PLANT SCIENCE TODAY
ISSN 2348-1900 (online)
Vol 12(sp1): 01–12
https://doi.org/10.14719/pst.8016

HORIZON
e-Publishing Group
HePG

REVIEW ARTICLE

Advancing pulse crop resilience: Leveraging DSSAT for climate-smart agriculture: A comprehensive review

Jayadharshan S[1], Marimuthu S[2*], Gurusamy A[1], Kannan P[3], Sivamurugan A P[3], Pazhanivelan S[3] & Sudarmanian N S[4]

[1]Department of Agronomy, Agricultural College and Research Institute, Tamil Nadu Agricultural University, Madurai 625 104, India

[2]National Pulses Research Centre, Vamban, Pudukkottai 622 303, India

[3]Centre for Water and Geospatial Studies, Tamil Nadu Agricultural University, Coimbatore 641 003, India

[4]Department of Remote Sensing and Geographic Information System, Tamil Nadu Agricultural University, Coimbatore 641 003, India

*Email: marimuthus@tnau.ac.in

OPEN ACCESS

ARTICLE HISTORY
Received: 01 March 2025
Accepted: 01 April 2025
Available online
Version 1.0 : 15 April 2025

Check for updates

Additional information

Peer review: Publisher thanks Sectional Editor and the other anonymous reviewers for their contribution to the peer review of this work.

Reprints & permissions information is available at https://horizonepublishing.com/journals/index.php/PST/open_access_policy

Publisher's Note: Horizon e-Publishing Group remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Indexing: Plant Science Today, published by Horizon e-Publishing Group, is covered by Scopus, Web of Science, BIOSIS Previews, Clarivate Analytics, NAAS, UGC Care, etc See https://horizonepublishing.com/journals/index.php/PST/indexing_abstracting

CITE THIS ARTICLE
Jayadharshan S, Marimuthu S, Gurusamy A, Kannan P, Sivamurugan AP, Pazhanivelan S, Sudarmanian NS. Advancing pulse crop resilience: Leveraging DSSAT for climate-smart agriculture: A comprehensive review. Plant Science Today. 2025; 12(sp1):01–12. https://doi.org/10.14719/pst.8016

Abstract

Climate change significantly threatens pulse crop production, particularly C_3 crops like chickpeas, pigeonpeas, lentils and blackgram, which are highly sensitive to rising temperatures and erratic weather patterns. Even brief exposure to heat stress during critical growth stages can cause substantial yield losses. Integrating advanced information technologies and geospatial tools into agricultural decision-making is crucial to mitigate these challenges. The Decision Support System for Agrotechnology Transfer (DSSAT) has emerged as a powerful crop simulation model that aids in assessing and mitigating climate change impacts on pulse crops. This review explores the role of DSSAT in climate-smart agriculture by integrating soil, weather and crop management data for precise yield predictions. By simulating diverse climatic scenarios, DSSAT facilitates the development of adaptive strategies, including selecting heat-tolerant genotypes, optimizing sowing dates and improving irrigation and nutrient management. Moreover, DSSATs' ability to evaluate extreme weather events such as droughts and heatwaves enhances its application in risk assessment and sustainable agricultural planning. Despite its advantages, challenges such as data availability, model calibration and regional specificity hinder its widespread adoption. Integrating DSSAT with remote sensing, Artificial Intelligence (AI) and Machine Learning (ML) algorithms further enhances its predictive capabilities, making it a more robust tool for climate-resilient pulse production. By leveraging DSSATs' potential, policymakers, researchers and farmers can develop climate-smart strategies to ensure sustainable pulse production and food security under changing climatic conditions.

Keywords

climate change; DSSAT model; precision agriculture; pulses; yield prediction

Introduction

India cultivates 28.9 million hectares of pulses, producing 26.06 million tonnes with a productivity rate of 902 kg/ha (Project Coordinator Report-Kharif Pulses, 2024). Pulses are an essential component of the Indian diet and agriculture, being rich in proteins (25 %), carbohydrates (60 %), fat (1.5 %) and various essential minerals, amino acids and vitamins (1). Due to their drought tolerance, redgram (*Cajanus cajan*) and cowpea (*Vigna unguiculata*) are crucial for food and feed security, particularly in arid regions. Redgram, a C_3 crop, is expected to benefit from rising atmospheric CO_2 levels and is primarily consumed as split pulse (*dal*), with India being the worlds' leading producer (2). Legumes are crucial in nitrogen fixation, enhancing soil fertility, supporting crop rotation and helping in weed, pest and disease management(3). However, while elevated CO_2 levels may increase biomass and yield in C_3 plants, climate change remains a pressing concern, primarily due to global warming (4).

Furthermore, pulses are highly susceptible to heat stress, with even short-term exposure leading to significant yield losses (5). To address these challenges, the Decision Support System for Agrotechnology Transfer (DSSAT) has emerged as a powerful software facilitating the efficient use of crop simulation models for over 42 crops. DSSAT has been extensively used to assess climate change impacts on crop growth and yield, enabling the identification of adaptation measures to mitigate adverse effects. It has operated over 15 years across over 100 countries (6).

The DSSAT model requires minimal input data, including daily weather data, soil surface and profile information, crop management data and genetic coefficients for pulse crops (7). It effectively estimates harvest index, total aboveground biomass and seed yield, considering variables such as tillage methods and sowing dates (8). DSSAT has been widely adopted and over 25000 researchers, educators, consultants, extension workers, farmers and policymakers utilize it across more than 187 countries.

The latest DSSAT Version 4.8.2 includes varietal characteristics for legume crops, making it a valuable tool for simulating the effects of various management and soil elements while providing farmers with optimized adaptation strategies (9). This review critically examines methodologies for integrating soil and weather data into agricultural decision-making, assessing the benefits and challenges associated with DSSAT implementation. It explores innovative approaches to enhance agrarian resilience, presents successful case studies and identifies future research directions for improving farming practices and sustainability amid climate variability.

Indian scenario of pulses

Indias' daily pulse requirement is approximately 47 grams per person. However, 24 % of the worlds' malnourished population still resides in the country with 15.2 % of the Indian population undernourished. Pulses play a crucial role in diet and food security, serving as an excellent plant-based protein source due to their 20-35 % protein content (10) (Fig. 1). The Pulse production revolution began in 2017-18 when Indias' total production surpassed 25 million tons. As the largest global producer and consumer of pulses, India contributes 25-28 % of the worlds' total production. The countrys' pulse production is dominated by chickpea (48 %) followed by redgram (17 %), blackgram (10 %) and greengram (7 %) (11). However, to meet the growing protein demand, India must achieve an annual growth rate of 3.62 %, targeting a pulse production of 33 million tons by 2025 (12). Due to this, India imports large quantities of pulses while exporting significantly fewer. The state-wise contribution to pulse production and cultivation area is represented in Fig.2.

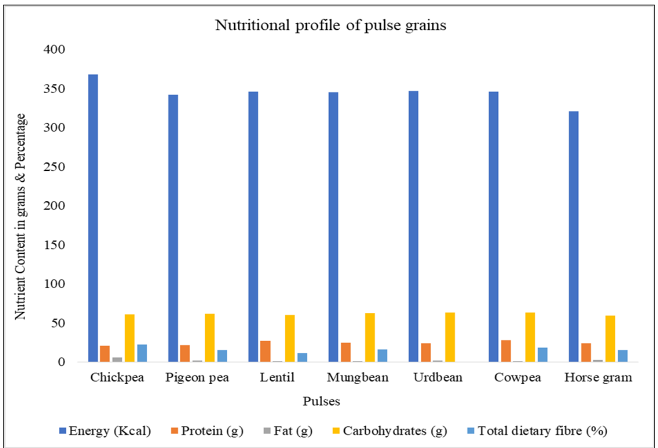

Fig. 1. Pulses for human health and nutrition, Technical Bulletin, IIPR, Kanpur.

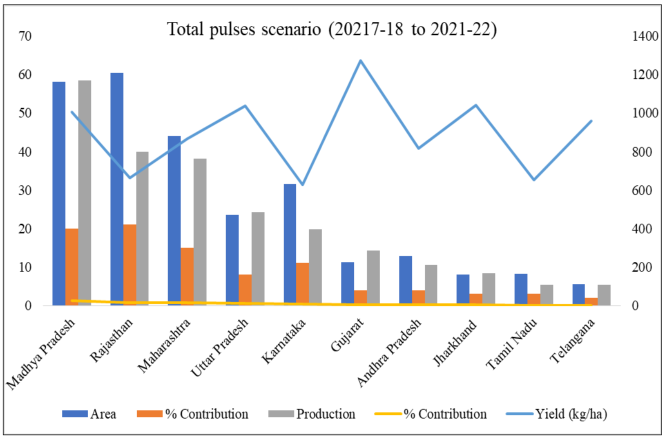

Fig. 2. States contribution in area and production of total pulses. Source: DES, Ministry of Agri. & FW (DA&FW), GoI. Normal Area & Prod. (2017-18 to 2021-22) (Annual Report 2022-23).

During the Green Revolution of the 1960s, the expansion of cereal-based cropping systems in northern India led to a decline in pulse cultivation, reducing the area from 13.5 million hectares to 7.5 million hectares. This shift contributed to decreased soil fertility, posing a significant challenge to sustainable crop production (13). Consequently, Indias' pulse imports increased while exports remained low, as depicted in Fig. 3A-B. Integrating pulses into crop rotations provides numerous environmental and economic benefits, such as enhancing soil organic carbon, improving nitrogen availability, reducing disease pressure, increasing overall crop yields and promoting soil health and establishing symbiotic relationships with nitrogen-fixing bacteria, forming root nodules that convert atmospheric nitrogen into plant-usable forms. This process reduces fertilizer dependency and enriches soil nitrogen levels, benefiting subsequent crop cycles (14).

DSSAT models

The Decision Support System for Agrotechnology Transfer (DSSAT) is a suite of models and software developed by an international team of scientists under the International Benchmark Sites Network for Agrotechnology Transfer (IBSNAT). It is designed to predict crop yield, resource usage and risks associated with various production strategies (15). DSSAT integrates multiple databases, models and application programs to incorporate essential agricultural data. These include soil data (S-Build), crop characteristics, weather data (Weatherman) and management data (X-Build) (16). By utilizing these components, DSSAT provides a comprehensive modelling framework to assess crop performance under different climatic and management scenarios. Several crop-based models available in DSSAT are widely used to predict

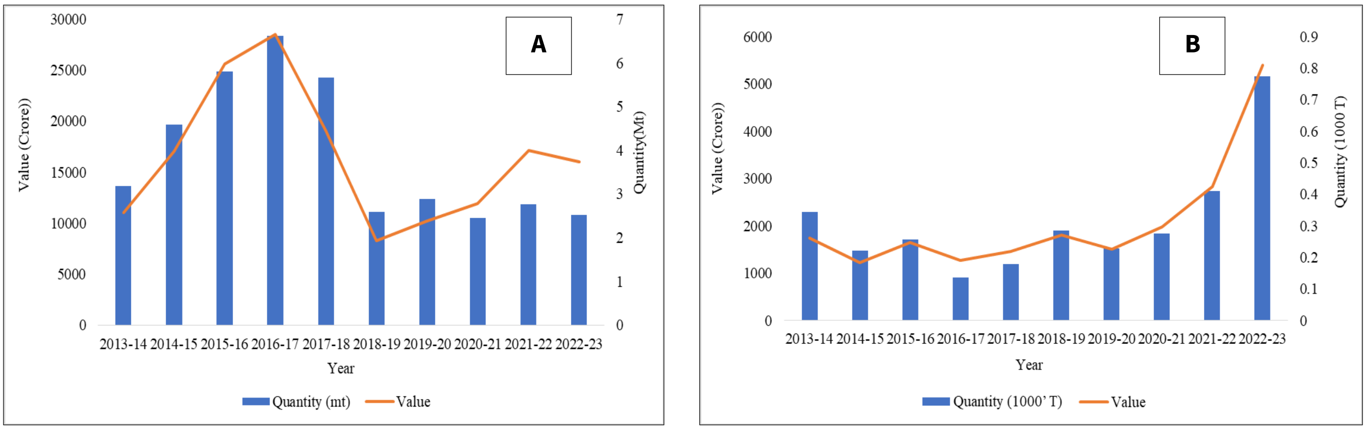

Fig. 3A. Pulses Import trends; B. Pulses Export trends in India. (Source: ICAR-Indian Institute of Pulses Research, Kanpur).

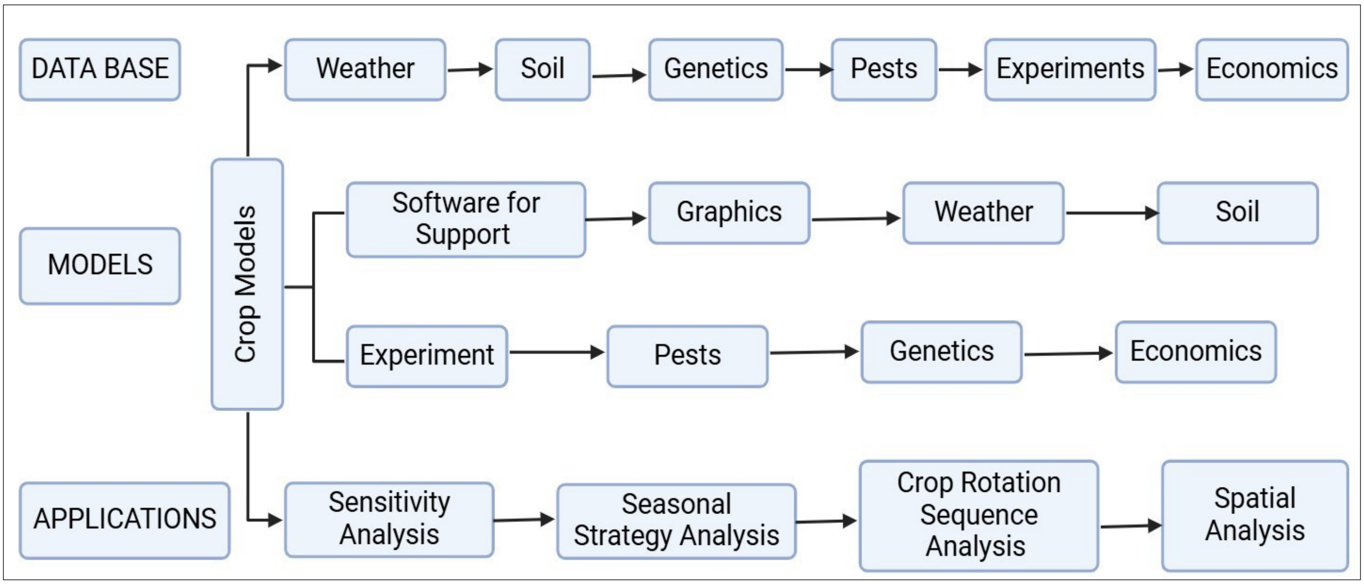

Fig. 4. Diagram of database, application and support software components in DSSAT.

yields under changing climatic conditions. The components required for DSSAT are illustrated in Fig. 4.

Simulation in DSSAT models

The "Genotype Coefficient Calculator" (GENCALC) tool in DSSAT is crucial in determining cultivar genetic coefficient parameters that influence phenological stages, growth parameters, yield parameters and overall yield in the CROPGRO model. These parameters are fine-tuned to achieve the best match between simulated and observed data and the "Generalized Likelihood Uncertainty Analysis" (GLUE) tool is used to optimize cultivar coefficients (17). This tool also provides functionalities for organizing calibration data and estimating genotype-specific parameters (GPSs), improving model accuracy and adaptability (18). The genetic coefficient module is a core component of DSSAT, enabling the simulation of crop-specific traits, such as phenology and yield potential. Furthermore, DSSAT aids in decision-making by simulating various tillage systems and crop rotations, allowing users to assess strategies for reducing environmental impacts under specific climatic conditions. By minimizing the time and manpower required to analyze complex agricultural alternatives, DSSAT enhances decision-making efficiency and provides a collaborative platform for scientists, facilitating research advancements and knowledge sharing (19).

DSSAT Models' Components

The DSSAT model consists of three primary modules, soil, crop and weather which collectively simulate the interactions within the cropping system. The soil module in DSSAT assesses soil texture, moisture, fertility and nutrient availability in legumes by incorporating key characteristics like layer thickness, clay, silt and organic carbon (20). The weather module analyses daily precipitation, temperature and solar radiation to evaluate climatic variability and its effects on pulse productivity. The crop module includes validated models like CROPGRO-Pulses, CERES-Rice and SOYGRO-Soybean, simulating crop growth under diverse conditions. Additionally, water use calculations using the AquaCrop model support agronomic management decisions. These modules collectively enhance decision-making by simulating soil-crop-climate interactions for improved agricultural planning. Recent advancements in DSSAT have led to the development of DSSAT-CSM, a new crop system model that integrates CROPGRO and other modules, allowing the simulation of a wide range of crops (18). This system predicts crop growth, development and yield by considering water, carbon and nitrogen balances within the soil -plant-atmosphere continuum (SPAC) (21).

DSSAT Model Parameters

The DSSAT model simulates various physiological processes, including crop growth, development, photosynthesis, dry matter accumulation, yield production and the dynamic interactions between cultivation methods and the environment. Implementing the DSSAT model requires input

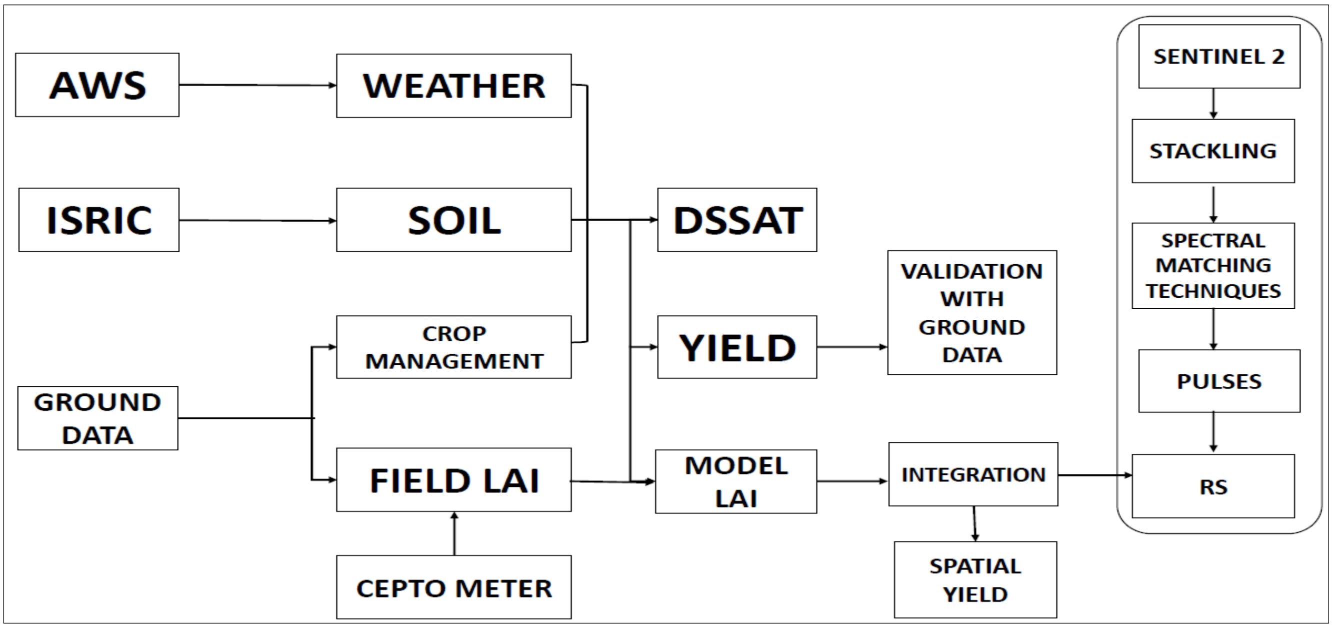

Fig. 5. Representing the Input data for the crop simulation model with remote sensing.

data such as field management practices, crop genetic factors, soil characteristics and meteorological parameters (22), as illustrated in Fig. 5. For greengram (*Vigna radiata*) (KUML4), the CSM-CROPGRO model integrates soil texture, moisture and depth data along with dry and rainy season weather data (23). Similarly, the CROPGRO-Soybean model applied to the JS-335, JS-9305 and TAMS 98-21 varieties relies on soil and weather data from Akola and phenological data, with genetic coefficients calibrated using the GLUE method. CERES-Maize uses field-specific soil conditions and medium-range weather forecasts to predict grain yields (24). The CROPGRO-Rice and CROPGRO-Sorghum models simulate rice and sorghum growth using soil and weather data tailored to photoperiod-insensitive rice cultivars and sorghum genetic coefficients (25). The CERES-Wheat model simulates wheat growth using soil moisture and temperature data, weather simulations and wheat-specific genetic coefficients (26). Similarly, DSSAT-CERES-Peanut employs peanut-specific genetic coefficients to address soil nitrogen and yield components.

The CROPGRO-Sorghum model incorporates soil organic matter and weather data for growth and yield estimations (27). For cultivar-specific predictions, cotton growth simulations using DSSAT v4.6 utilize soil texture and field station weather data (28). Monthly weather data for Tamil Nadu can be obtained from the Tamil Nadu Agriculture Weather Network (TAWN) (http://tawn.tnau.ac.in/). DSSAT v4.8 enhances rice growth simulations by incorporating historical weather data and rice-specific genetic coefficients. Table 1 provides an overview of DSSAT models and their parameters for crop improvement. These models offer a robust framework for understanding crop responses and improving yield predictions under diverse environmental conditions.

Soil data

The soil data in DSSAT include metadata for the site where soil properties were measured, encompassing bulk density, soil organic carbon, sand, silt, clay, drainage, permeability and soil surface colour. These properties are determined using multispectral data and spectral indices such as the Normalized Difference Vegetation Index (NDVI) and the Soil-Adjusted Vegetation Index (SAVI) through Sentinel-2 satellite imagery (29). Crop models in DSSAT simulate a one-dimensional water balance with vertical flow. At the same time, the soil file contains essential information, including potential hydrogen

Table 1. DSSAT models and their parameters for crop improvement

DSSAT model	Crop	Soil data	Weather data	Crop data	Genetic coefficient data	References
DSSATv4.8 CERES-Rice	Rice	Soil profile data, texture	Weather data based on season and region	Phenological stages, yield estimates	Genetic coefficients for early-maturing rice varieties	(70)
DSSAT v4.7	Wheat	Soil texture, bulk density, field capacity	Historical weather data (temperature, rainfall)	Yield and phenology data	Genotype-specific parameters (P1V, G3)	(71)
DSSAT v4.7-CERES-Maize	Maize	Soil moisture, texture, bulk density	Monthly weather data (temperature, precipitation)	Growth cycle, yield simulation	Genetic coefficients for maize hybrids	(72)
CSM-CROPGRO	Mung Bean (KUML4)	Soil texture, moisture, depth	Weather data from dry and rainy seasons	Plant growth data (V4, R3, R6, R7 stages)	Genetic coefficients calibrated with GLUE	(23)
DSSAT v4.6	Cotton	Soil texture, bulk density, soil moisture	Weather data from field stations	Growth, yield prediction	Cultivar-specific genetic coefficients	(28)
CROPGRO-Soybean	Soybean (JS-335, JS-9305, TAMS 98-21)	Soil data from the Akola region	Weather data from Akola region (seasonal)	Phenological data yield prediction	Genetic coefficients calibrated with GLUE	(73)
CROPGRO-Sorghum	Sorghum	Soil moisture and fertility	Weather data for growth simulation	Growth and yield data	Genetic coefficients for different sorghum cultivars	(51)

(pH), electrical conductivity (EC), soil slope and other relevant factors (18). Critical parameters such as moisture content and nutrient concentrations are tracked using inverse modelling approaches.

A recently developed Soil Profile Optimization (SPO) tool enables the creation of more realistic site-specific soil profiles based on measured site-specific yield and aboveground biomass (30). Soil files were created using the DSSAT S-Build software, which can be accessed by clicking the S-Build icon on the main DSSAT panel. Each soil profile is characterized by unique codes and names (7). The DSSAT model utilizes soil data from the Tamil Nadu soil database, accessible through the Department of Remote Sensing and GIS, Tamil Nadu Agricultural University (TNAU), as soil input (73).

Weather data

The weather module in DSSAT provides daily data on near-surface air temperature, relative humidity, rainfall, solar radiation, wind speed and direction. These data are available at a resolution of 0.5° latitude and longitude on the NASA POWER website (https://power.larc.nasa.gov/, accessed from November 1, 2020). Automatic Weather Stations (AWS) and regular observatories in the study districts provide daily meteorological information such as rainfall (mm), solar radiation (MJm^{-2} day^{-1}) and maximum and minimum temperatures (°C).

The collected weather data are fed into the DSSAT software from the XL File (31). These data contribute to modifying crop phenology, optimizing fertilizer rate-timing and diversifying crop rotations to reduce yield loss under varying climatic conditions (32). Temperature, precipitation and humidity data are crucial for forecasting crop performance and organizing agricultural operations (33). Ensuring food security in changing climates depends on developing climate-resilient crop cultivars, which is facilitated by DSSATs' ability to simulate responses to shifting weather conditions (34).

Crop data

Crop management data includes cultivar selection, planting date, density, row spacing, sowing depth, irrigation dates and fertilizer inputs (7). Decision-makers utilize Decision Support Systems (DSS) to answer questions and solve problems. Data collected from farmers during field visits were used to assess crop management techniques, including cultivar choice, transplant date, sowing depth, previous crop yield, timing, fertilizer application and irrigation interval. To ensure accurate model representation, the most widely cultivated varieties were selected for inclusion (35).

Genetic coefficient data

Genetic coefficient data is derived from cultivar files that describe the genetic traits of cultivars, which are calculated using field experiments and phenological factors through multiple runs of a GLUE coefficient estimator. The genetic coefficients were determined and the required data are presented in Fig. 5. For instance, GLUE improves accuracy compared to conventional methods in chickpea (*Cicer arietinum*) production, with an average relative error ranging from -23.4 % to 19 % (36). Key genetic factors include the relative response of development to photoperiod (PPSEN), the duration between plant emergence and flower appearance (EM-FL), the period from first flower to first pod (FL-SH), the time between first flower and seed formation (SD-PM), the duration between first flower and the end of leaf expansion (FL-LF) and various growth parameters. These growth parameters include the maximum leaf photosynthesis rate (LFMAX), leaf area of the cultivar under specific growth conditions (SLAVR), the size of a fully developed leaf (SIZLF), the maximum fraction of daily growth allocated to seed and shell (XFRT), seed weight per unit (WTPSD), seed filling duration for a pod cohort under growth conditions (SFDUR), average seeds per pod (SDPDV), the time required for the cultivar to reach its final pod stage (PODUR) and the maturity of seed and shell (THRSH) (37).To achieve a strong match between simulated and observed data, the relevant coefficients in the DSSAT model were systematically adjusted to identify the genetic parameters influencing developmental phases, phenological durations and yield estimates. Proper calibration of crop simulation models (CSMs) with high-quality datasets enhances the accuracy of phenology, leaf area index (LAI) and grain yield predictions (38).

DSSAT crop models for major field crops

Pulse crops: The DSSAT v4.6.1 model for chickpeas (*Cicer arietinum*) predicts variable yields based on climatic conditions. However, it is susceptible to temperature increases, leading to yield fluctuations (39). The DSSAT-CROPGRO-Pigeonpea model demonstrates improved yields with optimized management practices but requires extensive data for accurate simulations. Similarly, the DSSAT-CROPGRO-Mungbean model shows increased yields with early sowing but remains sensitive to variations in temperature and sowing dates (40). For chickpeas in India, the DSSAT-CROPGRO module exhibited a strong correlation between simulated and observed yields with calibration and validation R^2 values of 0.87 and 0.88, respectively. It effectively calibrated anthesis and maturity day variations, ranging from 4.8 % to 10 % and 1.7 % to 5.5 %, respectively (41).

Rice: The DSSAT v4.7 model for rice predicts yield reductions of -181.30 kg/ha per decade for early planting and -276.16 kg/ha per decade for late planting, making it a valuable tool for climate change impact analysis and growth season prediction; however, simulating the effects of climate change on yield and the growth season remains challenging (42). High-resolution (3m) Synthetic Aperture Radar (SAR) imagery was used to map and track rice-growing regions (SKYMED) to assess rice growth and calculate yields. Similarly, the DSSAT v4.7 CERES-Rice model predicts a yield of 3190 kg/ha when integrated with Sentinel-1A SAR data, although its accuracy depends on the quality of the SAR data (43). When combined with machine learning, the DSSAT model for rice shows yield increases of +0.1 % to +3.6 % in single-season scenarios. However, late-planted rice experiences yield losses under climate change and the DSSAT-CERES-Rice model evaluates plant density and nitrogen management strategies but requires calibration for specific environments (44).

Wheat: DSSAT v4.7 demonstrates improvements in biomass (+5.46 %) and yield (+2.9 %) when assessing the impact of aerosol reduction; however, its effectiveness is limited by insufficient data on aerosol radiative effects (45). The DSSAT-CERES-Wheat model enhances prediction accuracy for irrigation and nitrogen effects on crop growth but requires local modifications to the Penman-Monteith equation for accurate simulations (46). Despite its capabilities, DSSAT v4.7-CERES-Wheat is constrained by errors under extreme cold temperatures and lacks sufficient validation data for tropical regions (40). Additionally, DSSAT v4.7 for wheat predicts increased yields with improved solar radiation and comprehensive environmental data are essential for achieving more precise yield estimations (45).

Maize: The DSSAT model for maize simulates climatic scenarios and agronomic practices, with yield changes ranging from +11.6 % to -34 % under future climate conditions, highlighting the negative impacts of climate change (24). The DSSAT v4.7-CROPGRO model estimates maize yield based on weather and soil data. However, it requires extensive data preparation, making the process time-consuming (47). When root proliferation strategies are applied, the DSSAT-CERES-Maize model predicts a 27 % yield increase. However, genetic modifications are necessary for successful implementation and DSSAT v4.7 for maize indicates an 8.8 % to 11 % reduction in nitrogen uptake, reflecting its sensitivity to nitrogen application rates(30). CERES-Maize in DSSAT effectively estimated maize yield during the Kharif 2017 season in Ariyalur and Perambalur, achieving 90.4 % accuracy with R^2 = 0.502 and RMSE = 538.6 kg/ha, thereby validating its spatial simulation capabilities (48).

Other crops: The DSSAT-CROPGRO-Sorghum model encounters calibration challenges across diverse environmental conditions, particularly under varying water stress levels (49). Similarly, DSSAT-CERES-Sorghum struggles with high temperatures and limited water availability, often leading to underestimating early growth stages (16). For faba bean, DSSAT-CROPGRO-Faba Bean focuses on restrictive irrigation to enhance yield; however, its limited representation in major crop models restricts its broader application (50). In sugarcane, DSSAT-CANEGRO predicts a yield reduction ranging from 7.12 % to 29.05 % under drought stress, highlighting the crops' sensitivity to meteorological drought during its growth stages (51). For soybean, DSSAT v4.7-CROPGRO estimates yield changes between -1 % and +24 % based on weather and soil data, though its extensive simulation process is time-consuming (26).

Practical applications of the DSSAT models

DSSAT models in precision agriculture: The DSSAT model is a crucial tool in precision agriculture, providing robust capabilities for simulating crop growth and assessing environmental impacts under varying conditions. By integrating diverse datasets, such as soil characteristics, weather patterns and crop-specific parameters, DSSAT delivers precise recommendations for resource management. DSSAT helps narrow yield gaps in maize production by evaluating the effects of nitrogen fertilizer inputs and planting density, offering tailored solutions to regional climatic variability (52). Similarly, the model supports water-saving irrigation strategies for sugarcane and other crops by incorporating operational data to promote sustainable resource use. DSSATs' ability to assimilate remote sensing data has expanded its applicability, particularly in monitoring crop growth and spatial yield variability. For instance, DSSAT has been integrated with GIS tools to map winter wheat production potential across regions, enabling precise input allocation (53). By simulating various climatic scenarios, DSSAT aids in developing agronomic adaptation strategies, such as adjusting planting dates and optimizing crop spacing to mitigate potential yield losses in rainfed systems and the DSSAT-CSM model uses genetic coefficients for each cultivar, allowing for accurate regional yield forecasting (47).

Additionally, DSSAT simulates physiological processes in pulse crops, providing insights into biomass production and yield potential, particularly for crops using the C_3 photosynthetic pathway, thereby supporting optimized cultivation practices (5). Integrating IT and geospatial data, a sophisticated geostatistical tool within ArcGIS was used to evaluate soil fertility in key pulse-growing areas (54). Overall, DSSATs' integration of geospatial technology, high-resolution data and advanced simulation capabilities establishes it as a cornerstone of precision agriculture, driving efficiency and sustainability in modern farming practices.

Limitations of DSSAT models: DSSAT-CERES-Rice faces challenges in simulating phenology under water stress. However, specific crop models also present unique challenges. CROPGRO-Sorghum faces calibration difficulties in diverse environments (49). Another notable limitation is the high sensitivity of DSSAT-CROPGRO-Peanut to soil nitrogen (55). Despite these challenges, DSSAT models provide valuable simulations for various crops, offering insights into yield prediction, climate change impact analysis and optimal management practices. However, limitations such as sensitivity to temperature fluctuations, water stress and insufficient data for specific regions emphasize the need for continued calibration and refinement. Description for DSSAT models and their practical limitations in crop improvement are given in Table 2.

DSSAT models in climate change: The DSSAT model is a vital tool for assessing the impacts of climate change on agricultural systems, enabling simulation-based predictions to optimize crop performance and resilience under various climatic conditions. Crop simulation models are crucial in evaluating and implementing crop production practices under different climate scenarios. A study analyzing the impact of climate change on field crops across various regions used the DSSAT tool to assess these changes (56).DSSAT has also been applied to evaluate the effects of climate change on blackgram, using calibrated models for the popular cultivars CO6 and VBN6. The study found that blackgram (*Vigna mungo*) yields benefited from rising temperatures and elevated CO_2 levels, with cultivar VBN6 initially producing lower yields than CO6 but later surpassing it over time (5). Similarly, projections for the faba bean (*Vicia faba*) in the Kutaber area of Ethiopia indicate significant yield reductions of up to 50 % by the 2050s and 2080s due to increased temperatures and changing rainfall patterns (57). DSSAT has been widely applied to analyse the impacts of shifting rainfall patterns, temperature extremes and rising CO_2 concentrations on crop yields. For instance, DSSAT-CERES-Rice simulations have demonstrated the adverse effects of increased temperatures and seasonal rainfall variability on aerobic rice production while identifying optimal planting windows to minimize economic losses. Chickpea (*Cicer arietinum*) production in Andhra Pradesh is projected to decline under future climate scenarios, with yield reductions of up to 16.9 % without CO_2 enrichment and 2.7 % with CO_2 enrichment (58). Researchers are currently exploring adaptive management solutions to ensure sustainable agricultural

Table 2. Description for DSSAT models and their practical limitations in crop improvement

DSSAT model	Parameters	Limitations	References
DSSAT v4.6-CERES-Rice	Photoperiod sensitivity, genetic parameters and soil moisture	Issues in simulating responses to extreme drought and prolonged heat waves	(74)
CROPGRO-Rice	Cultivar-specific parameters, soil moisture	Limitations in simulating rice yield under changing rainfall patterns	(75)
DSSAT v4.7-CERES-Wheat	Genotype coefficients (P1V, G3), soil parameters and weather data	Errors under extreme cold temperatures, lack of data for validation in tropical areas	(40)
DSSAT v4.5-CERES-Maize	Crop growth parameters, irrigation scenarios	Requires accurate soil data, poor simulation under extreme weather patterns	(76)
CERES-Maize v4.7	Soil water availability, genotype-specific parameters	High sensitivity to soil nutrient levels and temperature variations	(77)
DSSAT-CROPGRO-Maize	Genotype coefficients (P1, P2, P5), soil water holding capacity	Sensitivity to nitrogen fertilization rates, limited data for tropical regions	(78)
DSSAT v4.8-CERES-Sorghum	Genotype parameters, rainfall scenarios, soil profile	Sensitivity to water stress and high temperatures underestimates early growth	(16)
DSSAT v4.6	Crop-specific parameters (planting dates, irrigation)	Difficulty in incorporating field management practices for validation	(79)
DSSAT v4.7	Crop-specific coefficients, soil properties, weather data	Sensitive to input data accuracy, difficulty in simulating yield under extreme climate	(80)
DSSAT-CROPGRO-Peanut	Water stress, temperature sensitivity, soil moisture	High sensitivity to soil nitrogen content	(69)
DSSAT-CROPGRO-Faba Bean	Water stress sensitivity, temperature threshold parameters	Limited research on legume-specific soil interaction modelling	(81)
DSSAT-CROPGRO-Pea	Crop-specific parameters, soil moisture, weather data	Limited research on legume-specific parameters, poor adaptation to high-temperature stress	(82)

production in the face of climate change. Various crop models, including the Agricultural Production Systems Simulator (APSIM), Cropping Systems Simulation Model (CROPSYST), Simulateur Multidisciplinaire Pour les Cultures Standard (STICS) and World Food Studies (WOFOST), are widely used for yield assessments (56). Studies have shown that DSSAT predicts yields with remarkable accuracy, with a correlation between simulated and observed yields ranging from 0.81 to 0.85 (35). DSSAT achieved 99.78 % accuracy in grain yield predictions and 91.67 % accuracy in straw yield predictions for rice production (59). Representative Concentration Pathway (RCP) climate scenarios from the Agricultural Model Intercomparison and Improvement Project (AgMIP) provide a framework for generating future weather data specific to different regions. Furthermore, altering planting dates, either earlier or later, has significantly enhanced crop production under changing climate conditions (37).

Practical validation of DSSAT CROPGRO models in field crops

The practical validation of DSSAT models has confirmed their reliability and versatility across diverse crops and environmental conditions. For wheat, the CERES-Wheat model was calibrated and validated using long-term experimental data, accurately simulating phenological stages, the leaf area index (LAI) and grain yield. Validation metrics such as RMSE, D-index and percentage error have demonstrated the models' ability to replicate real-world outcomes, particularly under optimal irrigation and sowing conditions (46). Similarly, the DSSAT-CANEGRO model for sugarcane was validated for the northern Indian region, showing a strong correlation (R^2 = 0.69) between measured and simulated yields, with a low normalized RMSE value of 7.5 %. The model successfully simulated phenological and yield attributes, highlighting its utility in improving crop management practices. In cotton, DSSAT modelling effectively simulated growth, phenology and yield under varying nitrogen levels and planting times. Validation results with RMSE values of less than two days for phenology and reliable yield predictions further emphasized its effectiveness in guiding region-specific management decisions (60). The validated results demonstrated

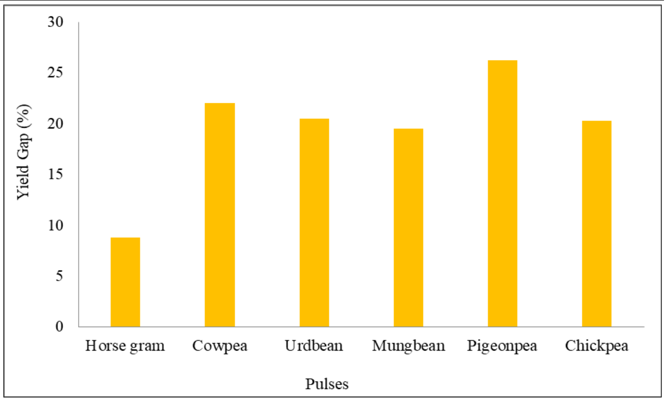

Fig. 6. Yield gap in different pulse crops (2022-23) (Source: ICAR-Indian Institute of Pulses Research, Kanpur).

that DSSAT models could effectively simulate yield attributes from observed crop data and predict crop growth, phenology and water management for both potential and actual yields, as illustrated in Fig. 6.

The AquaCrop model was calibrated and validated to simulate cowpea (*Vigna unguiculata*) growth, yield and water productivity under different irrigation regimes. While the model performed well overall, it struggled to simulate canopy cover accurately under severe water-deficit conditions (61). The model evaluated the effects of different sowing dates and tillage practices in Egypts' western desert on yield of faba bean (*Vicia faba*). Calibration has proven essential, as simulations of varying chickpea cultivars showed less than 20 % variances compared to observed yields (62). The Cropping System Model (CSM), a DSSAT component, has been developed using mathematical equations that integrate agrometeorological, soil, crop physiology and management data to predict crop growth, development and yield. Validation metrics, including mean bias error (MBE), Normalized Root Mean Square Error (nRMSE) and Root Mean Square Error (RMSE) were employed to assess simulation accuracy. For instance, using observed growth and yield characteristics of the TMV13 and G7 varieties, the model was validated based on agreement percentage RMSE and nRMSE as test criteria (63).With RMSE values ranging from 237 to 573 kg ha^{-1}, the model demonstrated dependable predictions of phenological characteristics and seed cotton yield when validated against field data in Pakistan (64). The RMSE was calculated as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Si - Oi)^2}{n}} \qquad \text{(Eqn. 1)}$$

Where, n = total number of observations, Si = simulated values and Oi = observed values. The nRMSE is computed using:

$$nRMSE = \frac{RMSE}{X} \qquad \text{(Eqn. 2)}$$

Where, X = mean of the observed values. Simulation accuracy is categorized based on normalized root mean square error (nRMSE) values, with less than 10 % indicating excellent accuracy, 10-20 % classified as good, 20-30 % considered fair and values exceeding 30 % regarded as poor. The MBE is determined as follows:

$$MBE = \frac{\sum_{i=1}^{n}(Si - Oi)}{n} \qquad \text{(Eqn. 3)}$$

These metrics provide a robust framework for evaluating the agreement between simulated and observed values (17). When calibrated with region-specific data, these validations demonstrate that DSSAT models offer strong tools for simulating crop growth and yield, enabling informed decision-making for sustainable agricultural practices.

DSSAT models for pulse crop improvements in India

DSSAT models have demonstrated diverse applications for pulse crops in India, providing valuable tools for optimizing agronomic practices and improving productivity under various climatic conditions. These models have been extensively used to assess the effects of sowing dates, irrigation levels and fertilization on crops such as redgram (*Cajanus cajan*) and chickpeas. (*Cicer arietinum*). Table 3 shows practical applications in crop improvement. DSSAT simulations for redgram (*Cajanus cajan*) in Tamil Nadu evaluated adaptation strategies such as nitrogen application and altered sowing dates. The model highlighted significant yield variations across agro-climatic zones, emphasizing the necessity of region-specific management strategies (39). Additionally, pigeonpea (*Cajanus cajan (L.) Millsp.*) yields under various fertigation levels were successfully simulated using the DSSAT-CROPGRO model. The results demonstrated that optimal nutrient management increased seed yield by 8.0-11.0 % compared to traditional approaches (65). These applications of DSSAT models in pulse crop research reinforce their significance in developing climate-resilient and resource-efficient cropping strategies for sustainable agriculture in India.

Current challenges

Climate change threatens agriculture through rising temperatures, unpredictable rainfall and extreme weather impacting pulse yields. Limited access to technology and regional variability hinder adaptation, necessitating resilient crops, sustainable practices and GIS-based climate monitoring (66). The DSSAT model, when integrated with the Root Zone Water Quality Model, has been employed to simulate the effects of various agricultural management strategies, including irrigation, fertilization, planting dates, crop rotation, pesticide use, water efficiency and crop productivity (67). Additionally, models such as DNDC and DSSAT have been extensively used to simulate the soil water cycle, greenhouse gas

Table 3. DSSAT models and their applications in crop improvement

DSSAT model	Crop	Yield (kg/ha)	Applications	References
DSSAT v4.7	Rice	Early: -181.30 kg/ha per decade, Late: -276.16 kg/ha per decade	Climate change impact analysis, yield prediction, growth season analysis	(42)
DSSAT-4.7 CERES-Rice	Rice	3190 kg/ha	Yield prediction using Sentinel-1A SAR data integration	(43)
DSSAT	Rice	Single-season: +0.1-3.6 %, Early: +4.6-9.5 %, Late: -2.3-8.8 %	Integration with machine learning for yield prediction	(83)
DSSAT v4.7	Wheat	+5.46 % in biomass, +2.9 % in yield	Impact of aerosol reduction on wheat yield prediction	(45)
DSSAT-CERES-Maize	Maize	27 % increase under root proliferation adaptation strategy	Adaptation strategy to mitigate climate change impact	(70)
DSSAT v4.7	Maize	8.8 % to 11 % reduction in nitrogen uptake	Assessment of nitrogen application rates for yield optimization	(30)
DSSAT-CERES-Millet	Millet, Pearl Millet	Varied by variety and sowing window	Assessment of climate change impact and adaptation strategies	(84)
DSSAT v4.7-CROPGRO	Soybean	-1 % to +24 %	Yield estimation using weather and soil data	(47)
DSSAT v4.6.1	Groundnut	Decreased with temperature increase	Assessing climate change impact, productivity under various CO2 levels	(85)
CROPGRO-Pigeonpea	Pigeonpea	1875 kg/ha	Evaluating fertigation impacts on pigeonpea under different nutrient dosages	(65)
DSSAT v4.6.1	Chickpea	Varied based on climatic conditions	Assessing the impact of sowing dates, climate change on chickpea productivity under various CO2 levels	(85)
DSSAT v4.7	Cowpea	Varied with water stress	Simulating water stress impact on cowpea growth and yield	(86)
DSSAT	Blackgram	Beneficial stimulus under enriched CO_2	Assessing climate change impact on yield	(5)
DSSAT v4.7	Red gram	Increased yield under CO_2 enrichment and optimized sowing date	Evaluating sowing date and genotype impact on yield, Adaptation strategies under changing climate	(87)
DSSAT-CROPGRO-Mungbean	Mungbean	Increased with early sowing	Assessing sowing date impact	(40)
DSSAT-CROPGRO-Lentil	Lentil	Improved with conservation tillage	Evaluating conservation tillage practices & Simulating lentil growth and development using the CROPGRO model	(88)

emissions, crop growth and soil carbon and nitrogen dynamics under different management techniques and climatic conditions (26). However, DSSAT still faces particular challenges in pulse crop modelling, mainly due to region-specific calibration requirements, discrepancies in soil nitrogen and water modelling and an overall emphasis on cereal crops. Refinements are necessary to improve phenology predictions and stress tolerance modelling in pulses to enhance the models' accuracy and applicability (68). Addressing these challenges is crucial to ensuring food security and sustainable agricultural practices in the face of ongoing climate change.

Future climate resilience by using the DSSAT model

Ensuring the reliability and effectiveness of DSSAT models for crop improvement and climate resilience requires accurate input data, thorough model validation and the ability to simulate complex environmental conditions (40). Future research should focus on integrating real-time data from remote sensing and Internet of Things (IoT) devices to enhance the precision of DSSAT. GPS-enabled wireless sensor networks (WSNs) can continuously update crop growth and topography data, providing more accurate and timely information for decision-making. Recent advancements in digital photography and signal processing have further enhanced the capabilities of WSNs, allowing for precise assessments of crop health and quality, ultimately improving crop yields (69).To increase the adoption of DSSAT among resource-constrained farming communities, the development of simplified user interfaces and region-specific modules for underutilized crops is essential. Additionally, leveraging machine learning to automate the calibration process could significantly reduce the labour-intensive nature of model setup, making DSSAT more accessible and practical for pulse crop management. Addressing these challenges will enable DSSAT to play a transformative role in ensuring the sustainability and resilience of pulse crop production systems amid climate change.

Conclusion

This review underscores the critical role of the DSSAT model in enhancing pulse crop resilience amid climate change. By simulating various agronomic practices, DSSAT aids in optimizing sowing dates, irrigation and fertilization to mitigate climate-induced yield losses. Despite its effectiveness, challenges such as region-specific calibration, limited accessibility and the need for improved pulse crop modelling persist. Future research should focus on integrating real-time data from remote sensing and IoT technologies, refining stress-tolerance parameters and leveraging machine learning for automated calibration. Collaborative efforts among researchers, policymakers and farmers are essential for promoting climate-smart agriculture. Prioritizing adaptive strategies, including the development of heat-resistant cultivars and sustainable management practices, is crucial to ensuring food security and the long-term viability of pulse crop production in an increasingly unpredictable climate.

Acknowledgements

We want to thank Tamil Nadu Agricultural University, Coimbatore and the Agricultural College and Research Institute, Madurai, for their invaluable technical support and guidance. The author(s) declare that no financial support was received for this articles' research, authorship and/or publication.

Authors' contributions

All authors have contributed significantly to this review. JS conceptualized the study, MS reviewed the literature and drafted the manuscript. KP focused on integrating soil data and its relevance to pulse crop systems, providing detailed insights and analyses. GA analysed the impact of weather data on crop productivity and contributed to the discussion of geospatial tools. SAP and SNS critically reviewed and revised the manuscript to ensure scientific rigour and coherence. All the authors collaborated to synthesize the findings, provide expert opinions and approve the final manuscript. Their collective efforts aimed to advance sustainable practices in pulse agriculture.

Compliance with ethical standards

Conflict of interest: Authors do not have any conflict of interest to declare. The sole objective of this review is to advance the knowledge and support sustainable agricultural practices for the benefit of researchers, policymakers and farmers.

Ethical issues: None

References

1. Nandhini P, Muthumanickam D, Pazhanivelan R, Kumaraperuma R, Ragunath K, Sudarmanian N. Intercomparision of Drone and Conventional Spraying Nutrients on Crop Growth and Yield in Black Gram. Intl J Pl Soil Sci. 2022;34(20):845–52. https://doi.org/10.9734/ijpss/2022/v34i2031231
2. Sowmyasri S, Rani CS, Sudhakar C, Triveni S. Influence of integrated nutrient management on the productivity of kharif Redgram (*Cajanus cajan* L.). Intl J Environ Clim Chan. 2023;13(10):2528–32. https://doi.org/10.9734/ijecc/2023/v13i102918
3. Amiri S, Rahimi-Moghaddam S, Eyni–Nargeseh H. Adopting a strategic approach to dormant seeding and initial soil water management for rainfed lentil agroecosystems. Discover Life. 2024;54(1):1-21. https://doi.org/10.1007/s11084-024-09675-0
4. Gull R, Bhat TA, Sheikh TA, Wani OA, Fayaz S, Nazir A, et al. Climate change impact on pulse in India-A review. J Pharmac Phytochem. 2020;9(4):3159–66.
5. Pradipa C, Panneerselvam S, Geethalakshmi V, Bhuvaneeswari K, Maragatham N. Potential impact of future climate change on spatial variability of blackgram yield over Tamil Nadu. J Agromet. 2022;24(2):157–64. https://doi.org/10.54386/jam.v24i2.1030
6. Kumar N, Kumar S, Nain A. Response of CERES-wheat and CROPGRO-urd model (DSSAT model v 4.5) for tarai region of Uttarakhand. Mausam. 2014;65(1):109–14. https://doi.org/10.54302/mausam.v65i1.930
7. Hoogenboom G, editor The application of crop modeling for irrigation and water management. Am Soc Agric Biol Engin. https://doi.org/10.13031/irrig.2020–084
8. El–Sadek AN. Evaluating the Effects of different sowing dates and tillage practices on faba bean yield based on dssat model. Intl J Environ Agric Biotechnol. 2024;9(1):115–25.

9. Corbeels M, Chirat G, Messad S, Thierfelder C. Performance and sensitivity of the DSSAT crop growth model in simulating maize yield under conservation agriculture. Europ J Agron. 2016;76:41–53. https://doi.org/10.1016/j.eja.2016.02.001

10. Grdeń P, Jakubczyk A. Health benefits of legume seeds. J Sci Food Agric. 2023;103(11):5213–20. https://doi.org/10.1002/jsfa.12585

11. Marimuthu S, Vanitha C, Surendran U, El–Hendawy S, Mattar MA. Conception of improved blackgram (*Vigna mungo* L.) production technology and its propagation among farmers for the development of a sustainable seeds production strategy. Sustainability. 2024;16 (11):4750. https://doi.org/10.3390/su16114750

12. Rajender B, Tiwari A, Chaturvedi S. Pulses revolution in India through rice-fallows management. In: Wani, SP, Raju K, Bhattacharyya T, editors. Scaling-up solutions for farmers. Cham: Springer; 2021. p. 229–263. https://doi.org/10.1007/978–3–030–77935–1_6

13. Kumar S, Gopinath K, Sheoran S, Meena RS, Srinivasarao C, Bedwal S, et al. Pulse–based cropping systems for soil health restoration, resources conservation and nutritional and environmental security in rainfed agroecosystems. Front Microbiol. 2023;13:1041124. https://doi.org/10.3389/fmicb.2022.1041124

14. Mousavi H. Nitrogen–Enriched Organic fertilizers' (NEO) effects on crop yields, soil functions and species. PhD [Thesis]; 2023. Rena: Inland Norway University of Applied Sciences. https://hdl.handle.net/11250/3102971

15. Abayechaw D. Review on decision support system for agrotechnology transfer (DSSAT) model. Inform Sys. 2021;10 (6):126–33. https://doi.org/10.11648/j.ijiis.20211006.13

16. Woli P, Smith GR, Long C, Rouquette Jr FM. Assessing Cowpea-Wheat Double Cropping Strategies in the Southern United States Using the DSSAT Crop Model. Agricultural Sciences. 2022;13 (6):758–75. https://doi.org/10.4236/as.2022.136049

17. Chandran MAS, Banerjee S, Mukherjee A, Nanda MK, Venugopalan VK, Laing AM, et al. Coupling crop simulation modelling and multi-criteria decision aid for ranking the sustainability of cropping sequences. Front Sustain Food Syst. 2023;7:1208283. https://doi.org/10.3389/fsufs.2023.1208283

18. 18. Hoogenboom G, Porter CH, Boote KJ, Shelia V, Wilkens PW, Singh U, et al. The DSSAT crop modeling ecosystem. In: Boote K, editor. Advances in crop modelling for a sustainable agriculture. Sawston: Burleigh Dodds Science Publishing; 2019. p. 173–216.

19. Sachin G, Mohammed Ahamed J, Nagajothi K, Rana M, Murugan B. Automation of the DSSAT crop growth simulation model. Intl Arch Photogram Remote Sens Spatial Inform Sci. 2019;42:251–6. https://doi.org/10.5194/isprs–archives–XLII–3–W6–251–2019

20. Geethalakshmi V, Gowtham R, Gopinath R, Priyanka S, Rajavel M, Senthilraja K, et al. Potential Impacts of future climate changes on crop productivity of cereals and legumes in Tamil Nadu, India: A mid-century time slice approach. Adv Meteorology. 2023;2023 (1):4540454. https://doi.org/10.1155/2023/4540454

21. Cuadra SV, Kimball BA, Boote KJ, Suyker AE, Pickering N. Energy balance in the DSSAT-CSM-CROPGRO model. Agric Forest Meteoro. 2021;297:108241. https://doi.org/10.1016/j.agrformet.2020.108241

22. Ma H, Malone RW, Jiang T, Yao N, Chen S, Song L, et al. Estimating crop genetic parameters for DSSAT with modified PEST software. Europ J Agron. 2020;115:126017. https://doi.org/10.1016/j.eja.2020.126017

23. Shoukat MR, Wang J, Habib-ur-Rahman M, Hui X, Hoogenboom G, Yan H. Adaptation strategies for winter wheat production at farmer fields under a changing climate: Employing crop and multiple global climate models. Agric Sys. 2024;220:104066. https://doi.org/10.1016/j.agsy.2024.104066

24. Mirshekarnezhad B. Integrating agrotechnical practices to optimize maize yield potentials in a regional variable climate: DSSAT and Python tools. Cereal Res Comm. 2024;52(1):301–12. https://doi.org/10.1007/s42976–023–00368–4

25. Suanphrom N, Khurnpoon L, Phakamas N. Small scale method for estimation of genetic coefficients of photoperiod-insensitive rice using generalized likelihood uncertainty estimation. Agric Nat Res. 2023;57(2):211–22. https://doi.org/10.34044/j.anres.2023.57.2.02

26. Singh PK, Sankar SAG, Agarwal SSK, Singh RS, Singh KK, Gupta A, et al. Simulating impact of climate change on growth and yield of wheat crop grown in various agro-climatic zones of India by using CERES-Wheat (DSSAT v 4.6). Brazil J Develop. 2024;10(6):e70228–e. https://doi.org/10.34117/bjdv10n6–013

27. Sivamurugan A, Pazhanivelan S, Suganthi A, Bharathi C, Raju M, Manivannan V, et al. Efficacy of new generation herbicide mixtures in irrigated maize (*Zea mays*). Ind J Agric Sci. 2024;94 (11):1183–8. https://doi.org/10.56093/ijas.v94i11.147139

28. Kothari K, Ale S, Bordovsky JP, Munster CL, Singh VP, Nielsen-Gammon J, et al. Potential genotype–based climate change adaptation strategies for sustaining cotton production in the Texas High Plains: A simulation study. Field Crops Res. 2021;271:108261.https://doi.org/10.1016/j.fcr.2021.108261

29. Charishma D, Kuligod V, Gundlur S, Potdar M, Doddamani M, Nagaveni H. Estimation of top soil properties by Sentinel-2 imaging. Geol Ecol Landscap. 2024:1–10. https://doi.org/10.1080/24749508.2024.2392920

30. Trenz J, Memic E, Batchelor WD, Graeff-Hönninger S. Generic optimization approach of soil hydraulic parameters for site-specific model applications. Precision Agric. 2024;25(2):654–80. https://doi.org/10.1007/s11119–023–10087–9

31. Srinivasan G, Pazhanivelan S, Krishnasamy SM, Sudarmanian N, Rajeswari S, Kannan B. Estimating genetic parameters for DSSAT CROPGRO-cotton model calibration and validation. Intl J Pl Soil Sci. 2021;33(24):165–72.

32. Mulla DJ, Tahir M, Jungers JM. Comparative simulation of crop productivity, soil moisture and nitrate-N leaching losses for intermediate wheatgrass and maize in Minnesota using the DSSAT model. Front Sustainable Food Sys. 2023;7:1010383. https://doi.org/10.3389/fsufs.2023.1010383

33. Reddy TV, Saikumar K, Reddy RA, Chary VB, Srinija P, Reddy THV, editors. Integrating soil sensing and rainfall modelling for precision crop recommendation systems. IEEE. 2024. https://doi.org/10.1109/I2CT61223.2024.10543793

34. Lal D, Niwas R. Yield Predication by DSSAT Model of wheat crop: A Review. Intl J Environ Climate Change. 2024;14(2):519–24. https://doi.org/10.9734/ijecc/2024/v14i23965

35. Mandapati R, Gumma MK, Metuku DR, Bellam PK, Panjala P, Maitra S, et al. Crop yield assessment using field-based data and crop models at the village level: a case study on a homogeneous rice area in Telangana, India. AgriEngineering. 2023;5(4):1909–24. https://doi.org/10.3390/agriengineering5040117

36. Kancheti M, Pazhanivelan S, Kumar N, Geethalakshmi V, Kaliaperumal R, Ramanathan S, et al. exploring dssat model genetic coefficient estimation methodologies for chickpea in Bundelkhand Region of Uttar Pradesh, India. Int J Plant Soil Sci. 2023;35(18):1880–6. https://doi.org/10.9734/ijpss/2023/v35i183471

37. SN, Ahamed I. Assessing the black gram (*Vigna mungo*) yield due to climate change impacts and its adaptation strategies in the Cauvery delta region of South India. Theo Appl Climat. 2023;153 (3):1049–62. https://doi.org/10.1007/s00704–023–04516–y

38. Appiah M, Bracho-Mujica G, Svane S, Styczen M, Kersebaum K-C, Rötter RP, editors. The impact of high quality field data on crop model calibration. EGU General Assembly Conf. 2022. https://doi.org/10.5194/egusphere–egu22–2783

39. Yadav M, Patel C, Singh R, Singh K, Balasubramanian R, Mall R, et al. Assessment of climate change impact on different pigeonpea

maturity groups in north Indian condition. J Agrometeo. 2021;23 (1):82–92. https://doi.org/10.54386/jam.v23i1.92

40. Chen S, He L, Cao Y, Wang R, Wu L, Wang Z, et al. Comparisons among four different upscaling strategies for cultivar genetic parameters in rainfed spring wheat phenology simulations with the DSSAT-CERES-Wheat model. Agric Water Manage. 2021;258:107181. https://doi.org/10.1016/j.agwat.2021.107181
41. Janghel Y, Puranik H. Calibration and validation of cropgro (DSSAT 4.7) Model for Chickpea (Cicer arietinum L.) Crop in Raipur. Intl J Environ Clim Chan. 2023;13(12):1080–86. https://doi.org/10.9734/ijecc/2023/v13i123771
42. Fang L, Struik PC, Girousse C, Yin X, Martre P. Source-sink relationships during grain filling in wheat in response to various temperature, water deficit and nitrogen deficit regimes. J Exp Bot. 2024;75(20):6563–78. https://doi.org/10.1093/jxb/erae310
43. Bhatt CK, Nain AS. Integration of Sentinel-1A SAR data with crop simulation model for rice yield prediction in Udham Singh Nagar, Uttarakhand. Mausam. 2024;75(3):649–58. https://doi.org/10.54302/mausam.v75i3.5905
44. Tefera S, Tesfaye K, Tadesse T, Alem T, Ademe D. Evaluating the effects of the CERES-Rice model to simulate upland rice (*Oryza sativa* L.) yield under different plant density and nitrogen management strategies in Fogera Plain, Northwest Ethiopia. Heliyon. 2024;10(13). https://doi.org/10.1016/j.heliyon.2024.e33556
45. Bai Z, Zhang D, Wang Z, Harrison MT, Liu K, Song Z, et al. Challenges and strategies in estimating soil organic carbon for multi-cropping systems: A review. Carbon Footprints. 2024;3 (4):15. https://doi.org/10.20517/cf.2024.15
46. Ghasemi–Saadatabadi F, Zand-Parsa S, Gheysari M, Sepaskhah AR, Mahbod M, Hoogenboom G. Improving prediction accuracy of CSM-CERES-Wheat model for water and nitrogen response using a modified Penman-Monteith equation in a semi-arid region. Field Crops Research. 2024;312:109381. https://doi.org/10.1016/j.fcr.2024.109381
47. Singh R, Singh K, Gohain GJMES, Environment. Simulating crop yield using the DSSAT v4. 7-CROPGRO-soyabean model with gridded weather and soil data. Model Earth Syst Environ. 2024;10 (1):845–53. https://doi.org/10.1007/s40808–023–01807–1
48. Venkatesan M, Pazhanivelan S. Estimation of maize yield at spatial level using DSSAT crop simulation model. Madras Agric J. 2018;105:548–552. https://doi.org/10.29321/MAJ 2018.000201
49. Wu J-z, Zhang J, Ge Z-m, Xing L-w, Han S-q, Chen S, et al. Impact of climate change on maize yield in China from 1979 to 2016. J Integ Agric. 2021;20(1):289–99. https://doi.org/10.1016/S2095–3119(20)63244–0
50. Marrou H, Ghanem ME, Amri M, Maalouf F, Sadoun SB, Kibbou F, et al. Restrictive irrigation improves yield and reduces risk for faba bean across the Middle East and North Africa: A modeling study. Agric Syst. 2021;189:103068. https://doi.org/10.1016/j.agsy.2021.103068
51. Yang K–W. Integrating crop growth models and remote sensing for predicting performance in sorghum Indiana: Purdue University; 2021.
52. Ren H, Li Z, Cheng Y, Zhang J, Liu P, Li R, et al. Narrowing yield gaps and enhancing nitrogen utilization for Summer maize (*Zea mays* L) by combining the effects of Varying nitrogen fertilizer input and planting density in DSSAT simulations. Front Pl Sci. 2020;11:560466. https://doi.org/10.3389/fpls.2020.560466
53. Lang T, Yang Y, Jia K, Zhang C, You Z, Liang Y. Estimation of winter wheat production potential based on remotely–sensed imagery and process–based model simulations. Remote Sens. 2020;12 (17):2857. https://doi.org/10.3390/rs12172857
54. Ramamoorthy P, Mary P, Saravanapandian P, Gurusamy A, Kumutha K. Geo Statistical tool for soil fertility assessment in pulses growing area of Melur Block, Madurai District, Tamil Nadu. Indian J Agric Res. 2024;58(2). https://doi.org/10.18805/IJARe.A–5929
55. Chaganti VN, Culman SW, Herms C, Sprunger CD, Brock C, Leiva Soto A, et al. Base cation saturation ratios, soil health and yield in organic field crops. Agron J. 2021;113(5):4190–200. https://doi.org/10.1002/agj2.20785
56. Gunawat A, Sharma D, Sharma A, Dubey SK. Assessment of climate change impact and potential adaptation measures on wheat yield using the DSSAT model in the semi-arid environment. Nat Hazards. 2022:1–20. https://doi.org/10.1007/s11069–021–05130–9
57. Kebede T, Kebede A. The impact of future climate on faba bean crop phenology and yield in Kutaber Wereda, South Wollo Zone of North Eastern Ethiopia. Research Square. 2023. https://doi.org/10.21203/rs.3.rs–3790673/v1
58. Kadiyala M, Charyulu DK, Nedumaran S, Shyam DM, Gumma MK, Bantilan M. Agronomic management options for sustaining chickpea yield under climate change scenario. J Agromete. 2016;18(1):41–7. https://doi.org/10.54386/jam.v18i1.897
59. Ashwini S, Sakthivel N, Pazhanivelan S, Ramah K, Janaki P, Ravichandran V, et al. Evaluating rice yield and resource efficiency: DSSAT analysis of conventional vs. AWD techniques in Coimbatore. Plant Sci Tod. 2024. https://doi.org/10.14719/pst.4770
60. Dias HB, Inman-Bamber G. Sugarcane: Contribution of process-based models for understanding and mitigating impacts of climate variability and change on production. Systems Model. 2020:217–60. https://doi.org/10.1007/978–981–15–4728–7_8
61. Sabarinathan B, Pazhanivelan S, Ragunath K, Sivamurugan A, Sudarmanian N. Calibration and validation of CERES-sorghum module of DSSAT model for rabi sorghum under rainfed condition. Pharma Innov J. 2021;10(1):715–8. https://doi.org/10.22271/tpi.2021.v10.i1j.5613
62. Ragul A, Pazhanivelan S, Sivamurugan A, Boomiraj K, Raghunath K, Mrunalini K. Evaluation of DSSAT-CROPGRO module for spatial yield estimation of chickpea in vidisha (Madhya Pradesh) and Nagaur (Rajasthan), India. Intl J Environ Climate Change. 2023;13 (9):2279–88.
63. Thirumeninathan S, Pazhanivelan S, S Sudarmanian N, P Ragunath K, Gurusamy A, Sritharan N. Calibration and validation of DSSAT CROPGRO peanut model for yield and yield attributing characters of groundnut varieties in northern agro-climatic zone of Tamil Nadu. Intl J Environ Climate Change. 2021. https://doi.org/10.9734/IJECC/2021/v11i1130535
64. Arshad MN, Ahmad A, Wajid SA, Cheema MJM, Schwartz MW. Adapting DSSAT model for simulation of cotton yield for nitrogen levels and planting dates. Agron J. 2017;109(6):2639–48. https://doi.org/10.2134/agronj2017.04.0233
65. Jeyajothi R, Pazhanivelan S, Vinothini N, Indhushree A, Ramadass S, Marimuthu S. Evaluation of DSSAT CROPGRO model on growth and yield of pigeonpea cultivars under different fertigation levels. J Appl Nat Sci. 2023;15(3):1071–9. https://doi.org/10.31018/jans.v15i3.4740
66. Kannan P, Sankar M, Prabhavathi M. Remote sensing and GIS for land use mapping and crop planning in Cauvery delta region of Tamil Nadu, India. Indian J Soil Conserv. 2010;38(3):199–204.
67. Wu W, Ma B. Integrated nutrient management (INM) for sustaining crop productivity and reducing environmental impact: A review. Sci Tot Environ. 2015;512:415–27. https://doi.org/10.1016/j.scitotenv.2014.12.101
68. Dar EA, Hoogenboom G, Shah ZA. Meta analysis on the evaluation and application of DSSAT in South Asia and China: Recent studies and the way forward. J Agromet. 2023;25(2):185–204. https://doi.org/10.54386/jam.v25i2.2081
69. Dhanaraju M, Chenniappan P, Ramalingam K, Pazhanivelan S, Kaliaperumal R. Smart farming: Internet of Things (IoT)-based

sustainable agriculture. Agric. 2022;12(10):1745. https://doi.org/10.3390/agriculture12101745

70. Onyekwelu I, Sharda VJSotTE. Root proliferation adaptation strategy improved maize productivity in the US Great Plains: Insights from crop simulation model under future climate change. Sci Tot Environ. 2024;927:172205. https://doi.org/10.1016/j.scitotenv.2024.172205
71. Shawon AR, Memic E, Kottmann L, Uptmoor R, Hackauf B, Feike TJAJ. Comprehensive evaluation of the DSSAT-CSM-CERES-Wheat for simulating winter rye against multi-environment data in Germany. Agron J 2024;116(4):1844–68. https://doi.org/10.1002/agj2.21590
72. Ahmed M, Rehman A, Sarwar N, Doğan H, Abbas G, Khan MA, et al. Deciding sowing–window for maize-based cropping system in arid and semiarid environments in Punjab, Pakistan. Turkish J Agric Forest. 2023;47(6):1078–98.
73. Nath A, Karunakar A, Kumar A, Yadav A, Chaudhary S, Singh SPJE, Environment, et al. Evaluation of the CROPGRO-soybean model (DSSAT v 4.5) in the Akola region of Vidarbha, India. Ecol Environ Conserv. 2017;23:153–9.
74. Paschapur NS, Medhi K, Sarmah K, Goswami B, Bal SK, Subbarao AV, et al. Assessing Impact of Projected Climate Change on Sali Rice in a Representative District of Upper Brahmaputra Valley Zone of Assam. Intl J Environ Climate Change. 2022;12(10):16–30.
75. Debnath S, Mishra A, Mailapalli D, Raghuwanshi NJJoW, Change C. Identifying most promising agronomic adaptation strategies to close rainfed rice yield gap in future: a model–based assessment. J Water Clim Change. 2021;12(6):2854–74. https://doi.org/10.2166/wcc.2021.094
76. Chisanga CB, Phiri E, Chinene VRJN. Evaluating APSIM-and-DSSAT -CERES-Maize models under rainfed conditions using zambian rainfed maize cultivars. Nitrogen. 2021;2(4):392–414. https://doi.org/10.3390/nitrogen2040027
77. Yao N, Wei Y, Jiang K, Liu J, Li Y, Ran H, et al. Nonlinear water stress response functions can improve the performance of the DSSAT-CERES-Wheat model under water deficit conditions. Agric Water Manage. 2025;307:109235. https://doi.org/10.1016/j.agwat.2024.109235
78. da Silva FAM, de Oliveira AD, de Carvalho AM, Marchão RL, Luiz AJB, Ribeiro FP, et al. Effects of agricultural management and of climate change on N2O emissions in an area of the Brazilian Cerrado: Measurements and simulations using the STICS soil-crop model. Agric Ecosyst Environ. 2024;363:108842. https://doi.org/10.1016/j.agee.2023.108842
79. Shen H, Xu F, Zhao R, Xing X, Ma XJTotA. Optimization of Sowing date, irrigation and nitrogen management of summer maize using the DSSAT-CERES-Maize Model in the Guanzhong Plain, China. Transactions of the ASABE. 2020;63(4):789–97.
80. Gao Y, Xu X, Sun C, Ding S, Huo Z, Huang GJAWM. Parameterization and modeling of paddy rice (*Oryza sativa* L. ssp. japonica) growth and water use in cold regions: Yield and water-saving analysis. Agric Water Manage. 2021;250:106864. https://doi.org/10.1016/j.agwat.2021.106864
81. EL–Mansoury M, Saleh SJJoSS, Engineering A. Influence of climatic changes on faba bean (*Vicia faba* L.) yield in North Nile Delta. J Soil Sci Agric Engin. 2017;8(1):29–34. https://doi.org/10.21608/jssae.2017.37065
82. Kumagai E, Yamada T, Hasegawa TJF, Security E. Is the yield change due to warming affected by photoperiod sensitivity? Effects of the soybean E4 locus. Food Ener Sec. 2020;9(1):e186. https://doi.org/10.1002/fes3.186
83. Zhang D, Liu J, Li D, Batchelor WD, Wu D, Zhen X, et al. Future climate change impacts on wheat grain yield and protein in the North China Region. Sci Tot Environ. 2023;902:166147. https://doi.org/10.1016/j.scitotenv.2023.166147
84. Tofa AI, Kamara AY, Mohamed AM, Garba M, Souley AM, Salissou H, et al. Assessment of climate change impact and adaptation strategy for millet in the Sudano-Sahelian region of Niger. Reg Environ Change. 2024;24(4):151. https://doi.org/10.1007/s10113–024–02313–5
85. Yadav M, Patel C, Singh R, Singh K, Balasubramanian R, Mall R, et al. Assessment of climate change impact on different pigeonpea maturity groups in north Indian condition. J Agrometeorol. 2021;23(1):82–92. https://doi.org/10.54386/jam.v23i1.92
86. Angourakis A, Bates J, Baudouin J-P, Giesche A, Walker JR, Ustunkaya MC, et al. Weather, land and crops in the Indus Village model: A simulation framework for crop dynamics under environmental variability and climate change in the Indus Civilisation. Quaternary. 2022;5(2):25. https://doi.org/10.3390/quat5020025
87. Chinnasamy P, Shanmugam P, Vellingiri G, Jaganathan R, Bhuvaneeswari K, Vigneswaran SJJoA. Modelling adaptation strategies towards climate smart red gram production in Tamil Nadu. J Agrometeorol. 2023;25(4):525–31. https://doi.org/10.54386/jam.v25i4.2280
88. El–Sadek A, Abd EL-Ghany F, Shaalan A. Simulating the effect of tillage practices on the yield production of wheat and barley under dryland conditions. Agronomy Res. 2020;18(4):2374–90. https://doi.org/10.15159/ar.20.188