



RESEARCH ARTICLE

# Decision support system for agrotechnology transfer-crop environment resource synthesis model for developing genetic coefficients to simulate late-sown wheat crop for Indo-Gangetic Plain, India

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## Abstract

The Indo-Gangetic Plains (IGP) account for nearly 75 % of India's wheat production; however, more than 40 % of farmers in the region practice delayed sowing of wheat, resulting in substantial yield reductions. The research aim were to develop the genetic coefficient parameters and calibrate the model under late sown wheat growing region of IGP, in India. Decision support system for agrotechnology transfer (DSSAT) is a comprehensive software platform for the crop environment resource synthesis (CERES) wheat model. The CERES wheat model has been simulating crop growth and development in response to climate, soil, genotypes and management at various temporal and spatial scales. The required files of the model was prepared using the input data such as daily weather data, soil characteristics, crop management, crop phenology and productivity. The genetic coefficient codes were developed through the trail and error approach. The CERES wheat model was calibrated with two years data (i.e., 2008–2009 and 2009–2010) and validated through a separate data of 7 years long-term field experimental trail from 2011–12 to 2017–18. The model's performance was evaluated using difference statistical indices i.e., root mean squared error (RMSE), normalised root mean squared error (NRMSE), mean absolute error (MAE) and D-index. Crop phenology (appearance of anthesis days and physiological maturity days) and productivity variables (grain yield and straw yield) were simulated using the calibrated model. The model effectively simulated trends in phenological stages namely appearance of anthesis days, physiological maturity, grain yield and straw yield for wheat cultivars i.e. HUW 243, HUW 510, Kundan and PBW 373. The values across all variables were indicated excellent agreement between simulated and observed data with deviations of less than 5 %, except for straw yield 9.15 %. The successfully calibrated model and the developed genetic coefficients provide a reliable tool for assessing the impact of environmental factors on late-sown wheat production in the region.

**Keywords:** calibration; crop environment resource synthesis; decision support system for agrotechnology transfer; genetic coefficients; wheat

## Introduction

India's population is over 1.45 billion, making it world most populous country in the world that surpassing China (1) but India has only 2.4 % of the world's land (2). Supply rising cereal demand amidst biotic-abiotic stresses is a major challenge along with necessitating sustainable agricultural practices. The cereal demand of India is projected to reach 202 million tonnes by years 2035–36 and 2,014 million tonnes by 2047–48 (3). The rice-wheat cropping system of the Indo-Gangetic Plains (IGP) is a major cereal producing system, as the region covers about 13 % of the country's total geographic area and produces approximately 75 % of its wheat and 45 % of its rice (4–7). Farmers of the IGP are recommended to sow wheat between 15 and 25 November to enable the crop to escape

terminal heat stress and protect grain yield (8, 9). In this approach, crop get additional time to mature ahead the terminal heat than delay sowing (10). Despite this, the majority of farmers are unable to sow wheat within recommended sowing window. A numerous reason are delay sowing of wheat crop such as rice crop did not achieved its physiological maturity still standing, additionally farmer think that they sow on time, lack of irrigation, water logging, etc.

All these things directly associated with delayed wheat sowing (10). Due to their reliance on monsoon and canal irrigation and the challenges stood by floods and waterlogging, numerous farmers continue to grow long-duration rice cultivars also. Consequently, more than 40 % of farmers delayed sown of the wheat crop (10). It accounts for about 40 % of the wheat-growing

area in the IGP and is a major contributor to wheat production (11). Since 1850, the Earth's average temperature has risen by approximately 0.06 °C per decade (12). It is expected that IGP face some of the largest negative impacts on crop phenology and yields due to warming temperatures (13–15). In delay wheat sowing condition, grain yield declined by 399 kg ha<sup>-1</sup> per 1 °C rise in maximum temperature during 50 % flowering to maturity stage using decision support system for agrotechnology transfer (DSSAT) crop environment resource synthesis (CERES) model (15–17). Farmers are also conscious of the sudden rise air temperature during the last week of March and it is time of grain filling and elevated temperature reduce grain number and weight (18, 19).

A substantial body of studies have focused on developing genetic coefficients, calibrating models under optimum conditions and its application for simulating the environmental impact, crop management and develop genetic coefficient of cultivars; however, the present study specifically focuses on developing genetic coefficients and calibrating the CERES-wheat model for more than 40 % of delayed sowing of wheat crop. This study assists to researchers and policymakers to understand how shifts in planting time affect crop growth, yield, more accurate in crop yield forecasting and resilience to climate variability. This information is essential for optimising sowing windows, improving resource-use efficiency and sustaining wheat productivity and food security, especially in regions like the IGP.

## Materials and Methods

### Study area

Numerous field experiments were conducted on wheat crops as the part of the forecasting agricultural output using space, agro-

meteorology and land based observations (FASAL) project at the Agricultural Research Farm (ARF) of Banaras Hindu University (BHU), Varanasi, India from 2009–10 to 2010–11. The field experiment were laid out at a latitude of 25° 15' 17.5104" and a longitude of 82° 59' 34.011", with 84 m AMSL. The climatic condition of Varanasi is classified as humid subtropical (Cwa) according to the Köppen classification system (20). Monthly observed weather parameters (21) air temperature maximum, minimum and rainfall (mm) were presented in Fig. 1. These data are growing period of wheat crop from 2011–12 to 2017–18. Soil file for DSSAT model was created with the soil data that is presented in Table 1. The soil has very deep (> 100 cm soil depth), Alluvium geology, moderately well drain, Fine loamy soil textural class with Typic Haplustepts.

### Data and analysis

Statistical indices i.e. root mean squared error (RMSE), normalised root mean squared error (nRMSE), mean absolute error (MAE) and D index were used to evaluate the model's performance during calibration and validation.

#### Root mean square error

This statistical index commonly applied to measures the deviation between simulated and observed values. The studies applied the RMSE index for both the calibration and validation of models (22, 23). The unit of the RMSE is the same as that of the parameter. However, a limitation of RMSE is that it can not be used to compare two different variable with different units, such as anthesis days and grain yield in plants (24). For this condition, suggested that use the nRMSE as a relative measure for evaluating different models (25). The formula of RMSE is given in Eqn. 1.

$$RMSE = \sqrt{[(\sum P_i - O_i)^2/n]} \quad (\text{Eqn. 1})$$

**Table 1.** Soil parameters used for the calibration and validation of decision support system for agrotechnology transfer crop environment resource synthesis wheat model

| Soil depth (cm) | Soil horizon | SLL  | SDUL | SSAT  | Bulk density (Mg/m <sup>3</sup> ) | Soil organic carbon (%) | Clay (%) | Silty (%) | Sand (%) | Soil water pH | CEC cmol(+)/kg |
|-----------------|--------------|------|------|-------|-----------------------------------|-------------------------|----------|-----------|----------|---------------|----------------|
| 5               | Ap1          | 0.15 | 0.28 | 0.43  | 1.44                              | 0.49                    | 23       | 32        | 45       | 7.5           | 15             |
| 15              | Ap2          | 0.16 | 0.28 | 0.434 | 1.43                              | 0.48                    | 24       | 33        | 43       | 7.2           | 14             |
| 30              | Bw1          | 0.17 | 0.29 | 0.434 | 1.43                              | 0.45                    | 26       | 33        | 41       | 7.6           | 13             |
| 60              | Bw2          | 0.17 | 0.29 | 0.429 | 1.45                              | 0.20                    | 28       | 34        | 38       | 7.8           | 12             |
| 90              | Bw3          | 0.17 | 0.30 | 0.436 | 1.43                              | 0.17                    | 28       | 37        | 35       | 8.0           | 11             |
| 120             | Bw4          | 0.18 | 0.31 | 0.436 | 1.43                              | 0.16                    | 30       | 36        | 34       | 8.1           | 10             |
| 150             | C1           | 0.17 | 0.28 | 0.422 | 1.47                              | 0.15                    | 22       | 18        | 60       | 8.2           | 8              |
| 180             | C2           | 0.15 | 0.27 | 0.411 | 1.50                              | 0.11                    | 15       | 17        | 68       | 8.3           | 5              |

SLL: Soil lower limit (also known as wilting point); SDUL: Soil drained upper limit (also known as field capacity); SSAT: Soil saturation water content; CEC: Cation exchange capacity.

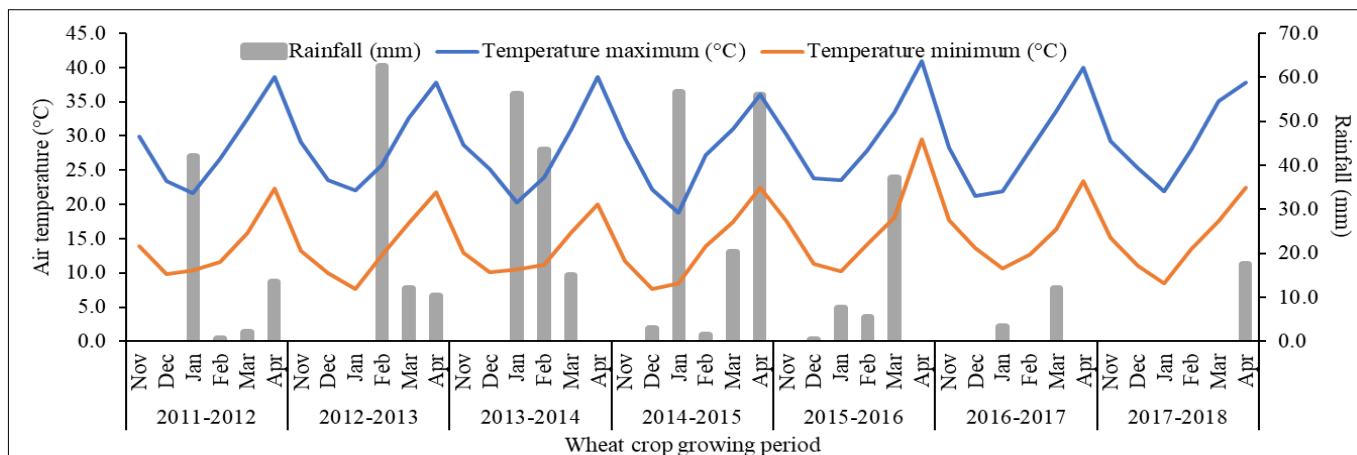


**Fig. 1.** Monthly weather parameters maximum and minimum temperature, rainfall during the wheat growing seasons from 2011–12 to 2017–18.

Where:  $P_i$  = predicted value,  $O_i$  = observed value,  $n$  = number of observations

### Normalised root mean square error

Measuring of a fraction of the total range effectively by using nRMSE of simulated output. The nRMSE allows for easier comparison across models datasets with varying scales (24, 26). The formula of nRMSE is given in Eqn. 2:

$$\text{nRMSE} = \text{RMSE}/\bar{x} \quad (\text{Eqn. 2})$$

Where  $\bar{x}$  is the mean of the observed values.

### Mean absolute error

It is a metric used to measured the errors that occur when comparison of two observations of the same event. A comparisons example is the comparison of the absolute difference between predicted and observed versus (24). The formula of MAE is given in Eqn. 3:

$$\text{MAE} = \sum |y_i - x_i|/n \quad (\text{Eqn. 3})$$

Where:  $y_i$  = observed value,  $x_i$  = predicted value,  $n$  = number of observations

### D Index

The D Index is intended to be a descriptive, bounded and relative measure that is widely used for cross-model comparisons (24, 27). It is also important for determining how much of the RMSE is "systematic" versus "unsystematic" as a good model should be able to explain most of the significant trends of patterns in the observed data. The formula of the D Index is given in Eqn. 4:

$$D = 1/2p \sum_{i=1}^n \beta |p_i - \bar{p}| \quad (\text{Eqn. 4})$$

Where

$\bar{p}$  = predicted value,  $p_i$  = mean of predicted values,  $\beta$  and  $p$  = parameters (these should be defined more clearly if available),  $n$  = number of observations

### Decision support system for agrotechnology transfer

As of Version 4.8.2, DSSAT is a big platform that includes crop simulation models for over 42 crops. The model, which allows sub-models to be linked for agricultural system simulation, was created by the international benchmark sites network for agrotechnology transfer (IBSNAT) in the United States. The system includes soil, weather, crop management, experimental data, utilities and application programs as part of its file and database management framework. The models simulate the day wise growth, crop stages and yield of crops in relation to soil-plant-atmosphere dynamics (28).

### Crop environment resource synthesis model description

Wheat yield research project of the United State Department of Agriculture-Agricultural Research Service (USDA-ARS) was initially sponsored the development of the CERES simulation model (29). Later, DSSAT was updated to include the CERES model and cropping system (30). The CERES-wheat model simulates key environmental factors that influence wheat growth, development and yield including weather, major soil properties, soil type and crop management. The CERES-wheat model requires inputs related to agricultural management, plant traits, soil characteristics and climatic conditions. The minimum weather data inputs include daily solar radiation, rainfall (mm) and maximum and minimum air temperatures (31). A field experiment on wheat was conducted on a soil classified as fine-loamy, mixed mineralogy, hyperthermic and typic haplustepts. Fertiliser was applied at recommended doses:

nitrogen (120 kg ha<sup>-1</sup>), phosphorus (80 kg ha<sup>-1</sup>) and potassium (60 kg ha<sup>-1</sup>). On the initial day of the of the simulation, the model also incorporated precipitation, saturated soil water status and initial soil water content. The model file includes crop genetic coefficients for traits such as photoperiod sensitivity, duration taken for grain-filling, mass to grain number conversion, rates of grain filling and vernalisation (32).

### Calibration

Wheat cultivars HUW 243, HUW 510, Kundan and PBW 373 were calibrated using separate crop data sets of years 2009–10 and 2011–12. The details steps for calibration of model are presented in Fig 2. Daily weather parameter i.e. temperature maximum and minimum (°C), rainfall (mm) and sun shine hours were collected from Agrometeorology Observatory, BHU, Varanasi for creation of DSSAT format Weather file. The genetic coefficients of wheat cultivar were calculated using recommended doses of fertiliser (RDF) and irrigation. Development of the genetic coefficient of wheat cultivars has been done trail and error method. The resulting coefficients were then used for subsequent model validation and application.

### Validation

The validation process was completed using a new data set from the experimental years 2012–13 to 2017–18. All observed data were collected from the FASAL project, Agro-Meterological Field Unit (AMFU), BHU, Varanasi, India. The flow chart of model calibration and validation are depicted in Fig. 2. For simulation purposes, standardised management practices were followed, including sowing dates, crop spacing, irrigation schedule and quantity and timing of fertiliser application. The CERES model validated using parameters such as days to anthesis, days to physiological maturity, grain yield (kg ha<sup>-1</sup>) and straw yield (kg ha<sup>-1</sup>) (33). Statistical methods - namely RMSE, nRMSE, MAE and the D Index were used to evaluate the performance model. Table 2 presents the genetic coefficients derived for the wheat cultivars.

**Table 2.** Genetic coefficient parameters developed for wheat cultivars

| Code  | Coefficient value |         |        |         |
|-------|-------------------|---------|--------|---------|
|       | HUW 234           | HUW 510 | Kundan | PBW 373 |
| P1V   | 20                | 20      | 20     | 20      |
| P1D   | 80                | 75      | 70     | 65      |
| P5    | 750               | 725     | 695    | 690     |
| G1    | 25                | 26      | 24     | 22      |
| G2    | 38                | 36      | 38     | 40      |
| G3    | 1.1               | 1.3     | 1.1    | 1.2     |
| PHINT | 95                | 90      | 100    | 105     |

P1V: optimum vernalising temperature required for vernalisation (days), P1D: photoperiod response (% reduction in development rate per 10 h<sup>-1</sup> drop in photoperiod), P5: grain filling stage duration in growing degree days (gdd), excluding lag, G1: kernel (grain) number per unit canopy weight at anthesis (#/g), G2: standard kernel size (weight of 1000 grains) under optimum conditions (mg), G3: standard non-stressed mature tiller weight, including grain (g dry weight), PHINT: interval between successive leaf tip appearances in gdd.

## Results and Discussion

### Anthesis days

The ability of the model to predict anthesis days is crucial to its overall accuracy and usefulness. The results of observed and simulated are presented in Table 3. In field experiment trail, anthesis days taken to appearance were ranged from 74 to 83, with a minimum of 74 days taken by two cultivars HUW 234 and HUW 510. While, maximum 83 days taken to appearance of anthesis by

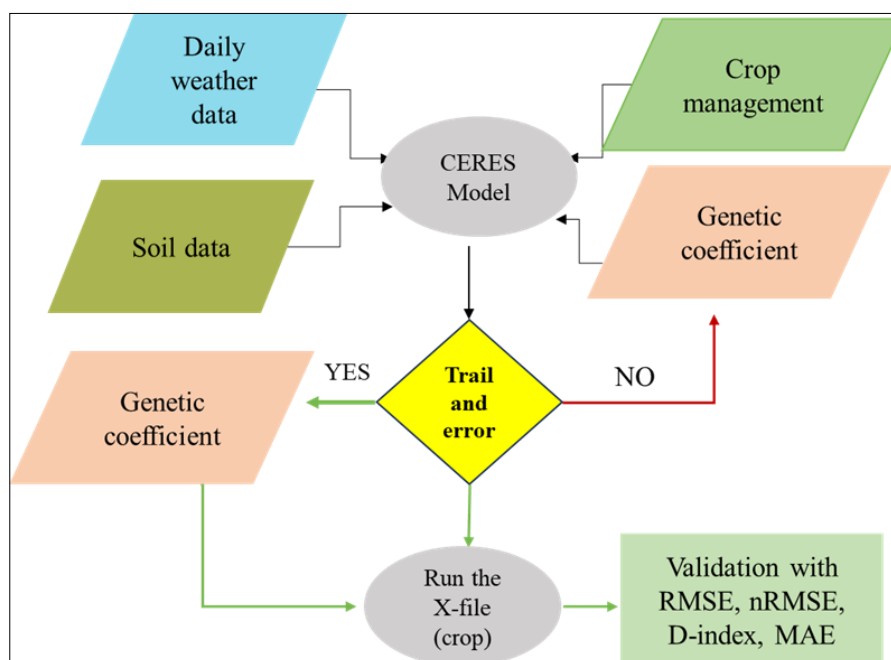


**Fig. 2.** Calibration and validation process flow chart for DSSAT CERES wheat model.

cultivars PBW 373. In contrast, simulation of anthesis days using CERES model ranged from 76 to 86, minimum 76 days after sowing (DAS) by HUW 234 and HUW 510. The maximum of 86 days taken by cultivar PBW 373. Analysis of statistical indices i.e. RMSE, nRMSE, MAE and D index ranged from 1.69 to 3.30 days, 2.22 to 4.04 %, 1.43 to 3.14 days and 0.36 to 0.71 respectively. HUW 510 cultivar achieved the highest R<sup>2</sup> value, more than 0.7 and 0.5 by HUW 234, as presented in Fig. 3. The daily thermal time is required to achieve the crop growth stages that appear after completing the thermal time accumulation (34). Similar report achieved with highly accurate anthesis simulation (RMSE 1.90 days; D-index 0.99), whereas another reported CERES model overestimation of anthesis by 16–19 days with nRMSE >10 % (35, 36). Overall, the model performed excellently and accurately simulated anthesis days of wheat cultivars, reliably predicting the transition from vegetative to reproductive growth

**Table 3.** Evaluation of statistical analysis of the decision support system for agrotechnology transfer crop environment resource synthesis -wheat model for anthesis days

| Statistical indices | HUW 234 |     | HUW 510 |     | Kundan |     | PBW 373 |     |
|---------------------|---------|-----|---------|-----|--------|-----|---------|-----|
|                     | Sim     | Obs | Sim     | Obs | Sim    | Obs | Sim     | Obs |
| Minimum             | 76      | 74  | 76      | 74  | 82     | 80  | 83      | 80  |
| Maximum             | 80      | 78  | 81      | 79  | 85     | 82  | 86      | 83  |
| Average             | 78      | 76  | 79      | 76  | 83     | 81  | 85      | 82  |
| Std                 | 1.4     | 1.2 | 1.8     | 1.8 | 1.0    | 0.7 | 0.9     | 1.2 |
| RMSE                | 1.69    |     | 2.24    |     | 2.73   |     | 3.30    |     |
| nRMSE               | 2.22    |     | 2.93    |     | 3.38   |     | 4.04    |     |
| MAE                 | 1.43    |     | 2.14    |     | 2.57   |     | 3.14    |     |
| D Index             | 0.65    |     | 0.71    |     | 0.36   |     | 0.42    |     |

DAS: Days after sowing; Sim: Simulated, Obs: Observed.

stages (37). That can support the study of climate-related risks (36, 38). Anthesis-derived meaningfully improves the accuracy of the yield estimation compared to the fixed-season method (39).

### Physiological maturity

The physiological maturity of the wheat crop is vital for ensuring sustainable grain yield and quality in the amidst of climate change.

The observed physiological maturity days of all cultivars ranged between 102 to 116, with the minimum days (102 DAS) taken by the HUW 510 cultivar and the highest 116 days taken by the Kundan cultivar in fully irrigated conditions. Physiological maturity days of cultivar HUW 234 ranged between 107 to 114 days and by PBW 373, 107 to 115 days. The analysis value of the statistical indices was as follows: RMSE ranged from 1.46 to 3.27 days, nRMSE from 1.32 to 2.92 %, MAE from 0.71 to 2.71 days and the D index from 0.68 to 0.92. This shows the model has a high acceptable rate for the simulation of wheat crop phenological stages. These results are presented in Table 4. All cultivars have an R<sup>2</sup> of more than 0.60, that show the good fit to strong fit. It is presented in Fig. 4. The statistical analysis confirms that the model performed excellently for simulating

**Table 4.** Evaluation of statistical analysis of the decision support system for agrotechnology transfer crop environment resource synthesis -wheat model for physiological maturity days

| Statistical indices | HUW 234 |     | HUW 510 |     | Kundan |     | PBW 373 |     |
|---------------------|---------|-----|---------|-----|--------|-----|---------|-----|
|                     | Sim     | Obs | Sim     | Obs | Sim    | Obs | Sim     | Obs |
| Minimum             | 108     | 107 | 102     | 102 | 112    | 107 | 113     | 107 |
| Maximum             | 114     | 114 | 114     | 112 | 117    | 116 | 117     | 115 |
| Average             | 111     | 111 | 111     | 109 | 115    | 112 | 115     | 112 |
| Std                 | 1.8     | 2.0 | 4.1     | 3.9 | 1.8    | 3.2 | 1.5     | 3.2 |
| RMSE                | 1.46    |     | 2.33    |     | 3.00   |     | 3.27    |     |
| nRMSE               | 1.32    |     | 2.15    |     | 2.68   |     | 2.92    |     |
| MAE                 | 0.71    |     | 2.00    |     | 2.43   |     | 2.71    |     |
| D Index             | 0.85    |     | 0.92    |     | 0.70   |     | 0.68    |     |

DAS: Days after sowing; Sim: Simulated; Obs: Observed.

physiological maturity (40). Model simulated a similar and highly accurate simulation (RMSE = 2.41 days; D-index = 0.98) even of physiological maturity days taken 310 days (35). Accurate simulation of wheat crop maturity supports adaptation to climate change-related risks, enabling farmers to maintain crop health and achieve potential yields despite environmental challenges (36, 38, 41, 42).

### Grain yield

Observed grain yield reflects the success of crop production. The observed grain yield ranged from 2597 to 3938 kg ha<sup>-1</sup> (HUW 234), 3113 to 4286 kg ha<sup>-1</sup> (HUW 510), 2501 to 3494 kg ha<sup>-1</sup> (Kundan) and

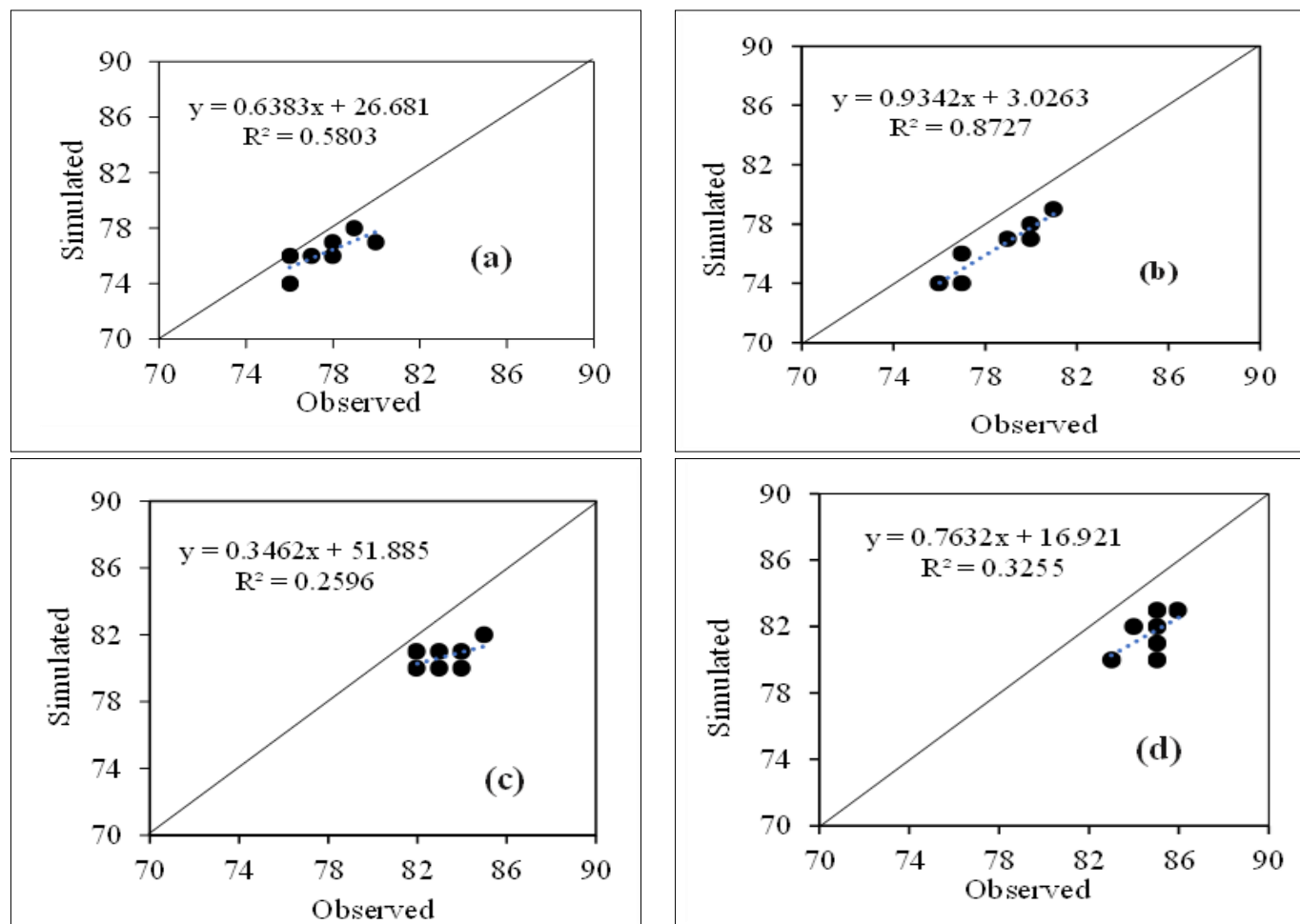


**Fig. 3.** Compare of simulated versus observed days of anthesis appearance for wheat cultivars; (a): HUW 234, (b): HUW 510, (c): Kundan and (d): PBW 373.

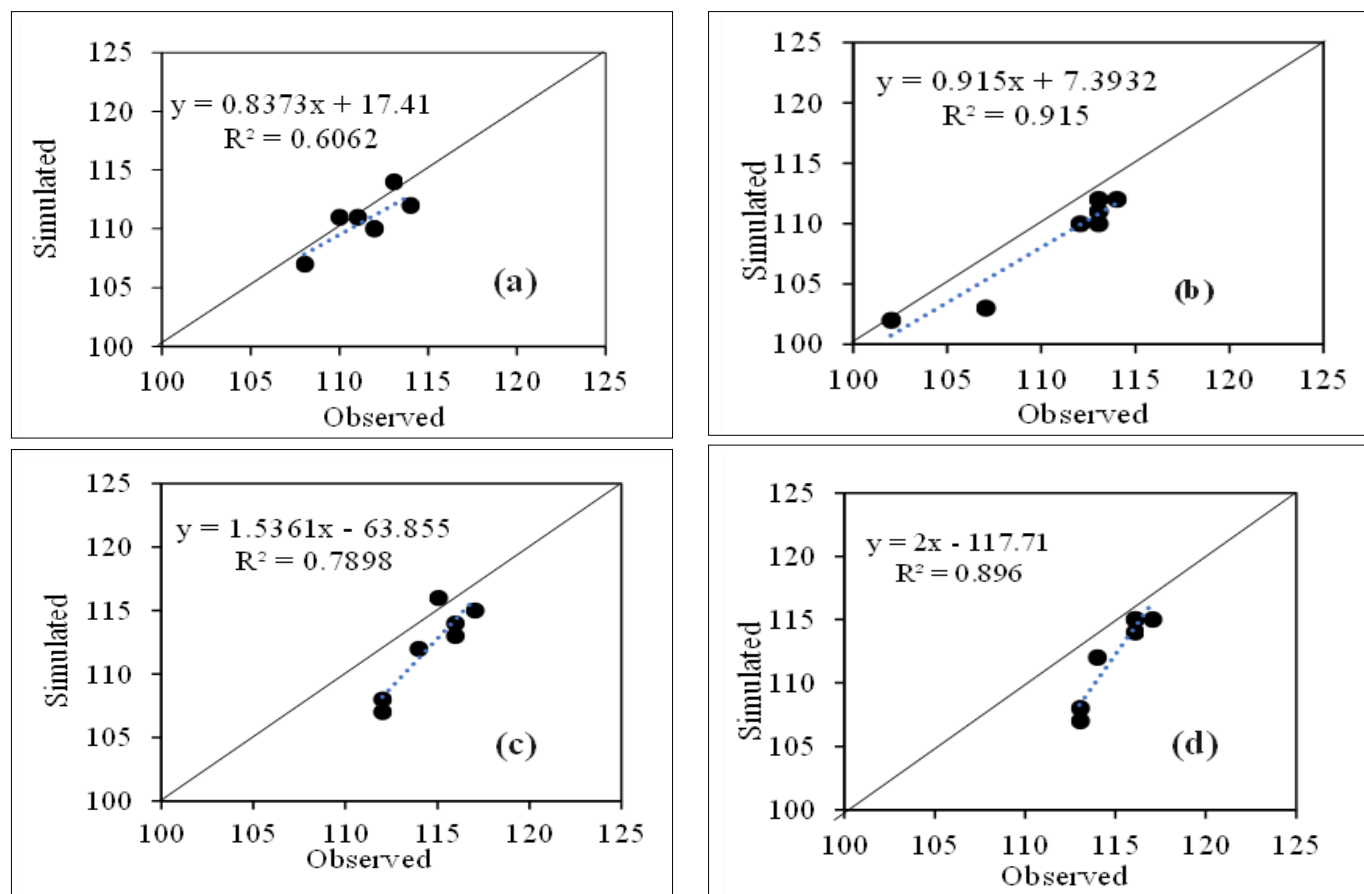


**Fig. 4.** Compare of simulated versus observed days of physiological maturity for wheat cultivars. a: HUW 234; b: HUW 510; c: Kundan; d: PBW 373.

**Table 5.** Evaluation of statistical analysis of the decision support system for agrotechnology transfer crop environment resource synthesis-wheat model for grain yield (kg ha<sup>-1</sup>)

| Statistical indices | HUW 234 |       | HUW 510 |        | Kundan |        | PBW 373 |        |
|---------------------|---------|-------|---------|--------|--------|--------|---------|--------|
|                     | Sim     | Obs   | Sim     | Obs    | Sim    | Obs    | Sim     | Obs    |
| Minimum             | 2645    | 2597  | 3213    | 3113   | 2562   | 2501   | 2730    | 2694   |
| Maximum             | 4156    | 3938  | 4368    | 4286   | 3754   | 3494   | 4212    | 4127   |
| Average             | 3521    | 3393  | 3739.9  | 3601.4 | 2845.0 | 2762.8 | 3187.4  | 3110.0 |
| Std                 | 496.3   | 429.0 | 345.4   | 350.8  | 381.7  | 315.5  | 463.1   | 452.4  |
| RMSE                | 153.34  |       | 148.91  |        | 126.59 |        | 86.85   |        |
| nRMSE               | 4.52    |       | 4.13    |        | 4.58   |        | 2.79    |        |
| MAE                 | 127.86  |       | 138.43  |        | 82.22  |        | 77.41   |        |
| D Index             | 0.97    |       | 0.96    |        | 0.97   |        | 0.99    |        |

DAS: Days after sowing; Sim: Simulated; Obs: Observed.

2694 to 4127 kg ha<sup>-1</sup> (PBW 373). While simulated yield indicates the effectiveness of growth conditions and management practices. In comparison, the simulated grain yield using the CERES model ranged from 2645 to 4156 kg ha<sup>-1</sup> (HUW 234), 3213 to 4368 kg ha<sup>-1</sup> (HUW 510), 2562 to 3754 kg ha<sup>-1</sup> (Kundan) and 2730 to 4212 kg ha<sup>-1</sup> (PBW 373), as shown in Table 5. The calculated value of the statistical indices ranged in RMSE from 86.85 to 153.34 kg ha<sup>-1</sup>, nRMSE from 2.79 to 4.58 %, MAE from 77.41 to 127.86 kg ha<sup>-1</sup> and D index from 0.96 to 0.99. Coefficient of variance of simulated versus observed grain yield were strong more than 0.95 and presented in Fig. 5. The results closely matched with RMSE of 144 kg ha<sup>-1</sup> and a D index of 0.98, indicating good agreement between simulated and observed values (35). The process-based crop model accurately simulated wheat grain yield, demonstrating excellent performance and providing reliable insights for yield forecasting, resource use

efficiency, climate change impact assessment and food security planning (16,38,43–45).

### Straw yield

Straw yield is essential to ensure the accuracy and reliability of models, sensors and methodologies used in crop production and management. The observed straw yield ranged from 6349 to 6621 kg ha<sup>-1</sup> (HUW 234), 5022 to 6825 kg ha<sup>-1</sup> (HUW 510), 3417 to 6190 kg ha<sup>-1</sup> (Kundan) and 3666 to 6349 kg ha<sup>-1</sup> (PBW 373). In comparison, simulated straw yield using the CERES model ranged from 6542 to 6851 kg ha<sup>-1</sup> (HUW 234), 5369 to 7274 (HUW 510), 4030 to 6452 kg ha<sup>-1</sup> (Kundan) and 4257 to 6881 kg ha<sup>-1</sup> (PBW 373) as presented in Table 6. The calculated statistical indices were RMSE ranged from 266.64 to 411.02 kg ha<sup>-1</sup>, nRMSE from 4.13 to 9.15 %, MAE from 260.0 to 354.24 kg ha<sup>-1</sup> and a D index from 0.44 to 0.96. The coefficient of variance is presented in Fig. 6. The

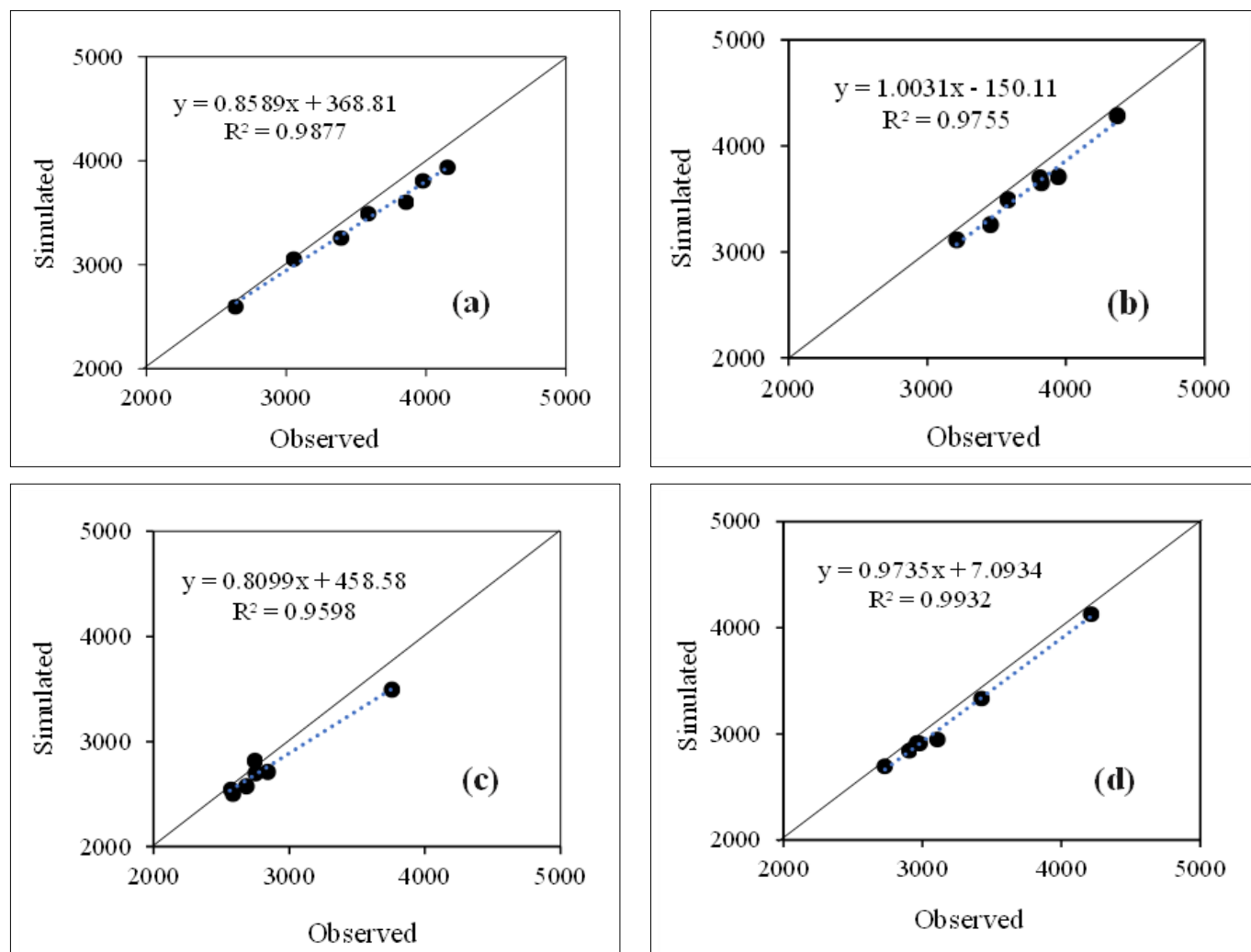
**Fig. 5.** Compare of simulated versus observed grain yield for wheat cultivars. a: HUW 234; b: HUW 510; c: Kundan; d: PBW 373.

**Table 6.** Evaluation of statistical analysis of the decision support system for agrotechnology transfer crop environment resource synthesis-wheat model for straw yield ( $\text{kg ha}^{-1}$ )

| Statistical indices | HUW 234 |      | HUW 510 |       | Kundan |        | PBW 373 |        |
|---------------------|---------|------|---------|-------|--------|--------|---------|--------|
|                     | Sim     | Obs  | Sim     | Obs   | Sim    | Obs    | Sim     | Obs    |
| Minimum             | 6542    | 6349 | 5369    | 5022  | 4030   | 3417   | 4257    | 3666   |
| Maximum             | 6851    | 6621 | 7274    | 6825  | 6452   | 6190   | 6881    | 6349   |
| Average             | 6722    | 6462 | 6378    | 6036  | 4745   | 4390   | 5194    | 4856   |
| Std                 | 93.2    | 93.4 | 606.9   | 579.5 | 936.2  | 1022.8 | 1041.9  | 1012.3 |
| RMSE                | 266.64  |      | 3.27    |       | 401.94 |        | 411.02  |        |
| nRMSE               | 4.13    |      | 2.92    |       | 9.15   |        | 8.46    |        |
| MAE                 | 260.00  |      | 2.71    |       | 354.24 |        | 337.72  |        |
| D Index             | 0.44    |      | 0.68    |       | 0.96   |        | 0.96    |        |

DAS: Days after sowing; Sim: Simulated; Obs: Observed

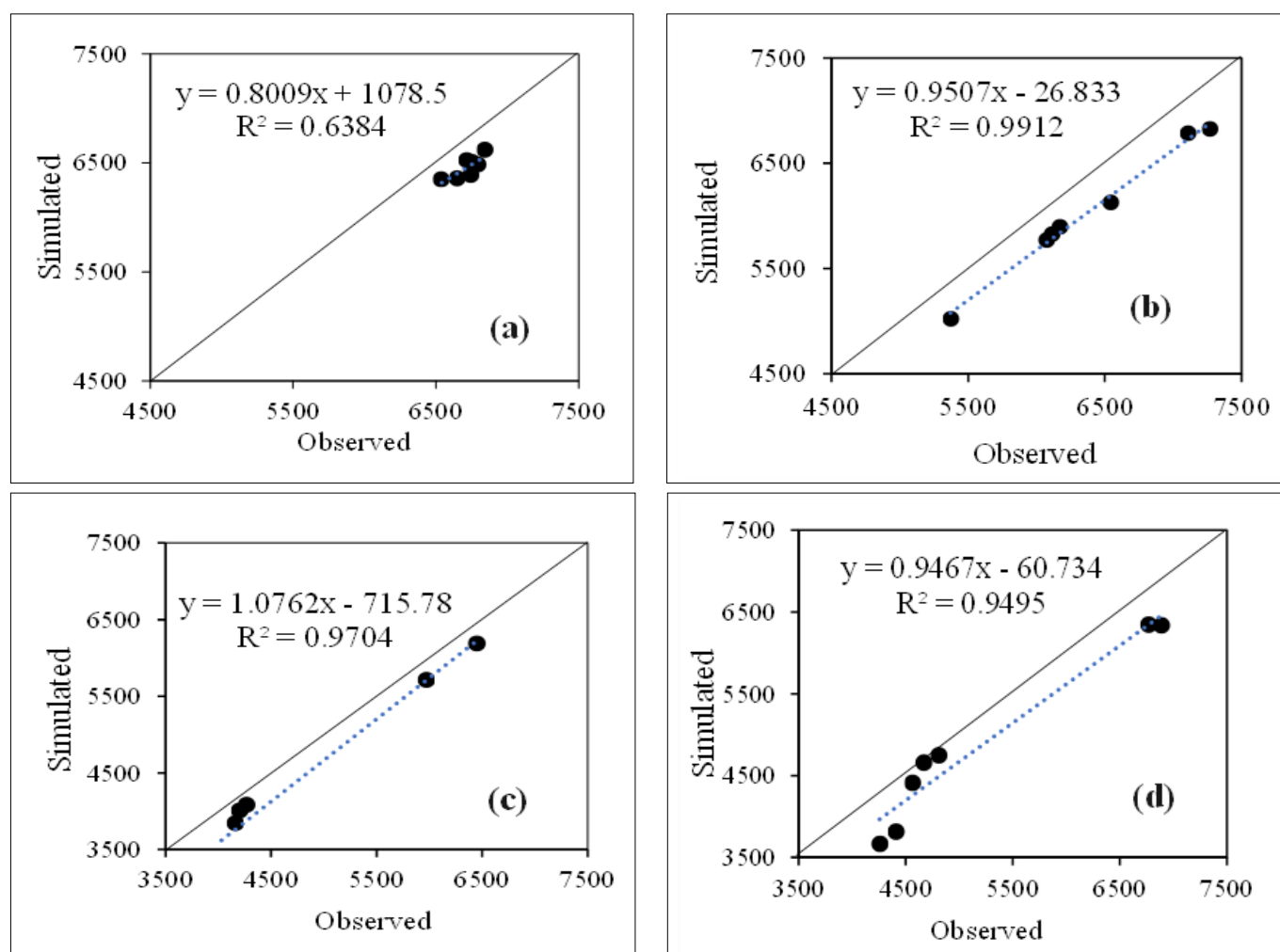


**Fig. 6.** Compare of simulated versus observed straw yield for wheat cultivars. a: HUW 234; b: HUW 510; c: Kundan; d: PBW 373.

output indicates that model performance was good for simulating straw yield. Similar results were recorded for biomass yield by a model that predicted reasonably well (RMSE = 13–16 %; D-index = 0.86–0.97) (46). The statistical indices indicated that the model has scope for robustness to enhance straw yield simulation compared to other variables. Straw yield data is essential for optimising agricultural practices and enhancing water use efficiency and nutrient management, soil organic carbon dynamics and residue management strategies (13, 16, 47–49).

## Conclusion

The DSSAT-CERES wheat model effectively simulated trends in phenological stages, namely anthesis days, physiological maturity and productivity of grain yield and straw yield of wheat cultivars for the Gangetic plain zone. Phenology and yield were recorded over

multiple experimental years, with deviations of less than 5.0 %, except for straw yield of more than > 9.0 %. The nRMSE statistical index indicated the lowest error between simulated and observed by physiological maturity. A good agreement was also observed for grain yield simulation, as evidenced by the highest D Index values, demonstrating that the model performed better in estimating grain yield. The model has proven to be a valuable tool for the estimation of phenological stages and wheat yield. As such, it can be reliably used for applications including crop growth prediction, phenological development, yield estimation and evaluating wheat crop performance under climate change scenarios. The study found that observed phenology and yield varied significantly with weather conditions, particularly temperature and with management practices. In this context, it can be concluded that the model performs satisfactorily and may be suitable for simulating the late sowing wheat crop also.

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## Authors' contributions

CP conducted field experiments and was responsible for data compilation, model calibration and validation using the CERES software. RSS contributed to project administration, formal analysis and manuscript conceptualisation. MKY contributed to data curation, development of data-analysis software, formal analysis and model calibration. VK contributed to data analysis and manuscript writing. GP actively participated in field experiments, data compilation and manuscript refinement. MKS provided overall guidance, edited the manuscript and contributed to figure preparation. SMS provided guidance and editorial support in the preparation of tables. DKV offered suggestions for overall manuscript development. AKS contributed to manuscript editing and provided critical suggestions. All authors read and approved the final manuscript.

## Compliance with ethical standards

**Conflict of interest:** Authors do not have any conflict of interests to declare.

**Ethical issues:** None

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