



Assessment of the Simple Model for Durum Wheat Biomass and Yield Prediction in Semi-arid Algeria

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Received: October 28, 2025 Accepted: February 20, 2026

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Citation

Mourad, H., Boulelouah, N., Haddad, D.D., and Mabane, M.Z. 2026.

Assessment of the simple model for durum wheat biomass and yield prediction in semi-arid Algeria. *Annals of Arid Zone* 65(1): 53-69

<https://doi.org/10.56093/aaz.v65i1.172840>

<https://epubs.icar.org.in/index.php/AAZ/article/view/172840>

<https://epubs.icar.org.in/index.php/AAZ>

Abstract: Production of durum wheat (*Triticum durum* Desf.) in semi-arid Mediterranean regions is often limited by water and heat stress. Parsimonious crop models are valuable tools for supporting management decisions in such environments. This study evaluated the performance of the SIMPLE model in simulating biomass accumulation and grain yield of durum wheat under diverse agro-environmental conditions in Algeria. The model was calibrated using data from a controlled trial (ITGC site, 2012-2013 season) and independently validated with data from three additional sites across two seasons (2012-2013 and 2023-2024), including contrasting management practices (rainfed vs. supplementary irrigation). During validation, model performance was high, with a coefficient of determination (R^2) > 0.74, modeling efficiency (EF) > 0.90, and normalized root mean square error (nRMSE) < 25% for both biomass and yield. The model accurately predicted grain yields, ranging from 4.91 t ha⁻¹ under rainfed conditions to 6.37 t ha⁻¹ at the irrigated site. Deviations between simulated and observed values were mainly associated with errors in total biomass simulation (source-driven) rather than biomass partitioning to the grain (sink-driven). Overall, these results demonstrate that, despite its minimal parameter requirements, the SIMPLE model reliably reproduces wheat growth dynamics and final yield across different seasons, sites, and water regimes. Therefore, it is a robust tool for in-season yield forecasting and for evaluating the potential benefits of management strategies, such as supplementary irrigation, in semi-arid agricultural systems.

Key words: Durum wheat, SIMPLE simulation model, biomass, yield, semi-arid conditions, irrigation management.

Durum wheat (*Triticum turgidum* ssp. durum) is a crop of major strategic importance for food security and the economy in the countries of the Mediterranean basin, including Algeria (Broccanello *et al.*, 2023). This region, which accounts for the majority of global durum wheat production, with output ranging between 37 and 40 mt, is facing increasing climatic challenges (Zampieri *et al.*, 2020). Climate projections indicate rising temperatures and altered precipitation patterns that could lead to a significant reduction in the climatically suitable area for durum wheat cultivation by mid-century, thereby directly threatening production and food security (Constantinidou *et al.*, 2016; Ceglar, 2021). In the face of this threat, developing effective adaptation strategies has become a key priority to ensure the resilience of agricultural systems (Toreti *et al.*, 2022).

Crop simulation models are used in agronomic decision-making and climate change impact assessment. These models combine physiological and environmental factors to estimate crop development, growth, and yield under different management strategies across crop scenarios (Ritchie *et al.*, 1985; Brisson *et al.*, 1998; Asseng *et al.*, 2013). For nearly a half-century, they have been appreciated as tools for assessing the responses of crops to changes in the environment and crop management (Monteith, 1965; Sinclair, 2000). The crop simulation models: DSSAT (Jones, *et al.*, 2003), CERES (Ritchie *et al.*, 1985), STICS (Brisson, *et al.*, 1998), APSIM wheat (Wang, *et al.*, 2003), and AquaCrop (Steduto, *et al.*, 2009) are being widely used but do differ in the number of parameters and their complexity. The AquaCrop model, which simulates water-driven growth with 29 parameters (Steduto *et al.*, 2009), depending on data for soil, climate, crop phenotype, and management; however, DSSAT typically requires many more genotype-specific parameters. While the inclusion of numerous parameters enhances simulation precision, the acquisition and estimation of these parameters remain challenging, especially in semi-arid regions with limited data availability.

A significant gap exists between the advanced capabilities of complex crop models (e.g., DSSAT, APSIM) and their practical applicability in data-limited agricultural systems. Their extensive data requirements for calibration often render them unusable

for local decision-making in many regions, including Algeria. To address these constraints, the SIMPLE crop model was developed as a general and parsimonious approach, requiring only thirteen parameters (nine species-specific and four cultivar-specific) to simulate crop phenology, biomass accumulation, and yield in a user-friendly manner (Zhao *et al.*, 2019). Such parsimonious models have been proposed as pragmatic alternatives to more data-intensive systems. However, the performance of any crop model depends strongly on local genotype \times environment \times management interactions. Although the SIMPLE model has been successfully evaluated for wheat in neighboring Tunisia (El Melki *et al.*, 2024), its accuracy and reliability for simulating durum wheat growth and yield under the distinct semi-arid conditions of Algeria have not yet been assessed.

To achieve this, the model adopts an alternative structure characterized by a simple, flexible, and biologically grounded approach. It simulates the following growth stages: emergence, vegetative phase, flowering, senescence, and finally maturity. Its daily simulation is based on a static calibration, applying only the parameters described in the paragraph below.

The model accounts for radiation interception dynamics, biomass growth, and yield potential across environments under varying CO₂ concentrations, temperature extremes, and drought stress levels. At its core, the model is founded upon basic physiological principles like radiation use efficiency and responses to water stress through an ARID index for simulating growth processes while accommodating scenarios of temperature, atmospheric CO₂, and water availability, all while relying on a low number of fitted parameters (Zhao *et al.*, 2019).

SIMPLE crop model is a computationally efficient leaf-level model that tracks phenological development with cumulative thermal time, and determines growth by assimilated solar radiation following the Beer-Lambert law, corrected for environmental stresses (but without the additional complexity of more comprehensive models) (Zhao *et al.*, 2019). The model is a recent, mechanistic and follows parsimonious approach to crop simulation (Zhao *et al.*, 2019). Thus, making it simple to parameterize when

Table 1. Detailed features of the four sites

Feature	Site Dehal1	Site Dehal2	Site ITGC	Site Bouras
Latitude and longitude	36°15'41''N 05°30'11''E	36°15'41''N 05°30'11''E	36°08'17''N 05°20'48''E	36°12'42''N 05°27'27''E
Average elevation (m)	1212	1212	953	1136
Agricultural season	2012-2013	2023-2024	2012-2013	2023-2024
Wheat cultivar	Boussellam	Boussellam	Boussellam	Boussellam
Sowing date	12/12/2012	15/11/2023	12/12/2012	05/12/2023
Harvesting date	07/07/2013	02/07/2024	04/07/2013	28/06/2024
Average total annual rainfall (mm)	697.15 (2013)	384.3(2024)	697.15 (2013)	384.3 (2024)
Average annual temperature (°C)	14.7 (2013)	17.3 (2024)	14.9 (2013)	17.3 (2024)
Growing season duration (day)	208	231	205	207

data are limited. Its potential has been shown in field conditions, including applications to soybean (Pham *et al.*, 2023), oilseed flax (Li *et al.*, 2022), and common bean under irrigation (Servín-Palestina *et al.*, 2024). But it was not widely practiced in semi-arid durum wheat-producing regions. The model should be tested regarding its ability to simulate different types of variability, including spatial, temporal, and management-induced modifications (e.g., irrigation), which are highly relevant for semi-arid agroecosystems.

The application of the SIMPLE crop model in semi-arid systems is still constrained (Banerjee *et al.*, 2025). However, fixed cropping schedules are impractical due to significant inter-annual climatic variability. It requires adaptive management strategies every season (Asseng *et al.*, 2013). Biomass and yield can be improved through optimized irrigation and cultivar selection (Si *et al.*, 2023; Servin-Palestina *et al.*, 2024; Elsayed *et al.*, 2025). The SIMPLE model is considered suitable for addressing this issue. It accounts for spatial, temporal, and management-induced variability in semi-arid wheat systems (Zhao *et al.*, 2019; Li *et al.*, 2022). Therefore, this study aims to evaluate the performance of the SIMPLE model for simulating durum wheat growth and yield in the semi-arid region of Setif, Algeria. Specifically, we sought to: (i) calibrate the model using data from a controlled experimental trial; (ii) validate its accuracy using independent datasets from three distinct sites across two agricultural seasons, including both rainfed and supplementary irrigation conditions; and (iii) assess its potential as a decision-support tool for local wheat cropping systems.

Materials and Methods

Study area and site description

Field experiments were conducted during the 2012-2013 and 2023-2024 growing seasons at four sites located in the semi-arid region of Setif province, northeastern Algeria: Dehal1, Dehal2, the Technical Institute of Field Crops (ITGC-Setif), and Bouras. The trials were established both on experimental fields (ITGC) and on farmers' fields (Dehal1, Dehal2, and Bouras) following a participatory research approach. The region is characterized by a Mediterranean semi-arid climate with high inter-annual rainfall variability (Table 1).

Climatic data and meteorological variables

Daily climatic data required for the SIMPLE crop model simulations included maximum and minimum air temperature (°C), precipitation (mm), and solar radiation (MJ m⁻² d⁻¹). These data were obtained from the NASA POWER database (NASA, 2025) for the period 2010-2024.

Daily atmospheric CO₂ concentrations were obtained from the NOAA Global Monitoring Laboratory, Mauna Loa Observatory (NOAA, 2025), covering the same period.

In addition, daily relative humidity, wind speed at 2 m height, and sunshine fraction were collected from NASA POWER. These variables were used, together with temperature, radiation, and precipitation, to compute daily reference evapotranspiration (ET₀) using the FAO Penman-Monteith method implemented in CROPWAT 8.0 (FAO, 2009), following FAO-56 guidelines (Allen *et al.*, 1998). The resulting

Table 2. Soil variable indexes for the four field experimental sites

Sites	Soil characteristics clay (%) - silt (%) - sand (%)	Soil Texture	Soil Depth (m)	bulk density (g/cm ³)	Field capacity (FC) (cm ³ .cm ⁻³)	Permanent Wilting Point, PWP (cm ³ .cm ⁻³)	AWC	RCN	DDC	RZD (mm)
Dehal1	74.32-0.98- 24.70	Clay	0.40	1.35	0.40	0.20	0.20	89	0.08	700
Dehal2	74.32-0.98- 24.70	Clay	0.40	1.35	0.40	0.20	0.20	89	0.08	700
ITGC	47.20-44.80 -08.00	Clay-loam	0.40	1.3	0.37	0.21	0.16	89	0.18	700
Bouras	42.10-21.37- 36.53	Clay	0.40	1.2	0.36	0.15	0.21	89	0.12	700

Note: Soil Depth – tillage layer (m); AWC: Available Water Capacity (cm³ cm⁻³); Bulk density (g cm⁻³); FC: Field Capacity (cm³ cm⁻³); PWP: Permanent Wilting Point (cm³ cm⁻³); RCN: Runoff Curve Number (Mohammed *et al.*, 2020); DDC: Deep Drainage Coefficient (Ritchie, 1998); RZD: Root Zone Depth (mm). Data were obtained from DEDSPAZA laboratory.

ET₀ series were used as input for the crop simulation model.

Soil characterization

Soil samples were collected from each experimental site and analyzed at the Ecosystem Diversity and Agricultural Production System Dynamics in Arid Zones laboratory (DEDSPAZA), in Algeria. The main soil physical and hydraulic properties were determined using standardized laboratory methods. Soil texture was established by particle size analysis using the pipette method (Day, 1965). Bulk density was obtained using the core cylinder method (Blake and Hartge, 1986) after oven-drying samples at 105°C until constant weight. Field capacity (FC) and permanent wilting point (PWP) were measured using a pressure plate apparatus (Richards, 1948) at -0.33 bar and -15 bar, respectively, enabling calculation of available water capacity (AWC). The runoff curve number (RCN) was estimated using the SCS-CN method (USDA, 1972) as adapted by Mohammed *et al.* (2020), and the deep drainage coefficient (DDC) was determined following (Ritchie, 1998).

The analyses show that the sites generally have clay-dominated textures, with Dehal1 and Dehal2 both strongly clayey, ITGC presenting a clay-loam profile, and Bouras exhibiting a clay texture with notable sand content. All sites share a similar sampling depth, and present comparable bulk densities and water retention capacities. Hydrological indicators such as the Runoff Curve Number and deep drainage coefficients were generally uniform, suggesting consistent hydric conditions across the experimental network. The detailed numerical values for each parameter are provided in Table 2, which summarizes the main soil variables

that influence crop establishment and water dynamics at each location.

Experimental design and crop management

During the growing season 2012-2013, controlled field trials were established at the ITGC site and the Dehal1 site using a randomized complete block design (RCBD) with four replications. The experimental plot area covered 1666 m². During the 2023-2024 growing season, participatory research trials were conducted in farmers' fields at the Bouras site (14 ha) and the Dehal2 site (15 ha). The durum wheat cultivar 'Boussellam' was used at all sites. It is a pedigree selection from ITGC-Setif. This cultivar is characterized by its large grain size (Thousand Grain Weight (TGW) of 40-60 g), and its tolerance to cold and drought stress. Sowing density and fertilization rates varied slightly among sites in accordance with local practices. Nitrogen was applied using split applications of urea or compound fertilizers. Weed control was achieved through selective herbicide applications. Rainfed conditions prevailed at most sites, while supplementary irrigation was applied at the Bouras site. Sowing was carried out at a uniform row spacing of 17 cm. Seeding densities were adapted to local conditions: 270 g m⁻² at the ITGC and Dehal1 sites, 280 g m⁻² at the Bouras site, and 410 g m⁻² at the Dehal2 site.

Fertilizer management was adapted to site-specific conditions and followed local agronomic recommendations. During 2012-2013 Season at ITGC and Dehal1 sites a basal application of 100 kg ha⁻¹ of triple superphosphate (TSP, 46% P₂O₅) was applied at sowing. Nitrogen was supplied as urea (46% N) in a split application totaling 100 kg ha⁻¹, with one-third applied at tillering (March 7-13, 2013) and two-

thirds at stem elongation (April 17-21, 2013). During 2023-2024 Season at Bouras 80 kg ha⁻¹ of monoammonium phosphate (MAP) was applied pre-sowing (Nov 20, 2023), followed by two urea applications (100 kg ha⁻¹ on Feb 10, 2024, and 150 kg ha⁻¹ on March 5, 2024). But at Dehal2, 200 kg ha⁻¹ of NPK fertilizer (4-20-25) was applied at sowing, followed by two top-dressings with sulfur-coated urea (107 kg ha⁻¹ on Feb 9, 2024, and 180 kg ha⁻¹ on March 23, 2024).

Weeds in the field were managed with selective herbicides (Olympus Flexed or Cossack) based on site-specific needs. The Bouras site received two supplementary irrigations: 46.28 mm on 19 April and 46.28 mm on 30 April 2024 (totaling 92.56 mm), while all other sites were exclusively rainfed.

Plant sampling and data collection

At the controlled trial sites (2012-2013), sampling was conducted on three central rows (50cm for each row). At the farmer-field sites (2023-2024), sampling was performed along 1-meter linear transects. At all sites, three

replications were collected at four key growth stages: tillering, stem elongation, flowering, and maturity. Above-ground biomass was collected at each stage. At physiological maturity, straw and grain were separated. All samples were oven-dried at 80°C for 72 hours to a constant weight to determine dry matter. Final yield (t ha⁻¹) was adjusted to 0% moisture content.

Leaf area index (LAI) was inferred from Sentinel-2 multispectral data (10-m spatial resolution). The Normalised Difference Vegetation Index (NDVI) computed from the red (Band 4) and near-infrared (Band 8) reflectance, was used as the predictor variable for LAI estimation. Sampling stages and the availability of satellite scenes closest to the field measurements were considered to determine NDVI values. The empirical relationship developed by Haboudane *et al.* (2004) was applied:

$$LAI = 0.57 \times \exp(2.33 \times NDVI) \quad \dots 1$$

This relationship has been widely validated across semi-arid regions ($R^2 = 0.85$) and

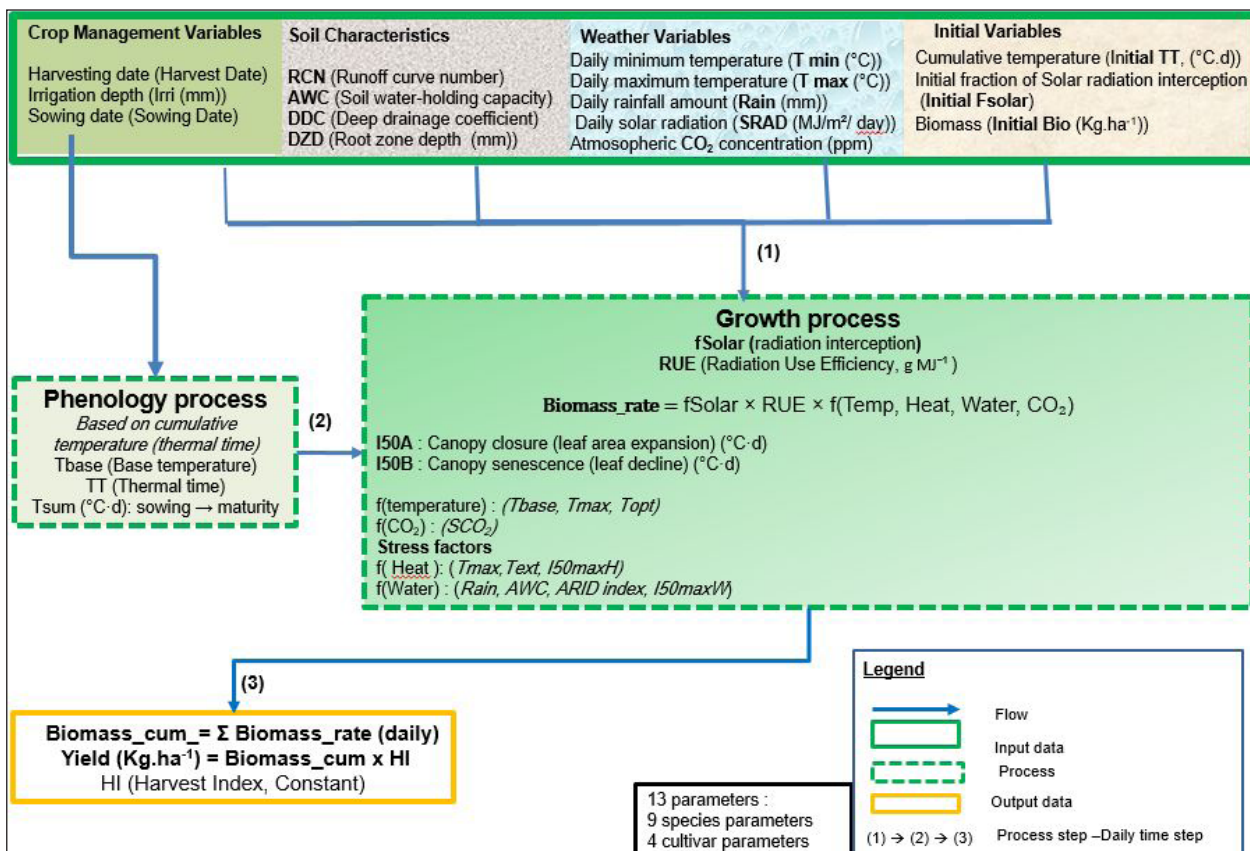


Fig. 1. Structure of SIMPLE growth crop model.

is considered robust under water-limited conditions (Haboudane *et al.*, 2004).

The fraction of solar radiation intercepted by the canopy (f_{solar}) was derived from NDVI values, following the approach of converting NDVI to an equivalent LAI and applying the Beer-Lambert law.

$$f_{\text{solar}} = 1 - \exp(-0.6 \times \text{LAI}) \quad \dots(2)$$

This methodology is supported by the work of Gitelson (2004), who demonstrated that NDVI and its derivatives can reliably quantify canopy biophysical characteristics such as LAI and absorbed photosynthetically active radiation (fPAR). Similarly, Sellers (1985) provided the theoretical basis for linking vegetation indices to canopy light interception.

Description of the SIMPLE Crop Model

Model structure: The SIMPLE crop model, adapted from the work of Zhao *et al.* (2019), is a dynamic model that simulates crop growth on a daily time step (Fig. 1) and are defined by only 13 parameters (Table 3). It is based on the radiation-use efficiency (RUE) principle, where the accumulated biomass is proportional to the light energy intercepted by the plant canopy. Growth is modulated by the plant's responses to environmental factors (Li *et al.*, 2022; Pham *et al.*, 2023; Servín-Palestina *et al.*, 2024).

The model requires four types of input data (Fig.1):

- **Meteorological:** Daily minimum and maximum temperatures, precipitation, solar radiation, and CO₂ concentration.
- **Soil:** Available water holding capacity (AWC), rooting zone depth (RZD), and coefficients for runoff (RCN) and deep drainage (DDC).
- **Crop management:** Sowing and harvest dates, as well as irrigation amounts.
- **Initial conditions:** Biomass, accumulated thermal time, and fraction of intercepted radiation at the start of the simulation.

Phenology component

The crop's phenological development is driven by thermal time, calculated as the sum of daily average temperatures above a base temperature (T_{base}). The total duration of the cycle, from sowing to maturity, is determined

by a variety-specific parameter, T_{sum} . The canopy dynamics (its establishment and senescence) are also controlled by thermal time-based parameters (I_{50A} and I_{50B}), which define the speed at which the canopy develops and ages

Biomass growth component: The daily biomass accumulation (Biomass_rate) is the core of the model. It is calculated *via* the following equation:

$$\text{Biomassrate} = \text{Radiation} \times f_{\text{Solare}} \times \text{RUE} \times f(\text{CO}_2) \times f(\text{Temp}) \times \min(f(\text{Heat}), f(\text{Water})) \quad \dots(3)$$

$$\text{Biomass_cum}(i+1) = \text{Biomass_cum}i + \text{Biomass_rate} \quad \dots(4)$$

where,

- Biomass_{rate} is the daily biomass growth rate
- Biomass_{cumi} is the cumulative biomass until the *i*th day
- fSolar is the fraction of solar radiation intercepted by a crop canopy
- RUE is the radiation use efficiency
- f(heat), f(CO₂), f(Temp) and f(Water) are the heat stress, CO₂ impact, temperature impact, and drought stress on biomass growth, respectively
- f(solar): is based on Beer-Lambert's law of light attenuation and solar radiation interception, but not leaf area index, similar to the AquaCrop model (Steduto *et al.*, 2009)

The model considers that the most limiting factor between water stress and heat stress ($\min(f(\text{Heat}), f(\text{Water}))$) is the one that affects daily growth. Particular attention was given to these two stresses, as they are predominant in semi-arid environments.

Yield is calculated as the product of biomass and harvest index (HI):

$$\text{Yield} = \text{Biomass_cum maturity} \times \text{HI} \quad \dots(5)$$

where,

- Yield: Grain yield at harvest
- Biomass cum maturity: cumulative aboveground biomass at physiological maturity
- HI is the harvest index, assumed constant for the cultivar

Table 3. Species and cultivar parameters used in the SIMPLE Crop Model

Parameters	Description	Nominal	Threshold*	Cite
9 species parameters				
T _{base}	Base temperature for phenology development and growth (°C).	0	-----	Z
T _{opt}	Optimal temperature for biomass growth (°C).	15	-----	Z
RUE	Radiation use efficiency (above ground only and without respiration) (g MJ ⁻¹ m ⁻²).	1.24	-----	Z
I _{50maxH}	The maximum daily reduction in I _{50B} due to heat stress (°C d).	100	-----	Z
I _{50maxW}	The maximum daily reduction in I _{50B} due to drought stress (°C d).	25	-----	Z
T _{max}	Threshold temperature to start accelerating senescence from heat stress (°C).	32	-----	p
T _{ext}	The extreme temperature threshold when RUE becomes 0 due to heat stress (°C).	37	-----	p
S _{CO2}	Relative increase in RUE per ppm elevated CO ₂ above 350 ppm.	0.08	-----	Z
S _{water}	Sensitivity of RUE (or harvest index) to drought stress (ARID index).	0.4	-----	Z
4 cultivar parameters				
T _{sum}	Cumulative temperature requirement from sowing to maturity (°C d).	2115	2112-3140	*
HI	Potential Harvest Index.	0.36	0.30-0.45	*
I _{50A}	Cumulative temperature requirement for leaf area development to intercept 50% of radiation (°C d).	480	200-500	*
I _{50B}	Cumulative temperature till maturity to reach 50% radiation interception due to leaf senescence (°C d).	200	50-250	*

*Minimum and maximum limits. Cite: Z = Zhao *et al.* (2019), P=Porter and Gawith, 1999).

Model outputs

Total biomass is obtained by accumulating daily growth over the entire season. The final grain yield is then estimated by multiplying the biomass accumulated at maturity by a Harvest Index (HI), which is a variety-specific parameter, demonstrated in Table 3.

Data analysis

The experimental datasets were organized in Microsoft Excel, while MATLAB (R2017) was used for model programming, simulation, and graphical outputs. Leaf area index (LAI) values were derived from NDVI obtained through satellite image processing in order to evaluate the fraction of intercepted solar radiation (solar). The dataset was partitioned into a calibration set (one site) and an independent validation set (three sites).

Statistical indicators: The Model performance was evaluated using five statistical indicators: The coefficient of determination (R²), the root mean square error (RMSE), the normalized root mean square error (nRMSE), Willmott's index of agreement (d) and the Nash-Sutcliffe efficiency (EF). These provide complementary measures of the association between observed and simulated values.

$$R^2 = \frac{[\sum_{i=1}^n (O_i - \bar{O}) (S_i - \bar{S})]^2}{\sum_{i=1}^n (O_i - \bar{O})^2 \sum_{i=1}^n (S_i - \bar{S})^2} \quad \dots(6)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (S_i - O_i)^2} \quad \dots(7)$$

$$nRMSE = \frac{RMSE}{\bar{O}} \times 100 \quad \dots(8)$$

$$EF = 1 - \frac{\sum_{i=1}^n (S_i - O_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2} \quad \dots(9)$$

$$d = 1 - \frac{\sum_{i=1}^n (S_i - O_i)^2}{\sum_{i=1}^n (|S_i - \bar{O}| + |O_i - \bar{O}|)^2} \quad \dots(10)$$

where,

- O_i : observed value of the studied variable (biomass or yield)
- S_i: simulated value by the model
- \bar{O} : mean of observed values
- \bar{S} : mean of simulated values
- n : total number of observations

In addition to numerical values, the interpretation of model performance was illustrated in table 4.

Model calibration: Calibration was performed using constrained nonlinear optimization

Table 4. Indicators of model performance

Indicator	References	Poor	Moderate	Good	Excellent
R ²	(Moriassi <i>et al.</i> , 2007)	< 0.5	0.5-0.7	0.7-0.9	≥ 0.9
nRMSE	(Moriassi <i>et al.</i> , 2007)	≥ 30%	20-30%	10-20%	< 10%
EF (NSE)	(Moriassi <i>et al.</i> , 2007)	< 0	0-0.5	0.65-0.8	≥ 0.8
d	(Willmott, 1981)	< 0.6	0.6-0.8	0.8-0.9	≥ 0.9

(*fmincon* in MATLAB) combined with MultiStart. The objective consisted in minimizing the squared differences between observed and simulated above-ground biomass and grain yield. Bounds were set from Zhao *et al.* (2019) and experimental constraints. Convergence was reached within 20 iterations (calibration) and 25 (validation) at a tolerance of 10^{-6} . Cultivar-specific parameters (T_{sum} , I_{50A} , I_{50B} , HI) were estimated from the ITGC dataset, whereas species-level parameters (e.g. RUE, S_{CO_2}) were taken from Zhao *et al.* (2019). The combined *fmincon* + MultiStart framework constitutes a substantial improvement over the previous *fminimax* approach by providing more robust parameter estimates and improved convergence behavior.

The calibration of cultivar-specific parameters (T_{sum} , HI, I_{50A} , I_{50B}) was guided by the coefficient of determination (R^2) between simulated and observed values of biomass dynamics and yield and the *nRMSE*. Following other applications of the SIMPLE model (Zhao *et al.*, 2019; Kourat *et al.*, 2022; Servín-Palestina *et al.*, 2024), absolute and relative error indicators (RMSE, *nRMSE*) were subsequently calculated to assess the quality of the fit. In this framework, an *nRMSE* lower than 20% is generally considered satisfactory to excellent.

Validation Data: Following calibration at the ITGC site, model validation was carried out using three independent sites representing different evaluation contexts. For the spatial validation case, the Dehal1 site was used, corresponding to the same period and region as the ITGC calibration trial. In the 2024 growing season, two further sites were included: Dehal2, which enabled temporal validation of model performance, and Bouras, which facilitated the assessment of crop management practices, particularly irrigation efficiency. All validation datasets were independent from calibration, and model performance was assessed using the same statistical indicators (R^2 , *nRMSE*; EF and d) as in calibration.

Sensitivity analysis

A sensitivity analysis was conducted to identify the parameters exerting the greatest influence on SIMPLE model outputs (biomass accumulation and grain yield). An OAT (one-at-a-time) approach was applied, in which each parameter was varied by $\pm 20\%$ around its baseline value while all others were held constant. The analysis focused on cultivar parameters (T_{sum} , HI, I_{50A} , I_{50B}) and key physiological parameters (RUE and S_{CO_2}), with common parameter values applied across the three evaluation modalities (spatial, temporal, and management). This procedure enabled a systematic assessment of the model's sensitivity to each parameter under contrasting conditions.

Results and Discussion

Following the description of the experimental setup and model configuration, the results of the calibration, validation, and sensitivity analyses are presented and discussed in this section. The objective was to assess the accuracy, robustness, and applicability of the model under Mediterranean conditions through spatial, temporal, and management validations

Model calibration

The model calibration yielded high statistical performance, demonstrating its capacity to reproduce the observed dynamics of wheat growth. The coefficient of determination between simulated and observed biomass reached $R^2 = 0.95$, indicating that 95% of the experimental variability was captured by the model. The model efficiency (EF = 0.95) and the index of agreement ($d = 0.98$) confirmed excellent concordance between observed and predicted data. The normalized root mean square error (*nRMSE* = 18.9%) was below the 20% threshold typically regarded as acceptable for process-based crop models (Moriassi *et al.*, 2007; Wallach *et al.*, 2019).

The calibrated cultivar-specific parameters – photoperiod sensitivity indices ($I_{50A} = 492.12$,

$I_{50B} = 204.02$), thermal time requirement ($T_{sum} = 2266.07^{\circ}\text{Cd}$), and harvest index ($HI = 0.4194$) – were physiologically consistent with reported characteristics of winter wheat under Mediterranean climates. These results are in agreement with previous findings indicating that T_{sum} values between 2,200-2,400 $^{\circ}\text{Cd}$ and HI between 0.35-0.50 are typical for high-yielding cultivars (Porter and Gawith, 1999; Shearman et al., 2005). The estimated radiation use efficiency ($RUE = 1.24 \text{ g MJ}^{-1}\text{m}^{-2}$) also falls within the expected range for Mediterranean wheat (Sinclair and Muchow, 1999).

Figure 2 illustrates the close alignment between observed and simulated data for biomass accumulation, yield, and intermediate growth stages. The lower R^2 for intercepted solar radiation ($R^2 = 0.86$) compared to biomass indicates some limitations in the model’s representation of light interception dynamics, likely linked to canopy architecture or LAI estimation. Nonetheless, the high consistency across variables demonstrates that the calibration was successful and provides a solid basis for further validation analyses.

Spatial validation of the model

The spatial validation confirmed the model’s robustness when applied to different locations. The R^2 values for intercepted solar radiation (0.74) and biomass (0.93) indicated a strong capacity to capture spatial variability in crop growth. The performance metrics: $EF = 0.933$, $d = 0.982$, and $nRMSE = 24.4\%$, remained comparable to the calibration phase, showing good transferability of model parameters. These findings align with studies using DSSAT, WOFOST, and APSIM models, where R^2 typically ranges between 0.70 and 0.90 under spatial extrapolation (Holzkämper et al., 2015; Asseng et al., 2019).

Analysis of the limiting factors revealed near-optimal water availability ($f(\text{water}) = 0.995$) and moderate temperature stress ($f(\text{Temp}) = 0.655$). The thermal limitation reduced potential growth by approximately 35%, which is consistent with common patterns in Mediterranean wheat systems where high temperatures during grain filling constrain yield potential (Trnka et al., 2014). The simulated yield of 4914.21 kg ha^{-1} and final biomass of

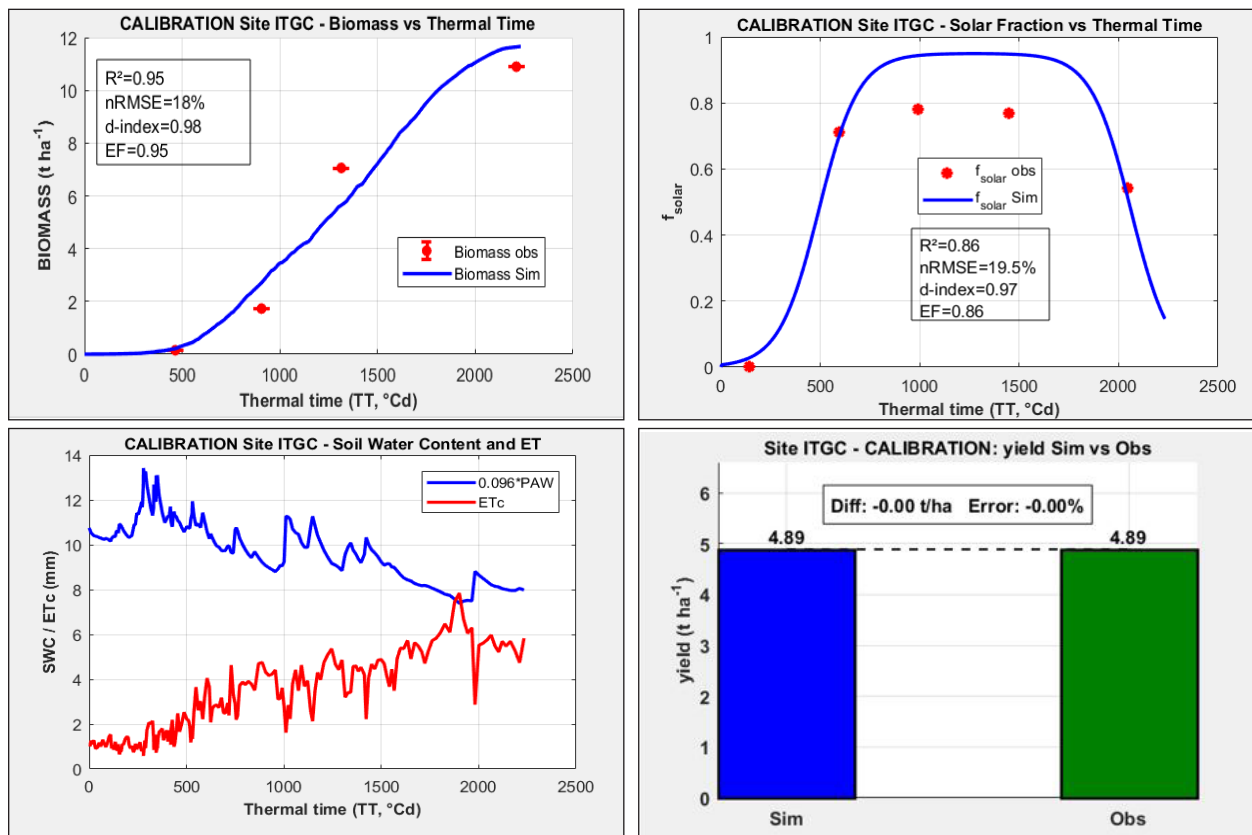
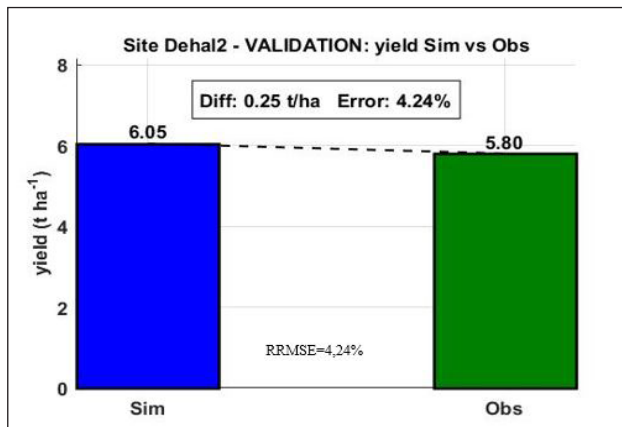
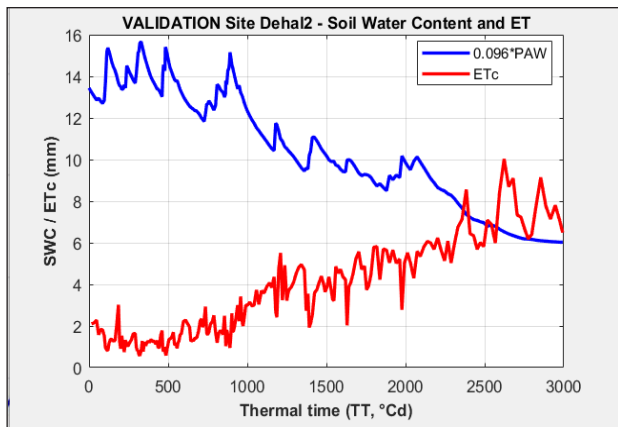
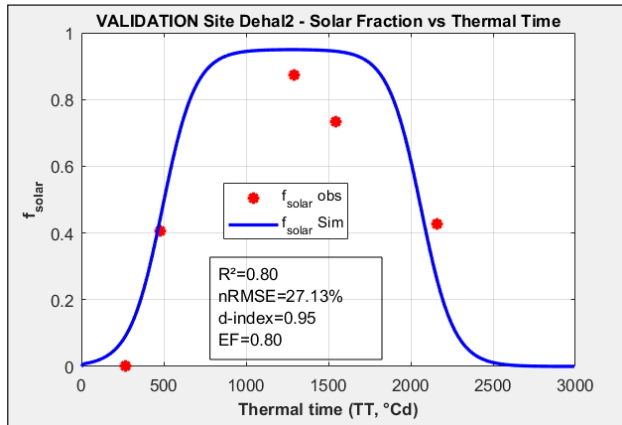
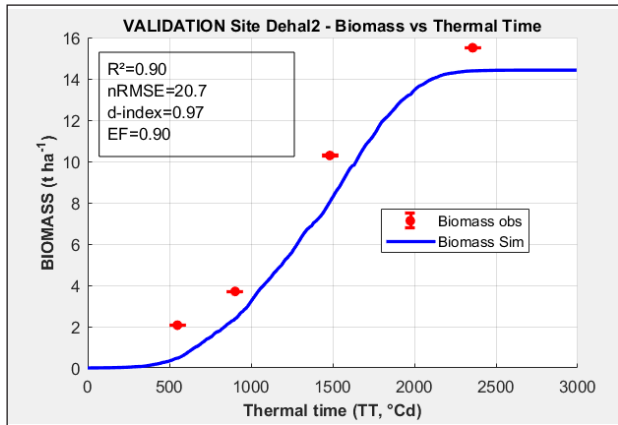
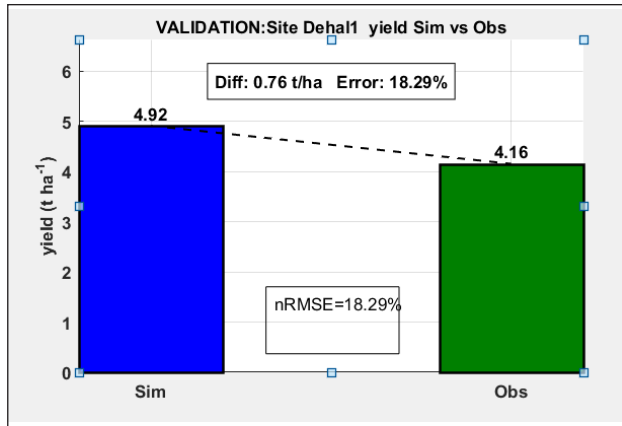
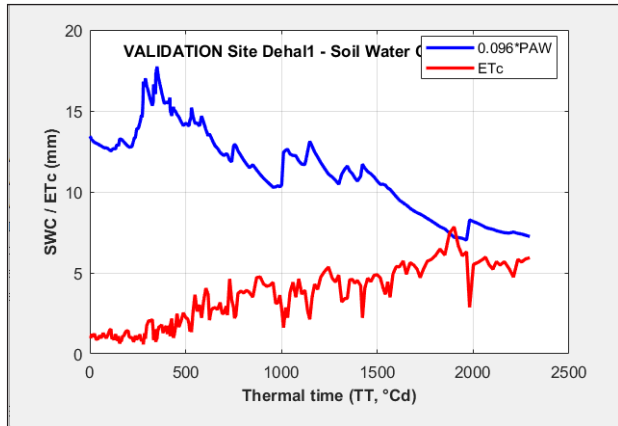
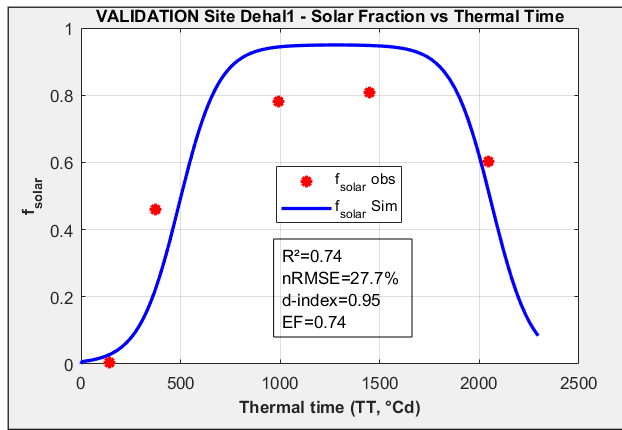
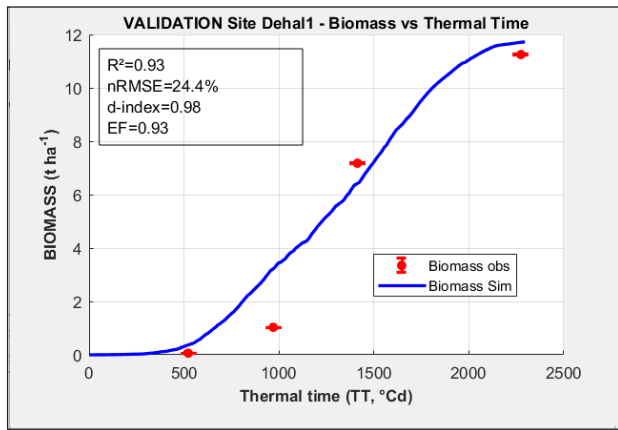


Fig. 2. Calibration of simulated (Sim) and observed (Obs) yield, biomass, and f_{solar} and the Swater of the site ITGC (measured).



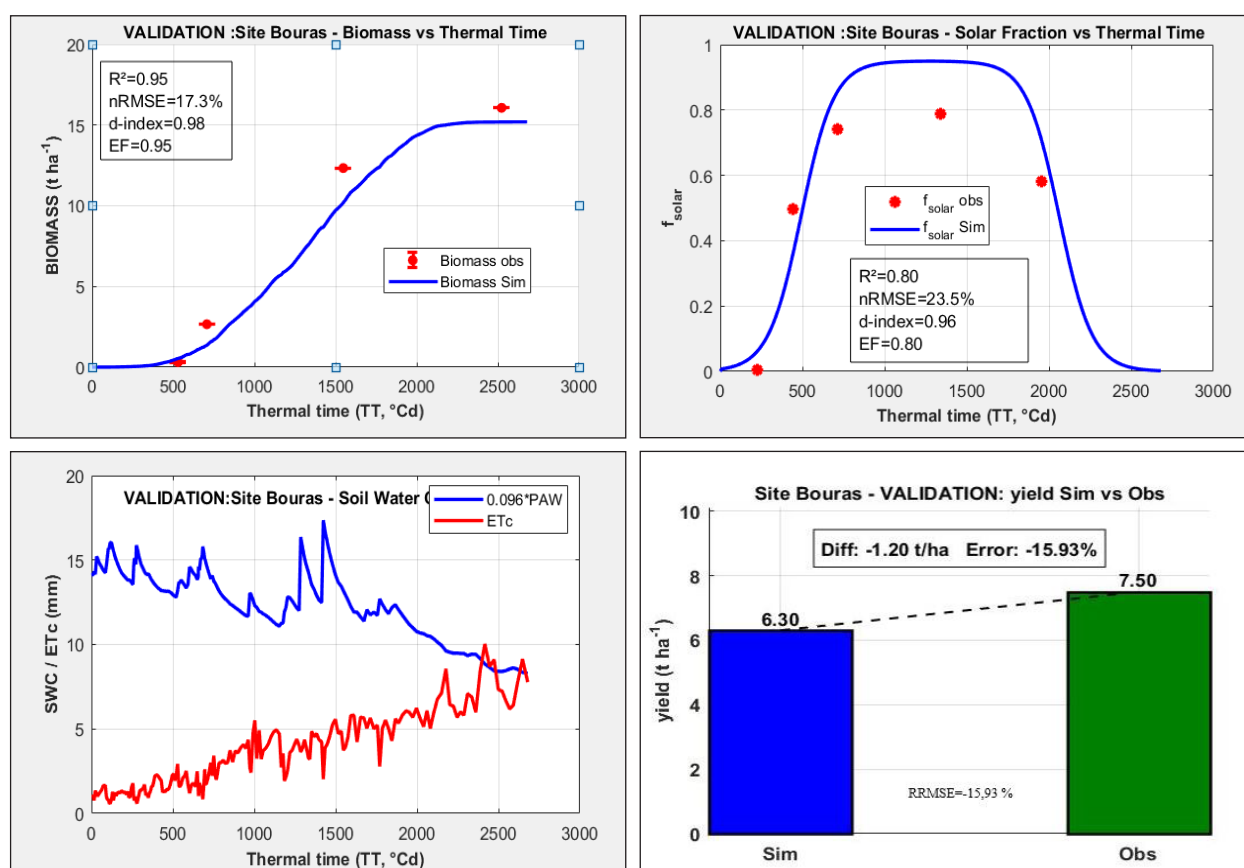


Fig. 3. Validation of simulated (Sim) and observed (Obs) yield, biomass, and f_{solar} and $Swater$ of the three sites: Spatial (Dehal1), temporal (Dehal2) and crop management (Site Bouras).

11717.24 kg ha⁻¹ corresponded closely with the calibrated harvest index, confirming the internal coherence of assimilate partitioning between vegetative and reproductive components. Figure 3 demonstrates the consistency of spatial predictions across different locations.

Temporal validation

The temporal validation results further reinforced the model's stability across growing seasons. Coefficients of determination for solar interception and biomass were $R^2 = 0.80$ and $R^2 = 0.90$, respectively. These values confirm that the model effectively reproduces interannual variations despite differences in climatic conditions. The relative yield error of only 4.24% indicates excellent temporal fidelity, supporting the model's suitability for long-term yield projections (Liu *et al.*, 2021).

Under temporal validation, simulated yield increased to 6048 kg ha⁻¹ and biomass to 14420 kg ha⁻¹ compared with spatial validation. This improvement reflected more favorable

temperature conditions ($f(\text{Temp}) = 0.73$) and near-optimal water availability ($f(\text{water}) = 0.9951$). Figure 3a-d highlights the close match between simulated and observed seasonal growth patterns, underscoring the model's capacity to capture environmental variability. Such interannual stability is essential for assessing the impact of climate variability and evaluating adaptation strategies (Martre *et al.*, 2015; Webber *et al.*, 2018).

Crop management validation

The model achieved its highest predictive performance under management validation scenarios. The R^2 for biomass reached 0.95, with $EF = 0.959$, $d = 0.989$, and $nRMSE = 17\%$. Simulated yields averaged 6373 kg ha⁻¹, with corresponding biomass of 15196 kg ha⁻¹. The relative yield error of 15% remains within acceptable limits for operational modelling (< 20%) (Wallach *et al.*, 2019). These results confirm that the model successfully represents the effects of agronomic management on crop growth and yield (Seidel *et al.*, 2018).

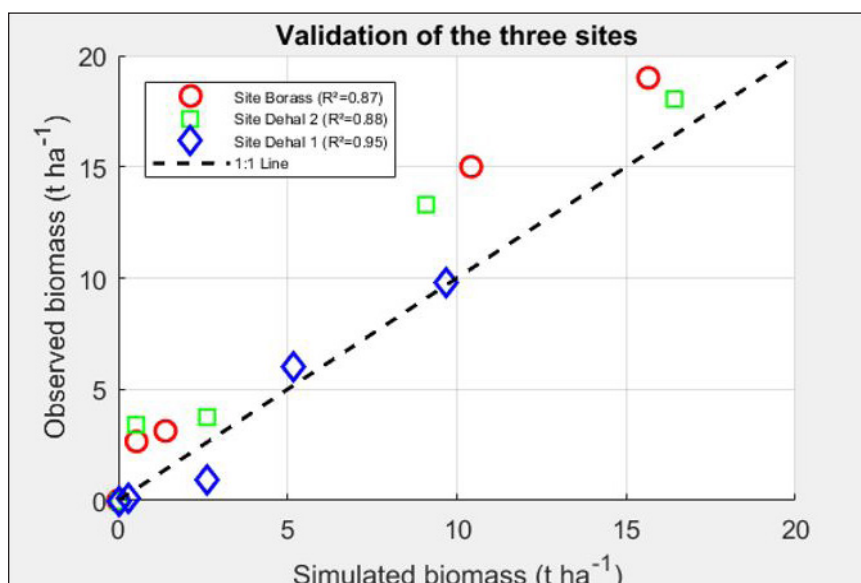


Fig. 4. Validation process of observed and simulated biomass of the three sites.

The favourable simulated environmental conditions ($f(\text{solar}) = 0.539$, $f(\text{water}) = 0.995$, $f(\text{Temp}) = 0.730$) reflected near-optimal resource utilization. The 5.4 % increase in biomass relative to temporal validation, while maintaining the same harvest index, suggests improved resource capture efficiency due to optimized management practices. Figure 3 illustrates the alignment between observed and simulated yield responses under contrasting management regimes, validating the model's capacity to support precision agriculture and sustainable intensification analyses (Basso *et al.*, 2013; Ewert *et al.*, 2015).

Model performance

The overall performance summary (Fig. 4) shows a clear hierarchy in model accuracy: management > temporal > spatial validations. This pattern reflects the expected improvement in performance under more controlled and optimized conditions. Across all validations, the model maintained $R^2 > 0.74$, $EF > 0.90$, and $nRMSE < 25\%$, confirming strong predictive accuracy and generalizability (Wallach *et al.*, 2021). The results conform to the standard evaluation benchmarks of crop models established by the Agricultural Model Intercomparison and Improvement Project (AgMIP) (Asseng *et al.*, 2013).

Although the model performed consistently well, certain limitations were identified. The lower R^2 values for solar radiation interception (0.75-0.81) suggest possible refinements in

canopy light interception algorithms or leaf area index parameterization. Moreover, the moderate relative yield errors (4.3-18.3%) highlight the influence of unmodelled factors such as extreme weather events or management variability. Nevertheless, the model's robustness across multiple datasets establishes its reliability for operational yield forecasting and climate impact assessments.

Sensitivity analysis

The sensitivity analysis conducted across the three contrasting sites – Bouras, Dehal1, and Dehal2 – revealed clear spatial differences in the influence of parameters on model outputs. Figure 5 (Site Bouras, Site Dehal2 and Site Dehal1) illustrates how the relative sensitivity of physiological and environmental parameters changes with site-specific conditions. Across the three sites, Tsum is consistently the most influential parameter, indicating that thermal duration overwhelmingly controls the dynamics reproduced by SIMPLE. RUE and HI form the second tier of sensitivity, confirming that the ability to convert intercepted radiation into biomass and to partition it into grain are major drivers of predictive behavior across contexts. Sco₂ shows moderate and stable influence at all sites, reflecting its secondary but non-negligible role in modulating growth under the current climatic range.

The canopy development parameters (I_{50A} and I_{50B}) exhibit lower influence overall, though their contribution is higher at Bouras

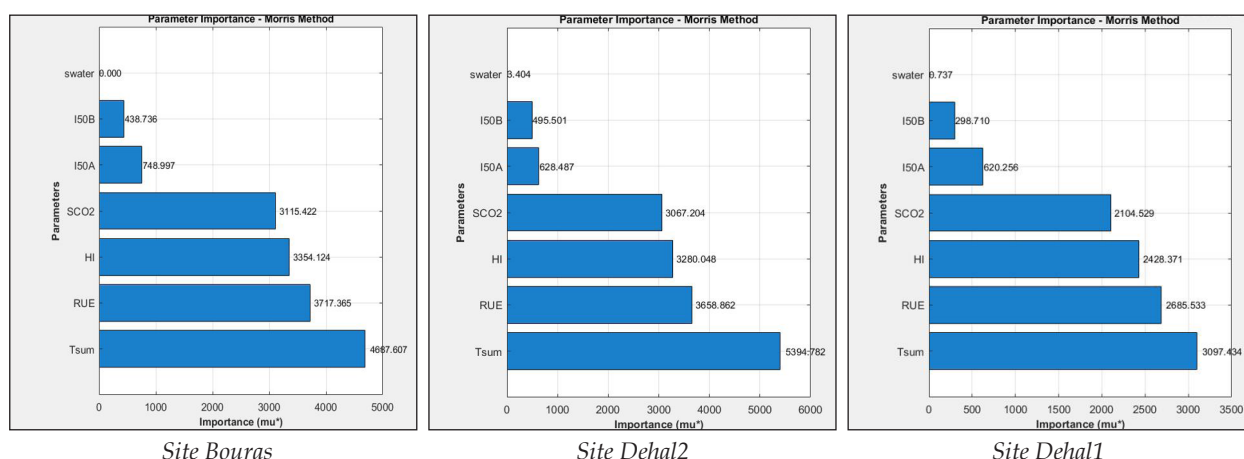


Fig. 5. Sensitivity analysis of model performance during the validation phase at Bouras, Dehal2 and Dehal1.

and Dehal2 than at Dehal1, consistent with conditions where management or season-specific variability affects canopy timing. In all sites, S_{water} has a marginal influence, which is coherent with the empirical finding that water stress was weak across the tested environments.

This study attempted to use a Simple Crop Model based on the criterion of parsimony to simulate durum wheat production under Algerian semi-arid conditions. The results showed that when properly adjusted using local data, the model can reflect the best time for key growth stages, such as flowering and the grain filling period. The model's ability to approximate final outputs was validated against field measurements. Despite a parsimonious calibration approach, the simulations closely matched observed values for both above-ground biomass and grain yield. This is evidenced by the strong coefficients of determination (R^2) of 0.91 for biomass and 0.94 for grain yield (Fig. 1)

Furthermore, the model demonstrated good predictive accuracy for grain yield, achieving a normalized root mean squared error (nRMSE) of only 17%. Achieving this level of accuracy with a parsimonious model is a significant finding, as it directly addresses the primary barrier to the wider adoption of crop models in data-sparse environments (Zhang *et al.*, 2025) and (Reddy *et al.*, 2025). The performance of the SIMPLE model in this study is therefore highly encouraging when compared to other research.

The results of this study are in perfect agreement with a recent study from nearby Tunisia, where El Melki *et al.* (2024) established that SIMPLE is as good as the mighty AquaCrop at forecasting the growth and yield of wheat. In

addition, such error levels for yield predictions as revealed by this field test can also be found in large-scale comprehensive models such as DSSAT and APSIM. For example, Wajid *et al.* (2021) reported root mean square error values of 436 kg ha⁻¹ for DSSAT and 592 kg ha⁻¹ when evaluating wheat yield in farmers' fields using APSIM (Wajid *et al.*, 2021). This implies that for its primary mission of yield prediction as tested, the SIMPLE model offers a performance level equivalent to these big data models and does not require huge amounts of data, offering the best balance between simplicity and precision (Gavasso-Rita *et al.*, 2023).

With an overall good performance, the model had site-specific biases: it tended to overestimate yield at the Bouras site and underestimate yield at Dehal1. The SIMPLE model does not explicitly model any nutrient dynamics, particularly nitrogen, which is a key determinant of yield. Any local nitrogen deficiency or other stress that occurred in the field would reduce the observed yield, while the model, assuming no such constraints, would predict a higher potential yield. The underestimation at Dehal, especially during the high-yielding season of 2023-2024, may suggest a structural limitation of the model's response to very favourable conditions or its treatment of temperature stress. Wheat becomes more susceptible to diseases when exposed to hot weather, and any model can be affected because of this (Garrett *et al.*, 2006).

Therefore, the primary message of this study is that parsimonious models, if correctly calibrated, would be of great value to Algerian farmers, as the operational use

of a complex model by extension services or farmer cooperatives is often limited by its high data demand (Habib-ur-Rahman *et al.*, 2022). A validated simple model, such as SIMPLE, could predict yields in-season, estimate the yield gap, or otherwise offer some initial advice about management strategies (such as the optimal sowing windows) without any need for datasets of extensive genetic or soil parameters on additional information. This study thus provides a proof-of-concept that supports a wider use of readily available valuation tools to make the region's farmers better able to deal with climate change. However, the limitations of this study, particularly the model itself, must be recognised. First, the model was validated in a single region (Setif) and for two disjoint seasons using separate datasets. Therefore, the robustness of the model should be further tested across a broader range of Algerian agro-ecological zones and over several years. Second, the study used only one cultivar, "Boussellam" to be of general applicability, a range of cultivar parameters for other major Algerian durum wheat varieties needs to be established. Lastly, the model's lack of structure, particularly its absence of a nitrogen balance module, prevents it from providing recommendations for fertilizer management, which are essential in modern agronomy (Ierna *et al.*, 2015). Therefore, this must be a major focus of future research. A direct comparison between SIMPLE and a complex model, such as APSIM or DSSAT, could be another valuable next step to measure the trade-offs between simplicity and accuracy.

Furthermore, the error levels for yield predictions observed in this field test are comparable to those found in large-scale, comprehensive models such as DSSAT (Decision Support System for Agrotechnology Transfer) and APSIM (Agricultural Production Systems sIMulator) (Gavasso-Rita *et al.* (2023) and Wajid *et al.* (2021)). They reported root mean square error (RMSE) values of 436 kg ha⁻¹ for DSSAT and 592 kg ha⁻¹ for APSIM when evaluating wheat yield in farmers' fields. This implies that for its primary mission of yield prediction, the SIMPLE model offers a performance level equivalent to these data-intensive models without requiring extensive datasets, thereby providing an optimal balance

between simplicity and precision (Pham *et al.*, 2023) and (Gavasso-Rita *et al.*, 2023).

Therefore, parsimonious crop models, when properly calibrated and validated, can provide substantial value for Algerian agronomists and farmers. The operational use of complex crop models by extension services or farmer cooperatives is often constrained by their high data, parameterization, and expertise requirements (Wallach *et al.*, 2019). In contrast, a validated simple model such as SIMPLE can be effectively used to predict in-season yields, estimate yield gaps, and provide preliminary management guidance without relying on extensive genetic, soil, or management datasets (Manschadi *et al.*, 2021). This study thus provides a proof of concept supporting the broader adoption of accessible modeling tools to enhance farmers' adaptive capacity to climate variability and change.

Conclusions

The results of this study indicate that the SIMPLE model can simulate grain yield and biomass accumulation of durum wheat with satisfactory accuracy under a wide range of soil, climate, and irrigation conditions representative of semiarid environments. Despite its parsimonious parameterisation, the model demonstrated robust performance, highlighting its potential usefulness for yield forecasting and irrigation management in water-limited systems. Nevertheless, several limitations should be acknowledged. Structurally, the model presents simplifications in carbon allocation under combined stresses and does not include an explicit nitrogen balance module. In addition, model validation was restricted to a single durum wheat cultivar and two non-consecutive growing seasons, which limits the generalisation of the results across broader temporal and genetic variability. Consequently, future research should focus on multi-location and multi-year validation, as well as testing across multiple cultivars, to enhance model reliability and applicability. Such improvements are essential for the effective use of SIMPLE as a decision-support tool for wheat production in Algeria.

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