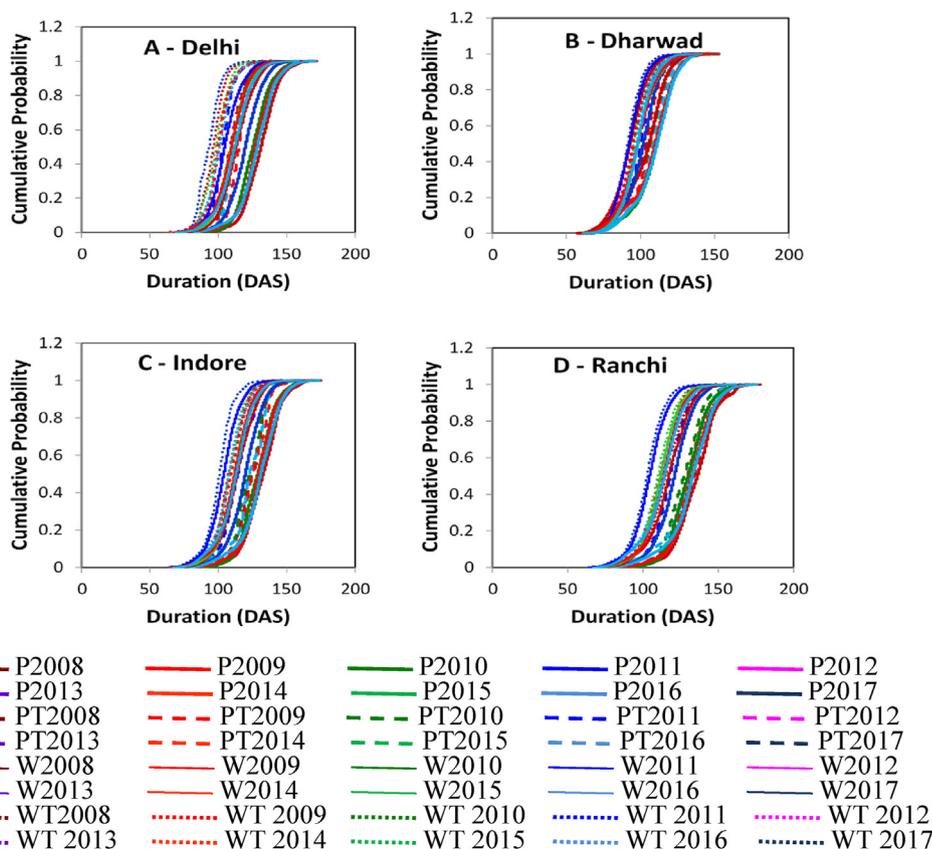
Figure 6. Cumulative distribution functions of wheat total crop duration over the 10 years of the study in hot, dry, semi-arid region -Delhi (A), hot dry sub humid region-Dharwad (B), Semi-arid region-Indore (C) and Hot Sub humid region -Ranchi (D). Each line represents one of the 10 years and shows the effect of crop parameter uncertainty. P = Potential, W = water-limited, T = high temperature WT = combined water and high temperature stress conditions.

3.1.4. Crop duration uncertainty

This study showed that, for the simulation of wheat crops, growth condition did not influence the crop duration uncertainty outcomes, as the influence of moisture stress on growth period was not significantly modelled (Figure 6). In addition, uncertainty in crop duration was more evident in Delhi and Ranchi than in Dharwad due to the stability in crop duration both across and within years. By means of the yearly distributions of crop duration, the minimum and maximum duration differed by 1 day in Dharwad and Indore. On the other hand, this difference was 16 days, in Delhi. The yearly distributions were depicted by CVs stretching from 14 to 16% in Dharwad and 7–20% in Delhi.

3.2. Sensitivity analysis

3.2.1. Influence of year on parameter ranking

For all model outputs at all agro-ecological regions, ranking of cultivar parameters was not influenced by the year of study. This inference indicates that variations in the yearly distributions of model outputs (Figure 5) did not reveal considerable differences in ranking of cultivar parameters. For each combination of agro-ecological region and crop growth condition, the TDCC test of differences within parameter rankings in various years gave a p-value predominantly lesser than 0.05. Thus, in this study the stability of parameter rankings showed that model output sensitivity to cultivar parameter uncertainty was orthogonal to weather variability among the different years considered.

3.2.2. Association between cultivar parameter and yield

PRCC values for the most statistically significant cultivar parameters for final grain yield, for all the ten years of the simulation at all the four

crop growth conditions and four agro-ecological regions is given in Figure 7. At all the agro-ecological regions considered in this study, under moisture stress condition, KDFMAX was the most essential cultivar parameter for yield, with the maximum PRCC of 0.82, on the basis of two important causes. First, KDFMAX defines the amount of leaf canopy cover and it also decides the amount of solar radiation available for canopy photosynthesis, therefore had an important role in the estimation of crop moisture stress. But in case of the crop temperature stress, the important parameter is TTVG and not KDFMAX. The order of the remaining parameters, TPMAXD, RGRPOT, RUE, SensHighTemp, TTGERM, SensLowTemp, TTGF, ZRTPOT, IndexGreen varied with agro-ecological region. In general TPOPT seemed to be more influential at lower latitudes (Dharwad and Indore) while PHOTOSENS was more significant at high latitudes (Delhi and Ranchi). Rankings for grain yield and total dry matter were analogous. The main contrast within these two model outputs was that for grain yield, an important cultivar parameter, GNOCF, appeared with maximum PRCC values of 0.70 in Ranchi (Figure 7), this was anticipated as the storage organ is an important component of grain yield. This reveals the fact that irrespective of the agro-ecological region and growth condition TPOPT, TPMAXD, RGRPOT and NMAXGR were negatively associated with grain yield while TTVG, KDFMAX, POTGWT, and GNOCF were positively associated.

3.2.3. Association between cultivar parameter and total dry matter

At all the crop growth conditions namely, potential, moisture stress, high temperature and moisture & high temperature stress conditions, TTGERM, IndexGreen, SensLowTemp, SensHighTemp were not significant (less than 0.02 p-value from PRCC test) on total dry matter at harvest in all four agro-ecological regions (Figure 8). In Delhi and Ranchi, the

sequence of preference of the parameters at potential production condition was TTVG, PHOTOSENS, TPOPT, GNOCF, NMAXGR, KDFMAX, SLA, POTGWT, TPMAXD, RGRPOT, RUE, SensHighTemp, TTGERM, SensLowTemp, TTGF, ZRTPOT, and IndexGreen. An analogues ranking was perceived in Indore and Dharwad. Total dry matter showed a positive relationship with TTVG, KDFMAX and GNOCF. However, was negatively related to TPOPT and PHOTOSENS (Figure 8).

3.2.4. Association between cultivar parameter and crop duration

Growth condition did not affect crop duration sensitivity because as stated before for uncertainty analysis, Web InfoCrop - wheat even though accounts for the influence of moisture stress on growth duration, results were not significant. Even though the sensitive parameters were not influenced by agro-ecological region, but their rankings were. Cultivar parameters with PRCC values greater or equal to 0.1 (Figure 9) were PHOTOSENS, TTVG, TPOPT, GNOCF, POTGWT, TPMAXD, SLA, NMAXGR, RGRPOT, KDFMAX, SensHighTemp, SensLowTemp, IndexGreen, ZRTPOT, RUE, TTGERM, TTGF in this order in Delhi. However at Indore and Dharwad, TTVG was ranked second instead, underlying the influence of TTVG in warmer regions. For example, in Delhi and Ranchi, TTVG had a PRCC of 0.33 while PHOTOSENS had a PRCC of 0.434. In Dharwad, the order of significance of the PRCC was opposite with 0.29 for PHOTOSENS and 0.33 for TTVG. Likewise, TOPT, TPMAXD and PHOTOSENS were negatively related to crop duration while TTVG, POTGWT, GNOCF and NMAXGR were positively related to crop duration

(Figure 9). The uniformity of these associations across agro-ecological regions was an evidence, to prove that they revealed the model structure rather than a particular agro-ecological region. The intensity of these associations differed, yet, significance of each parameter in the sensitivity analysis was characterized based on agro-ecological region, growth condition and model output.

3.3. Simulation of wheat yield with the most sensitive cultivar parameters

Crop simulations for ten cultivars of wheat were conducted in two ways. First crop simulation by incorporating all the cultivar parameters of the model and second by incorporating only the most sensitive cultivar parameters namely TPOPT, TTVG, KDFMAX, GNOCF, POTGWT and PHOTOSENS, with the model based default values for the rest of the cultivar parameters. In both the cases the model was initialized prior to wheat sowing in the cropping season of 2014–15. The cultivar parameters used for the simulation of Web InfoCrop - wheat are given in Table 4. In both the cases for calibrating the Web InfoCrop - wheat model, the parameters were adjusted for the dataset of 2014–15 for all cultivars. The calibrated model was implemented to generate data on wheat yield.

After calibration of the model for wheat 2014–15, it was validated for 2015–16 and 2016–17, in both sets of simulation (First case: incorporating all the cultivar parameters of the model and second case: by
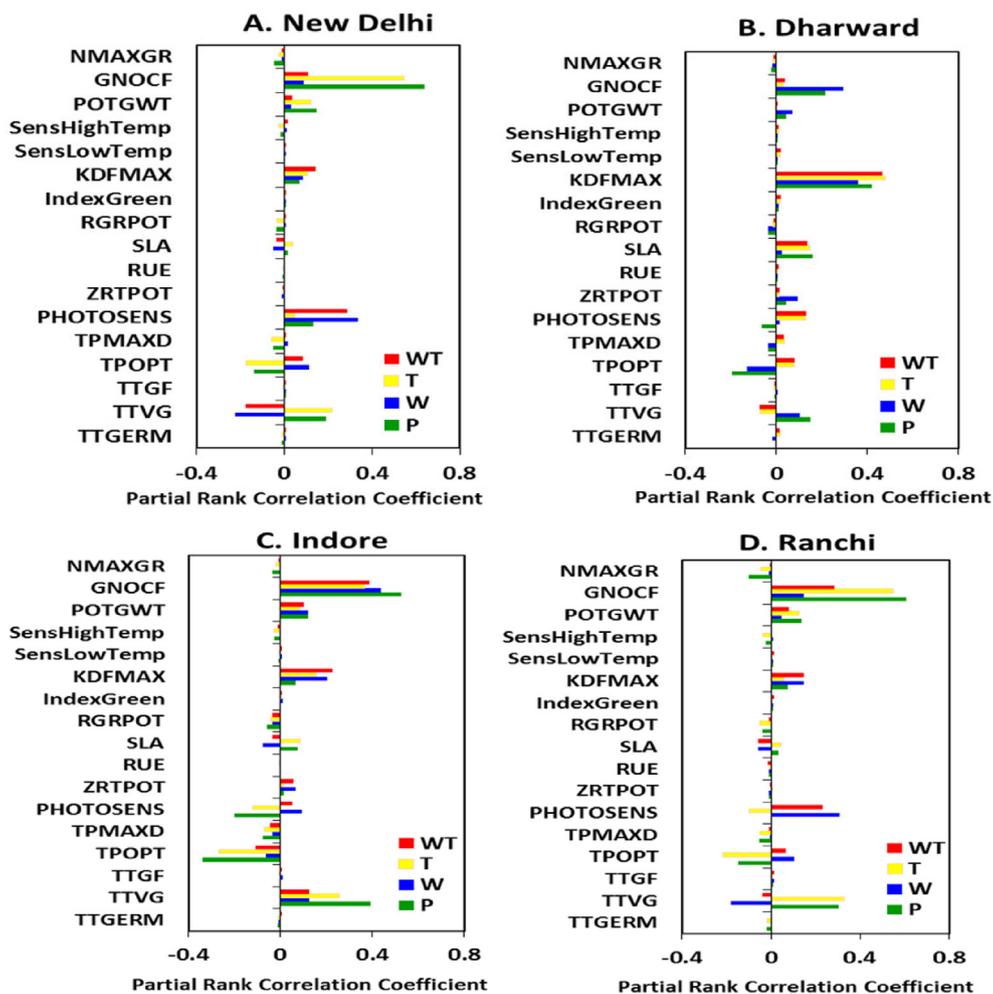

Figure 7. Partial rank correlation coefficients among potential (P), water-limited (W), temperature elevated (T), water limited and temperature elevated (WT) among wheat grain yield and InfoCrop-cultivar parameters in semi-arid region -Delhi (A), hot dry sub humid region-Dharwad (B), Semi-arid region - Indore (C) Hot Sub humid region - Ranchi (D) (P < 0.05 = 0.051, P < 0.01 = 0.066).
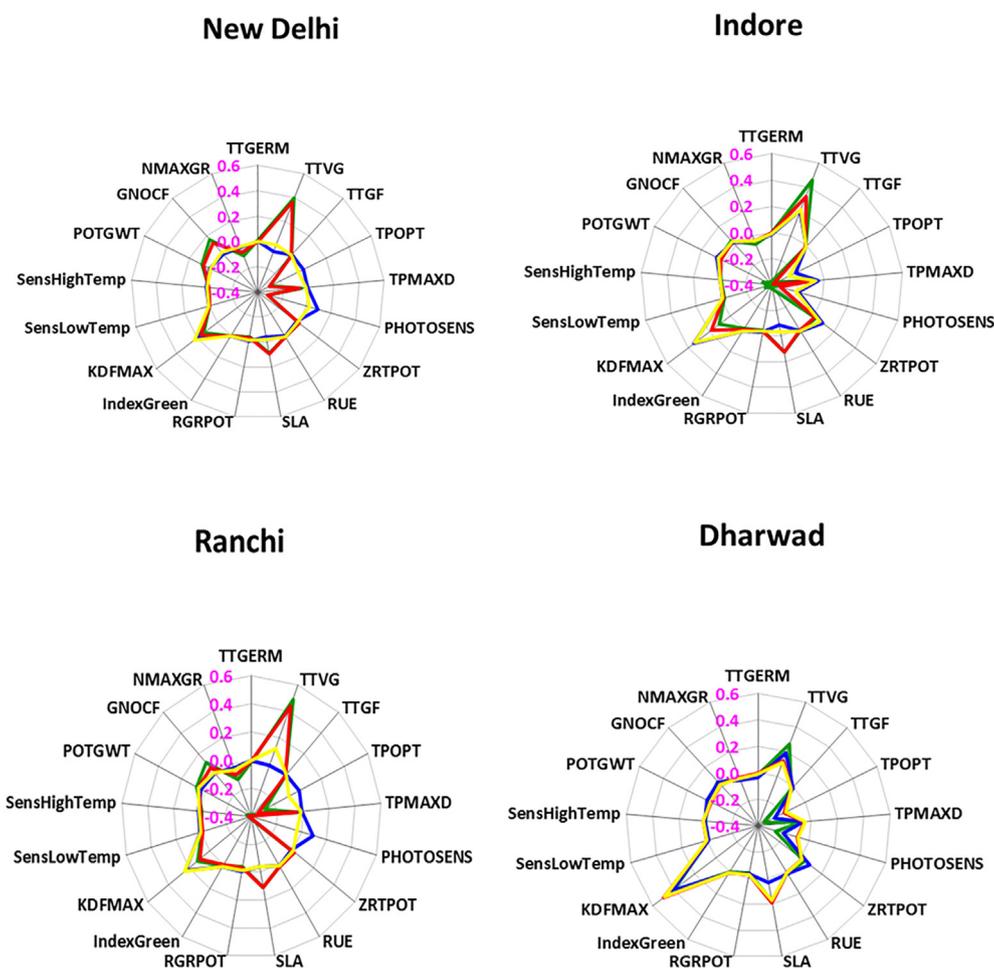
Figure 8. Correlation of cultivar parameters with Biomass (P < 0.05 = 0.051, P < 0.01 = 0.066).

incorporating only the most sensitive cultivar parameters). Comparisons of observed and model simulated results with respect to yield are shown in the Figure 10. Evaluation of model performance was also carried out by using different statistical tools.

The model responded well to both types of simulation with significant R^2 (~0.9) values between observed and predicted. Also, other statistical tools, viz., RMSE (<8%), MAE (~6%) and MBE (~6%) were much higher under both simulation using all cultivar parameters and with only the sensitized cultivar parameters (Table 6). RMSE for grain yield was 5.3 and 7.3% of the observed mean. These low values of RMSE indicated that the Web InfoCrop - wheat model when simulated using most sensitized cultivar parameters is still accurate at predicting wheat yield. Also, the higher R^2 values (~0.9) for yield indicate that the model is fit for predicting yield when it is simulated using the most sensitive cultivar parameters.

4. Discussion

Sensitivity analysis outcomes showed that TTGERM (applied to estimate time of germination and emergence) did not have a substantial function in the simulation of total dry matter, grain yield or crop duration within their magnitude of uncertainty. These results were in agreement with the observations made by previous researchers (Dzotsi et al., 2013) where thermal time methodology did not simulate germination properly. Within the operative cultivar parameters selected, they could be classified into three types: parameters directly associated to total dry matter accumulation (PHOTOSENS, GNOCF, POTGWT, NMAXGR, IndexGreen, ZRTPOT, RUE), LAI parameters (KDFMAX, SLA, RGRPOT), and temperature parameters (TTVG, TTGERM, TTGF, TPMAXD, SensHighTemp,

SensLowTemp, TPOPT). Further, some parameters, on account of their precise role in defining targeted growth conditions or model outputs, they were always important in those growing conditions. Restricted model uncertainty and sensitivity of this kind was very much confirmed by Jin et al. (2018) and by Jones et al. (2012), in their study on uncertainties in simulating crop performance under low input production systems.

Total dry matter and grain yield were much sensitive to TTVG as this cultivar parameter structured the transformation of accumulated degree days into dry matter in the model. Total dry matter and grain yield were also extremely sensitive to LAI parameters because they demarcated the maximum ability of the canopy to harness light (KDFMAX). The sensitivity of crop duration to PHOTOSENS and TTVG was primarily because of the maximum correlation between TPOPT and SLA. In general, crop duration has been observed to be sensitive to crop growth parameters in crop models (Pathak et al., 2007). Similarly, in this investigation, accumulation of thermal time and the temperature parameters were largely dominant on crop duration. Confalonieri et al. (2010) observed TTVG to be the most important cultivar parameters, in their study. The large sensitivity of thermal time by means of the base temperature was similarly emphasized in the sensitivity analysis by Dzotsi et al. (2013); Richter et al. (2010), they described the parameter to define the thermal time to be of significant prominence in a wheat crop model.

This investigation based on Sensitivity Analysis, clearly indicate that a small number of parameters in crop model are extremely sensitive, on the other hand many of the parameters have a sensitivity that is two or three orders of degree lesser (Jing et al., 2013; Liu et al., 2019; Jabloun et al., 2018). We also identified the most salient activities such as leaf area dynamics and phenological growth for healthy and sustained plant development. Physiological and morphological parameters were low in
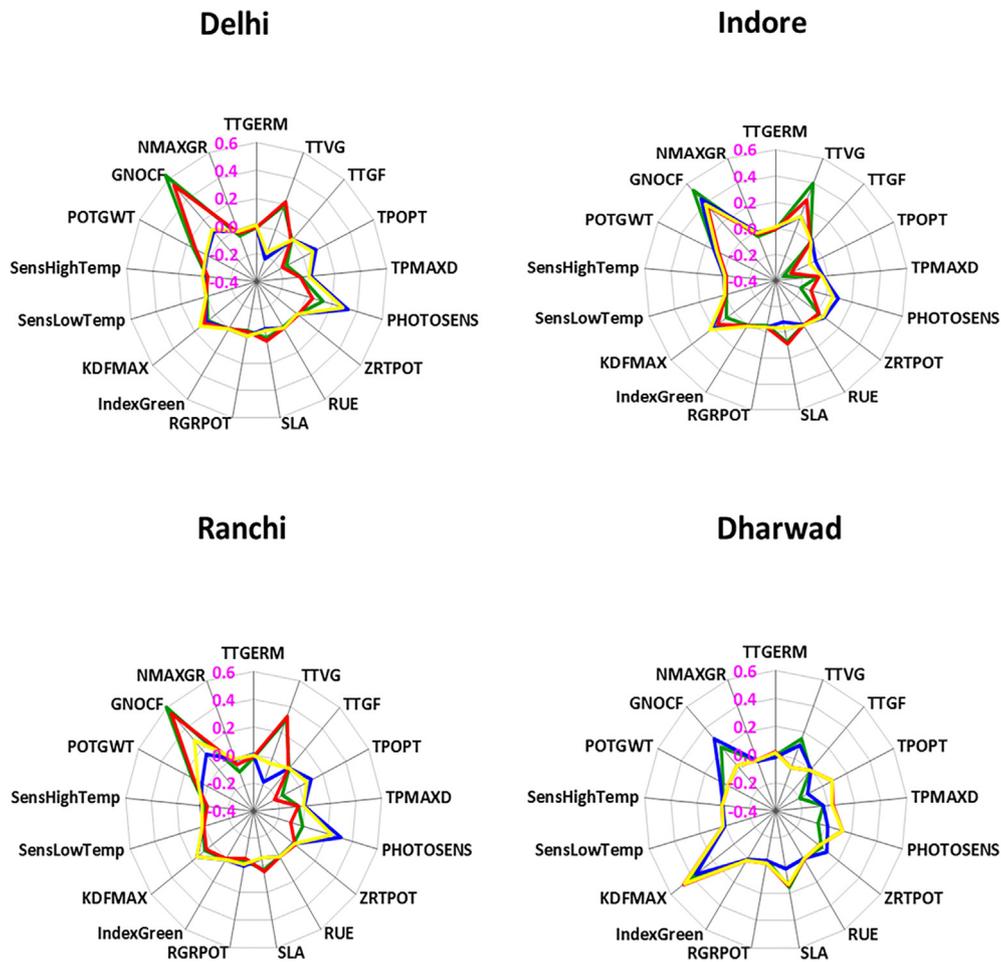
Figure 9. Correlation of cultivar parameters with yield (P < 0.05 = 0.051, P < 0.01 = 0.066).

the rank but were sensitive to environmental modifications on account of agro-ecological region and stress effects. In the four dissimilar agro-ecological regions characterised in this study, the outcomes of SA are obviously diverse for the same crop however in different growing and stress conditions.

This agrees with the inference of Jabloun et al. (2018) and Francos et al. (2003) that sensitivity denotes to particular conditions and is not a common feature of a model, despite, whether a specific or common technique is used to determine the parameter sensitivity. Nevertheless, both the environmental and the methodological effects on the SA did not produce a significant difference in the ranking of the parameters in this study, therefore conforming the statement that specific parameter classes and particular parameters are the most crucial for a particular wheat cultivar in the four diverse tested agro-ecological regions and

varied stress conditions. The results obtained from executing the model for simulating the wheat yield clearly showed that the simulation of wheat yield using sensitive cultivar parameters are comparable to those of the simulation results using all the cultivar parameters.

Present investigation focused mainly on cultivar parameter uncertainty and examined the effects of growth conditions and environmental conditions on model outputs. Uncertainty in model inputs owing to locations was not quantified by us owing to spatial variations in soil properties and tremendously varying weather inputs like rainfall. Effects of these inputs to the model output uncertainty in general could be estimated only when they were deemed to be uncertain. Besides, the influence of longer period weather variability demonstrated the importance of the year on the outcomes of uncertainty and sensitivity analysis
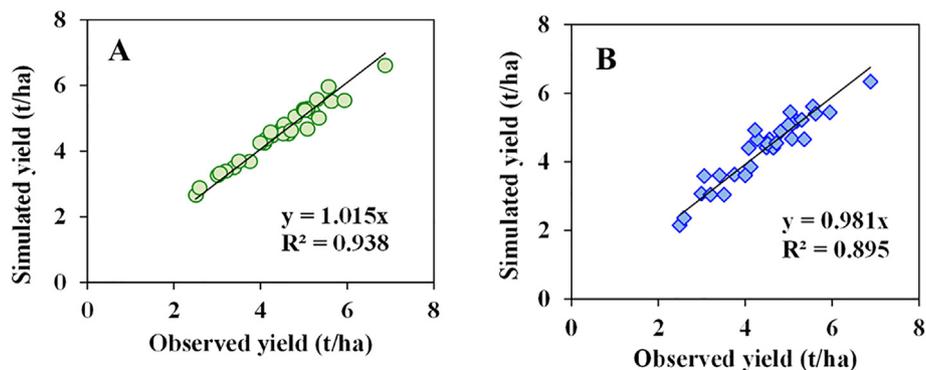

Figure 10. Validation of observed yield in simulation by inputting (A) all the cultivar parameters (B) only the most sensitive cultivar parameters.

Table 6. Evaluation of yield simulation outputs using different statistical tools.

		All cultivar parameter	Sensitised cultivar parameter
1	Observed mean (t ha^{-1})	4.449	
2	Predicted mean (t ha^{-1})	4.543	4.379
3	MAE (t ha^{-1})	0.261	0.289
4	MAE (%)	5.8	6.6
5	R^2	0.938	0.895
6	RMSE (t ha^{-1})	0.241	0.319
7	RMSE (%)	5.3	7.3
8	ME (%)	8.92	9.43
9	MBE (t ha^{-1})	0.681	0.657
10	MBE (%)	1.5	1.6

(Jing et al., 2013; Liu et al., 2019; Jabloun et al., 2018). Results of this study reinforced the identification of parameters for which precise measurement is required for dependable simulation of crop performance. Future work will be on analysing the sensitivity of weather and soil inputs within the range of variation characteristic for the study region. Additional investigation is required on the issues pertaining to sensitivity analysis (a) the variation of the parameters that are too small in relation to the mean value; or (b) parameters that are not considered due to a priori neglection of a process. At the end, parameter selection should not result in the over-parameterisation of the model. SA should be explored on the possibility of omitting parameters that are closely linked, complementary, like sequential growth stages, partitioning or phenology.

5. Conclusions

Inconsistency in total dry matter, crop yield and crop duration simulated by Web InfoCrop - wheat was significantly related to uncertainty in cultivar parameter. While the model adopts basic associations to characterize dry matter production and LAI, the type and degree of the associations within cultivar parameters and model outputs were reliable with characteristic responses of crop growth processes to the environment. Outcomes of the sensitivity analysis showed that the model's outcomes to cultivar parameter uncertainty were not influenced by the year under consideration however was dependent on growth conditions and agro-ecological regions. A huge number of cultivar parameters were observed to be prevailing on the model outputs considered with their relative importance varying with the state considered. As common practice of crop model involves one or a combination of these conditions, it is adequate to infer that all 15 significant cultivar parameters are necessary and vital for accurate crop evaluations. Likewise, inconsistency in model outputs may be dependent on how the cultivar parameters' depictions signify the precise parameters' uncertainty. Evaluating parameter uncertainty extents is usually complicated by the discrepancy in quantification techniques adopted, may increase measurement and quantification errors. The representation of cultivar parameter uncertainty through a more multifarious crop model not only increased the statistical relationships acquired but also assist in the determination of correlations within cultivar parameters employed in this investigation. These correlations ascertain, the need for precise combinations of cultivar parameters for better crop simulations.

Declarations

Author contribution statement

P. Krishnan: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.

Pragati Pramanik Maity, Monika Kundu: Performed the experiments; Analyzed and interpreted the data.

Data availability statement

The authors do not have permission to share data.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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