

# Adapting Noah-MP-Crop for sorghum modeling in a semi-arid environment: a case study of Gedaref region in East Sahel

Yasir Hageltom<sup>a,b,\*</sup>, Joël Arnault<sup>a</sup>, Nadir Ahmed Elagib<sup>c</sup>, Patrick Laux<sup>a</sup>, Harald Kunstmann<sup>a,b</sup>

<sup>a</sup> Institute of Meteorology and Climate Research - Atmospheric Environmental Research (IMKIFU), Campus Alpin, Karlsruhe Institute of Technology (KIT), Garmisch-Partenkirchen, Germany

<sup>b</sup> Institute of Geography and Center for Climate Resilience, University of Augsburg, Augsburg, Germany

<sup>c</sup> Institute of Geography, Faculty of Mathematics and Natural Sciences, University of Cologne, Cologne, Germany

## ARTICLE INFO

### Keywords:

Noah-MP-Crop  
Sorghum  
Land surface model  
Semi-arid regions  
Crop simulation  
Sowing dates  
Crop yield

## ABSTRACT

Semi-arid agricultural regions are highly vulnerable to rainfall variability and heat stress, yet crop modeling in these areas is often constrained by limited field observations. Land surface models provide an important advantage over standalone crop models by simulating crop growth within a coupled water-energy-carbon framework, enabling interactions between vegetation development and land-atmosphere exchanges. This study adapted the Noah-MP-Crop model to simulate rainfed sorghum in Sudan's Gedaref region by introducing sorghum-specific phenological and physiological parameters. To represent spatial and interannual variability in sowing timing, we used normalized difference vegetation index (NDVI) data from the Moderate Resolution Imaging Spectroradiometer (MODIS) to estimate sowing dates. The model was calibrated using a stepwise approach constrained by satellite-derived leaf area index (LAI), observation-based surface energy fluxes, and multi-year field yield observations. The adapted model reproduced the seasonal evolution of sorghum canopy development and surface energy fluxes across different hydro-climatic conditions. Compared with a conventional fixed sowing-date approach, dynamic sowing improved LAI simulation during validation, increasing Nash-Sutcliffe efficiency (NSE) from 0.27 to 0.57 while reducing mean absolute error (MAE) from 0.21 to 0.16. Dynamic sowing also improved yield simulation, reducing MAE by 27% during calibration and 55% during validation relative to the fixed sowing date approach. The results indicate that integrating satellite-derived sowing dates with crop-specific calibration improves sorghum growth simulation in the rainfed Gedaref region.

## 1. Introduction

Semi-arid regions are characterized by strong interannual rainfall variability, frequent dry spells, and recurrent heat extremes that threaten crop productivity (Scholes, 2020). These environments typically have a short, highly concentrated rainy season followed by a prolonged dry period. Most cropping systems in these regions rely on rainfall, leaving them highly exposed to seasonal fluctuations and drought episodes (Lesk et al., 2022). Reliable simulations of crop growth and yield estimates under such conditions are essential for guiding agricultural planning and supporting food security. However, limited ground observations and sparse monitoring networks make this task challenging.

Sorghum plays a central role in these environments. It is the world's fifth most important cereal crop and a staple food for more than 500 million people, particularly in the arid and semi-arid zones of sub-Saharan Africa and South Asia (Khalifa and Eltahir, 2023; Yahaya and Shimelis, 2022). Its resilience to drought, heat, and even temporary waterlogging makes it indispensable in climates where other cereals fail (Abreha et al., 2021). In Africa, sorghum ranks second in cereal production, with Sudan, Nigeria, and Ethiopia together providing most of the continent's output (Yahaya et al., 2023). Despite its hardiness, yet sorghum productivity remains highly vulnerable because it is almost entirely rainfed and occasionally cultivated on marginal areas in terms of climate and soils (Elagib et al., 2024, 2019).

Sudan illustrates both the potential and the fragility of this crop. The

\* Corresponding author at: Institute of Meteorology and Climate Research - Atmospheric Environmental Research (IMKIFU), Campus Alpin, Karlsruhe Institute of Technology (KIT), Garmisch-Partenkirchen, Germany.

E-mail address: [yasir.hageltom@kit.edu](mailto:yasir.hageltom@kit.edu) (Y. Hageltom).

<https://doi.org/10.1016/j.agrformet.2026.111533>

Received 16 March 2026; Received in revised form 8 October 2026; Accepted 10 October 2026

Available online 17 October 2026

0168-1923/© 2026 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

Open access funding enabled and organized by Projekt DEAL.

mechanized rainfed sector cultivates millions of hectares annually, yet mean yields have declined from about  $1 \text{ t ha}^{-1}$  in the 1960s to roughly  $0.4 - 0.5 \text{ t ha}^{-1}$  since the early 2000s. The decline has largely been attributed to erratic rainfall, extended dry spells, and limited adaptive capacity and infrastructure (Elagib et al., 2019). With climate change projected to further intensify rainfall variability and heat stress, maintaining sorghum productivity in Sudan and across the Sahel is critical for sustaining regional food security. These challenges highlight the need for modeling frameworks that capture interactions between climate variability and crop development.

Land surface models (LSMs) can simulate key biophysical processes affecting crop growth, including surface energy balance, soil moisture, and carbon and water exchanges with the atmosphere. Unlike stand-alone crop models that treat meteorological conditions as prescribed inputs, LSMs embed crops within a coupled energy-water-carbon framework, enabling interactions between crop growth and land-surface conditions (Busschaert et al., 2026; Wang et al., 2024b). This coupling allows LSMs to simulate how crop development alters surface properties, such as albedo, roughness, and stomatal conductance, thereby affecting local temperature, humidity, and evaporative demand (Partridge et al., 2021). Major LSMs, including Noah-Multiparameterization (Noah-MP), Community Land Model (CLM), and Joint UK Land Environment Simulator (JULES), integrate dynamic crop modules to simulate crop growth, development, and carbon allocation in response to changing weather, soil, and management conditions (Boas et al., 2021; Prudente Junior et al., 2022).

The Noah-MP-Crop model, introduced by Liu et al. (2016), incorporates crop growth into the Noah-MP land surface model. It simulates crop phenology, carbon allocation, and leaf area index (LAI) development together with surface energy and water fluxes. Crop growth responds to atmospheric and soil conditions, while evolving canopy properties feedback to modify surface temperature, evapotranspiration, and energy partitioning (Zhang et al., 2020). Over the past decades, the model has undergone several developments to improve its representation of crop growth and land-atmosphere interactions. Early work incorporated dynamic crop growth modules for corn and soybean into Noah-MP to simulate seasonal variations in LAI, yield, and surface fluxes at field sites in the United States (Liu et al., 2016). Subsequent efforts refined soil-crop-atmosphere feedback by introducing a dynamic rooting-depth formulation, improving soil moisture and energy flux simulations (Liu et al., 2020). Later studies expanded the model's scope to regional and coupled Weather Research Forecasting (WRF) simulations to investigate the influence of weather-driven crop growth on land-atmosphere feedback across varying spatial scales (Partridge et al., 2021). Further enhancements have focused on extending crop types and management processes. Zhang et al. (2023) incorporated spring wheat and implemented temperature-based dynamic sowing and harvest dates. Wang et al. (2024b) improved winter-wheat representation through a refined phenology and vernalization scheme. Furthermore, Wang et al. (2024a) introduced a prognostic sowing and harvesting module based on thermal and temperature thresholds. An interactive irrigation and double-cropping framework for the North China Plain was developed by Fan et al. (2024).

Collectively, these studies show progress in developing Noah-MP-Crop, but applications have largely focused on temperate regions and major cereals. The model has seen limited application in African drylands, where crop production is strongly influenced by rainfall variability and heat stress. The model also lacks parameterization for sorghum, an important cereal crop across semi-arid Africa. In addition, most applications rely on fixed planting dates, which may not capture the rainfall-dependent sowing decisions that characterize rainfed agriculture in Sub-Saharan Africa (Laux et al., 2010, 2008).

Accordingly, this research aims to adapt and evaluate Noah-MP-Crop for rainfed sorghum in the semi-arid Gedaref region of Sudan. The work specifically focuses on three objectives: (1) to develop sorghum-specific

physiological and phenological parameters using a stepwise calibration approach; (2) to introduce a dynamic sowing-date scheme informed by remote-sensing observations to better reflect rainfall-driven management practices; and (3) to assess the model's skill in reproducing sorghum growth, canopy development, and yield.

## 2. Materials and methods

### 2.1. Study area

The study focuses on the semi-arid region of Gedaref State, Sudan, located in the eastern Sahel within the lower part of the Blue Nile Basin, approximately  $33 - 37^\circ \text{E}$ ,  $12 - 15^\circ \text{N}$  (Fig. 1). Gedaref State lies on a gently undulating plain with elevations ranging from 425 to 655 m above sea level. The climate has a unimodal rainfall pattern concentrated between June and October, with a prolonged dry season for the rest of the year. Mean annual rainfall varies between 400 and 800 mm, with high interannual variability characteristic of semi-arid regions (Elagib and Elhag, 2011; Salih et al., 2018). Mean monthly temperatures range from  $22^\circ \text{C}$  in January to over  $33^\circ \text{C}$  in May, with peak temperatures reaching  $43^\circ \text{C}$  coinciding with the pre-rainy season. The region has also experienced a sustained warming trend since the 1980s (Hawkins et al., 2025; Sulieman and Elagib, 2012). These combined rainfall fluctuations and rising temperatures strongly influence crop development, water stress, and yield variability in the region.

Agriculture in Gedaref is dominated by semi-mechanized rainfed systems occupying approximately 50 – 75% of the cultivated area in the central and northern parts of the state (Bereir et al., 2022). Sorghum (*Sorghum bicolor* L.) is the principal crop across Gedaref State, accounting for approximately 60 – 70% of the cultivated area, followed by sesame and millet. Most fields are cultivated on heavy clay Vertisols, which exhibit high water-holding capacity but are prone to waterlogging during intense rainfall events (Sulieman and Buchroithner, 2009). Fertilizer and pesticide use in rainfed sorghum production in Gedaref is generally low and highly variable across farms and years, often constrained by limited access and high-cost input (Ahmed and Sanders, 1998; Bussmann et al., 2016; Elagib and Elhag, 2011). Sorghum yields in the mechanized sector average 500 – 700 kg/ha, substantially below potential productivity and exhibiting high interannual variability ( $\pm 30 - 50\%$ ) linked to rainfall fluctuations (Khalifa and Eltahir, 2023). Historical analysis reveals yields have declined significantly from 744 kg/ha in the 1970s to approximately 476 kg/ha since 1982 (Elagib et al., 2019).

Sowing decisions are primarily driven by the onset of seasonal rains (Laux et al., 2010), typically occurring between late July and early August. Farmers generally intend to plant once sufficient soil moisture is achieved, based on local rainfall measurements or traditional field indicators such as the closure of soil cracks in clay-rich Vertisols. However, farmers often delay sowing because of non-climatic constraints, such as weed presence and slow soil preparation (Bussmann et al., 2016).

This region represents a typical semi-arid agricultural environment where crop productivity is tightly coupled to rainfall variability and heat stress. The high dependence on rainfed agriculture, combined with minimal adaptive capacity and limited input use, makes Gedaref an ideal testbed for evaluating process-based crop models under water- and heat-limited conditions.

### 2.2. Model description

#### 2.2.1. Noah-MP land surface model

We employed the community Noah-MP land surface model, an open-source framework that provides an advanced representation of land surface physical processes and supports multiple parameterization options (Chen et al., 1996; Niu et al., 2011). Noah-MP simulates the exchange of energy, water, and momentum between the land surface and

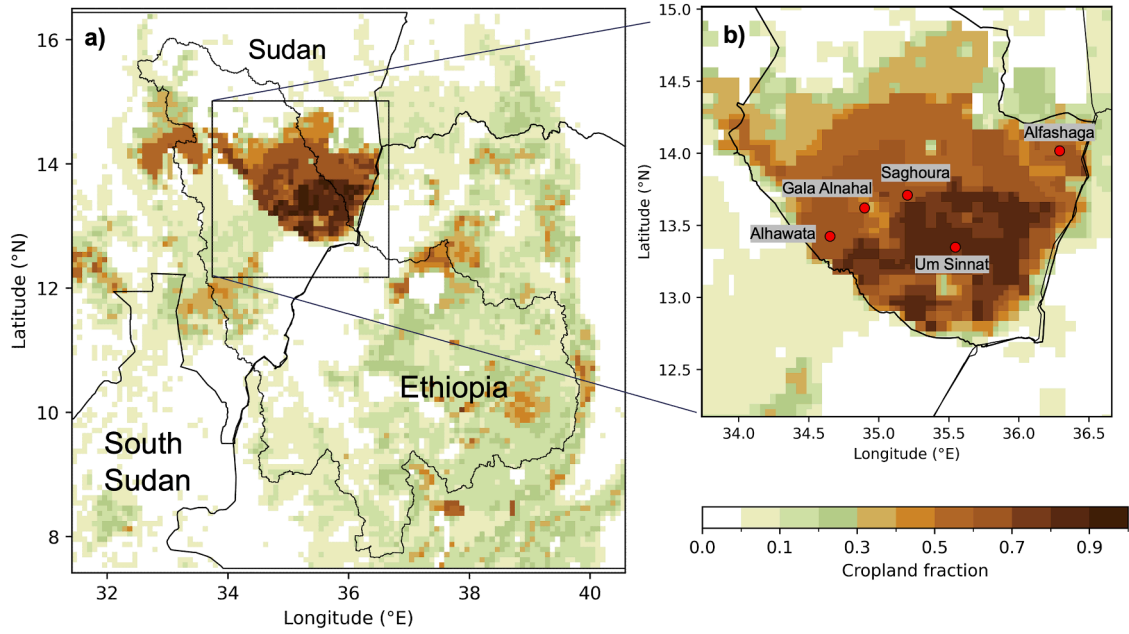


**Fig. 1.** Spatial distribution of cropland in the Blue Nile Basin: (a) basin-wide cropland fraction and (b) sorghum cropland fraction in Gedaref State. Red circles indicate the locations of field sites used for model calibration and validation.

atmosphere while resolving vegetation-soil-atmosphere interactions. Its multi-physics structure and explicit treatment of vegetation dynamics make Noah-MP well suited for dynamic crop modeling applications.

Land surface heterogeneity in Noah-MP is represented using a semi-tile approach, in which each grid cell is divided into a vegetated fraction ( $F_{veg}$ ) and a bare soil fraction ( $1 - F_{veg}$ ). Incoming shortwave radiation is computed over the entire grid cell, whereas longwave radiation, latent heat flux ( $LE$ ), sensible heat flux ( $H$ ), and ground heat flux ( $G$ ) are calculated separately for vegetated and bare-soil tiles. The surface energy balance is expressed as:

$$S_{av} + S_{ag} = L_a + LE + H + G \quad (1)$$

where  $S_{av}$  and  $S_{ag}$  are the shortwave radiation absorbed by the vegetation and ground, respectively, and  $L_a$  is the net longwave radiation. The flux components are solved iteratively to determine canopy temperature ( $T_v$ ) and ground surface temperatures under vegetated and bare conditions ( $T_{g,v}$  and  $T_{g,b}$ , respectively).

Noah-MP includes multiple options for representing stomatal resistance ( $\gamma_s$ ), which regulates transpiration. In this study, we selected the Ball-Berry scheme, which links stomatal conductance to photosynthetic activity and atmospheric  $CO_2$  concentration. Latent heat flux from the vegetation canopy transpiration is formulated using a resistor network approach:

$$LE_v = \frac{\rho C_p}{\gamma} \left( \frac{LAI_{sun}}{r_b + r_{s, sun}} + \frac{LAI_{sha}}{r_b + r_{s, sha}} \right) (e_{sat, v}(T_v) - e_{av}) \quad (2)$$

where  $\rho$  is air density,  $C_p$  is the specific heat capacity of air,  $\gamma$  is the psychrometric constant,  $LAI_{sun}$  and  $LAI_{sha}$  refer to sunlit and shaded leaf area index, respectively, and  $r_b$  and  $r_{s, sha}$  denote boundary layer and stomatal resistances.  $e_{sat, v}(T_v)$  is the saturation vapor pressure at the canopy temperature and  $e_{av}$  is the vapor pressure within the canopy air space. The vapor pressure gradient between the canopy and atmosphere drives transpiration, which constitutes a major component of  $LE$  and directly responds to vegetation physiological state.

These features enable Noah-MP to dynamically represent interactions between vegetation growth and surface energy fluxes. Consequently, the model provides a consistent framework for integrating crop models, such as Noah-MP-Crop. Within this framework,

crop growth dynamically alters canopy properties (e.g., LAI and stomatal resistance), thereby affecting energy flux partitioning and land-atmosphere exchanges. In this study, we configured Noah-MP within the WRF-Hydro framework using physical options appropriate for the study region. Appendix A (Tables S1 and S2) of the Supplementary Material summarizes the model configuration and selected parameterization options.

### 2.2.2. Noah-MP-Crop model

Noah-MP-Crop extends the Noah-MP land surface model by simulating crop phenology, biomass growth, and carbon allocation, replacing static vegetation properties with dynamically evolving crop states (Liu et al., 2016). The model prognostically simulates LAI and biomass pools (leaf, stem, root, and grain), allowing crop development to directly influence surface energy and water fluxes (Liu et al., 2016; Zhang et al., 2020). Crop yield is estimated from grain biomass accumulated at the physiological maturity stage.

Crop development in Noah-MP-Crop is represented using a set of phenological growth stages (PGSs) that describe progression from sowing to harvest. Development is initiated by the sowing date, after which stage transitions are controlled by cumulative growing degree days (GDD), linking crop development directly to temperature conditions rather than fixed calendar dates. The model includes eight stages: before sowing (PGS1), emergence (PGS2), initial vegetative growth (PGS3), normal vegetative growth (PGS4), initial reproductive development (PGS5), physiological maturity (PGS6), post-maturity (PGS7), and after harvest (PGS8).

From an agronomic perspective, sorghum development is described using a finer sequence of growth stages. These stages include emergence, early leaf development, growing-point differentiation, flag-leaf appearance, flowering, grain filling, and physiological maturity, each associated with characteristic physiological processes and GDD ranges (Roozeboom and Prasad, 2019). To align agronomic understanding with the Noah-MP-Crop framework, we aggregated these detailed sorghum stages into the model's PGSs based on their dominant physiological characteristics.

Early sorghum stages from emergence through growing-point differentiation are mapped to initial vegetative growth (PGS3), representing canopy establishment and early biomass accumulation (Borrell

et al., 2014; Roozeboom and Prasad, 2019). Stages encompassing flag-leaf development and booting are assigned to normal vegetative growth (PGS4), during which final leaf number is fixed, and the transition to reproductive development occurs (Roozeboom and Prasad, 2019). Flowering and early grain filling are grouped within initial reproductive development (PGS5), a period when assimilates are increasingly allocated to grain (Gutjahr et al., 2013; Roozeboom and Prasad, 2019). Late grain filling through black-layer formation is mapped to physiological maturity (PGS6), marking the completion of dry-matter accumulation and determining final yield (Gutjahr et al., 2013; Roozeboom and Prasad, 2019). Fig. 2 illustrates the correspondence between agronomic sorghum growth stages and the Noah-MP-Crop phenological growth stages. This aggregation preserves key physiological transitions controlling sorghum growth while remaining consistent with the simplified phenological structure of Noah-MP-Crop, enabling realistic simulation without unnecessary model complexity.

### 2.3. Data

Given the limited availability of ground observations in the study area, we integrated multiple sources of atmospheric, land-surface, satellite, and field-survey data. These datasets serve two main purposes: (i) providing model inputs, including meteorological forcing, land cover, crop distribution, soil properties, and sowing dates; (ii) supporting model calibration and evaluation through observations of vegetation dynamics, surface energy fluxes, and crop yield. Together, they provide the spatially and temporally consistent information required to simulate and evaluate sorghum growth in Gedaref State.

#### 2.3.1. Model input data

Atmospheric forcing was derived from a hybrid dataset combining ERA5-Land reanalysis and the Integrated Multi-satellite Retrievals for GPM (IMERG) precipitation product. ERA5-Land provides hourly meteorological variables at 0.1° spatial resolution, including near-surface wind speed, 2-m air temperature, 2-m specific humidity, surface pressure, and downward shortwave and longwave radiation (Muñoz-Sabater, 2019). These variables are generated by replaying the European Centre for Medium-Range Weather Forecasts (ECMWF) global

reanalysis through a land-surface model, ensuring physical consistency across meteorological fields. ERA5-Land has been extensively validated for temperature, radiation, and wind variables and is widely adopted in land surface modeling applications (Muñoz-Sabater et al., 2021).

Precipitation forcing was obtained from IMERG at 0.1° spatial resolution and half-hourly temporal resolution (Huffman et al., 2023), replacing ERA5-Land rainfall to improve the representation of rainfall magnitude and temporal variability. Multiple regional studies across East Africa have shown that IMERG outperforms ERA5-Land in capturing rainfall intensity and temporal structure (Dezfuli et al., 2017; Zargar et al., 2025). We evaluated both precipitation products against rain-gauge observations in Gedaref State for 2001 – 2020 (Appendix B). IMERG consistently showed better performance across daily to annual timescales and more accurately reproduced the timing and intensity of the June–October rainy season. Conversely, ERA5-Land exhibited systematic overestimation. Based on this evaluation, IMERG was selected for precipitation, whereas ERA5-Land was retained for the remaining atmospheric variables. ERA5-Land meteorological variables and IMERG precipitation were resampled from their native resolution to the 4-km Noah-MP-Crop, using bilinear grid refinement followed by nearest-neighbour mapping.

Land-cover information was obtained from the Copernicus Global Land Service (CGLS) Dynamic Land Cover product, which was resampled to the standard 17-class International Geosphere-Biosphere Programme (IGBP) classification scheme used by the Moderate Resolution Imaging Spectroradiometer (MODIS) for compatibility with the Noah-MP LSM (Buchhorn et al., 2020). The product is available at 100-m spatial resolution and has been widely applied in land-surface modeling studies (Demuzere et al., 2023). Soil properties are derived from the FAO/UNESCO Digital Soil Map of the World at 30-arc-second (~1 km) resolution (FAO/UNESCO, 1988). FAO soil classes are reclassified to the 16 soil texture categories used in Noah-MP using standard lookup tables, preserving the hydraulic and thermal properties required to simulate soil moisture and energy fluxes. We incorporated land-cover and soil datasets into the model domain through the standard WRF geogrid preprocessing system.

Sorghum distribution was represented using the Spatial Production Allocation Model (SPAM) 2020 dataset, which provides crop-specific harvested area fractions at approximately 10-km resolution (IFPRI,

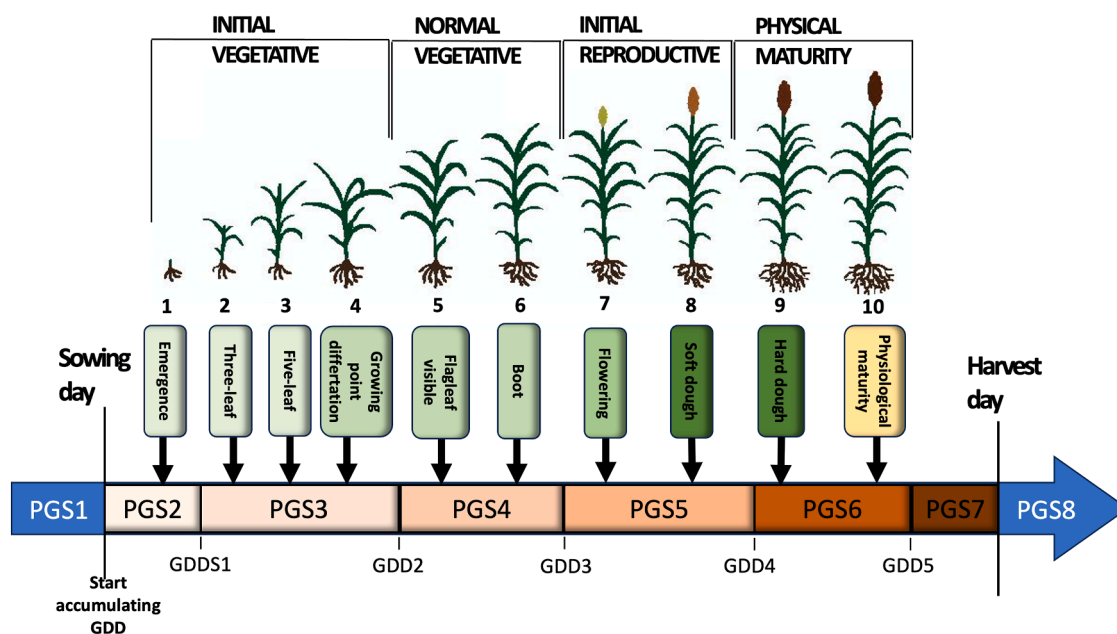


Fig. 2. Sorghum growth stages and their corresponding Noah-MP-Crop phenological growth stages (PGS1 – PGS8). GDD1 – GDD5 indicate the GDD thresholds defining transitions between stages. Adapted from Wang et al. (2024b).

2023). Sorghum harvested area fractions were extracted and resampled to the model grid using a conservative area-preserving method, preserving total cultivated area during spatial transformation.

Farmer-reported sowing dates for sorghum were obtained from Elagib et al. (2025). Sowing date observations were available for 80 locations during the 2022 growing season. We used this dataset to parameterize and evaluate the sowing-date estimation method. The locations of the field observations are shown in Figure S2.

### 2.3.2. Model evaluation data

Model evaluation was conducted using satellite-based products and field survey data to assess both biophysical variables and agricultural indicators. Surface energy fluxes were evaluated using the FLUXCOM MLM-ERA5 ensemble product, which provides global energy flux estimates at 0.1° spatial resolution and daily temporal resolution for the period 2000–2020 (Jung et al., 2019). The MLM-ERA5 ensembles are derived using machine-learning models trained on eddy-covariance observations and driven by ERA5 meteorology (Jung et al., 2020; Tramontana et al., 2016).

Vegetation dynamics were evaluated using the Global Land Surface Satellite (GLASS) LAI product version 6, which provides global LAI estimates at 500-m spatial resolution and 8-day temporal resolution (Liang et al., 2013; Xiao et al., 2016). GLASS LAI has demonstrated improved temporal continuity and reduced noise relative to standard MODIS LAI products, and has been widely used in crop and land-surface modeling studies (Fang et al., 2019; Liang et al., 2021; Xiao et al., 2016).

Sorghum yield records were obtained from the Mechanized Farming Corporation of Gedaref State. We assessed the available raw data based on time-series availability and site characteristics. Five locations were selected for model calibration and validation (Fig. 1b). Yield data for these locations covered 2014–2021, except for 2017 records. Yields were originally reported in sacks per feddan (1 sack = 90 kg; 1 feddan ≈ 0.42 ha). We converted them to kg ha<sup>-1</sup> for comparison with model

outputs.

### 2.4. Sowing-date estimation

Accurate sowing-date information is essential for crop modeling and yield estimation (Manfron et al., 2017). However, such data are rarely available at spatial scales suitable for regional modeling. Satellite-derived vegetation indices provide an alternative by detecting crop phenology from seasonal vegetation dynamics. Threshold-based methods are widely used for this purpose due to their simplicity and computational efficiency (Htitiou et al., 2024). These techniques identify phenological transitions when a vegetation index reaches a pre-defined level during the growth cycle (Fischer, 1994). Specifically, dynamic threshold methods define this point as a fraction of the seasonal amplitude (White et al., 1997; Yang et al., 2021) and consistently outperform fixed thresholds (Huang et al., 2019; Yang et al., 2021). Following this approach, we used MODIS observations to estimate sorghum sowing dates in Gedaref. The flowchart in Fig. 3 provides an overview of this methodology.

Daily MODIS Surface Reflectance data from the MOD09GQ Collection 6.1 product at 250 m spatial resolution (Justice et al., 2002) were accessed through Google Earth Engine (Gorelick et al., 2017). We used the quality control layer within the MOD09GA Collection 6.1 product to mask pixels contaminated by clouds and cloud shadows. The normalized difference vegetation index (NDVI; Rouse et al., 1974) was calculated at the pixel level as:

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad (3)$$

Where *NIR* and *RED* are the near-infrared and red surface reflectance, respectively. Temporal gaps between valid observations were linearly interpolated to obtain a daily NDVI time series. A Savitzky–Golay filter (Savitzky and Golay, 1964) was then applied to reduce short-term

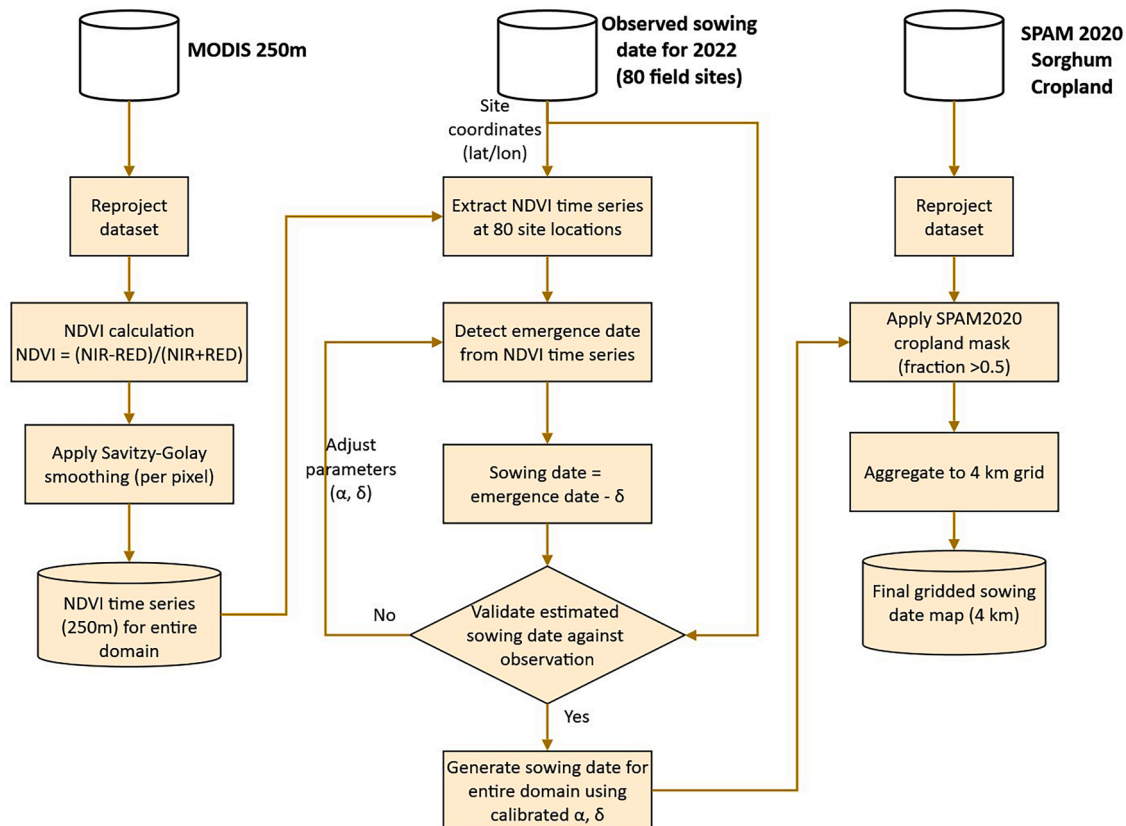


Fig. 3. Workflow for deriving gridded sowing dates from NDVI.

fluctuations while preserving the seasonal vegetation signal. The smoothed NDVI time series were extracted at the surveyed field locations to evaluate the sowing date estimation method. To detect the emergence date, the search window was restricted to the main sorghum growing season from 1 July to 30 November (Alshikh et al., 2017). Within this period, the green-up phase was defined between the seasonal minimum ( $NDVI_{min}$ ) and the subsequent seasonal maximum ( $NDVI_{max}$ ). The dynamic threshold ( $NDVI_{thr}$ ) was calculated as:

$$NDVI_{thr} = NDVI_{min} + \alpha (NDVI_{max} - NDVI_{min}) \quad (4)$$

where  $\alpha$  is the fraction of the seasonal amplitude used to define the emergence. The emergence date ( $t_{em}$ ) was identified as the first day during the green-up phase when the smoothed NDVI reached  $NDVI_{thr}$ . The sowing date ( $t_{sow}$ ) was then estimated by subtracting a fixed offset:

$$t_{sow} = t_{em} - \delta \quad (5)$$

where  $\delta$  represents the lag between sowing and visible emergence. Sorghum emergence typically occurs within approximately 2 to 6 days after sowing, depending on cultivar, seed treatment, temperature, and soil moisture conditions (Chivasa et al., 2000; Wawo et al., 2024).

To generate annual sowing date maps across Gedaref, the NDVI data were upscaled to a 4 km Noah-MP-Crop grid using area-weighted averaging. A sorghum cropland mask derived from the SPAM2020 dataset was applied, retaining only grid cells with a sorghum fraction  $\geq 0.5$ . The sowing date estimation method was subsequently applied to these retained cells.

## 2.5. Crop model calibration

The Noah-MP-Crop model was calibrated for sorghum by targeting key parameters related to crop growth and productivity (Table 1), as identified in previous studies (Arsenault et al., 2018; Wang et al., 2024b; Yu et al., 2022; Zhang et al., 2020). To address the equifinality problem, in which different parameter combinations can produce similar model results (Beven and Binley, 1992; Ingwersen et al., 2018), we adopted a stepwise calibration strategy. Such approaches have been widely applied in land surface model calibration to reduce parameter uncertainty and improve physical consistency (Vrugt et al., 2005).

Calibration was performed over the period 2014 – 2018, preceded by a two-year spin-up period (2012 – 2013) to stabilize soil moisture conditions. Parameters were optimized sequentially in three physio-

logically coherent groups: (1) phenological controls, (2) canopy and photosynthetic processes, and (3) biomass partitioning. This sequential strategy preserves logical dependencies among processes, and has been shown to improve calibration robustness and parameter interpretability (Makowski et al., 2002). We sourced calibration parameter ranges (Table S3) from the literature and expanded them to test broader physical bounds and account for regional transfer uncertainties (Wallach et al., 2006).

We employed the Latin Hypercube Sampling (LHS) method (McKay et al., 1979) to explore the multi-dimensional parameter space efficiently. LHS has been shown to provide better coverage of the parameter space compared with simple random sampling, particularly for high-dimensional problems (Helton and Davis, 2003). For each parameter group, the initial iteration generated 100 parameter sets using LHS. Following each iteration, the sample size was reduced by 10% (100, 90, 81, 73, ..., etc.), while refining the parameter ranges using the top 10% best-performing parameter sets from the previous iteration. Parameter sets were ranked according to the objective function, and the retained parameter sets were used to progressively constrain the search toward the most promising regions of the parameter space. This iterative sampling-evaluation procedure continued until convergence or a pre-defined maximum number of iterations was reached. We further evaluated the influence of the initial LHS sample size on calibration using 200 parameter sets (Appendix D; Figure S9).

We evaluated the model performance using a multi-objective function based on four observational targets: LAI, grain yield,  $LE$ , and  $H$ . For LAI,  $LE$ , and  $H$ , model outputs were spatially averaged over the cropland area prior to evaluation. For grain yield, performance was assessed using field observations from five yield locations in the Gedaref State (Fig. 1b). Because these observations represent field-scale production rather than point measurements, simulated yield was extracted as the mean of a  $3 \times 3$  grid-cell window centered on each observation location. Performance metrics were calculated for each site, and the mean value across all sites was used in the calibration objective.

Performance for each objective variable ( $v$ ) was quantified using the residual Kling–Gupta Efficiency ( $KGE$ ) score:

$$Score_v = 1 - KGE_v \quad (6)$$

where  $v$  represents LAI, yield,  $LE$ , and  $H$ .  $KGE$  is defined following Gupta et al. (2009) :

$$KGE = 1 - \sqrt{(r - 1)^2 + (\alpha - 1)^2 + (\beta - 1)^2} \quad (7)$$

Here  $r$  is the Pearson correlation coefficient between observed and simulated values,  $\alpha$  is the variability ratio (ratio of simulated to observed standard deviation), and  $\beta$  is the bias ratio (ratio of simulated to observed mean). The  $KGE$  metric provides a balanced assessment of model performance by jointly accounting for correlation, variability, and bias. This metric has been widely applied in hydrological and land surface modeling studies (Gupta et al., 2009; Knoben et al., 2019). Lower values of  $Score_v$  indicate better model performance.

The overall objective function was formulated as a weighted sum of the residual scores:

$$\text{Total Score} = \sum w_v \text{Score}_v \quad (8)$$

where  $w_v$  denotes the weighting factor assigned to variable  $v$ . A total of 70% of the calibration objective weight was assigned to yield and LAI (0.35 each), while the remaining 30% was assigned to  $LE$  and  $H$  (0.15 each). This weighting scheme reflects the primary focus on crop growth and production, while retaining the energy fluxes as complementary constraints on surface energy exchange. We further evaluated the calibration's sensitivity to the weighting scheme in Appendix D (Figure S8). Convergence was assessed using the mean total score of the retained top 10% parameter sets. The calibration was terminated when the relative improvement in the mean total score between consecutive iterations was

**Table 1**

List of Noah-MP-crop parameters used for sorghum calibration and their functional roles.

| Group                      | Parameter  | Description                                                                    |
|----------------------------|------------|--------------------------------------------------------------------------------|
| Phenology control          | GDDS1      | GDD from seeding to emergence                                                  |
|                            | GDDS2      | GDD from seeding to initial vegetative                                         |
|                            | GDDS3      | GDD from seeding to post-vegetative                                            |
|                            | GDDS4      | GDD from seeding to initial reproductive                                       |
|                            | GDDS5      | GDD from seeding to physiological maturity                                     |
| Canopy and crop physiology | MP         | The slope of conductance to photosynthesis (Ball-Berry slope)                  |
|                            | VCMX25     | The maximum rate of carboxylation at 25 °C                                     |
|                            | QE25       | Quantum efficiency at 25 °C ( $\mu\text{mol Co}_2 \text{ m}^{-2} / \text{s}$ ) |
| Biomass partitioning       | BIO2LAI    | Leaf area per living leaf biomass ( $\text{m}^2/\text{kg}$ )                   |
|                            | LFPT_S3    | Fraction of carbohydrate flux to leaf at initial vegetative stage              |
|                            | LFPT_S4    | Fraction of carbohydrate flux to leaf at post-vegetative stage                 |
|                            | GRAINPT_S5 | Fraction of carbohydrate flux to grain at initial reproductive stage           |
|                            | GRAINPT_S6 | Fraction of carbohydrate flux to grain at physical maturity stage              |

less than 1%, or when a maximum of six iterations was reached.

## 2.6. Sensitivity analysis

Sensitivity analysis was conducted in parallel with the calibration process. We used the LHS parameter ensembles generated during calibration to quantify the influence of individual parameters on simulated LAI,  $LE$ ,  $H$ , and grain yield. Using the same LHS ensembles ensures sensitivity is assessed over the full parameter space explored during calibration. This is achieved without incurring additional computational cost.

Parameter sensitivities were quantified using the Partial Rank Correlation Coefficient, PRCC (Helton, 1993; Marino et al., 2008). PRCC measures the strength and direction of the monotonic relationship between a given parameter and a model output while accounting for the confounding effects of all other parameters (Dzotsi et al., 2013). This approach makes PRCC more robust than simple rank-based correlation metrics (e.g., Spearman correlation), particularly in systems with interdependent parameters, which are common in crop and land surface models (Krishnan et al., 2021). The PRCC for parameter  $i$  with respect to an output variable  $Y$  is computed as:

$$PRCC_i = \frac{r_{Y,i|-i}}{\sqrt{(1 - R_{i,-i}^2)(1 - R_{Y,-i}^2)}} \quad (9)$$

where:

- $Y$  is the model output (LAI,  $LE$ ,  $H$ , or yield);
- $i$  is the parameter of interest;
- $i$  denotes all remaining parameters (i.e., all parameters except  $i$ );
- $r_{Y,i|-i}$  is the partial correlation coefficient between  $Y$  and parameter  $i$  after removing the linear effect of all remaining parameters;
- $R_{i,-i}$  is the multiple correlation coefficient relating parameter  $i$  to all other parameters;
- $R_{Y,-i}$  is the multiple correlation coefficient relating output  $Y$  to the remaining parameters (excluding  $i$ ).

The partial correlation coefficient  $r_{Y,i|-i}$  quantifies the relationship between the ranks of output variable  $Y$  and parameter  $i$  after accounting for the influence of all other parameters. PRCC values range from  $-1$  to  $1$ , and their magnitude indicates the strength of sensitivity. Following Marino et al. (2008), parameter influence was classified as weak ( $|PRCC| < 0.25$ ), moderate ( $0.25 \leq |PRCC| < 0.5$ ), and strong ( $|PRCC| \geq 0.5$ ). Positive coefficients indicate that increasing a parameter increases the model output, whereas negative coefficients indicate an inverse relationship.

## 2.7. Model evaluation and simulation experiments

Model performance was evaluated against the observational datasets described in Section 2.3. The evaluation focused on the model's ability to reproduce seasonal canopy development, surface energy fluxes, and grain yield. Three evaluation experiments were performed. First, the model was assessed using dynamic sowing dates during the calibration period (2014–2018) and validation period (2019–2021). The availability of observational datasets constrained the selection of these periods. Because FLUXCOM data were available only through 2020,  $LE$  and  $H$  validation was limited to 2019–2020. The calibration period included both notably wet and dry years, whereas the validation period comprised one below-normal rainfall year (2019), followed by two above-normal rainfall years (2020–2021).

Second, the benefit of dynamic sowing dates was assessed by comparing the calibrated model against the standard Noah-MP-Crop configuration using a fixed sowing date. We applied a fixed day of year (DOY = 212) uniformly across the domain and all simulation years.

We selected this date based on studies reporting late July as a common sorghum sowing period in Gedaref (Bussmann et al., 2016; Alshikh et al., 2017; Mohammed et al., 2010). This simulation experiment assessed whether accounting for spatial and interannual variations in sowing improves the simulation compared with a fixed-date approach.

Third, to examine spatial and temporal patterns of sorghum yield and their relationship with interannual rainfall variability across the region, we applied the dynamic sowing approach in a long-term simulation (2000–2024).

Model performance was quantified using three widely applied statistical metrics: the coefficient of determination,  $R^2$  (Legates and McCabe Jr., 1999), the Nash–Sutcliffe Efficiency,  $NSE$  (Nash and Sutcliffe, 1970), and the mean absolute error,  $MAE$  (Willmott and Matsuura, 2005). Together, these metrics quantify agreement between simulated and observed values, predictive skill relative to the observed mean, and absolute error magnitude, respectively.

The coefficient of determination is defined as:

$$R^2 = \left( \frac{\sum_{t=1}^n (O_t - \bar{O})(S_t - \bar{S})}{\sqrt{\sum_{t=1}^n (O_t - \bar{O})^2} \sqrt{\sum_{t=1}^n (S_t - \bar{S})^2}} \right)^2 \quad (10)$$

The Nash–Sutcliffe Efficiency is defined as:

$$NSE = 1 - \frac{\sum_{t=1}^n (S_t - O_t)^2}{\sum_{t=1}^n (O_t - \bar{O})^2} \quad (11)$$

The mean absolute error is defined as:

$$MAE = \frac{1}{n} \sum_{t=1}^n |S_t - O_t| \quad (12)$$

In Eqs. (10) to (12),  $S_t$  and  $O_t$  represent simulated and observed values, respectively,  $\bar{S}$  and  $\bar{O}$  are their respective means, and  $n$  is the number of observations. For  $R^2$ , values near 1 indicate the model explains most of the variance. For  $NSE$ , values close to 1 reflect high predictive skill, whereas negative values indicate performance worse than simply using the mean of the observed data as a predictor.

## 3. Results

### 3.1. Sowing dates

The satellite-based method was evaluated against observed sorghum sowing dates from the 2022 growing season. Performance varied among the tested combinations of threshold percentage and emergence lag (Figure S3). Among the tested combinations, a threshold of 20% and an emergence lag of 3 days provided the best balance of low  $MAE$  and minimal bias. We therefore selected this combination to generate the final sowing date maps. Using these values, the estimated sowing dates showed a mean bias of  $-2$  days and an  $MAE$  of 12.8 days across the 80 validation sites (Fig. 4a). About 46.6% of the sites showed absolute errors within 10 days, while 86.2% fell within 20 days (Fig. 4b).

Fig. 5 presents the spatial distribution of estimated sorghum sowing dates across Gedaref State for 2014–2022, with each map representing a single year. The derived sowing dates revealed a clear spatial gradient. Sowing is earliest in the south and southeast, progressing to later dates toward the center and north. This pattern closely follows the progression of rainfall and soil moisture in Gedaref State (Bussmann et al., 2016; Omay et al., 2023). Although the absolute timing of sowing varied between years, the spatial gradient remained remarkably stable. A notable exception was 2015, which showed a markedly delayed sowing pattern across much of the Gedaref State, with sowing extending into mid- and late August. This behavior aligns with reports of a late and weak rainy season in eastern Sudan during 2015 (FAO, 2016; Omay et al., 2023), which was also characterized by widespread seasonal drought conditions (Elagib et al., 2024). These conditions likely delayed soil wetting

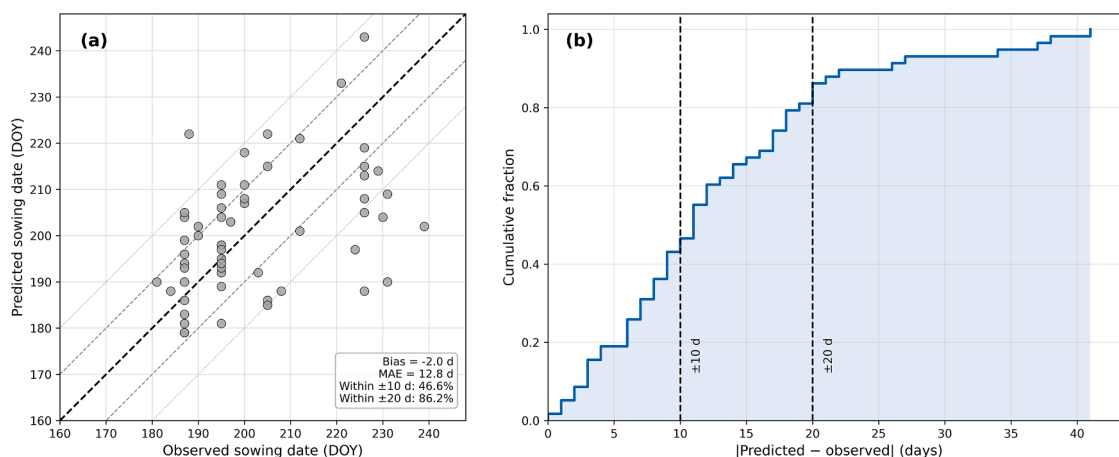


**Fig. 4.** Evaluation of estimated sorghum sowing dates for the 2022 season. (a) Scatter plot comparing observed versus predicted sowing dates (day of year, DOY) across 80 validation sites; the dashed line indicates the 1:1 relationship, and dotted lines show  $\pm 10$ - and  $\pm 20$ -day error bounds. (b) Cumulative distribution of absolute sowing date errors, showing the percentage of sites falling within  $\pm 10$  and  $\pm 20$  days.

and postponed planting activities in rainfed systems. In contrast, years such as 2019 and 2020 exhibited earlier and more spatially extensive sowing, consistent with earlier rainfall onset and wetter seasonal conditions (Elagib et al., 2021).

### 3.2. Crop phenology

Fig. 6 shows the simulated sorghum phenological stages for three contrasting years: 2015, a dry year with late sowing; 2017, a year with average conditions; and 2020, a wet year. The timing of the phenological stages followed the differences in sowing date (Fig. 6a). In 2015, late sowing shifted all subsequent stages later in the season compared with 2017 and 2020. Fig. 6b shows that the time from sowing to the subsequent phenological stages was generally shorter in 2015. Across the three years, emergence occurred shortly after sowing, with a median of about 4 days. Growing point differentiation occurred after about 29 days in 2015 and 2017 and 32 days in 2020. Booting was reached after about 50, 51, and 55 days, and soft dough after about 67, 69, and 74 days, respectively. The median time to physiological maturity was about 79 days after sowing in 2015, 80 days in 2017, and 85 days in 2020.

The simulated phenological progression from early vegetative development to booting was consistent with that reported by Roozeboom and Prasad (2019). These stages, which are primarily governed by vegetative growth processes, were well represented by temperature-driven development. Larger differences occurred during the reproductive stages, with the model reaching physiological maturity earlier than reported in their study.

The simulated growing period was also within the range reported for sorghum in Gedaref. Bussmann et al. (2016) reported growing periods of 75–110 days for early- and late-maturing sorghum varieties. The simulated crop durations fell mainly within the early-maturing range. This is consistent with commonly grown varieties such as Arfa Gadamak and Wad Ahmed, which have relatively short growing periods (Kenya et al., 2017; Mohamed et al., 2011).

### 3.3. Leaf area index

Fig. 7a and the corresponding performance metrics (Table S4) show improved LAI simulation with the dynamic sowing approach. During the calibration period, the dynamic sowing configuration achieved  $R^2 = 0.75$ ,  $NSE = 0.64$ , and  $MAE = 0.12$ . The fixed sowing configuration produced a similar  $R^2$  (0.70) but a lower  $NSE$  (0.36), indicating poorer agreement with the observed LAI dynamics. This improvement was also evident during the validation period, with the dynamic sowing configuration showing a higher  $NSE$  (0.57 versus 0.27) and lower  $MAE$  (0.16

versus 0.21) than the fixed sowing configuration.

Fig. 7a further shows that the dynamic sowing approach better captured the timing of canopy development, whereas the fixed sowing configuration consistently overestimated peak LAI. However, some discrepancies remained between the simulated and observed seasonal patterns. At the beginning of the growing season, the observed LAI increased slightly earlier than the simulated LAI. This discrepancy likely reflects early-season grass growth captured by the satellite observations but omitted by the crop model. Toward the end of the growing season, the simulated LAI declined earlier than the satellite observations, indicating a shorter simulated canopy persistence period.

### 3.4. Energy fluxes

Figure 7(b) and (c) show the seasonal variation in  $LE$  and  $H$  for the dynamic and fixed sowing configurations. In contrast to LAI, differences between the two sowing configurations were small for both fluxes. For  $LE$ , both configurations reproduced the seasonal pattern well during the calibration and validation periods (Table S5). During calibration,  $R^2$  ranged from 0.89 to 0.90,  $NSE$  from 0.72 to 0.73, and  $MAE$  from 0.91 to  $0.92 \text{ MJ m}^{-2} \text{ d}^{-1}$ . Similar performance was maintained during validation, with  $R^2$  of 0.85–0.86,  $NSE$  of 0.75 for both configurations, and  $MAE$  ranging from 0.94 to  $0.95 \text{ MJ m}^{-2} \text{ d}^{-1}$ .

The simulation of  $H$  showed lower performance than  $LE$ , particularly during calibration. Both configurations achieved an  $R^2$  of 0.55 during calibration, while  $NSE$  was  $-0.08$  for dynamic sowing and  $-0.11$  for fixed sowing. Performance improved during validation, with both configurations reaching an  $R^2$  of 0.64 and  $NSE$  values of 0.44 and 0.43, respectively.  $MAE$  decreased from  $1.01 - 1.02 \text{ MJ m}^{-2} \text{ d}^{-1}$  during calibration to 0.89 during validation.

### 3.5. Yield

Yield simulation with the dynamic sowing configuration varied considerably across the five sites (Fig. 8). During calibration, the best performance was obtained at Alhawata, with  $R^2 = 0.99$ ,  $NSE = 0.89$ , and  $MAE = 43 \text{ kg ha}^{-1}$ . Good agreement was also obtained at Um Sinnat, Saghoura, and Gala Alnahal, with  $R^2$  values ranging from 0.64 to 0.69 and  $MAE$  from 56 to  $140 \text{ kg ha}^{-1}$  although  $NSE$  was lower at these sites (0.15–0.35). In contrast, Alfashaga showed poor performance during calibration, with  $R^2 = 0.14$ ,  $NSE = -2.10$ , and  $MAE = 207 \text{ kg ha}^{-1}$ . Lower performance at Alfashaga remained consistent throughout the calibration process (Figure S6). For all sites combined, the dynamic sowing configuration achieved an  $R^2$  of 0.20,  $NSE$  of  $-0.06$ , and  $MAE$  of

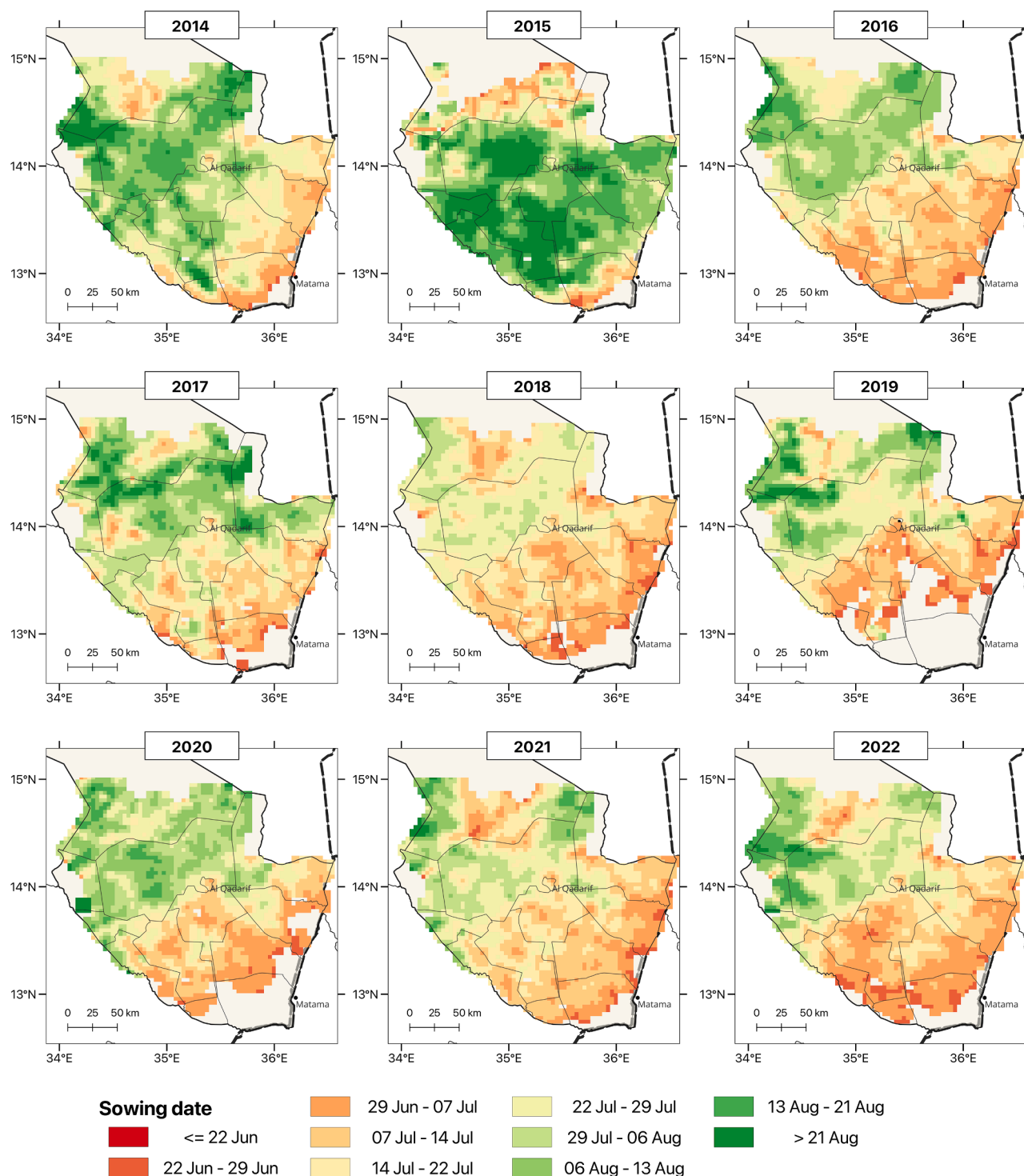


Fig. 5. Spatial distribution of estimated sorghum sowing dates across the Gedaref State for the period 2014 – 2022.

104 kg  $ha^{-1}$ , compared with 0.02,  $-0.52$ , and 143 kg  $ha^{-1}$ , respectively, for fixed sowing (Table S6).

During validation, dynamic sowing generally performed better and more consistently across sites. Alfashaga and Saghoura showed the strongest agreement, with  $R^2$  values of 0.92 and 0.94 and MAE values of 28 and 34 kg  $ha^{-1}$ , respectively. Galah Alnahal showed moderate performance ( $R^2 = 0.58$ ,  $NSE = 0.46$ , and  $MAE = 55$  kg  $ha^{-1}$ ). Larger errors occurred at Alhawata and Um Sinnat, with MAE values of 99 and 76 kg  $ha^{-1}$ , respectively. For all sites combined, dynamic sowing achieved an  $R^2$  of 0.52,  $NSE$  of 0.48, and  $MAE$  of 59 kg  $ha^{-1}$ . In comparison, fixed

sowing resulted in an  $R^2$  of 0.20,  $NSE$  of  $-1.23$ , and  $MAE$  of 131 kg  $ha^{-1}$ . With dynamic sowing, a 55.4% reduction in MAE was achieved. A leave-one-site-out analysis revealed that the improvement in validation was not influenced by any single site (Table S7). The improvement was maintained even when each site was sequentially excluded, with MAE reductions ranging from 43.8% to 62.4%.

An exploratory analysis of the calibrated model over the 2000 – 2024 period revealed distinct spatial and interannual patterns in simulated sorghum yield that closely corresponded with rainfall variability. Mean annual rainfall showed a clear west-east gradient, with

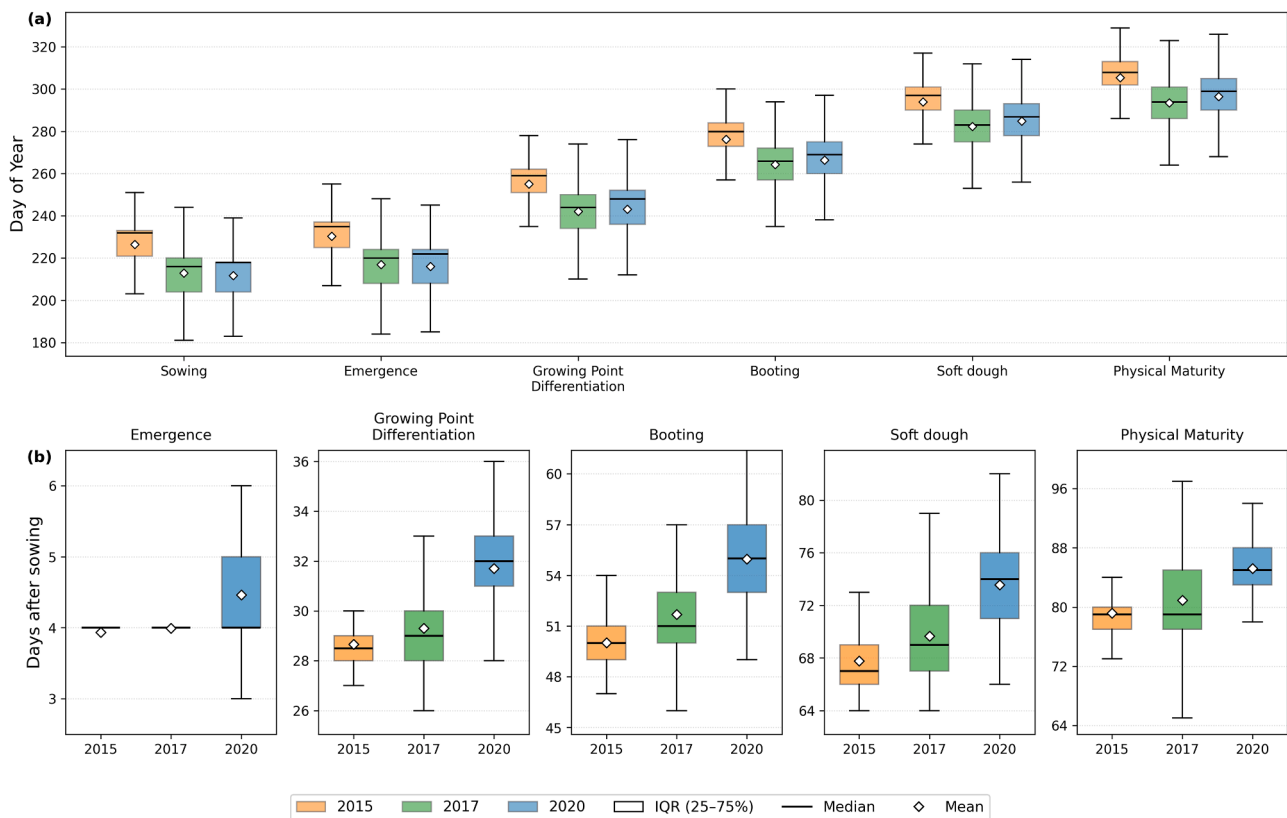


**Fig. 6.** Boxplots of simulated sorghum phenological stages across cropland grid cells for 2015, 2017, and 2020, showing (a) the calendar timing of sowing and subsequent phenological stages as day of year, and (b) the timing of phenological stages as days after sowing. Boxes represent the interquartile range (25th-75th percentiles), horizontal lines indicate the median, and diamonds indicate the mean.

lower rainfall totals in the western part of the domain and progressively wetter conditions toward the southeast near the Ethiopian border (Fig. 9a). Simulated mean sorghum yield showed a broadly similar spatial pattern (Fig. 9b). Higher yields concentrated in the central and southeastern croplands, while lower yields occurred in drier western and northwestern regions. Interannual rainfall variability, expressed as the coefficient of variation (CV), also varied spatially across the region (Fig. 9c). Simulated yield variability showed some corresponding spatial patterns, with relatively high yield variability occurring in several areas characterized by greater rainfall variability (Fig. 9d). In the absence of independent long-term yield observations, these patterns should be interpreted as exploratory model results rather than validated regional yield estimates.

### 3.6. Model sensitivity analysis

Fig. 10 presents the PRCCs between the selected Noah-MP-Crop model parameters (Table 1) and the simulated LAI, yield, and energy fluxes. Parameter sensitivity varied considerably among the four model outputs. LAI and yield showed strong sensitivity to several phenological, physiological, and biomass-allocation parameters, whereas *LE* was generally less sensitive. Stronger response was shown by *H* to a smaller number of parameters, particularly those related to biomass allocation.

Among the phenological parameters, GDDS1 – GDDS3 showed the strongest influence on LAI, with  $|PRCC|$  values of approximately 0.63 – 0.68. GDDS1 was negatively associated with LAI, whereas GDDS2 and GDDS3 showed positive associations. In contrast, GDDS4 and GDDS5 had weak effects on LAI ( $|PRCC| < 0.25$ ). Yield showed a different

sensitivity pattern, with the strongest responses to GDDS3 – GDDS5 ( $|PRCC| = 0.76 – 0.86$ ). GDDS3 and GDDS4 were negatively associated with yield, whereas GDDS5 showed a strong positive association. GDDS3 therefore had opposite effects on LAI and yield, with a positive PRCC for LAI and a negative for yield.

*LE* showed generally weak sensitivity to GDDS1 – GDDS4, while a moderate sensitivity was observed for GDDS5. The relatively weak response of *LE* coincided with the small contribution of transpiration to total evapotranspiration during much of the growing season (Fig. 11a). The transpiration fraction increased later in the season, reaching approximately 30% around October (Fig. 11b). Moderate sensitivity to several phenological parameters was observed by *H*, showing both positive and negative responses.

Among the crop physiology parameters, Quantum efficiency at 25°C (QE25) showed the strongest sensitivity, with a strong positive effect on yield ( $PRCC \approx 0.9$ ) and a moderate positive effect on LAI ( $PRCC \approx 0.5$ ). BIO2LAI was moderately sensitive for LAI ( $PRCC \approx 0.5$ ) but showed little sensitivity for the other model outputs. In contrast, MP and VCMX25 showed weak or negligible sensitivity across LAI, yield, *LE*, and *H*.

The biomass-allocation parameters produced distinct responses among the model outputs. LFPT\_S3 showed a strong positive sensitivity for LAI and *H*, while LFPT\_S4 showed moderate-to-strong sensitivity for both variables. Their effects on yield were weak to moderate and negative, particularly for LFPT\_S3. In contrast, the grain-allocation parameters GRAINPT\_S5 and GRAINPT\_S6 exerted a strong influence on yield, but had a weak effect for LAI and *LE*. Their influence on *H* was moderate, particularly for GRAINPT\_S5.

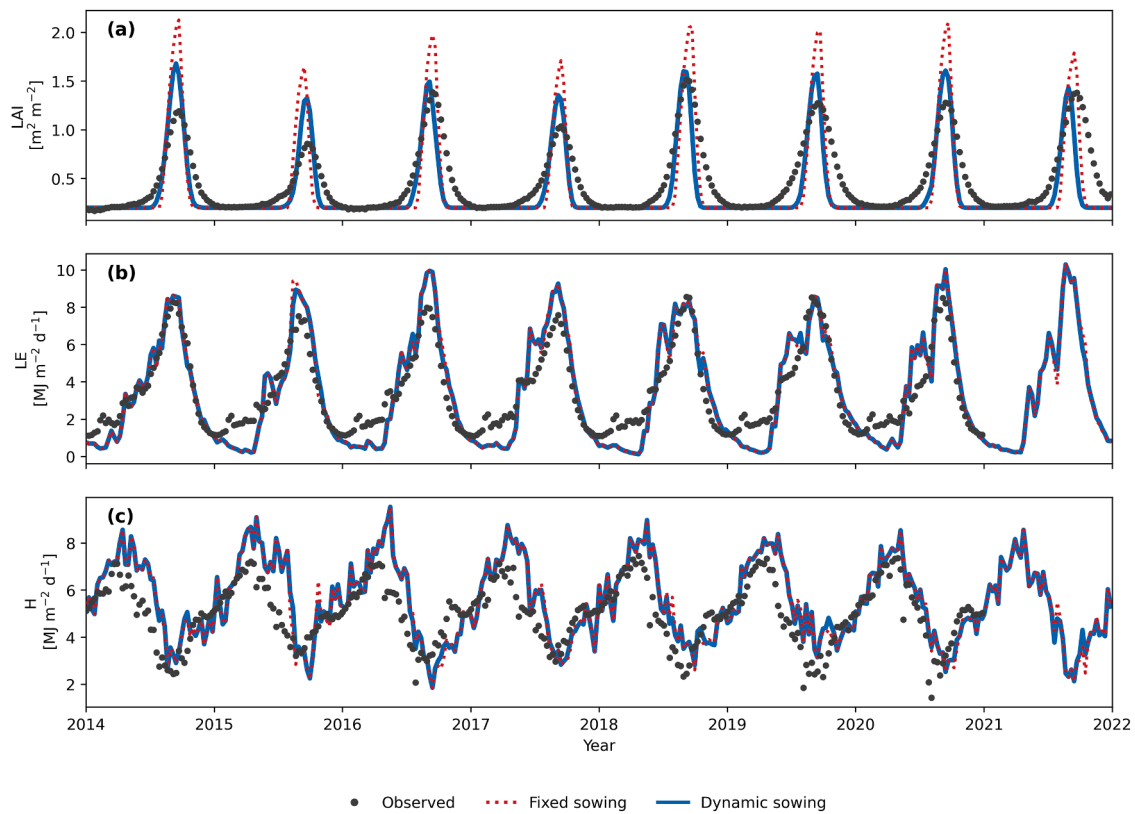


**Fig. 7.** Cropland-mean seasonal cycles of (a) LAI, (b) LE, and (c) H over the study domain, comparing observations (points) with Noah-MP-Crop simulations using fixed sowing (dotted lines) and dynamic sowing (solid lines).

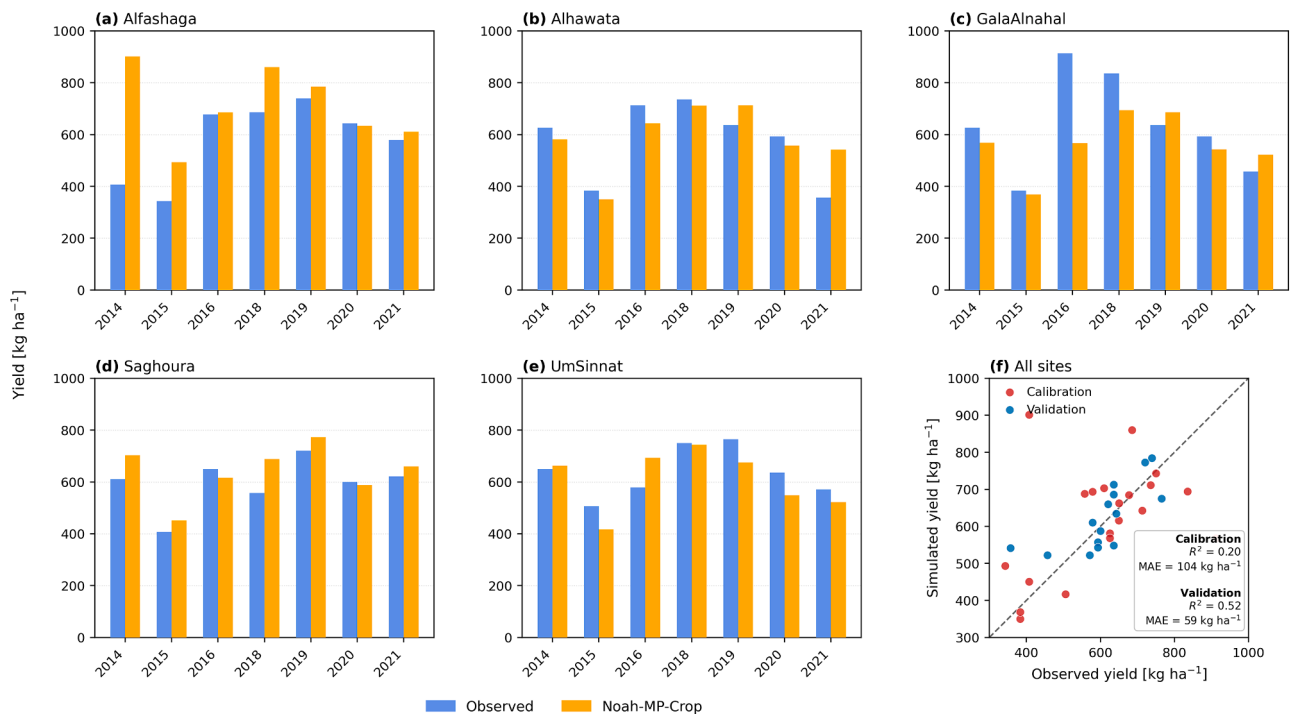


**Fig. 8.** Observed and simulated sorghum yields at five sites in the Gedaref State from 2014 to 2021. (a – e) Site-level comparison of observed and simulated yields using the dynamic sowing configuration; observations for 2017 were unavailable. (f) Scatter plot of observed versus simulated yields across all sites during the calibration and validation periods. The dashed line represents the 1:1 line.

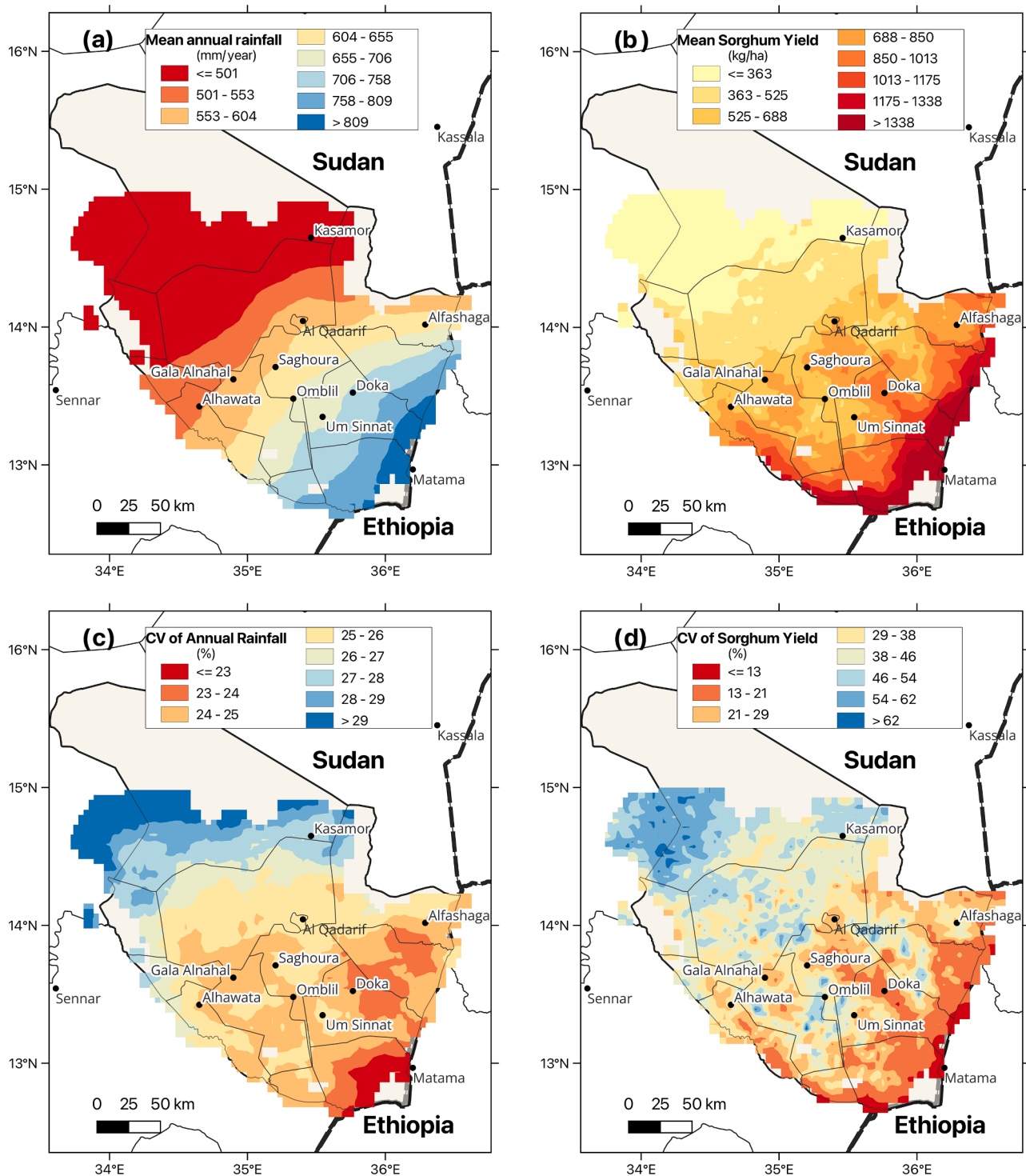


**Fig. 9.** Exploratory analysis of long-term spatial patterns of rainfall and simulated sorghum yield over 2000 – 2024: (a) mean annual rainfall, (b) mean simulated sorghum yield ( $\text{kg ha}^{-1}$ ), (c) interannual rainfall variability expressed as CV, and (d) interannual simulated yield variability as CV.

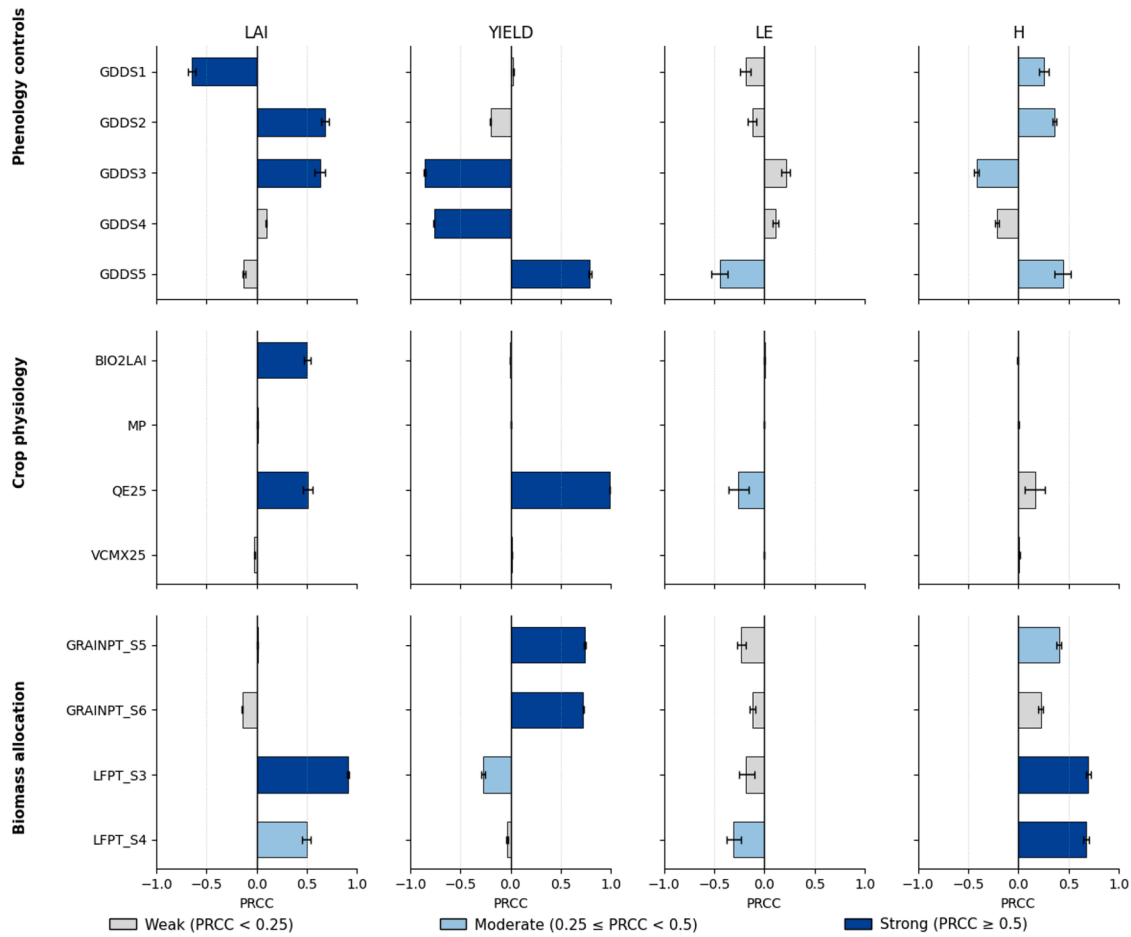


**Fig. 10.** PRCCs between model parameters and simulated LAI, crop yield, LE, and H derived from LHS experiments. Bars represent mean PRCC values across the evaluation period, and horizontal lines indicate 95% bootstrap confidence intervals. Positive PRCC values mean the variable increases with the parameter, while negative values indicate an inverse effect.

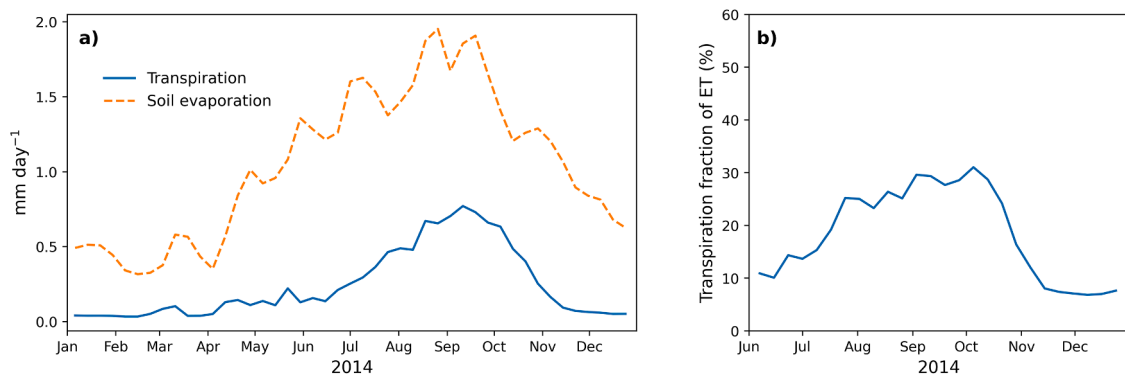


**Fig. 11.** Seasonal evolution of evapotranspiration components over cropland for 2014: (a) transpiration and soil evaporation; (b) transpiration fraction of total evapotranspiration.

## 4. Discussion

### 4.1. Sorghum parameterization in Noah-MP-Crop

Introducing sorghum-specific phenological and physiological parameters enabled Noah-MP-Crop model to explicitly simulate sorghum in the Gedaref region. This capability is not included in the default model configuration. Sorghum differs from the temperate cereals for which existing crop parameterizations were originally developed, particularly in its thermal requirements, drought tolerance, and biomass

allocation. Similar studies have shown that tailoring crop parameters to locally relevant species is important for improving the representation of crop growth and its interaction with the land surface (Ingwersen et al., 2018; Wang et al., 2024b; Zhang et al., 2023).

The stepwise calibration provided a practical approach to constrain the sorghum parameters while accounting for different aspects of crop growth and surface energy exchange. The calibration showed progressive convergence, with the largest improvement generally occurring during the first iterations (Figure S5). Yield and LAI showed the largest improvements across the calibration iterations, while the performance

of latent and sensible heat fluxes remained relatively stable. Figure S7 further illustrates a progressive shift in the parameter sets toward better combined yield and LAI performance across the calibration iterations.

#### 4.2. Dynamic sowing and model performance

Representing spatial and temporal variations in sowing dates improved rainfed sorghum simulation compared with fixed sowing assumptions. In semi-arid regions, sowing decisions are closely linked to rainfall onset and early-season soil moisture rather than fixed calendar dates (Laux et al., 2010; Agoungbome et al., 2023; Black et al., 2023; Lala et al., 2021). The dynamic sowing approach therefore better represents the year-to-year variation in the start of the growing season. This improvement was most evident for LAI, where the dynamic sowing improved the timing and seasonal development of the crop canopy compared with fixed sowing (Fig. 7a).

In contrast, dynamic sowing had little influence on latent and sensible heat fluxes (Fig. 7b-c). Both sowing configurations produced similar seasonal patterns and performance metrics, particularly for latent heat flux. This consistency suggests that the differences in crop development introduced by the two sowing approaches had a relatively small effect on the simulated surface energy fluxes. Atmospheric forcing and soil moisture strongly control surface energy partitioning in semi-arid environments, and may partly explain the limited response to changes in sowing date (Lu et al., 2015; Rahman et al., 2019).

The advantages of the dynamic sowing approach were also evident in the yield simulations (Fig. 8, Table S6). Across all sites, dynamic sowing improved yield simulation relative to fixed sowing, with MAE reduced by 27% during calibration and 55% during validation. However, model performance varied across sites. During calibration, agreement between simulated and observed yields varied considerably across sites, with the largest mismatch at Alfashaga. The lower performance at Alfashaga was also apparent throughout calibration, as this site consistently exhibited the weakest results across successive calibration iterations (see Figure S6). Agricultural production in this area has been affected by instability and disruptions to farming activities (Suliman, 2025). This volatility may introduce yield variations that a model driven by weather and crop development cannot capture. Importantly, the poor agreement at Alfashaga did not persist during validation. This performance suggests that the calibration period mismatch at this site may not indicate systematic model bias.

The variation in performance across sites highlights the difficulty of reproducing observed farm yields using Noah-MP-Crop. Reported yields reflect not only weather and sowing conditions but also management practices and other production constraints. In Gedaref, weeds and parasitic plants, for example, can reduce sorghum yields through competition for water, nutrients, and radiation under low-input farming conditions (Bussmann et al., 2016). Such factors are not represented in the model and may contribute to the remaining differences between simulated and observed yields. Similar challenges in simulating crop yield have also been reported in previous Noah-MP-Crop applications (Liu et al., 2016; Yu et al., 2022; Zhang et al., 2023).

#### 4.3. Crop parameter sensitivity

The sensitivity analysis highlights the importance of phenological parameters for simulating sorghum growth and yield in the semi-arid conditions of Gedaref. Yield was particularly sensitive to phenological parameters controlling the later development stages, while LAI was more sensitive to parameters controlling early and intermediate development. This finding is consistent with Krishnan et al. (2021), who also reported a strong influence of phenological parameters on wheat simulations in semi-arid India using the Web InfoCrop model. In contrast, Wang et al. (2024b) found a smaller influence of phenological parameters for winter wheat in the temperate East China region, where canopy-related parameters were more influential. These differences

suggest that crop parameter sensitivity can vary with crop type and environmental conditions. In Gedaref, the growing season is closely linked to a relatively short and variable rainfall period (Suliman and Elagib, 2012). Consequently, changes in the timing of crop development can alter the environmental conditions experienced during important growth stages, which may partly explain the strong sensitivity of yield and LAI to phenological parameters.

Among the physiological and biomass allocation parameters, the sensitivity patterns reflected their different roles in crop growth and yield formation. The strong yield sensitivity to photosynthetic efficiency (QE25) and biomass allocation to grain (GRAINPT\_S5 and GRAINPT\_S6) indicates the importance of carbon assimilation and its subsequent allocation to grain in determining simulated yield. In contrast, LAI was more sensitive to the biomass-to-LAI conversion (BIO2LAI) and biomass allocation to leaves (LFPT\_S3 and LFPT\_S4), consistent with their role in canopy development. Other physiological parameters, particularly the stomatal slope (MP) and maximum Rubisco carboxylation capacity (VCMX25), had relatively little influence on the evaluated model outputs. Their low sensitivity may partly reflect the high atmospheric demand during the growing season, with vapor pressure deficit frequently exceeding 2–3 kPa during the reproductive period (Figure S11). Under such conditions, stomatal conductance is strongly constrained by environmental forcing, limiting both transpiration and carbon assimilation (Flore et al., 1984; Sinclair, 2018).

#### 4.4. Limitations and uncertainty

This study attempted to adapt the Noah-MP-Crop model to simulate sorghum under the semi-arid conditions of Gedaref and to represent spatial and temporal variations in sowing dates using satellite observations. However, several limitations and uncertainties remain. We validated the dynamic sowing approach using field observations collected during a single growing season (2022), with a mean bias of –2 days and an MAE of 12.8 days. Previous studies have reported errors of similar magnitude (Prudente et al., 2025; Suksomnuek et al., 2026), reflecting the challenges associated with estimating sowing dates from satellite vegetation indices. These errors nevertheless introduce considerable uncertainty into the timing of crop development in the model. Furthermore, the lack of multi-year field observations limits the assessment of the approach's performance across years with different rainfall conditions.

Some limitations relate to how Noah-MP-Crop represents crop development. The model controls crop phenological development solely through GDD. However, under semi-arid conditions, water availability and plant stress can also affect sorghum development, particularly during later stages (Gaona et al., 2022). This limitation may partly explain the earlier decline in simulated LAI compared with the observations (Fig. 7a). Incorporating the effects of water stress on crop development could improve the representation of late-season phenology.

Representing rooting depth introduces additional structural uncertainty. Noah-MP-Crop assumes a constant rooting depth of 1 m, whereas sorghum roots can extend to approximately 1.5–2.0 m (Stone et al., 2001). This limitation may matter more in semi-arid environments, where access to water stored in deeper soil layers can support crop growth as the upper soil layers dry. Liu et al. (2020) found that incorporating dynamic rooting depth improved Noah-MP-Crop simulations of soil moisture during the middle and late growing season compared with a constant-rooting formulation. The fixed rooting depth may therefore limit access to deeper soil moisture, potentially affecting late-season LAI and yield development.

Uncertainty also arises from the calibration and evaluation strategy. We evaluated LAI and energy fluxes using spatially averaged time series over cropland. While this approach effectively constrains seasonal dynamics, it does not explicitly evaluate spatial variability. Previous studies have shown that incorporating spatial information into model

calibration can effectively constrain distributed land surface and hydrological models (Demirel et al., 2024; Soltani et al., 2021; Dembélé et al., 2020). Future applications should therefore incorporate both temporal and spatial information in model calibration.

## 5. Conclusion

This study attempted to adapt Noah-MP-Crop to simulate rainfed sorghum in the semi-arid Gedaref region of Sudan. Sorghum-specific parameters derived through a stepwise calibration approach enabled the model to reproduce the seasonal canopy development and represent variations in crop yield. Incorporating dynamic sowing dates derived from satellite observations improved representation of spatial and interannual variability in sowing timing compared with a fixed-sowing assumption. This improvement was particularly evident for LAI and yield, with dynamic sowing reducing yield MAE by 27% during calibration and 55% during validation. In contrast, differences between dynamic sowing and fixed sowing configurations were small for latent and sensible heat fluxes.

The sensitivity analysis showed that LAI and yield were particularly sensitive to parameters controlling phenological development, photosynthetic efficiency, and biomass allocation. In contrast, latent heat flux was less sensitive to the evaluated crop parameters. The study further highlights uncertainties associated with simplified representations of crop phenology and rooting depth, as well as limitations in the available observational datasets. Despite these limitations, the results indicate that combining crop-specific parameterization with satellite-informed management practices can improve rainfed sorghum simulation in Gedaref. Further evaluation across a wider range of agro-climatic conditions and management practices is needed to assess the framework's broader applicability.

## CRedit authorship contribution statement

**Yasir Hagelto**: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Joël Arnault**: Writing – review & editing, Software, Methodology. **Nadir Ahmed Elagib**: Writing – review & editing, Conceptualization. **Patrick Laux**: Writing – review & editing, Methodology, Formal analysis. **Harald Kunstmann**: Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Acknowledgements

This research has been supported by the German Federal Ministry for Research, Technology, and Space (Bundesministerium für Forschung, Technologie und Raumfahrt, BMFT), under grant no 02WGR1643A-C through the SPS-Blue Nile project. The authors gratefully acknowledge Hussien M. Suliman for his assistance in collecting farm-level sowing data used in this research. Thanks also go to Abubaker Omer for assisting in obtaining the yield data.

## Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.agrformet.2026.111533](https://doi.org/10.1016/j.agrformet.2026.111533).

## Data availability

Data will be made available upon reasonable request.

## References

- Abreha, K.B., Enyew, M., Carlsson, A.S., Vetukuri, R.R., Feyissa, T., Motlhaodi, T., Ng'uni, D., Geleta, M., 2022. Sorghum in dryland: morphological, physiological, and molecular responses of sorghum under drought stress. *Planta* 255, 20. <https://doi.org/10.1007/s00425-021-03799-7>.
- Agoungbome, S.M.D., ten Veldhuis, M.-C., van de Giesen, N., 2023. Optimal sowing windows under rainfall variability in rainfed agriculture in West Africa. *Agronomy* 13, 167. <https://doi.org/10.3390/agronomy13010167>.
- Ahmed, M.M., Sanders, J.H., 1998. Shifting from extensive to intensive agricultural systems: a case study in the Sudan. *Agric. Syst.* 58, 253–268. [https://doi.org/10.1016/S0308-521X\(98\)00053-5](https://doi.org/10.1016/S0308-521X(98)00053-5).
- Alshikh, M.A.A., Hassn, I.M., Salah, A.R.S., Ali, H.K., Khalid, A.A.M., 2017. Adaptation of sowing date for improving sorghum yield in rainfed areas in Sudan using AQUACROP model. *J. Agric. Sci.* 9, 220.
- Arsenault, K.R., Nearing, G.S., Wang, S., Yatheendradas, S., Peters-Lidard, C.D., 2018. Parameter sensitivity of the Noah-MP land surface model with dynamic vegetation. *J. Hydrometeorol.* 19, 815–830. <https://doi.org/10.1175/jhm-D-17-0205.1>.
- Bereir, A., Abdalla, A., Elfadil, A., 2022. Farmers adoption of agricultural mechanization in rainfed sector. *Gedaref State Sudan, Middle East J. Agric. Res.* 11, 556–562.
- Beven, K., Binley, A., 1992. The future of distributed models: model calibration and uncertainty prediction. *Hydrol. Process.* 6, 279–298. <https://doi.org/10.1002/hyp.3360060305>.
- Black, E., Asfaw, D.T., Sananka, A., Aston, S., Boulton, V.L., Maidment, R.I., 2023. Application of TAMSAT-ALERT soil moisture forecasts for planting date decision support in Africa. *Front. Clim.* 4. <https://doi.org/10.3389/fclim.2022.993511>.
- Boas, T., Bogen, H., Grünwald, T., Heinesch, B., Ryu, D., Schmidt, M., Vereecken, H., Western, A., Hendricks Franssen, H.-J., 2021. Improving the representation of cropland sites in the community land model (CLM) version 5.0. *Geosci. Model Dev.* 14, 573–601. <https://doi.org/10.5194/gmd-14-573-2021>.
- Borrell, A.K., Mullet, J.E., George-Jaeggli, B., van Oosterom, E.J., Hammer, G.L., Klein, P.E., Jordan, D.R., 2014. Drought adaptation of stay-green sorghum is associated with canopy development, leaf anatomy, root growth, and water uptake. *J. Exp. Bot.* 65, 6251–6263. <https://doi.org/10.1093/jxb/eru232>.
- Buchhorn, M., Lesiv, M., Tsendbazar, N.-E., Herold, M., Bertels, L., Smets, B., 2020. Copernicus global land cover layers—collection 2. *Remote Sens.* 12, 1044. <https://doi.org/10.3390/rs12061044>.
- Busschaert, L., Bechtold, M., Modanesi, S., Massari, C., Raes, D., Kumar, S.V., De Lannoy, G.J.M., 2026. On the gap between crop and land surface models: comparing irrigation and other land surface estimates from AquaCrop and Noah-MP over the Po Valley. *Hydrol. Earth Syst. Sci.* 30, 2579–2611. <https://doi.org/10.5194/hess-30-2579-2026>.
- Bussmann, A., Elagib, N.A., Fayyad, M., Ribbe, L., 2016. Sowing date determinants for Sahelian rainfed agriculture in the context of agricultural policies and water management. *Land Use Pol.* 52, 316–328. <https://doi.org/10.1016/j.landusepol.2015.12.007>.
- Chen, F., Mitchell, K., Schaake, J., Xue, Y., Pan, H.-L., Koren, V., Duan, Q.Y., Ek, M., Betts, A., 1996. Modeling of land surface evaporation by four schemes and comparison with FIFE observations. *J. Geophys. Res.* 101, 7251–7268. <https://doi.org/10.1029/95JD02165>.
- Chivasa, W., Harris, D., Chduzza, C., Mashingaidze, A.B., Nyamudeza, P., 2000. Determination of optimum on farm seed priming time for maize and sorghum for improved stand establishment in semi-arid agriculture. *Tanzan. J. Agric. Sci.* 3, 103–112.
- Dembélé, M., Hrachowitz, M., Savenije, H.H.G., Mariéthoz, G., Schaeffli, B., 2020. Improving the predictive skill of a distributed hydrological model by calibration on spatial patterns with multiple satellite data sets. *Water Resour. Res.* 56, e2019WR026085. <https://doi.org/10.1029/2019WR026085>.
- Demirel, M.C., Koch, J., Rakovec, O., Kumar, R., Mai, J., Müller, S., Thober, S., Samaniego, L., Stisen, S., 2024. Tradeoffs between temporal and spatial pattern calibration and their impacts on robustness and transferability of hydrologic model parameters to ungauged basins. *Water Resour. Res.* 60, e2022WR034193. <https://doi.org/10.1029/2022WR034193>.
- Demuzere, M., He, C., Martilli, A., Zonato, A., 2023. Technical documentation for the hybrid 100-m global land cover dataset with local climate zones for WRF. *Zenodo*. <https://doi.org/10.5281/zenodo.7670791>.
- Dezfuli, A.K., Ichoku, C.M., Huffman, G.J., Mohr, K.I., Selker, J.S., van de Giesen, N., Hochreutener, R., Annor, F.O., 2017. Validation of IMERG precipitation in Africa. *J. Hydrometeorol.* 18, 2817–2825. <https://doi.org/10.1175/JHM-D-17-0139.1>.
- Dzotsi, K.A., Basso, B., Jones, J.W., 2013. Development, uncertainty and sensitivity analysis of the simple SALUS crop model in DSSAT. *Ecol. Modell.* 260, 62–76. <https://doi.org/10.1016/j.ecolmodel.2013.03.017>.
- Elagib, N.A., Elhag, M.M., 2011. Major climate indicators of ongoing drought in Sudan. *J. Hydrol.* 409, 612–625. <https://doi.org/10.1016/j.jhydrol.2011.08.047>.
- Elagib, N.A., Khalifa, M., Rahma, A.E., Babker, Z., Gamaledin, S.I., 2019. Performance of major mechanized rainfed agricultural production in Sudan: sorghum vulnerability and resilience to climate since 1970. *Agric. For. Meteorol.* 276–277, 107640. <https://doi.org/10.1016/j.agrformet.2019.107640>.
- Elagib, N.A., Al Zayed, I.S., Saad, S.A.G., Mahmood, M.I., Basheer, M., Fink, A.H., 2021. Debilitating floods in the Sahel are becoming frequent. *J. Hydrol.* 599, 126362. <https://doi.org/10.1016/j.jhydrol.2021.126362>.
- Elagib, N.A., Ali, M.M.A., Musa, A.A., 2024. Intensifying droughts render more Sahel drylands unsuitable for cultivation. *Sci. Total Environ.* 954, 176390. <https://doi.org/10.1016/j.scitotenv.2024.176390>.
- Elagib, N.A., Ahmed, B.M., Suliman, H.M., Rahma, A.E., Ali, M.M.A., Schneider, K., 2025. Capturing social sensing of farming activities for policymaking in fragile

- contexts. *J. Rural Stud.* 117, 103638. <https://doi.org/10.1016/j.jrurstud.2025.103638>.
- Fan, Y., Yang, Z., Lo, M.-H., Hur, J., Im, E.-S., 2024. Applying double cropping and interactive irrigation in the North China Plain using WRF4.5. *Geosci. Model Dev.* 17, 6929–6947. <https://doi.org/10.5194/gmd-17-6929-2024>.
- Fang, H., Zhang, Y., Wei, S., Li, W., Ye, Y., Sun, T., Liu, W., 2019. Validation of global moderate resolution leaf area index (LAI) products over croplands in northeastern China. *Remote Sens. Env.*, 233, 111377. <https://doi.org/10.1016/j.rse.2019.111377>.
- FAO, 2016. 2015–2016 El Niño: Early Action and Response for Agriculture, Food Security and Nutrition. Food and Agriculture Organization of the United Nations (FAO), Rome.
- FAO/UNESCO, 1988. Soil Map of the World, Revised Legend. World Soil Resources Report 60. Rome: FAO.
- Fischer, A., 1994. A model for the seasonal variations of vegetation indices in coarse resolution data and its inversion to extract crop parameters. *Remote Sens. Env.*, 48, 220–230. [https://doi.org/10.1016/0034-4257\(94\)90143-0](https://doi.org/10.1016/0034-4257(94)90143-0).
- Flore, J.A., Moon, J.W., Lakso, A.N., 1984. The effect of water stress and vapor pressure gradient on stomatal conductance, water use efficiency, and photosynthesis of fruit crops. In: *I International Symposium on Water Relations in Fruit Crops* 171, pp. 207–218.
- Gaona, J., Benito-Verdugo, P., Martínez-Fernández, J., González-Zamora, Á., Almendra-Martín, L., Herrero-Jiménez, C.M., 2022. Soil moisture outweighs climatic factors in critical periods for rainfed cereal yields: an analysis in Spain. *Agriculture* 12, 533. <https://doi.org/10.3390/agriculture12040533>.
- Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., Moore, R., 2017. Google Earth Engine: planetary-scale geospatial analysis for everyone. *Remote Sens. Env.*, 202, 18–27. <https://doi.org/10.1016/j.rse.2017.06.031>.
- Gupta, H.V., Kling, H., Yilmaz, K.K., Martinez, G.F., 2009. Decomposition of the mean squared error and NSE performance criteria: implications for improving hydrological modelling. *J. Hydrol.* 377, 80–91. <https://doi.org/10.1016/j.jhydrol.2009.08.003>.
- Gutjahr, S., Clément-Vidal, A., Soutiras, A., Sonderegger, N., Braconnier, S., Dingkuhn, M., Luquet, D., 2013. Grain, sugar and biomass accumulation in photoperiod-sensitive sorghums. II. Biochemical processes at internode level and interaction with phenology. *Funct. Plant Biol.* 40, 355–368. <https://doi.org/10.1071/FP12177>.
- Hawkins, E., Williams, R.G., Young, P.J., Berardelli, J., Burgess, S.N., Highwood, E., Randel, W., Roussinov, V., Smith, D., Plack, B.W., 2025. Warming stripes spark climate conversations: from the ocean to the stratosphere. *Bull. Am. Meteorol. Soc.* 106, E964–E970. <https://doi.org/10.1175/BAMS-D-24-0212.1>.
- Helton, J.C., Davis, F.J., 2003. Latin hypercube sampling and the propagation of uncertainty in analyses of complex systems. *Reliab. Eng. Syst. Saf.* 81, 23–69. [https://doi.org/10.1016/S0951-8320\(03\)00058-9](https://doi.org/10.1016/S0951-8320(03)00058-9).
- Helton, J.C., 1993. Uncertainty and sensitivity analysis techniques for use in performance assessment for radioactive waste disposal. *Reliab. Eng. Syst. Saf.* 42, 327–367. [https://doi.org/10.1016/0951-8320\(93\)90097-1](https://doi.org/10.1016/0951-8320(93)90097-1).
- Htitiou, A., Möller, M., Riedel, T., Beyer, F., Gerighausen, H., 2024. Towards optimising the derivation of phenological phases of different crop types over Germany using satellite image time series. *Remote Sens.* 16, 3183. <https://doi.org/10.3390/rs16173183>.
- Huang, X., Liu, J., Zhu, W., Atzberger, C., Liu, Q., 2019. The optimal threshold and vegetation index time series for retrieving crop phenology based on a modified dynamic threshold method. *Remote Sens.* 11, 2725. <https://doi.org/10.3390/rs11232725>.
- Huffman, G.J., Stocker, E.F., Bolvin, D.T., Nelkin, E.J., Tan, J. (2023). GPM IMERG Final Precipitation L3 Half Hourly 0.1 degree × 0.1 degree V07. Goddard Earth Sciences Data and Information Services Center (GES DISC). <https://doi.org/10.5067/GPM/IMERG/3B-HH/07>.
- IPFRI, 2023. Global Spatially-Disaggregated Crop Production Statistics Data for 2020 Version 1.0. International Food Policy Research Institute (IFPRI). Harvard Dataverse. <https://doi.org/10.7910/DVN/SWPENT>.
- Ingwersen, J., Högy, P., Wizemann, H.D., Warrach-Sagi, K., Streck, T., 2018. Coupling the land surface model Noah-MP with the generic crop growth model Gecros: model description, calibration and validation. *Agric. For. Meteorol.* 262, 322–339. <https://doi.org/10.1016/j.agrformet.2018.06.023>.
- Jung, M., Koirala, S., Weber, U., Ichii, K., Gans, F., Camps-Valls, G., Papale, D., Schwalm, C., Tramontana, G., Reichstein, M., 2019. The FLUXCOM ensemble of global land-atmosphere energy fluxes. *Sci. Data* 6, 74. <https://doi.org/10.1038/s41597-019-0076-8>.
- Jung, M., Schwalm, C., Migliavacca, M., Walther, S., Camps-Valls, G., Koirala, S., Anthoni, P., Besnard, S., Bodesheim, P., Carvalhais, N., Chevallier, F., Gans, F., Goll, D.S., Haverd, V., Köhler, P., Ichii, K., Jain, A.K., Liu, J., Lombardozzi, D., Nabel, J.E.M.S., Nelson, J.A., O'Sullivan, M., Pallandt, M., Papale, D., Peters, W., Pongratz, J., Rödenbeck, C., Sitoh, S., Tramontana, G., Walker, A., Weber, U., Reichstein, M., 2020. Scaling carbon fluxes from eddy covariance sites to globe: synthesis and evaluation of the FLUXCOM approach. *Biogeosciences* 17, 1343–1365. <https://doi.org/10.5194/bg-17-1343-2020>.
- Justice, C.O., Townshend, J.R.G., Vermote, E.F., Masuoka, E., Wolfe, R.E., Saleous, N., Roy, D.P., Morisette, J.T., 2002. An overview of MODIS Land data processing and product status. *Remote Sens. Env.*, 83, 3–15. [https://doi.org/10.1016/S0034-4257\(02\)00084-6](https://doi.org/10.1016/S0034-4257(02)00084-6).
- Kenji, E.J., Babikri, A., Omer, S.M., Wani, P., 2017. Evaluation of sorghum genotypes for tolerance to *Striga hermonthica* (Del.) Benth. (Lamiales: orobanchaceae) And yield in the rain fed areas of Damazin, Sudan. *Int. J. Life-Sci. Sci. Res.* 3, 1003–1006.
- Khalifa, M., Eltahir, E.A.B., 2023. Assessment of global sorghum production, tolerance, and climate risk. *Front. Sustain. Food Syst.* 7. <https://doi.org/10.3389/fsufs.2023.1184373>.
- Knoben, W.J.M., Freer, J.E., Woods, R.A., 2019. Technical note: inherent benchmark or not? Comparing Nash–Sutcliffe and Kling–Gupta efficiency scores. *Hydrol. Earth Syst. Sci.* 23, 4323–4331. <https://doi.org/10.5194/hess-23-4323-2019>.
- Krishnan, P., Maity, P.P., Kundu, M., 2021. Sensitivity analysis of cultivar parameters to simulate wheat crop growth and yield under moisture and temperature stress conditions. *Heliyon* 7, e07602.
- Lala, J., Yang, M., Wang, G., Block, P., 2021. Utilizing rainy season onset predictions to enhance maize yields in Ethiopia. *Environ. Res. Lett.* 16, 054035. <https://doi.org/10.1088/1748-9326/abf9c9>.
- Laux, P., Kunstmann, H., Bárdossy, A., 2008. Predicting the regional onset of the rainy season in West Africa. *Int. J. Climatol.* 28, 329–342. <https://doi.org/10.1002/joc.1542>.
- Laux, P., Jäckel, G., Tingem, R.M., Kunstmann, H., 2010. Impact of climate change on agricultural productivity under rainfed conditions in cameroon—a method to improve attainable crop yields by planting date adaptations. *Agric. For. Meteorol.* 150, 1258–1271. <https://doi.org/10.1016/j.agrformet.2010.05.008>.
- Legates, D.R., McCabe Jr., G.J., 1999. Evaluating the use of “goodness-of-fit” measures in hydrologic and hydroclimatic model validation. *Water Resour. Res.* 35, 233–241. <https://doi.org/10.1029/1998WR900018>.
- Lesk, C., Anderson, W., Rigden, A., Coast, O., Jägermeyr, J., McDermid, S., Davis, K.F., Konar, M., 2022. Compound heat and moisture extreme impacts on global crop yields under climate change. *Nat. Rev. Earth Env.*, 3, 872–889. <https://doi.org/10.1038/s43017-022-00368-8>.
- Liang, S., Zhao, X., Liu, S., Yuan, W., Cheng, X., Xiao, Z., Zhang, X., Liu, Q., Cheng, J., Tang, H., Qu, Y., Bo, Y., Qu, Y., Ren, H., Yu, K., Townshend, J., 2013. A long-term global land surface satellite (GLASS) data-set for environmental studies. *Int. J. Digit. Earth* 6, 5–33. <https://doi.org/10.1080/17538947.2013.805262>.
- Liang, S., Cheng, J., Jia, K., Jiang, B., Liu, Q., Xiao, Z., Yao, Y., Yuan, W., Zhang, X., Zhao, X., Zhou, J., 2021. The global land surface satellite (GLASS) product suite. *Bull. Am. Meteorol. Soc.* 102, E323–E337. <https://doi.org/10.1175/BAMS-D-18-0341.1>.
- Liu, X., Chen, F., Barlage, M., Zhou, G., Niyogi, D., 2016. Noah-MP-crop: introducing dynamic crop growth in the Noah-MP land surface model. *J. Geophys. Res.* 121 (13), 9133–9153. <https://doi.org/10.1002/2016JD025597>.
- Liu, X., Chen, F., Barlage, M., Niyogi, D., 2020. Implementing dynamic rooting depth for improved simulation of soil moisture and land surface feedbacks in Noah-MP-crop. *J. Adv. Model. Earth Syst.* 12, e2019MS001786. <https://doi.org/10.1029/2019MS001786>.
- Lu, Y., Jin, J., Kueppers, L.M., 2015. Crop growth and irrigation interact to influence surface fluxes in a regional climate-cropland model (WRF3.3-CLM4crop). *Clim. Dyn.* 45, 3347–3363. <https://doi.org/10.1007/s00382-015-2543-z>.
- Makowski, D., Wallach, D., Tremblay, M., 2002. Using a Bayesian approach to parameter estimation; comparison of the GLUE and MCMC methods. *Agronomie* 22, 191–203.
- Manfron, G., Delmotte, S., Busetto, L., Hossard, L., Ranghetti, L., Brivio, P.A., Boschetti, M., 2017. Estimating inter-annual variability in winter wheat sowing dates from satellite time series in Camargue, France. *Int. J. Appl. Earth Obs. Geoinf.* 57, 190–201. <https://doi.org/10.1016/j.jag.2017.01.001>.
- Marino, S., Hogue, I.B., Ray, C.J., Kirschner, D.E., 2008. A methodology for performing global uncertainty and sensitivity analysis in systems biology. *J. Theor. Biol.* 254, 178–196. <https://doi.org/10.1016/j.jtbi.2008.04.011>.
- McKay, M.D., Beckman, R.J., Conover, W.J., 1979. Comparison of three methods for selecting values of input variables in the analysis of output from a computer code. *Technometrics* 21, 239–245. <https://doi.org/10.1080/00401706.1979.10489755>.
- Mohamed, A.H., Gamar, Y.A., Elhassan, O.M., Elgada, M.H., Assar, A.H.A., 2011. Performance of selected sorghum genotypes under rain-fed areas of Sudan. *Life Sci. Int. J.* 5, 2119–2127.
- Mohammed, H.I., Omran, A.R.M.S.A., Abbas, M., 2010. Utilization of water budget model for early season forecasting of Sorghum yield and optimum sowing date in Gadafar mechanized rain fed areas-Sudan. *Agric. Biol. J. N. Am.* 4, 510–525.
- Muñoz-Sabater, J., Dutra, E., Agustí-Panareda, A., Albergel, C., Arduini, G., Balsamo, G., Boussetta, S., Choulga, M., Harrigan, S., Hersbach, H., Martens, B., Miralles, D.G., Piles, M., Rodríguez-Fernández, N.J., Zsoter, E., Buontempo, C., Thépaut, J.-N., 2021. ERA5-Land: a state-of-the-art global reanalysis dataset for land applications. *Earth Syst. Sci. Data* 13, 4349–4383. <https://doi.org/10.5194/essd-13-4349-2021>.
- Muñoz-Sabater, J., 2019. ERA5-land hourly data from 1950 to present. copernicus climate change service (C3S) climate data store (CDS) [WWWDocument]. <https://doi.org/10.24381/cds.e2161bac>.
- Nash, J.E., Sutcliffe, J.V., 1970. River flow forecasting through conceptual models part I — a discussion of principles. *J. Hydrol.* 10, 282–290. [https://doi.org/10.1016/0022-1694\(70\)90255-6](https://doi.org/10.1016/0022-1694(70)90255-6).
- Niu, G.-Y., Yang, Z.-L., Mitchell, K.E., Chen, F., Ek, M.B., Barlage, M., Kumar, A., Manning, K., Niyogi, D., Rosero, E., Tewari, M., Xia, Y., 2011. The community Noah land surface model with multiparameterization options (Noah-MP): 1. Model description and evaluation with local-scale measurements. *J. Geophys. Res.* 116. <https://doi.org/10.1029/2010JD015139>.
- Omay, P.O., Muthama, N.J., Oludhe, C., Kinama, J.M., Artan, G., Atheru, Z., 2023. Changes and variability in rainfall onset, cessation, and length of rainy season in the IGAD region of Eastern Africa. *Theor. Appl. Clim.*, 152, 871–893. <https://doi.org/10.1007/s00704-023-04433-0>.
- Partridge, T.F., Winter, J.M., Kendall, A.D., Hyndman, D.W., 2021. Cross-scale evaluation of dynamic crop growth in WRF and Noah-MP-crop. *Agric. For. Meteorol.* 296, 108217. <https://doi.org/10.1016/j.agrformet.2020.108217>.

- Prudente, V.H.R., Garcia-Medina, M., Krishna, V., Euler, M., Bhattarai, N., Lerner, A.M., McDonald, A.J., Sherpa, S., Rajan, H., Urfels, A., de Santana, C.T.C., 2025. Mapping grain crop sowing date in smallholder systems using optical imagery. *Remote Sens. Appl.* 39, 101660.
- Prudente Junior, A.C., Vianna, M.S., Williams, K., Galdos, M.V., Marin, F.R., 2022. Calibration and evaluation of JULES-crop for maize in Brazil. *Agron. J.* 114, 1680–1693. <https://doi.org/10.1002/agj2.21066>.
- Rahman, M.M., Zhang, W., Wang, K., 2019. Assessment on surface energy imbalance and energy partitioning using ground and satellite data over a semi-arid agricultural region in north China. *Agric. Water Manag.* 213, 245–259. <https://doi.org/10.1016/j.agwat.2018.10.032>.
- Roozeboom, K.L., Prasad, P.V.V., 2019. Sorghum growth and development. *Sorghum*. John Wiley & Sons, Ltd, pp. 155–172. <https://doi.org/10.2134/agronmonogr58>.
- Rouse, J.W., Haas, R.H., Schell, J.A., Deering, D.W., 1974. Monitoring vegetation systems in the Great Plains with ERTS. *Third Earth Resour. Technol. Satell. 1 Symp.* 1, 309–317.
- Salih, A.A.M., Elagib, N.A., Tjernström, M., Zhang, Q., 2018. Characterization of the Sahelian-Sudan rainfall based on observations and regional climate models. *Atmos. Res.* 202, 205–218. <https://doi.org/10.1016/j.atmosres.2017.12.001>.
- Savitzky, A., Golay, M.J.E., 1964. Smoothing and differentiation of data by simplified least squares procedures. *Anal. Chem.* 36, 1627–1639. <https://doi.org/10.1021/ac60214a047>.
- Scholes, R.J., 2020. The future of semi-arid regions: a weak fabric unravels. *Climate* 8, 43. <https://doi.org/10.3390/cli8030043>.
- Sinclair, T.R., 2018. Effective water use required for improving crop growth rather than transpiration efficiency. *Front. Plant Sci.* 9, 1442.
- Soltani, M., Bjerre, E., Koch, J., Stisen, S., 2021. Integrating remote sensing data in optimization of a national water resources model to improve the spatial pattern performance of evapotranspiration. *J. Hydrol.* 603, 127026. <https://doi.org/10.1016/j.jhydrol.2021.127026>.
- Stone, L.R., Goodrum, D.E., Jaafar, M.N., Khan, A.H., 2001. Rooting front and water depletion depths in grain sorghum and sunflower. *Agron. J.* 93, 1105–1110. <https://doi.org/10.2134/agronj2001.9351105x>.
- Suksomnuek, A., Losiri, C., Sitthi, A., 2026. Estimating sugarcane planting date from Multi-sensor satellite time series using derivative dynamic time warping. *Informatics* 13 (8), 134. <https://doi.org/10.3390/informatics13080134>.
- Suliman, H.M., Buchroithner, M.F., 2009. Degradation and abandonment of mechanized rain-fed agricultural land in the Southern Gadarif region, Sudan: the local farmers' perception. *Land Degrad. Dev.* 20, 199–209. <https://doi.org/10.1002/ldr.894>.
- Suliman, H.M., Elagib, N.A., 2012. Implications of climate, land-use and land-cover changes for pastoralism in eastern Sudan. *J. Arid. Env.* 85, 132–141. <https://doi.org/10.1016/j.jaridenv.2012.05.001>.
- Suliman, H.M., 2025. Agricultural land use change and its drivers in the Sudanese Ethiopian borderland: the case of Al-Fashaga region. *Geol. Ecol. Landsc.* 9, 1496–1506. <https://doi.org/10.1080/24749508.2024.2430038>.
- Tramontana, G., Jung, M., Schwalm, C.R., Ichii, K., Camps-Valls, G., Ráduly, B., Reichstein, M., Arain, M.A., Cescatti, A., Kiely, G., Merbold, L., Serrano-Ortiz, P., Sickert, S., Wolf, S., Papale, D., 2016. Predicting carbon dioxide and energy fluxes across global FLUXNET sites with regression algorithms. *Biogeosciences* 13, 4291–4313. <https://doi.org/10.5194/bg-13-4291-2016>.
- Vrugt, J.A., Diks, C.G.H., Gupta, H.V., Bouten, W., Verstraten, J.M., 2005. Improved treatment of uncertainty in hydrologic modeling: combining the strengths of global optimization and data assimilation. *Water Resour. Res.* 41. <https://doi.org/10.1029/2004WR003059>.
- Wallach, D., Makowski, D., Jones, J.W., Brun, F., 2006. Working With Dynamic Crop models: evaluation, analysis, parameterization, and Applications. Elsevier.
- Wang, F., Guo, L., Lin, X., Han, D., Wang, M., Fang, J., 2024a. Integration of prognostic sowing and harvesting schemes to enhance crop dynamic growth simulation in Noah-MP-Crop model. *Ecol. Inf.* 82, 102785. <https://doi.org/10.1016/j.ecoinf.2024.102785>.
- Wang, F., Li, Y., Li, Z., Cai, X., Lin, X., Guo, L., Han, D., Fang, J., 2024b. Enhancing winter wheat representation in Noah-MP-Crop for improved dynamic crop growth simulation in the North China plain. *J. Geophys. Res. Biogeosci.* 129, e2024JG008150. <https://doi.org/10.1029/2024JG008150>.
- Wawo, A.H., Lestari, P., Setyowati, N., Syarif, F., Juhaeti, T., Kartika, K., 2024. The influence of temperature on germination and seedling growth of sorghum. *Ital. J. Agrometeorol.* 95–107.
- White, M.A., Thornton, P.E., Running, S.W., 1997. A continental phenology model for monitoring vegetation responses to interannual climatic variability. *Glob. Biogeochem. Cycl.* 11, 217–234. <https://doi.org/10.1029/97GB00330>.
- Willmott, C.J., Matsuura, K., 2005. Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. *Clim. Res.* 30, 79–82.
- Xiao, Z., Liang, S., Wang, J., Xiang, Y., Zhao, X., Song, J., 2016. Long-time-series Global land surface satellite leaf area index product derived from MODIS and AVHRR surface reflectance. *IEEE Trans. Geosci. Remote Sens.* 54, 5301–5318. <https://doi.org/10.1109/TGRS.2016.2560522>.
- Yahaya, M.A., Shimelis, H., 2022. Drought stress in sorghum: mitigation strategies, breeding methods and technologies—a review. *J. Agron. Crop Sci.* 208, 127–142. <https://doi.org/10.1111/jac.12573>.
- Yahaya, M.A., Shimelis, H., Nebié, B., Mashilo, J., Pop, G., 2023. Response of African sorghum genotypes for drought tolerance under variable environments. *Agronomy* 13, 557. <https://doi.org/10.3390/agronomy13020557>.
- Yang, Y., Tao, B., Liang, L., Huang, Y., Matocha, C., Lee, C.D., Sama, M., Masri, B.E., Ren, W., 2021. Detecting recent crop phenology dynamics in corn and soybean cropping systems of Kentucky. *Remot. Sens.* 13, 1615. <https://doi.org/10.3390/rs13091615>.
- Yu, L., Liu, Y., Liu, T., Yu, E., Bu, K., Jia, Q., Shen, L., Zheng, X., Zhang, S., 2022. Coupling localized Noah-MP-Crop model with the WRF model improved dynamic crop growth simulation across Northeast China. *Comput. Electron. Agric.* 201, 107323. <https://doi.org/10.1016/j.compag.2022.107323>.
- Zargar, M., Bronstert, A., Francke, T., Zimale, F.A., Worku, K.B., Wiegels, R., Lorenz, C., Hagelto, Y., Sawadogo, W., Kunstmann, H., 2025. Comparison and hydrological evaluation of different precipitation data for a large tropical region: the Blue Nile Basin in Ethiopia. *Front. Water* 7. <https://doi.org/10.3389/frwa.2025.1536881>.
- Zhang, Z., Barlage, M., Chen, F., Li, Y., Helgason, W., Xu, X., Liu, X., Li, Z., 2020. Joint modeling of crop and irrigation in the central United States using the Noah-MP land surface model. *J. Adv. Model. Earth Syst.* 12, e2020MS002159. <https://doi.org/10.1029/2020MS002159>.
- Zhang, Z., Li, Y., Chen, F., Harder, P., Helgason, W., Famiglietti, J., Valayamkunnath, P., He, C., Li, Z., 2023. Developing spring wheat in the Noah-MP land surface model (v4.4) for growing season dynamics and responses to temperature stress. *Geosci. Model Dev.* 16, 3809–3825. <https://doi.org/10.5194/gmd-16-3809-2023>.