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Implementing nitrogen and its varieties to predict spring wheat productivity using DSSAT crop simulation modeling

S.G. Okbagabir[1], A. Hassouni[2], M.H. Al-Mamoori[1], Y. Wang[1], A.A. Ahmed[3], E.N. Pakina[1]

[1]RUDN University, Moscow, Russian Federation

[2]College of Agriculture, Misan University, Misan, Iraq

[3]Russian State Agrarian University - Moscow Timiryazev Agricultural Academy, Moscow, Russian Federation

Abstract

Background. The research focuses on using the DSSAT model (v4.8.2) to simulate spring wheat (*Triticum turgidum L.)* performance in Russian climatic conditions, addressing the need to optimize farming strategies amongst agroecological challenges. Crop models are effective tools to predict crop productivity in different management options and climatic conditions.

Purpose. The study aimed to forecast spring wheat yield by evaluating the impact of four nitrogen (N) levels (0, 15, 30, 45 kg/ha) on leaf area index (LAI), stem weight, leaf weight, and tops weight for two spring wheat varieties (Radmira and Kanyuk) to predict the enhancement of agricultural productivity.

Materials and methods. Field experiments at the Research Institute of Agrochemistry in Barybino during summer 2024 utilized the DSSAT model (v4.8.2) to simulate spring wheat (Triticum turgidum L.) performance. Statistical analyses (t-tests, RMSE, Std. Dev.) compared observed and simulated data, confirming the model's accuracy and significance.

Results. The DSSAT model accurately simulated outputs within observed ranges: LAI ranged from 0.42 (0 kg N/ha, V1) to 1.25 (30 kg N/ha, V1), and tops weight varied from 1704 kg/ha (45 kg N/ha) to 4248 kg/ha (30 kg N/ha). Simulated values showed less variability (LAI: 0.78–1.10; tops weight: 1749–3412 kg/ha). Model performance was strong for tops weight (r^2 = 0.88–0.95) and stem weight (r^2 = 0.90–0.95), but weaker for LAI (r^2 = 0.796–0.847) and leaf weight (r^2 = 0.74–0.90). Nitrogen rates significantly affected all parameters ($p < 0.05$), with Kanyuk (V2) outperforming Radmira (V1) at higher N levels.

The findings highlighted the importance of advanced DSSAT crop modeling for predicting and optimizing nitrogen use and varietal selection to improve agricultural productivity under varying agroecological conditions.

Keywords: calibration; dependent variables; DSSAT model; fertilizer; validation; wheat varieties

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Introduction

The capability of the simulation models, which were used in the late 1960s, have been increased over time with the development of technology, and models have been advanced for many different plant species. Plant simulation modes generally differ from each other in terms of complex equation systems describing the developmental process of the plant and the input parameters being used. Process-based crop models use weather, soil, crop, and management information as input to simulate plant development and growth [24]. Crop models are effective tools to predict crop productivity in different management options and climatic conditions. In the context of climate change, the importance of crop models in simulating crop production under different climatic scenarios has been growing steadily [10]. This strategy is effective in the US and Europe, where farms are often well-managed in terms of pest and disease control, fertilizer, and irrigation inputs. In the early 1980s, the United States Agency for International Development (USAID) made a bold step to support a project that was based on systems analysis of agricultural production to address food security in developing countries. The International Benchmark Sites Network for Agrotechnology Transfer (IBSNAT), a project designed to enhance agricultural production, was established by University of Hawaii soil physicist [3]. The scheme was launched in 1992, as an investigation methodology to study the assumption that modeling systems play an important role in agricultural improvement [23]. They are vital tools for analyzing the ecological, agricultural, and evolutionary drivers of resistance evolution and their interactions [3]. Modeling wheat production under future climate scenarios is imprecise because of the high dimensionality of climate stress is an altered physiological response of living organisms caused by physical, chemical, or biotic environmental factors that tend to shift their equilibrium away from its optimal thermodynamic state [4].

The Decision Support System for Agrotechnology Transfer (DSSAT) is a software application program that comprises crop simulation models for over 42 crops (as of Version 4.8.2) as well as tools to facilitate effective use of the models. The tools include database management programs for soil, weather, crop management and experimental data, utilities, and application programs. The crop simulation models simulate growth, development and yield as a function of the soil-plant-atmosphere dynamics [13]. DSSAT crop simulation models have been used for a wide range of applications at different spatial and temporal scales. This includes on-farm and precision management, regional assessments of the impact of climate variability and climate change, gene-based modeling and breeding selection, water use, greenhouse gas emissions, and long-term sustainability through the soil organic carbon and nitrogen balances. DSSAT has been used by more than 25,000 researchers, educators, consultants, extension agents, growers, and policy and decision makers in over 187 countries worldwide [14]. They have reported that traditional field methods have a drawback due to being time-consuming, expensive, and having a lack of generality, while crop models have become valuable tools for predicting crop growth, development, and yields based on meteorological, environmental conditions and agricultural management. J. Jones conceived DSSAT as an integrated crop modeling platform [13]. The system provides tools to assist users in preparing required input files for model execution, defining experimental designs, treatments, and simulation scenarios, and enabling streamlined analysis of crop model outputs, including observational data comparisons for model evaluation and strategic scenario assessments.

Crop models dynamically replicate crop production by integrating core principles of soil science, agrometeorology, and crop physiology. The crop modelling platforms could ensure combining models of many crops with a specific software, facilitating model testing and applications for various purposes [15]. Many developments in crop models were achieved for wheat crop such as Wheat [18] as well as the photosynthesis models still in use today. Crop modeling serves as a powerful methodology that quantifies crop-environment interactions through mathematical algorithms [16]. By significantly streamlining agricultural research processes, these models offer efficient alternatives to field experiments, reducing time and financial investments. Their application has expanded substantially in recent years, supporting agricultural decision-making and management across local, regional, and global scales. Specifically, models enable predictive advisories to help farmers mitigate yield losses by simulating crop responses to variable weather conditions [1]. Among these tools, the DSSAT model has been extensively applied for: yield gap analysis, agricultural planning and decision support, strategic/tactical management, and climate change impact studies. This study was undertaken in order to:

1. Assess wheat cultivars necessary for DSSAT model operation in Russian climatic conditions.
2. Calibrate and validate the DSSAT model to simulate growth and yield responses to nitrogen application rates and spring wheat varieties.

Materials and methods

Description of the study area

The study conducted in 2024 at the Research Institute of Agrochemistry (Barybino, Domodedovo District, Moscow Region), it utilized sod-podzolic heavy loamy soil at coordinates 55°15’52.6248’’N, 37°53’13.1712’’E (137 m elevation). Spring wheat was sown on May 22, 2024, at 250 kg/ha seeding density, with germination initiating 5–7 DAS. Experimental treatments combined two varieties – Variety 1 (Kanyuk) and Variety 2 (Radmira) with Azofoska fertilizer applied at four nitrogen rates (0, 15, 30, 45 kg N/ha). The DSSAT v4.8.2 CERES-Wheat module simulated crop growth and yield using field-collected soil analytics, daily weather records, and management data. These inputs were processed through dedicated database programs, structured within DSSAT’s model framework as Input files (soil/weather/cultivar parameters), Experiment files (treatment definitions), and Output files (simulation results) [8].

Soil properties

Post-harvest, composite soil samples from the same field were collected for physico-chemical analysis. The samples underwent air-drying, grinding, and 2-mm sieving before comprehensive parameter assessment. Field and laboratory data management supported subsequent DSSAT simulations, which evaluated varietal and fertilizer interaction efficacy under optimal management practices through parametric modeling

Weather data

Daily weather data for both the growing seasons, including precipitation (mm), minimum and maximum air temperatures (°C), and global solar radiation (MJ m^{-2}) was calculated from the daily weather station of Agrochemistry Barybino.

Crop growth and yield attributes

Wheat phenology was assessed through documented growth stages: germination at 5–7 DAS, with leaf weight (kg/ha), stem weight (kg/ha), and leaf area index measured during maximum tillering and heading/anthesis. Harvesting occurred 10-12 days after physiological maturity, collecting in 1 m² samples from each plot. Harvested bundles underwent 3-5 days of sun-drying before measuring biomass yield (tops weight, kg/ha) and other growth parameters. Grain processing involved manual harvesting, 2-3 days of sun-drying, digital balance weighing, and moisture content determination. All data were analyzed using DSSAT crop simulation software.

The cropping system model (CSM)

While most users operate DSSAT through its graphical interface, advanced practitioners can execute models via command-line on Linux, Unix, and iOS platforms. The initial DSSAT version [14] incorporated standalone models PNUTGRO, SOYGRO, CERES-Maize, and CERES-Wheat, which later evolved into integrated crop modules within a unified agricultural systems framework. For accurate simulation of experimental wheat data, cultivar-specific genetic parameters require calibration. Seven genetic parameters make up DSSAT: G1 (kernel number per unit canopy weight at anthesis), G2 (standard kernel size under optimum conditions), G3 (standard, non-stressed dry weight of a single tiller at maturity), P1V (vernalization sensitivity coefficient), P1D (photoperiod sensitivity coefficient), P5 (grain filling phase duration), and PHINT (phyllochron interval between successive leaf tip appearances) [15]. Several quality metrics were used to assess the simulations' level of quality. According to [10], some of the input files deal with the experiment, weather, and soil, while others approach the genotypes' properties. The standard applications of the DSSAT can be found in the *Tools*, *Accessories,* and *Utilities* section that are presented on the left side of the main screen (Fig. 1).

Model calibration

Crop simulation models utilize specific input coefficients to distinguish varietal performance across diverse environmental and management scenarios [11]. DSSAT's Genetic Coefficient Calculator v2 (GENCALC2) was used to determine these genotype-specific characteristics, also known as genetic coefficients, for the varieties under study. This software calculates cultivar coefficients governing growth phase durations, leaf development, canopy dynamics, biomass production, and senescence (Table 1). Cultivar calibration optimized growth and yield parameters to minimize discrepancies between observed and simulated data. This process required modifying existing ecotype and cultivar files while creating new experimental files, including (A) and (T) file types to incorporate essential input data [12].

Statistical evaluation

Statistical agreement between simulated and observed values was assessed using Root Mean Square Error (RMSE) [25], R^2, and standard deviation of the Mean Difference (MD). RMSE is a standard model evaluation metric [22] that quantifies prediction deviation through equation (1):

$$\textbf{RMSE} = \sqrt{[\Sigma(P_i - O_i)^2/N]} \quad \text{Equation (1)}$$

where P = predicted values, O = observed values, and N = observations per treatment. As a strictly positive measure, lower RMSE values indicate higher model accuracy. This metric was applied to evaluate output data and compare measured versus predicted results [7].

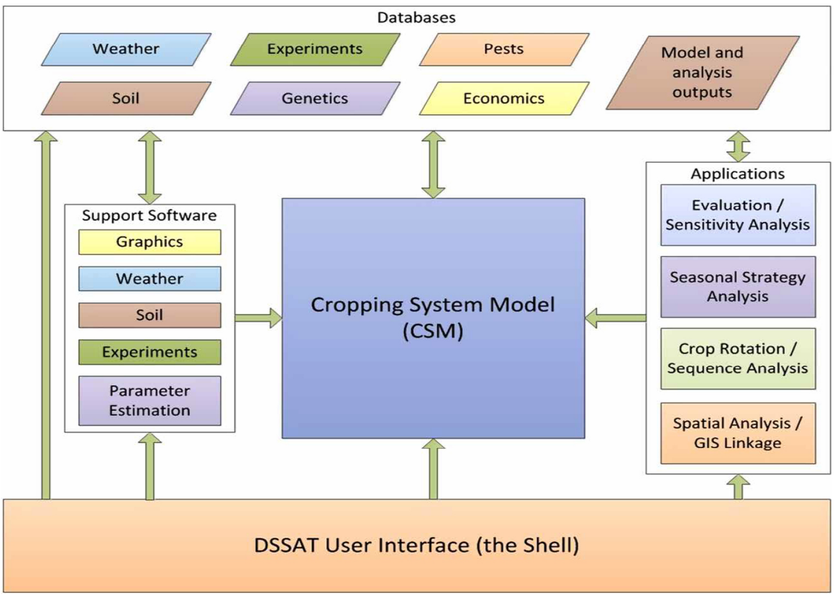

Fig 1. The DSSAT Model created in Weatherman [14]

Model quality evaluation

Multiple statistical metrics evaluated simulation quality. Model performance was summarized by plotting measured versus simulated values on a 1:1 graph with linear regression and correlation coefficients. High-quality simulations require correlation coefficients and regression slopes approaching unity. Data points are distributed closely along the 1:1 line. This graphical analysis assessed agreement between simulated and observed values [17].

Results and discussion

Analysis of nitrogen application rates and its varieties on growth and yield using DSSAT crop simulation model (CSM)

Effect of nitrogen rate application on main traits on tops weight (kg/ha)

This study investigated the influence of varying nitrogen application rates (0, 15, 30, and 45 kg N/ha) on the tops weight (kg/ha) of a crop in rainfed conditions, comparing observed and simulated mean values. The dataset, extracted from the result on top weight kg/ha, reported observed and simulated values across four nitrogen levels. This analysis explains the significance of differences between the highest and lowest recorded tops weight values and between observed and simulated means, offering insights into the impact of nitrogen fertilization on crop biomass. The results are contextualized with existing literature to provide a robust discussion, and conclusions are drawn to inform optimized agricultural practices. This study assessed nitrogen (N) rates (0, 15, 30, 45 kg/ha) on rainfed crop tops weight (kg/ha), comparing field observations with DSSAT simulations. the results show in (Fig. 2) reported that observed biomass peaked at 30 kg N/ha (4,248 kg/ha) and dropped sharply at 45 kg N/ha (1,704 kg/ha), indicating a 2,544 kg/ha range and suggesting an N optimization threshold.

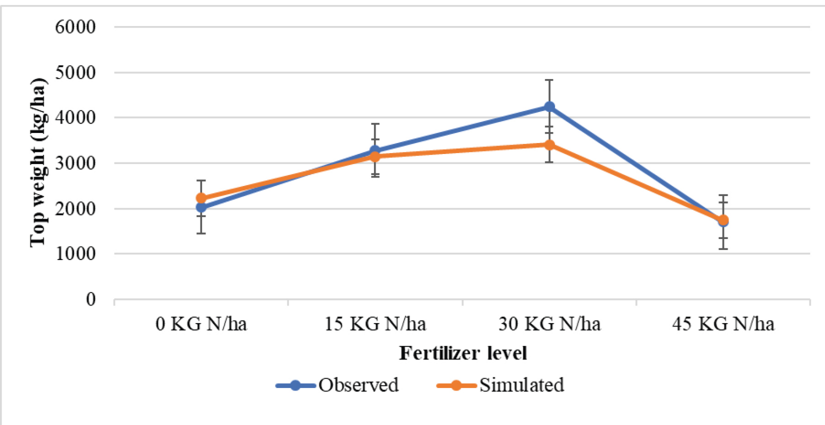

Fig 2. Measured and simulated top weight (kg/ha) of spring wheat

Simulated biomass showed lower variability (1,749-3,412 kg/ha; range: 1,663 kg/ha), underestimating the response at mid-level N rates. Statistical tests (t-test, $p<0.05$) confirmed significant differences between extreme observed values. Model differences revealed systematic errors such as overestimation at 0 and 45 kg N/ha, and underestimation at 15 and 30 kg N/ha (largest gap: 836 kg/ha at 30N). This highlights limitations in simulating non-linear biomass responses to N fertilization. The results reveal a non-linear response of tops weight to nitrogen application rates. Biomass peaks at 30 kg N/ha (4248 kg/ha observed, 3412 kg/ha simulated), indicating an optimal nitrogen level for maximizing tops weight in dry conditions. In line to these results, [1] confirmed the robustness of the CERES-Wheat model in simulating wheat grain yield, reporting very good model simulation results.

Effect of nitrogen rate application main traits on leaf area index (LAI)

This research explored how different nitrogen application rates (0, 15, 30, and 45 kg N/ha) affect the leaf area index (LAI) of a crop, comparing observed and simulated mean values from the DSSAT dataset. Observed LAI values ranged from 0.42 (0 kg N/ha) to 1.25 (30 kg N/ha), a difference of 0.83, highlighting nitrogen's strong influence on canopy growth, with 30 kg N/ha as the optimal rate presented (Figure 3). Simulated LAI values ranged from 0.78 (0 kg N/ha) to 1.10 (30 kg N/ha), a smaller difference of 0.32, suggesting the model underestimates LAI responsiveness to nitrogen. A t-test for independent samples, assuming unequal variances and typical standard deviations (0.3-0.5), indicates the observed LAI difference (0.83) is statistically significant ($p < 0.05$). The smaller simulated difference (0.32) reflects the model's tendency to reduce variability, possibly due to simplified nitrogen response assumptions. The largest discrepancy between observed and simulated LAI occurred at 0 kg N/ha (-0.36), where the model overestimated LAI, while the smallest was at 30 kg N/ha (0.15), showing better alignment at the optimal rate. Consistent overestimation at most nitrogen levels (except 30 kg N/ha) suggests the model overpredicts leaf area under non-optimal nitrogen conditions, with the discrepancy at 0 kg N/ha likely significant ($p < 0.05$).

The results demonstrated a clear positive relationship between nitrogen application rates and observed LAI, with values increasing from 0.42 (0 kg N/ha) to a peak of 1.25 (30 kg N/ha), followed by a slight decline to 0.84 (45 kg N/ha). This quadratic response suggests that nitrogen enhances leaf area up to an optimal threshold (around 30 kg N/ha), beyond which additional nitrogen may induce physiological stress or diminishing returns, possibly due to nutrient imbalances or environmental constraints. The simulated LAI values follow a similar trend but with less pronounced variability, ranging from 0.78 to 1.10. The model's overestimation at lower (0 and 15 kg N/ha) and higher (45 kg N/ha) rates and underestimation at 30 kg N/ha indicate limitations in capturing the non-linear dynamics of nitrogen-driven leaf expansion. In line to this finding, the points of the simulation should also be around the 1:1 line to evaluate simulated and measured values of LAI and Biomass (kg/ha) [17]. Studies on crops like maize and tobacco report similar quadratic responses, with LAI peaking at moderate nitrogen rates (30-40 kg N/ha) before declining due to excessive nitrogen causing osmotic stress or reduced nitrogen use efficiency [5].

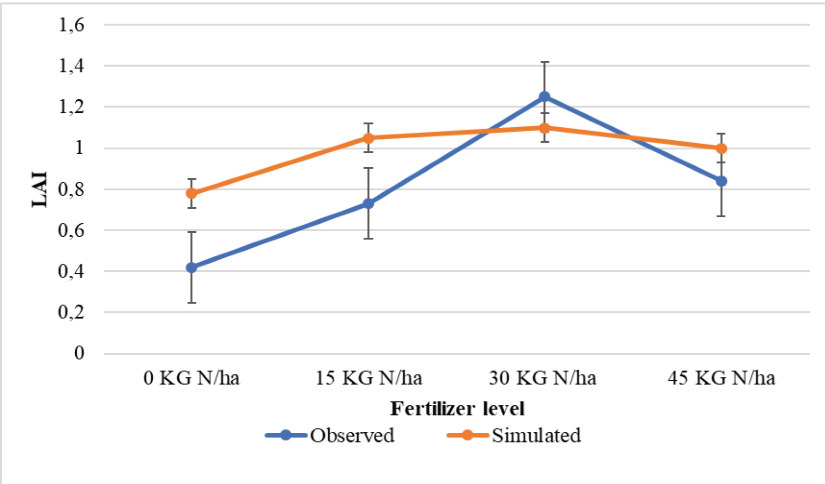

Fig 3. Measured and simulated LAI of spring wheat

Effect of nitrogen rate applications on growth and yield parameters using DSSAT CSM

This study assessed the impact of nitrogen application rates (0, 15, 30, and 45 kg N/ha) on crop parameters, leaf area index (LAI), tops weight, leaf weight, and stem weight using observed and simulated data from the DSSAT model. The dataset includes metrics such as mean, standard deviation, r-square, mean difference, mean absolute difference, RMSE, and d-statistic, revealing nitrogen's influence on crop performance. Key findings show a quadratic response, with optimal growth at 30 kg N/ha, where LAI (1.25), tops weight (4248 kg/ha), leaf weight (1707 kg/ha), and stem weight (2706 kg/ha) peaked, declining at 45 kg N/ha, possibly due to nitrogen toxicity or environmental constraints displayed (Table 1).

The largest discrepancies between observed and simulated values were for leaf weight at 30 kg N/ha (1319 kg/ha) and stem weight at 15 kg N/ha (-1212 kg/ha), indicating model inaccuracies. R-square values (0.796-0.847 for LAI, 0.883-0.952 for tops weight, 0.735-0.904 for leaf weight, 0.900-0.952 for stem weight) and RMSE (0.472-0.565 for LAI, 649.85-1631.43 for tops weight, 612.12-1885.26 for leaf weight, 751.74-1271.18 for stem weight) suggest moderate to high model accuracy, with better predictions for tops and stem weight than for LAI and leaf weight. Significant mean differences (e.g., 1319 kg/ha for leaf weight) relative to standard deviations indicate statistical significance ($p < 0.05$). The DSSAT model overestimates LAI at low (0, 15 kg N/ha) and high (45 kg N/ha) rates, underestimates it at 30 kg N/ha, underestimates tops and leaf weight, and overestimates stem weight, revealing systematic biases in biomass partitioning. High r-square values for tops and stem weight indicate robust model performance, while lower values for LAI and leaf weight highlight challenges in simulating leaf-level responses. Similar to this study the quadratic response of yield parameters to nitrogen aligns with research on nitrogen optimization in crops, where moderate rates (40-60 kg N/ha) maximize LAI and biomass by enhancing photosynthetic capacity and resource allocation [5].

The DSSAT model's overestimation of stem weight and underestimation of leaf weight indicates biases in simulating biomass partitioning, possibly due to simplified assumptions about nitrogen allocation to leaves versus stems. The moderate accuracy for LAI (r-square 0.796–0.847) suggests challenges in modeling canopy development, particularly under nitrogen stress. Integrating remote sensing data, such as normalized difference vegetation index (NDVI), could improve LAI predictions, as demonstrated in precision agriculture studies [19]. The model's better performance for tops weight (r-square 0.883-0.952) reflects its strength in integrating overall biomass accumulation, as seen in evaluations of DSSAT for maize and wheat [14].

Table 1.

Results of observed and simulated tops weight and RMSE for the studied treatments

variables	Nitrogen level, kg /ha	Mean Observed	Mean Simulated	Std. Dev. Observed	Std. Dev. Simulated	r-Square	RMSE
LAI	0	0.42	0.77	0.35	0.63	0.80	0.50
	15	0.73	1.05	0.66	0.91	0.83	0.52
	30	1.25	1.09	1.21	0.96	0.81	0.57
	45	0.35	0.71	0.30	0.56	0.85	0.47
Top weight (kg/ha)	0	3280.00	3144.00	3750.57	3510.46	0.95	843.18
	15	4248.00	3412.00	4825.84	3840.42	0.95	1631.43
	30	1704.00	1749.00	1885.71	1826.67	0.88	649.85
	45	3146.00	2600.00	3605.70	2747.82	0.95	1240.14

Leaf weight (kg/ha)	0	727.00	268.00	650.52	218.45	0.90	650.80
	15	1145.00	369.00	1015.92	315.42	0.88	1060.88
	30	1707.00	388.00	1653.56	331.96	0.74	1885.26
	45	639.00	237.00	615.47	191.41	0.76	612.12
Stem weight (kg/ha)	0	1304.00	2329.00	723.11	811.68	0.91	1043.00
	15	2182.00	3394.00	1240.97	1075.98	0.90	1271.18
	30	2706.00	3748.00	1543.05	1152.16	0.90	1192.61
	45	1094.00	1816.00	620.21	512.77	0.96	751.74

Influence of Nitrogen rate and Spring wheat varieties interactions on Leaf Area Index (LAI)

This study examines the impact of varying nitrogen application rates (0, 15, 30, and 45 kg N/ha) combined with two spring wheat varieties (V1 and V2) on growth and yield parameters during the growing season of a crop, comparing observed and simulated mean values. DSSAT crop simulation model was used to analyse data, provided as mean, standard deviation, r-square, mean difference, mean absolute difference, and root mean square error (RMSE). The dataset examines the effect of nitrogen application rates (0, 15, 45 kg N/ha) and crop varieties (V1, V2) on leaf area index (LAI), comparing observed and simulated values shows (Table 2). Observed LAI ranged from 0.57 (0 kg N/ha + V1) to 1.04 (15 and 45 kg N/ha + V2), a difference of 0.47, reflecting significant variation due to nitrogen and variety.

Simulated LAI ranged from 0.88 (0 kg N/ha + V1) to 1.02 (0 kg N/ha + V2), a smaller difference of 0.14, indicating the model predicts less LAI variability. A t-test with unequal variances, using standard deviations (0.391 for 0 kg N/ha + V1; 0.871 for 15 kg N/ha + V2), suggests the observed LAI difference (0.47) is statistically significant ($p < 0.05$), despite unspecified sample sizes. Mean differences (observed minus simulated) range from -0.04 (15 and 45 kg N/ha + V2) to 0.31 (0 kg N/ha + V1), showing the model often overestimates LAI, especially at lower nitrogen rates. RMSE values (0.578–0.760) and r-square values (0.29–0.506) indicate moderate model accuracy, with better performance at higher nitrogen rates and for V2 (r-square = 0.506 for 45 kg N/ha + V1). In line to this finding, the RMSE values for V1, V2, and V3 were 52.3, 33.0, and 29.1, respectively, between the simulated and observed harvest index [6]. The points of the simulation should also be around the 1:1 line to evaluate simulated and measured values of LAI and Drymatter (kg/ha) [17].

Influence of nitrogen rate and spring wheat varieties interactions on tops weight (kg/ha)

The dataset shows observed tops weight means ranging from 1810 kg/ha (0 kg N/ha + V1) to 2584 kg/ha (15 and 45 kg N/ha + V2), a difference of 774 kg/ha, indicating significant biomass enhancement due to nitrogen application and variety, with V2 outperforming V1 at higher rates. Simulated tops weight ranges from 1868 kg/ha (0 kg N/ha + V1) to 2473 kg/ha (30 kg N/ha + V2), a smaller difference of 605 kg/ha, suggesting the model underestimates biomass variability. High standard deviations for observed tops weight (e.g., 1993.63 for 15 kg N/ha + V2) compared to LAI reflect greater biomass variability. A t-test comparing the highest (2584 kg/ha) and lowest (1810 kg/ha) observed means would likely show statistical significance due to the substantial difference relative to standard deviations detailed (Table 2).

Table 2.

Model quality for spring wheat on LAI and top weight (kg/ha) in DSSAT

Variable Name	Treatments	Mean Observed	Mean Simulated	Std. Dev Observed	Std. Dev Simulated	R-Square	RMSE
LAI	0 kg N/ha + V1	0.57	0.88	0.391	0.702	0.365	0.64
	15 kg N/ha + V1	0.76	1.01	0.526	0.817	0.375	0.691
	30 kg N/ha + V1	0.87	1.01	0.475	0.802	0.29	0.69
	45 kg N/ha + V1	0.84	1.00	0.568	0.79	0.506	0.578
	0 kg N/ha + V2	0.92	1.02	0.714	0.807	0.446	0.634
	15 kg N/ha + V2	1.04	1.00	0.871	0.774	0.341	0.76
	30 kg N/ha + V2	0.96	1.00	0.633	0.778	0.355	0.649
	45 kg N/ha + V2	1.04	0.001	0.871	0.78	0.34	0.76
Top weight (kg/ha)	0 KG N/ha + V1	1810	1868	1486.045	1571.568	0.331	361.47
	15 kg N/ha + V1	1989	2141	1577.332	1805.613	0.949	573.91
	30 kg N/ha + V1	2350	2259	1793.084	1903.91	0.918	555.19
	45 kg N/ha + V1	2407	2332	1954.098	1963.327	0.947	458.08
	0 kg N/ha + V2	2526	2426	1926.586	2051.872	0.92	574.27
	15 kg N/ha + V2	2584	2448	1993.629	2066.537	0.968	595.23
	30 kg N/ha + V2	2569	2473	2045.993	2086.112	0.901	384.43
	45 kg N/ha + V2	2584	2448	1993.629	2067.537	0.958	595.23

This study analyzes the effects of nitrogen rates (0, 15, 45 kg N/ha) and crop varieties (V1, V2) on tops weight and leaf area index (LAI), comparing observed and simulated data. Mean differences for tops weight range from -136 kg/ha (15 and 45 kg N/ha + V2, indicating model underestimation) to 151 kg/ha (15 kg N/ha + V1, showing overestimation). High r-square

(0.912–0.968) and d-statistics (0.971-0.991) for tops weight, with RMSE (384.43-595.23 kg/ha), reflect strong model performance. However, the model struggles to fully capture nitrogen and varietal effects, particularly overestimating LAI at low nitrogen rates and underestimating it at higher rates for V2. Calibration issues were noted, with poor predictions (nRMSE > 30%) for tops weight (all cultivars), harvest index, and grain unit weight for specific cultivars [6]. Nitrogen application enhances LAI and tops weight, with V2 showing a stronger response, achieving peak LAI (1.04) at 15 and 45 kg N/ha and tops weight (2584 kg/ha) at higher rates. The model predicts tops weight more accurately (high r-square and d-statistics) than LAI (r-square 0.29-0.506), likely due to complexities in nitrogen, light, and varietal interactions affecting leaf area development. In agreement to this finding the points of the simulation should also be around the 1:1 line to evaluate simulated and measured values of LAI and Dry matter (kg/ha) [7; 21].

Conclusion

The study demonstrated that nitrogen application rates critically shape on LAI, tops weight, leaf weight, and stem weight, with optimal rates (30-45 kg N/ha) maximizing canopy development and biomass for varieties like V1 and V2. Beyond these thresholds, diminishing returns or yield reductions emerge due to physiological and environmental constraints. While the DSSAT model reliably predicts tops weight, it exhibits biases in LAI, leaf, and stem weight estimations, necessitating refined parameterization. Integrating real-time environmental data, remote sensing, and machine learning can enhance model accuracy and support precision nitrogen management. The current fertilization investigation strategies promise to optimize crop productivity while advancing sustainable agricultural practices by minimizing resource waste. The simulation results of wheat growth from the reviewed experiment were good, with overall model efficiencies of 0.95 (growth stages), 0.85 (LAI) and 0.92 (yield).

Generally, DSSAT model can be considered as an effective tool for predicting crop growth, development and, therefore as a decision supporter since it stimulates both growth stages and yield parameters perfectly.

The DSSAT ecosystem can play a major role in helping to understand the interaction between genotype, environment, and management (G * E * M) and to provide alternative management options that increase crop yield, optimize resource use, and minimize environmental impact for long-term sustainable agricultural production.

Conflict of interest information. The authors declared no conflict of interest.

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DATA ABOUT THE AUTHORS

Shimendi Gde Okbagabir

RUDN University
8, Miklukho-Maklaya Str., Moscow, 117198, Russian Federation
shimendigde@gmail.com
ORCID: https://orcid.org/0009-0006-8937-9230

Ali Hassouni

College of Agriculture, Misan University
Misan, Iraq
ORCID: https://orcid.org/0000-0003-2687-3638

Mohammed H. Al-Mamoori

RUDN University
8, Miklukho-Maklaya Str., Moscow, 117198, Russian Federation
madi0981@gmail.com
ORCID: https://orcid.org/0000-0003-0299-2608

Yuqing Wang

RUDN University
8, Miklukho-Maklaya Str., Moscow, 117198, Russian Federation
1515208408@qq.com

A.A. Ahmed

Russian State Agrarian University - Moscow Timiryazev Agricultural Academy
49, Timiryazevskaya Str., Moscow, 127434, Russian Federation

Elena N. Pakina

RUDN University
8, Miklukho-Maklaya Str., Moscow, 117198, Russian Federation
pakina-en@rudn.ru
ORCID: https://orcid.org/0000-0001-6493-6121

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