



LAWS: A new crop–water coupling model integrating an agricultural module into a process-based hydrological model (CWatM v1.08)

Zhonghao Fu^{1,2,3}, Shuqiu Yang^{1,2,3}, Dor Fridman⁴, Mikhail Smilovic⁴, Taisheng Du^{1,2,3}, David
5 Makowski⁵, Peter Burek⁴, Jinfeng Chang⁶, Xuanqin Luo^{1,2,3}, Wenfeng Liu^{1,2,3}

¹State Key Laboratory of Efficient Utilization of Agricultural Water Resources, China Agricultural University, Beijing, China

²National Field Observation and Research Station (Gansu Wuwei) for Efficient Water Utilization in Oasis Agriculture, Wuwei, China

10 ³Center for Agricultural Water Research in China, College of Water Resources and Intelligence Engineering, China Agricultural University, Beijing, China

⁴Water Security Research Group, Biodiversity and Natural Resources Program, International Institute for Applied Systems Analysis (IIASA), Laxenburg, Austria.

⁵Université Paris-Saclay, INRAE, AgroParisTech, UMR 518 MIA-PS, Palaiseau, France

15 ⁶Zhejiang Key Laboratory of Agricultural Remote Sensing and Information Technology, College of Environmental and Resource Sciences, Zhejiang University, Hangzhou, China.

Correspondence to: Wenfeng Liu (wenfeng.liu@cau.edu.cn)

Abstract.

20 It is essential to jointly represent crop growth, water availability, and human water management in an integrated framework to understand future water-food interactions. Although existing large-scale coupling models have improved the representation of crop-water interactions, few integrate detailed crop growth and hydrological processes, together with their interactions, within a unified process-based framework. Here, we developed the Large-scale Agriculture Water System model (LAWS) by integrating a process-based agricultural module into the Community Water Model (CWatM). We
25 evaluated its performance in simulating crop growth dynamics and yields across six experimental sites and at global, national, and grid-cell levels for maize, wheat and soybean. Results showed that, at the site level, LAWS reproduced the main seasonal dynamics of leaf area index and biomass for different crops and regions. Pearson temporal correlations between simulated and reference global yield-anomaly series were 0.68, 0.14, and 0.54 for maize, wheat, and soybean, respectively. Across the top 20-producing countries, the correlations between simulated and reference long-term mean yields were 0.74,
30 0.79, and 0.32 for maize, wheat, and soybean, respectively. At the grid-cell level, the simulated long-term mean yields showed broad spatial patterns consistent with those in the global gridded yield dataset. Overall, the yield performance of LAWS was broadly comparable to mainstream global crop models, supporting its application to large-scale assessments of crop production. Furthermore, LAWS can represent the interactions between crop growth and the water cycle, providing a framework for sustainable agricultural planning under water constraints. Through a case study, we demonstrated this



35 capability by assessing the contribution of nonrenewable groundwater to irrigated maize production globally. In addition, its open-source and modular architecture facilitates further development to improve the simulation of agricultural systems, the water cycle, and human water management.

1 Introduction

Climate change and population growth are increasing pressure on global food production and freshwater resources (Qin et al., 2019; Wada et al., 2016; Ray et al., 2022; Liu et al., 2025). Irrigation can buffer the negative effects of water and heat stress (Aggarwal et al., 2019) and supports approximately 40 % of global crop production (FAO, 2023). Still, it accounts for > 70% of global water withdrawals (Siebert and Döll, 2010) and > 85 % of global freshwater consumption (Scanlon et al., 2007). These high rates of water withdrawal and consumption have led to declines in groundwater levels (De Graaf et al., 2019; Dalin et al., 2017; Jasechko et al., 2024) and degradation of freshwater ecosystems (Su et al., 2021; Jägermeyr et al., 2017) in many regions. These impacts have raised concerns about the sustainability of irrigated agriculture (Rosa et al., 2019; Jägermeyr et al., 2017; Mekonnen and Hoekstra, 2020; Schmitt et al., 2022). In a warmer future, higher evaporative demand and more frequent water and heat stress may further increase crop water requirements, leading to potential crop yield losses or increased reliance on irrigation water (Huang et al., 2019; Rosa et al., 2020; Liu et al., 2022). The global irrigation area is expected to expand by 13–47 % to sustain the production of major cereals (He and Rosa, 2026). Such expansion would place greater demands on the coordinated management of crop production and irrigation water, highlighting the need to jointly represent crop production, water demand, and water availability for future irrigation management and food production planning.

Process-based crop models and hydrological models are important scientific tools for assessing crop production and water availability. Crop models simulate crop growth under varying environmental conditions and management practices. In contrast, hydrological models can simulate runoff generation, river routing, groundwater dynamics, reservoir management, and sectoral water withdrawals. Although both model types are useful, they are often used separately. Many process-based gridded crop models use automatic irrigation schemes that supply water when soil moisture falls below a certain threshold. Because data on water availability, irrigation amounts and timing are often unavailable, crop models often assume an unlimited irrigation water supply (Ozdogan et al., 2010). This assumption is problematic because irrigation water availability is constrained in many arid and semi-arid regions, particularly during dry seasons and severe droughts (Lutz et al., 2022) or when reservoirs are depleted (Di Baldassarre et al., 2018). River connectivity, upstream water withdrawals, reservoir availability and operation, and groundwater storage shape the availability of irrigation water. Increasing crop water demand across a large number of locations may have cumulative effects on river flow and downstream water availability and may lead to groundwater depletion, which cannot be fully captured when each location is treated independently (Rezaei and Nendel, 2026; Schmitt et al., 2022; Veldkamp et al., 2017). While hydrological models can represent these water availability constraints, these models suffer from their own limitations, as they often rely on prescribed vegetation parameters or



simplified crop development schemes, which limit their ability to capture feedbacks from dynamic crop growth to evapotranspiration, root water uptake, and irrigation demand. It is thus of primary interest to connect process-based crop growth models with hydrological models to constrain irrigation water use by water availability (Rezaei and Nendel, 2026).

70 Such model coupling is needed to assess crop production, irrigation demand, and water scarcity within a physically consistent framework.

The growing need to assess interactions between crop production and water resources in the food-water nexus has driven the development of large-scale crop–water coupling models, such as VIC–CropSyst (Malek et al., 2017), LPJmL (Schaphoff et al., 2018), VIC–EPIC (Zhang et al., 2021), DSSAT–SWAT (Mompremier et al., 2022), H08 (Ai and Hanasaki, 2023), 75 CROVER (Okada et al., 2015), VIC–WOFOST (Droppers et al., 2021), and PCR–GLOBWB 2–WOFOST (Chevuru et al., 2025). These efforts have improved the representation of crop–water interactions, allowing more realistic simulations of crop evapotranspiration, irrigation water demand, and crop yield. However, existing hydrological-crop coupling frameworks still suffer from several limitations. First, although several of these models have been applied directly to assess the impacts of water and agricultural management, their simulations of crop growth dynamics and interannual yield variability have not 80 been subjected to an in-depth evaluation (Droppers et al., 2021; Schaphoff et al., 2018). Second, several models have been developed and evaluated for specific regions or basins only, which may limit their transferability and applicability to larger scales (Okada et al., 2015; Malek et al., 2017; Zhang et al., 2021; Mompremier et al., 2022; Chevuru et al., 2025). Third, many coupling frameworks retain the crop and hydrological models as two standalone systems and connect them through offline data transfer for one-way coupling or predefined variable exchange at daily time steps for two-way coupling 85 (Droppers et al., 2021; Mompremier et al., 2022; Chevuru et al., 2025). Although the latter approach enables two-way feedbacks and preserves the independence of the coupled models, their interactions are confined to the variables connected through the coupling interface. Adding or modifying processes on crop growth and hydrology may therefore require coordinated changes to both models and the interface, limiting the flexibility of such frameworks for process-level modification and further model development.

90 To address these limitations, we developed the Large-scale Agriculture Water System model (LAWS), a new global crop–water coupling model, by integrating an agricultural module based on crop-growth processes from the Environmental Policy Integrated Climate model (EPIC, Williams et al., 1984) into the hydrological Community Water Model (CWatM, Burek et al., 2020). The agricultural and hydrological modules operate within the same modular architecture and daily calculation sequence. This integration enables daily interactions among crop growth, hydrological processes, and water management and 95 provides a flexible basis for further process-level development. We applied LAWS globally to three major crops (maize, wheat, and soybean), at a 0.5° spatial resolution and daily time step for 1980–2010. We evaluated model performance by comparing simulated leaf area index (LAI) and biomass with observations from six experimental sites and simulated crop yields with national and global yield statistics and gridded yield datasets. Finally, we illustrated the applicability of LAWS through a case study assessing the dependence of maize production on nonrenewable groundwater (NRGW).



100 2 Model description and evaluation

2.1 General description of the LAWS model

As schematically illustrated in Fig. 1, LAWS consists of the hydrological and data-management modules from CWatM and a newly developed agricultural module. CWatM is an open-source, grid-based hydrological model that simulates natural and human-influenced hydrological processes at a daily time step (Burek et al., 2020, <https://cwatm.iiasa.ac.at>, last access: 2 June 105 2025). CWatM has a flexible modular structure that facilitates coupling with other models, and it supports applications at spatial resolutions ranging from 30 arcmin to 30 arcsec. However, CWatM represents agricultural processes in a relatively simplified manner. It uses the FAO-56 single crop coefficient approach to calculate crop-specific evapotranspiration. Consequently, only limited crop–water interactions are represented, and actual crop yield is not simulated.

The newly developed agricultural module is based on EPIC processes for crop phenology, leaf area development, rooting 110 depth, crop height, biomass accumulation, environmental stress responses, and yield formation. Similar EPIC-based crop-growth processes have also been adopted or adapted in several large-scale crop and crop–hydrological models (Arnold et al., 1999; Liu et al., 2007; Liu et al., 2016a; Zhang et al., 2021). The agricultural module was implemented in Python, the programming language used for CWatM, and designed to fit within the modular structure of CWatM.

In LAWS, the calculation of potential crop evapotranspiration accounts for daily crop development, instead of relying on the 115 single crop coefficient approach used in CWatM. Potential crop transpiration is calculated by the agricultural module using the Penman–Monteith equation (Monteith, 1965) with daily aerodynamic and canopy resistances. By accounting for crop-specific height, LAI, stomatal resistance, and atmospheric CO₂ concentration, this calculation affects simulated soil moisture and irrigation water demand. The coupled model can therefore represent more detailed crop–soil–water interactions. The crop-growth component was integrated into the land-surface processes of CWatM to update crop LAI, crop height, and 120 biomass daily. The other hydrological and water management processes are based on those of CWatM, including land-surface hydrology, river routing, reservoirs and lakes, environmental flow requirements, and sectoral water withdrawals. Further details of the agricultural module and its implementation in CWatM are provided in Sect. 2.2.

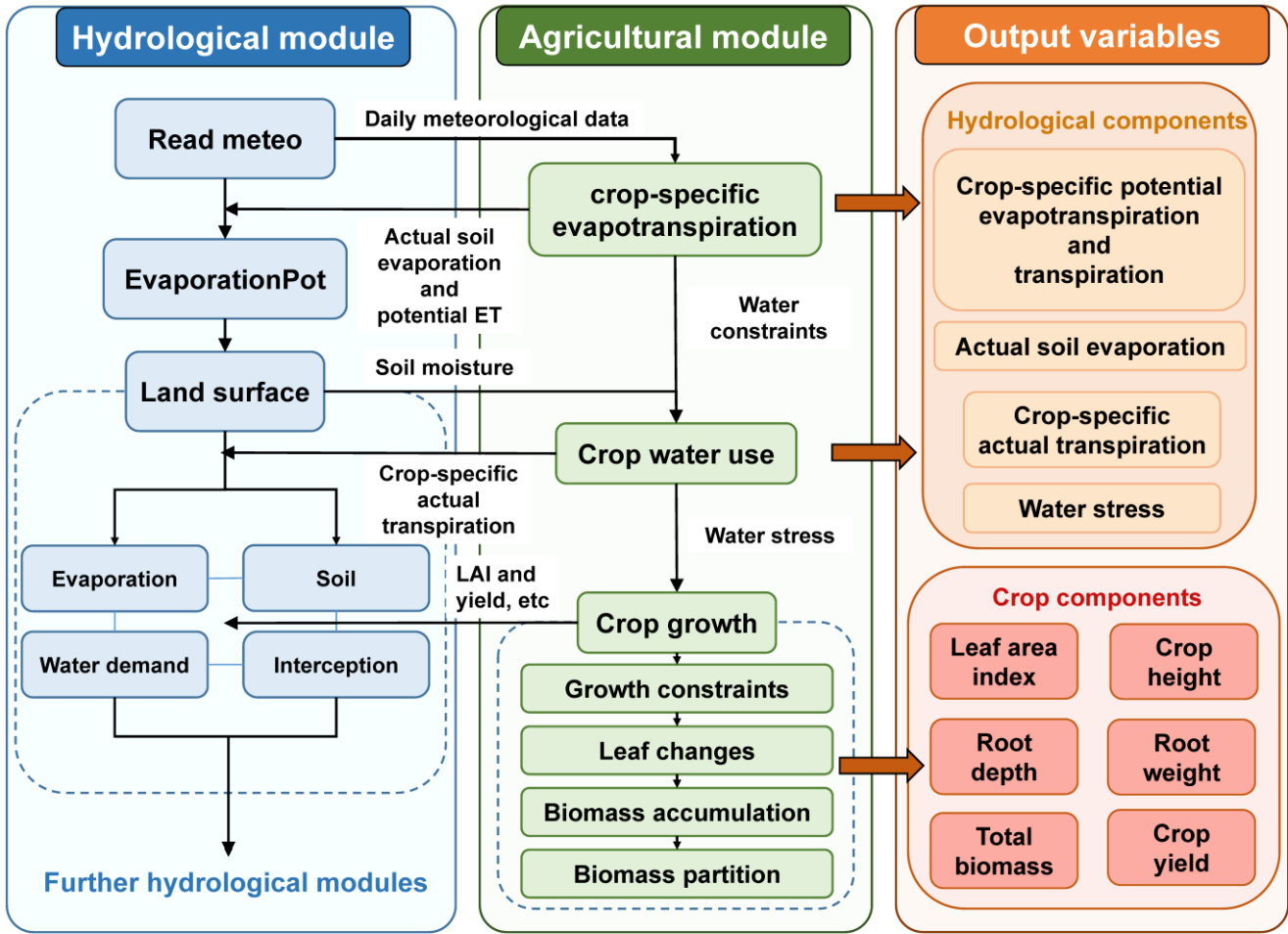


Figure 1. Schematic diagram of the LAWS model.

125 **2.2 Representation of agricultural processes**

The agricultural module consists of three sub-modules: crop-specific evapotranspiration, crop water use, and crop growth. During model initialisation, crop LAI, crop height, accumulated heat units, and biomass are initialised to zero. Crop development begins on the prescribed planting date, and these state variables are reset after harvest before the next growing season. Therefore, a spin-up period is needed to stabilize hydrological state variables, such as soil moisture and groundwater storage, and to exclude incomplete crop cycles at the beginning of the simulation.

130 During each daily time step, the three agricultural sub-modules are executed in sequence. First, the crop-specific evapotranspiration sub-module uses meteorological forcing, together with LAI and crop height simulated on the previous day, to calculate crop-specific potential evapotranspiration and actual evaporation. For cropland without a growing crop,

bare-soil evaporation is calculated instead. For non-paddy-irrigated land and the rainfed-cropland land-cover class, actual soil evaporation is calculated by accounting for the dynamic crop canopy cover. For paddy-irrigated land, evaporation from the ponded water layer is calculated as open-water evaporation following the CWatM approach. Second, the crop water-use sub-module simulates root water uptake from the three soil layers for both rice and non-rice crops. Crop-specific actual transpiration is determined by the potential evapotranspiration, rooting depth, and soil moisture in each layer. The sub-module calculates actual transpiration from each soil layer and the daily crop water stress. The resulting actual transpiration and evaporation are then passed to the soil-water dynamics component of the hydrological module to update soil water content in each layer. Finally, after soil-water dynamics have been updated, the crop-growth sub-module updates crop states for the current day. It simulates phenological development, leaf expansion, root growth, potential biomass accumulation, and environmental stresses, and calculates actual yield on the harvest date. The updated LAI, crop height, and rooting depth are carried forward to the next daily time step and used to calculate crop-specific evapotranspiration and root water uptake.

Crop-specific differences in growth and water use are represented by parameters supplied through the LAWS configuration file, which supports either as a single globally applied parameter set for each crop (.csv) or spatially explicit gridded values (.nc). The parameters used in LAWS were adopted from EPIC; they are summarized in Table 1, with their units are provided in Table S1.

Table 1. Parameters for crop growth simulation in LAWS.

Parameter abbreviation	Full name	Physical meaning
HUIS	Senescence heat-unit index	Heat-unit fraction at which leaf area starts to decline.
HUG	Germination heat units	Heat units required for germination either after planting or when soil temperature permits germination.
TO	Optimum growth temperature	Temperature at which thermal stress on crop growth is minimal.
TB	Base growth temperature	Lower temperature threshold for heat-unit accumulation and crop development.
LAIM	Maximum leaf area index	Sets the upper limit of canopy leaf area under favourable growth conditions.
LAR	LAI decline rate	Controls the rate of canopy decline after senescence begins.
LAC ₁	First LAI curve point	First control point used to shape potential LAI development.
LAC ₂	Second LAI curve point	Second control point used to shape potential LAI development before senescence.
HIO	Optimal harvest index	Defines the potential fraction of aboveground biomass converted to economic yield.
HIL	Lower harvest index	Sets the lower bound of harvest index under water-stressed reproductive growth.
WA	Radiation use efficiency	Defines the potential unstressed biomass growth per unit intercepted photosynthetically active radiation at CO ₂ = 330 ppm; used as the reference point for the CO ₂ response of radiation use efficiency.
RUC ₂	CO ₂ response point for radiation use efficiency	Defines an elevated CO ₂ concentration and the corresponding WA value used to derive the CO ₂ response curve of radiation use efficiency.
VPR	VPD effect on WA	Controls the reduction in radiation use efficiency under high vapour pressure deficit.
RDR	Radiation-use decline rate	Controls the late-season reduction in biomass conversion efficiency.
HCM	Maximum crop height	Defines the maximum crop height.



RDM	Maximum rooting depth	Defines the maximum rooting depth and the soil depth available for crop water uptake.
RTF ₁	Root fraction at emergence	Defines the fraction of biomass allocated to roots at emergence.
RTF ₂	Root fraction at maturity	Defines the fraction of biomass allocated to roots at physiological maturity.
GSM	Maximum stomatal conductance	Maximum stomatal conductance under high solar radiation and low vapour pressure deficit.
VPT	VPD threshold	Threshold below which stomatal conductance is not reduced by vapour pressure deficit.
VPC ₁	VPD conductance response point	VPD response point defining a VPD value above the threshold and the corresponding fraction of maximum leaf conductance.
FDM ₁	First frost damage point	First control point for frost-induced daily biomass loss.
FDM ₂	Second frost damage point	Second control point for frost-induced daily biomass loss.

2.2.1 Phenological development

Phenological development is based on daily heat unit accumulation (Monteith, 1977). Daily heat units are calculated from mean air temperature above a crop-specific base temperature. No development is allowed when the daily mean temperature is below the base temperature. A heat unit index (HUI) is then calculated by normalizing the accumulated heat units by the potential heat units required for maturity. HUI ranges from 0 at planting to 1 at physiological maturity and is used as the main development variable controlling leaf growth, leaf senescence, biomass partitioning, rooting depth, and harvest timing. HUI is calculated as follows:

$$HUI_t = \frac{\sum DHU_t}{PHU}, \quad (1)$$

$$DHU_t = \max(T_{avg,t} - T_b, 0), \quad (2)$$

where HUI_t is the heat unit index at day t , PHU is the potential heat units required for maturity, DHU_t is the daily heat unit at day t , $T_{avg,t}$ is the daily mean air temperature in °C at day t , and T_b is the crop-specific base temperature in °C (Table 1). PHU is calculated as the accumulated temperature above T_b during the growing season using long-term mean monthly air temperatures averaged over 1971–2010.

LAI is simulated as a function of heat units, crop water stress, and crop development stages. From emergence to the start of leaf decline, LAI is estimated as follows:

$$LAI_t = LAI_{t-1} + dHUF_t \times LAIM \times \sqrt{WS_t} \times LR_t, \text{ if } HUI_t < HUIS, \quad (3)$$

$$dHUF_t = HUF_t - HUF_{t-1} \quad (4)$$

$$HUF_t = \frac{HUI_t}{HUI_t + \exp(LAC_1 - LAC_2 \times HUI_t)}, \quad (5)$$

where LAI_t is the leaf area index at day t , $LAIM$ is the potential maximum LAI (Table 1), WS_t is the daily water stress factor at day t , LR_t represents the light regulation factor for leaf expansion, $HUIS$ is the crop development stage at which leaf senescence begins (Table 1), $dHUF_t$ is the daily change in the heat unit factor, and LAC_1 and LAC_2 are crop-specific parameters for the leaf area development curve (Table 1).

After the start of leaf senescence, the decline in LAI is estimated with the equation:



$$LAI_t = LAI_{t-1} \times \left(\frac{1-HUI_t}{1-HUIS} \right)^{LAR}, \text{ if } HUI_t \geq HUIS, \quad (6)$$

175 where LAR is a crop-specific parameter controlling the rate of LAI decline (Table 1), and $HUIS$ is the heat-unit fraction at which leaf area starts to decline (Table 1). Crop height and rooting depth are also updated as functions of crop development and crop-specific maximum values. The details for crop height and rooting depth are provided in Text S1.

180 Winter wheat enters dormancy during the overwintering period. During dormancy, crop growth is suspended, while simulated LAI and biomass gradually decline in response to frost and short day length. Growth resumes in spring as temperatures rise.

2.2.2 Potential increase in biomass

Potential biomass increase is estimated from intercepted solar radiation using a light-use-efficiency approach (Williams et al., 1984). Intercepted photosynthetically active radiation (PAR) is calculated from incoming solar radiation and LAI. Daily potential biomass increase is then determined from PAR and radiation use efficiency:

$$185 \quad PAR_t = 0.5 \times Rsds_t \times (1 - \exp(-0.65 \times LAI_t)), \quad (7)$$

where PAR_t is the intercepted photosynthetically active radiation in $\text{MJ m}^{-2} \text{d}^{-1}$ at day t , $Rsds_t$ is the incoming solar radiation in $\text{MJ m}^{-2} \text{d}^{-1}$ at day t , and 0.65 is the canopy light extinction coefficient (Uchijima et al., 1968).

Daily potential biomass growth is then calculated as follows:

$$PDM_t = 0.001 \times PAR_t \times (RUE - VPR * \max((VPD_t - 1), -0.5)), \quad (8)$$

$$190 \quad RUE = \frac{100 \times CO_2}{CO_2 + \exp(RUC_1 - RUC_2 \times CO_2)}, \quad (9)$$

where PDM_t is the daily potential biomass increase in t ha^{-1} at day t , RUE is radiation use efficiency for converting energy to biomass, VPD_t is vapour pressure deficit in kPa at day t , VPR is a crop parameter describing the effect of VPD on WA (Table 1), CO_2 is atmospheric CO_2 concentration in ppm and was fixed at 330 ppm in this study, corresponding to the reference concentration for Radiation use efficiency (WA) in EPIC, because the present simulations focused on historical
195 model evaluation rather than CO_2 -driven yield trends. Nevertheless, LAWS explicitly represents the effects of CO_2 on radiation use efficiency and stomatal conductance, allowing scenario-specific CO_2 concentrations to be used in climate-change applications. RUC_1 and RUC_2 are derived from the reference WA value at 330 ppm and the crop-specific RUC_2 parameter (Table 1), which provides a second CO_2 -RUE response point.

2.2.3 Growth constraints and actual yield

200 Potential crop growth is often not achieved due to environmental constraints. In the model, daily biomass accumulation is constrained by water and temperature stress, while nutrient stress is indirectly represented during final yield formation. Stress factors range from 0 to 1, where 1 indicates no stress and 0 indicates complete growth limitation. The daily actual biomass increase is calculated as:



$$ADM'_t = PDM_t \times GSF_t, \quad (10)$$

$$GSF_t = \min(TS_t, WS_t), \quad (11)$$

where ADM'_t is the actual biomass increase after stress limitation in $t \text{ ha}^{-1}$ at day t , PDM_t is the daily potential increase in biomass in $t \text{ ha}^{-1}$ at day t , GSF_t is the daily crop growth constraint factor at day t , and TS_t and WS_t are the respective daily stress factors for temperature and water at day t .

Water stress is estimated as the ratio of actual to potential crop transpiration:

$$WS_t = AT_t / PT_t, \quad (12)$$

where AT_t is actual crop transpiration in m d^{-1} at day t and PT_t is potential crop transpiration in m d^{-1} at day t . PT_t is calculated using the Penman–Monteith method (Monteith, 1965), which accounts for the effects of atmospheric CO_2 concentration, crop LAI and plant height on the crop water requirement. Details of the potential crop transpiration calculation are provided in Text S1.

The temperature stress factor is calculated as:

$$TS_t = \begin{cases} \sin(1.5707 \times RTO_t) & \text{if } 0 \leq RTO_t \leq 2.0 \\ 0 & \text{if } RTO_t < 0 \text{ or } RTO_t > 2.0 \end{cases}, \quad (13)$$

$$RTO_t = (T_{avg_t} - TB) / (TO - TB), \quad (14)$$

where T_{avg_t} is the daily mean air temperature in $^{\circ}\text{C}$, TB is the crop-specific base temperature in $^{\circ}\text{C}$ (Table 1), and TO is the crop-specific optimum temperature in $^{\circ}\text{C}$ (Table 1).

Total biomass is updated from the actual daily biomass increase (ADM'_t) after stress limitation. Root biomass and aboveground biomass (AGB) are then computed using a development-stage-dependent partitioning function controlled by the crop-specific root fraction parameters RTF_1 and RTF_2 (Table 1). The detailed biomass partitioning equations are provided in Text S1.

Actual crop yield is estimated as (Williams et al., 1984):

$$Yield = AGB \times HIF \times NS, \quad (15)$$

where $Yield$ is the actual crop yield in $t \text{ ha}^{-1}$, AGB is the aboveground biomass at harvest in $t \text{ ha}^{-1}$, and HIF is the actual harvest index. Details of the HIF calculation are provided in Text S1. NS is the nutrient-stress factor derived from the PEPIC simulations. PEPIC is a global gridded implementation of EPIC within a Python framework (Liu et al., 2016a) and represents crop growth using processes similar to those implemented in LAWS. We ran PEPIC for 1981–2010 under two N application scenarios: unlimited N supply and historical N application. The nutrient-stress factor was calculated for each crop and grid cell as the ratio of yield under historical N application to that under unlimited N supply. The resulting factors were then averaged over 1981–2010. All other inputs and settings were held constant between the two simulations, including meteorological forcing and crop calendars. The meteorological forcing and crop calendars were the same as those used by LAWS, as described in Sect. 2.3. Historical N application rates from mineral fertiliser and manure were obtained from

Jägermeyr et al. (2021) (<https://doi.org/10.5281/zenodo.4954582>, last access: 29 July 2025).



2.3 Simulation setup

We designed the simulation setup to support both global yield evaluation and site-level assessment of crop growth dynamics. For the global simulations, LAWS was run at a spatial resolution of $0.5^\circ \times 0.5^\circ$ and a daily time step for 1971–2010. The period 1971–1979 was used as the spin-up period. Agricultural land was divided into five crop categories, including maize, soybean, winter wheat, spring wheat, and other crops. All crops were simulated under both rainfed and irrigated conditions using the agricultural module. Site-scale simulations were conducted separately for each evaluation site. The site-scale simulations used the same meteorological forcing, hydrological inputs, crop area data, and crop parameter values as the global simulations. The only difference was that phenological inputs, primarily planting dates, were replaced with local observations at each evaluation site. The thermal requirement for maturity was then calculated from the local crop growing period. For each site considered, the simulation domain included the grid cell containing the site and all upstream grid cells draining to it, as determined by the flow direction map. This setting allowed the site simulations to account for lateral hydrological connectivity and upstream water supply.

The input data were as follows: (i) daily meteorological forcing from the ISIMIP3a GSWP3-W5E5 dataset (Lange et al., 2022), including downward shortwave radiation, downward longwave radiation, specific humidity, rainfall, air pressure, wind speed, and air temperature; (ii) hydrological input data from the CWatM-Earth-30min repository (<https://github.com/iiasa/CWatM-Earth-30min>, last access: 26 August 2025), including elevation, river network and flow direction, soil properties, lakes, reservoirs, and other static land-surface data required by the hydrological module; (iii) crop area fractions for irrigated and rainfed conditions from MIRCA2000 (Portmann et al., 2010), which provides monthly crop areas at 5' resolution that were aggregated to 0.5° ; and (iv) crop calendar data from the Global Gridded Crop Model Intercomparison (GGCMI) Phase 3 protocol (Jägermeyr et al., 2021; <https://doi.org/10.5281/zenodo.5062513>, last access: 29 July 2025), which provides planting and harvest dates separately for irrigated and rainfed conditions at 0.5° resolution.

2.4 Model evaluation

We evaluated the performance of LAWS in simulating maize, wheat, and soybean using four types of data: experimental site data (LAI and biomass), national yield data from FAO, global yield data from FAO, and grid-cell data from the Global Dataset of Historical Yield (GDHY; Iizumi and Sakai, 2020). Based on experimental site data, the temporal dynamics of simulated LAI and biomass were evaluated against observations from six experimental sites, including four maize sites and one site each for winter wheat and soybean. Observations for the maize sites at Lusignan, Rio Verde, and Iowa were obtained from the Agricultural Model Intercomparison and Improvement Project study of Bassu et al. (2014), whereas those for the Shiyang site were obtained from Ding et al. (2013). The winter wheat site was taken from Wang et al. (2007), and the soybean site from AmeriFlux (<http://ameriflux.ornl.gov/>). These sites have previously been used for crop model evaluation (Wang et al., 2007; Nagata et al., 2025; Liu et al., 2016b), and the site information is summarized in Table 2. Given the differences between local and global phenological data, we compared observations with both site-scale simulations using



local phenological data and global simulations using the global crop calendar. The same global crop parameter set was used in the site-scale simulations, without site-specific calibration.

270 Two other datasets were used to evaluate model performance in simulating crop yield. At the global and national levels, simulated crop yields were compared with FAOSTAT yield statistics (<https://www.fao.org/faostat/en/#data>, accessed: 9 Jan 2026). In addition, simulated yields were compared to grid-cell yield data provided by the GDHY, which provides gridded historical yield estimates at a spatial resolution of 0.5 °. The evaluation procedure was as follows:

First, the simulated gridded yields under rainfed and irrigated conditions were combined using their respective harvested areas and subsequently aggregated to the corresponding spatial levels.

$$AggYield_c = \frac{\sum_{i=1}^n (Yield_{c,i,rf} \times Area_{c,i,rf}) + \sum_{i=1}^n (Yield_{c,i,ir} \times Area_{c,i,ir})}{\sum_{i=1}^n (Area_{c,i,rf} + Area_{c,i,ir})}, \quad (16)$$

where $AggYield_c$ is the yield aggregated across n grid cells for crop c , $Yield_{c,i,rf}$ and $Yield_{c,i,ir}$ are the simulated rainfed and irrigated yield for crop c at grid cell i , respectively, and $Area_{c,i,rf}$ and $Area_{c,i,ir}$ are the corresponding rainfed and irrigated harvested areas at grid cell i . At the grid-cell level, n refers to one grid cell, whereas at the national level, n refers to all grid cells within a country. Rainfed and irrigated yields were combined within each grid cell. At the national and global levels, yields were further aggregated across grid cells within each country and across the global land domain, respectively. For wheat, simulated winter and spring wheat yields were combined using their respective harvested areas.

Second, following previous studies (Müller et al., 2017; Ai and Hanasaki, 2023), the simulated and reference annual yield series were detrended using a centred 5-year moving-average method. Annual yield series was first divided by its centred 5-year moving average to remove the long-term trend. The resulting relative series was then multiplied by a scaling factor, defined as the mean yield of the original series over the reference period divided by the mean of the relative detrended series, to restore the series to the original yield magnitude. The resulting series is hereafter referred to as the detrended annual yield series. Because a complete centred 5-year moving average was available only for 1982–2008, all subsequent yield evaluations were conducted over this period. Long-term mean yield was calculated as the mean of the detrended annual yields over 1982–2008, and yield anomalies were obtained by subtracting this long-term mean from each detrended annual yield. At the national level, R and $RMSE$ between simulated and reference long-term mean yields across the top 20-producing countries were used to evaluate their agreement and errors, respectively. $RMSE$ between the simulated and reference detrended annual yield series was also calculated separately for each country to evaluate errors in annual yield levels. Temporal correlations between simulated and reference yield-anomaly series were calculated at the global, national, and grid-cell levels to evaluate interannual yield variations.

We further compared the performance of LAWS with that of the GGCM Phase 3 (GCp3) ensemble of Jägermeyr et al. (2021) using the same evaluation period and reference datasets. The ensemble included ACEA (Mialyk et al., 2022), CROVER (Okada et al., 2015), CYGMA1P74 (Iizumi et al., 2017; Sultan et al., 2019), EPIC-IIASA (Balkovič et al., 2014), ISAM (Gahlot et al., 2020), LDNDC (Haas et al., 2013), LPJmL (Schaphoff et al., 2018), pDSSAT (Elliott et al., 2014), PEPIC (Liu et al., 2016a), PROMET (Zabel et al., 2019; Hank et al., 2015; Mauser et al., 2015), and SIMPLACE-LINTUL5



(Webber et al., 2018). Because GGCM model outputs are reported as consecutive growing-season yield series, the assigned simulation year may not always correspond to the reporting year in FAOSTAT and GDHY, particularly for growing seasons spanning two calendar years (Müller et al., 2017). To account for this potential mismatch, for each model we compared the correlations of FAOSTAT yield-anomaly series with both the original simulated series and the simulated series shifted backward by one year ($t + 1$) for the top 20-producing countries. A 1-year shift was applied when it increased the correlation coefficient by more than 0.3. Based on this criterion, we determined whether a time shift was required for each model and used the corresponding aligned time series in the subsequent correlation analysis. Whether a 1-year shift was applied to each model is summarized in Table S2.

Table 2. Evaluation site information in the site-scale simulation

Country	Site	Crop	Latitude	Longitude	Model grid-cell coordinates	Sowing Year	Irrigation
France	Lusignan	Maize	46.25 °N	00.07 °E	46.25, 0.25	1996	Yes
Brazil	Rio Verde	Maize	17.52 °S	51.43 °W	-17.75, -51.25	2003	No
USA	Iowa	Maize	42.01 °N	93.45 °W	41.75, -93.25	2010	No
China	Shiyang	Maize	37.52 °N	102.50 °E	37.75, 102.75	2009	Yes
China	Yucheng	Winter wheat	36.50 °N	116.34 °E	36.75, 116.25	1999	Yes
USA	Mead	Soybean	41.18 °N	96.44 °W	41.25, -96.25	2004	No

2.5 Simulation experiments for the case study

The coupled crop–water model was run in a case study to examine the extent to which irrigated maize production relies on nonrenewable groundwater (NRGW). We set up a limited water-withdrawal scenario in which NRGW abstraction was excluded. In this scenario, irrigation water demand was met only from available surface water and renewable groundwater (RGW), and any remaining demand was left unmet. The mean irrigated maize yields for 1980–2010 under the limited-withdrawal scenario were compared with those from the unlimited water-withdrawal scenario described in Sect. 2.3, in which NRGW was abstracted to meet demand that could not be supplied by available surface water and RGW. The share of yield attributable to NRGW was calculated as:

$$F = \frac{(Y_{unlimit} - Y_{limit})}{Y_{unlimit}} \times 100\% \quad (17)$$

where F is the share of irrigated maize yield attributable to NRGW, and $Y_{unlimit}$ and Y_{limit} are the irrigated maize yields under the no-limit-withdrawal and limited-withdrawal scenarios, respectively, both expressed in $t\ ha^{-1}$.

3 Results

3.1 Evaluation of crop growth dynamics based on site-specific data

As shown in Figs. 2 and 3, LAWS reproduced the main seasonal dynamics of LAI and biomass at most evaluation sites, although biases remained in the timing and magnitude of crop growth. For LAI, the simulated time series generally captured



the observed increase during the early and middle growth stages and the subsequent decline toward maturity. Under the local sowing-date setup, the R values between simulated and observed LAI were 0.87 for maize, 0.98 for winter wheat, and 0.65 for soybean (Fig. S1b). The use of local sowing dates improved the timing of LAI development at most sites, particularly for winter wheat at Yucheng, where the R value increased by 0.45 and the RMSE value decreased by 1.00 (Fig. S1). Nevertheless, LAWS did not fully reproduce the timing and magnitude of LAI at all sites. Simulated LAI increased too early at Lusignan and Mead, was delayed at Yucheng under the global setup, and still showed biases in maximum LAI or senescence timing at Lusignan, Shiyang, and Mead.

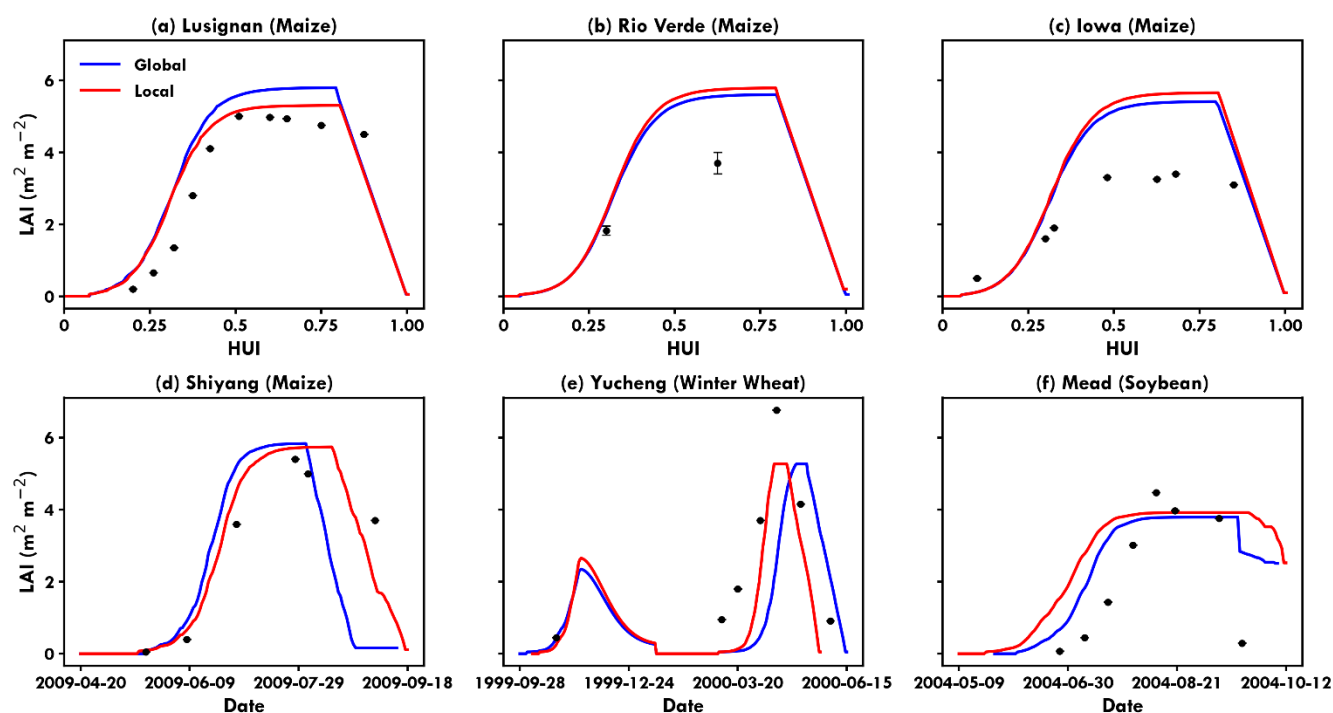


Figure 2. Temporal evaluation of simulated and observed LAI. (a) Lusignan (maize), (b) Rio Verde (maize), (c) Iowa (maize), (d) Shiyang (maize), (e) Yucheng (winter wheat), and (f) Mead (soybean). Red and blue lines indicate simulations using the local and global sowing dates, respectively. Black points indicate observations. Error bars (± 1 standard deviation) are provided only for Rio Verde. For panels (a)–(c), the observational data were reported against the heat unit index (HUI); for panels (d)–(f), the observational data were reported against calendar date.

For biomass, LAWS also reproduced the main accumulation pattern at most sites (Fig. 3). Under the local sowing-date setup, the R values between simulated and observed biomass were 0.98, 0.96, and 0.94 for maize, winter wheat, and soybean, respectively (Fig. S2), while the corresponding RMSE values were 2.42, 2.15, and 3.09 t ha^{-1} . Compared with the global setup, RMSE values decreased by 0.27 t ha^{-1} for maize and 0.67 t ha^{-1} for winter wheat, but increased by 0.97 t ha^{-1} for soybean. The increase in soybean RMSE was mainly related to the earlier local sowing date, which advanced simulated



345 biomass accumulation relative to the observations. Despite remaining timing errors during the growing season, final biomass was reasonably consistent with observations, with a relative bias of 3.8 % at the soybean site and 19.6 % across all sites. It should be noted that site observations reflect local cultivars, weather conditions, soil texture, elevation, and management practices, whereas LAWS uses grid-cell forcing, land-surface conditions, and a global parameter set; therefore, the site-level evaluation should be interpreted as a test of whether LAWS can reproduce the dominant LAI and biomass dynamics across
 350 different crops and regions under large-scale simulation conditions.

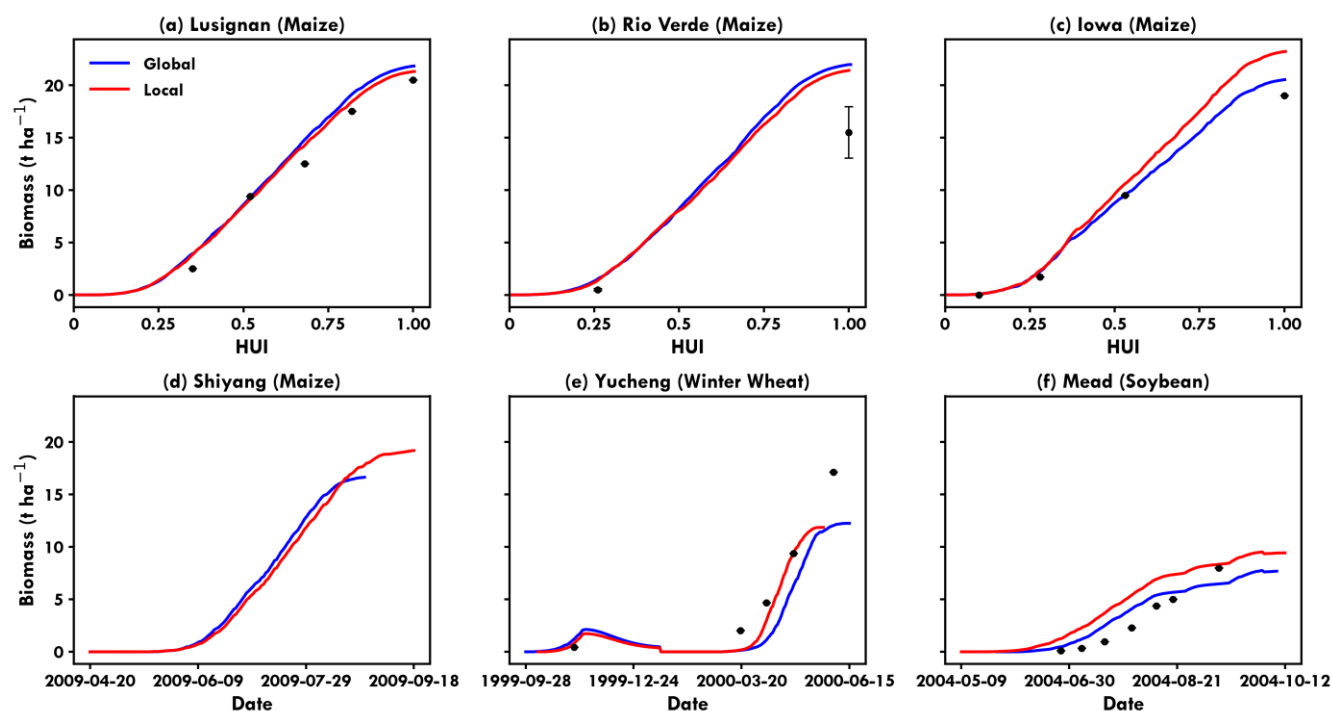


Figure 3. Temporal evaluation of simulated and observed biomass. (a) Lusignan (maize), (b) Rio Verde (maize), (c) Iowa (maize), (d) Shiyang (maize), (e) Yucheng (winter wheat), and (f) Mead (soybean). Red and blue lines indicate simulations using the local and global sowing dates, respectively. Black points indicate observations. Error bars (± 1 standard deviation) are provided only for Rio Verde. For
 355 panels (a)–(c), the observational data were reported against the heat unit index (HUI); for panels (d)–(f), the observational data were reported against calendar date. Biomass refers to aboveground biomass for maize and soybean, and to total biomass for winter wheat at Yucheng. No biomass observations were available for Shiyang.

3.2 Global- and national-level evaluation and model intercomparison

Comparisons of interannual yield variability between the simulations and FAOSTAT yield at the global level for each crop
 360 are shown in Fig. 4. In general, LAWS performed better for maize ($R=0.68$, $p < 0.001$) and soybean ($R=0.54$, $p < 0.01$) than wheat ($R=0.14$, $p > 0.05$). Although the correlation for wheat was not significant at the global level, statistically significant correlations ($p < 0.05$) between simulated and observed yield anomalies were still found in 8 of the top 20 wheat-producing



countries (Fig. S3), compared with 12 for maize and 7 for soybean (Fig. 5 and Fig. S4). Among the five largest producing countries for each crop, significant correlations were found in four countries for both maize—the USA (0.66), China (0.55), Brazil (0.47), and Argentina (0.75)—and soybean—the USA (0.52), Argentina (0.69), China (0.39), and India (0.52). In contrast, Russia was the only top-five wheat-producing country with a significant correlation (0.41). Because global yields were aggregated from country-level yields using crop production as weights, model performance in high-production countries had more weight on the global correlation, which explains the weaker correlation for wheat. We further investigated the model's capability to capture yield differences among countries by comparing long-term mean simulated and FAOSTAT yields across the top 20-producing countries for each crop (Fig. 6). LAWS generally captured the differences in yield levels between high- and low-yielding countries for maize and wheat. The R values between simulated and FAOSTAT yields were 0.74 ($p < 0.001$) for maize and 0.79 ($p < 0.001$) for wheat, while the corresponding RMSE values were 2.66 and 0.92 t ha⁻¹, respectively. For soybean, simulated and FAOSTAT yields showed a weak positive correlation ($R = 0.32$, $p > 0.05$), with an RMSE of 1.83 t ha⁻¹. LAWS also tended to overestimate long-term mean yields of soybean, particularly in countries in Africa, South America, and Southeast Asia.

The performance of LAWS was further compared with the GCp3 ensemble of Jägermeyr et al. (2021). At the global level, the GCp3 models and LAWS showed the same crop-specific pattern, with higher correlations for maize and soybean than for wheat (Fig. S5). The ensemble-mean R values were 0.67, 0.19, and 0.37 for maize, wheat, and soybean, respectively, compared with 0.68 (rank: 6/12), 0.14 (rank: 8/11), and 0.54 (rank: 1/12) for LAWS (Fig. S5). None of the models showed a significant global correlation for wheat. At the national level, LAWS showed higher correlations than the GCp3 ensemble mean in 14, 8, and 10 of the top 20-producing countries for maize, wheat, and soybean, respectively (Fig. 7). Model performance in reproducing national yield levels was further evaluated using the RMSE between simulated and reported detrended annual yields for each country. LAWS showed RMSE values equal to or lower than the GCp3 ensemble mean in most countries for maize and wheat (Fig. 8). Overall, LAWS reasonably reproduced interannual yield variability and long-term mean yield levels at global and national levels, and its performance was broadly comparable to that of the GCp3 ensemble.

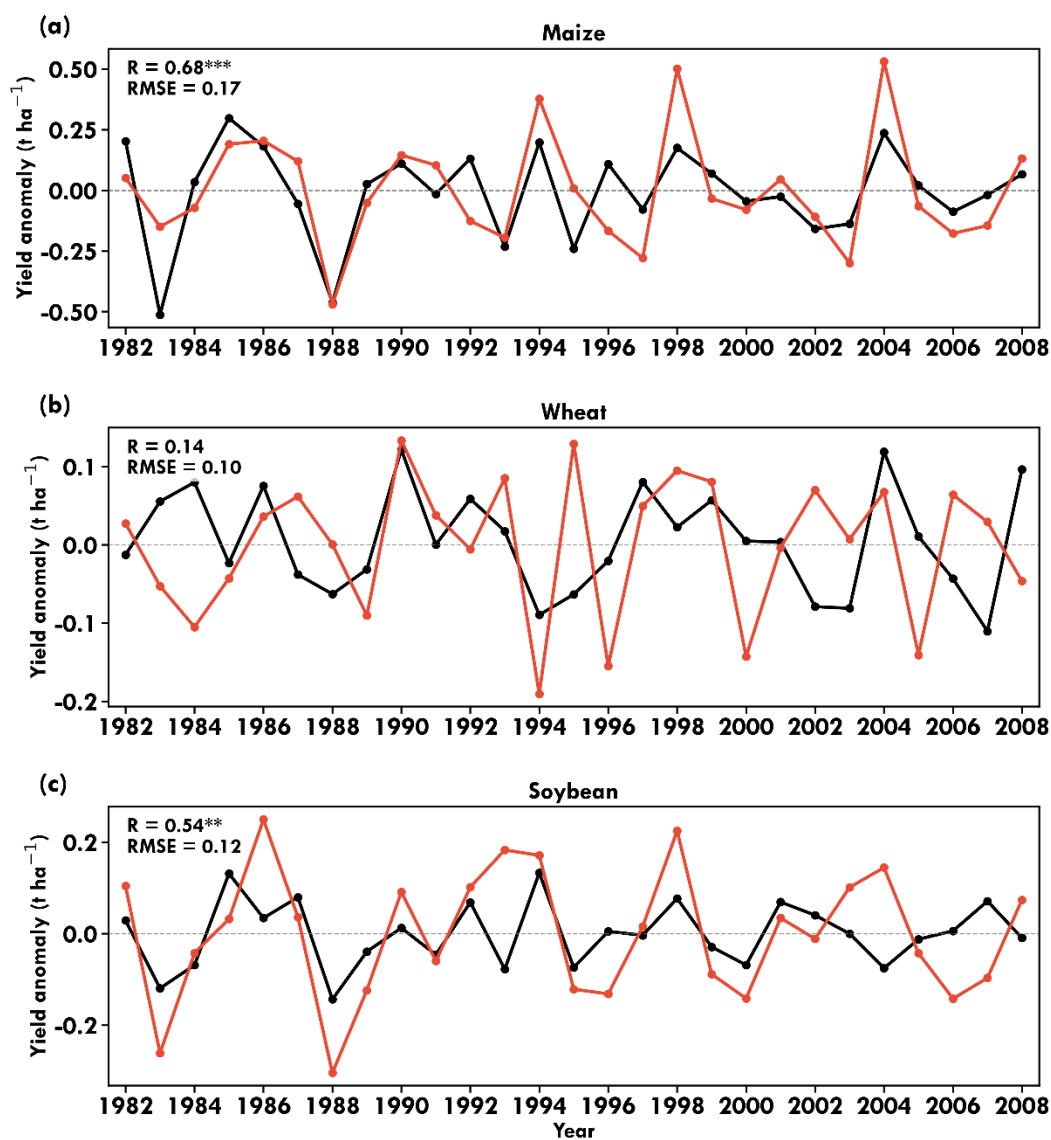


Figure 4. Time series of global yield anomalies from the simulations and FAOSTAT for (a) maize, (b) wheat, and (c) soybean. Red and black lines indicate the simulations and FAOSTAT yield anomalies, respectively. The symbols ** and *** indicate p values < 0.01 and 0.001.

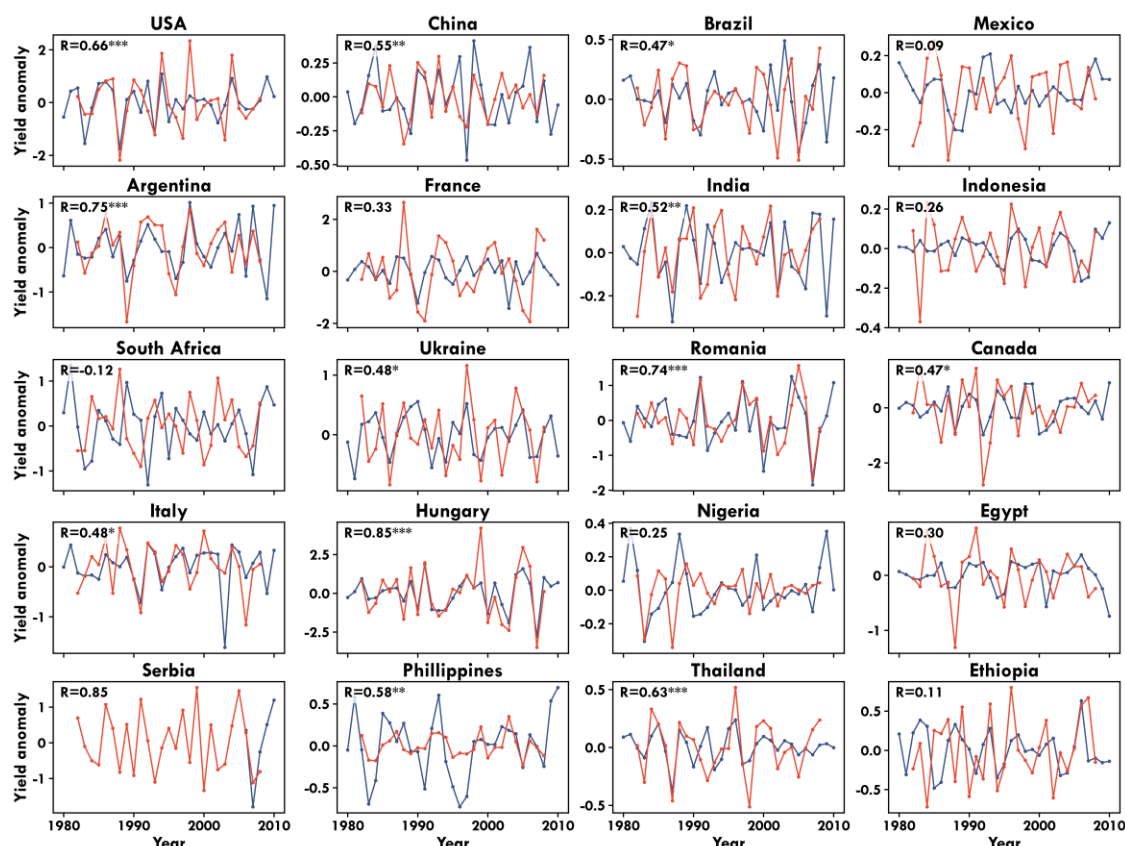


Figure 5. Comparison of yield anomalies simulated by LAWS (red lines) and FAOSTAT yields (blue lines) for maize in the top 20-producing countries. Panels show the country-level time series, with the Pearson correlation coefficients (R) reported in each panel. The symbols *, **, and *** indicate p values < 0.05 , 0.01 , and 0.001 .

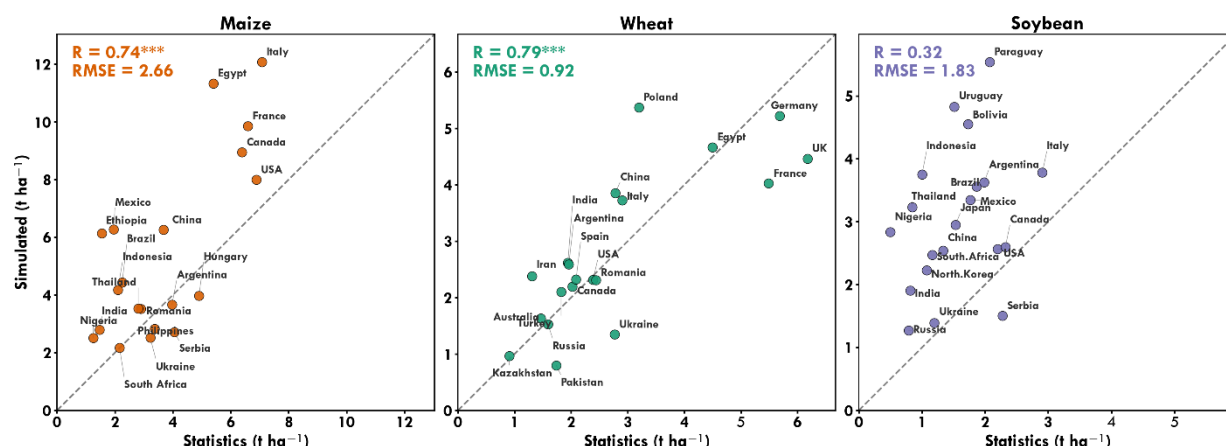


Figure 6. Comparison of long-term mean yields simulated by LAWS and reported by FAOSTAT during 1982–2008 for the top 20-producing countries of each crop: (a) maize, (b) wheat, and (c) soybean. The dashed line represents the 1:1 line. The symbol *** indicates p values < 0.001 .

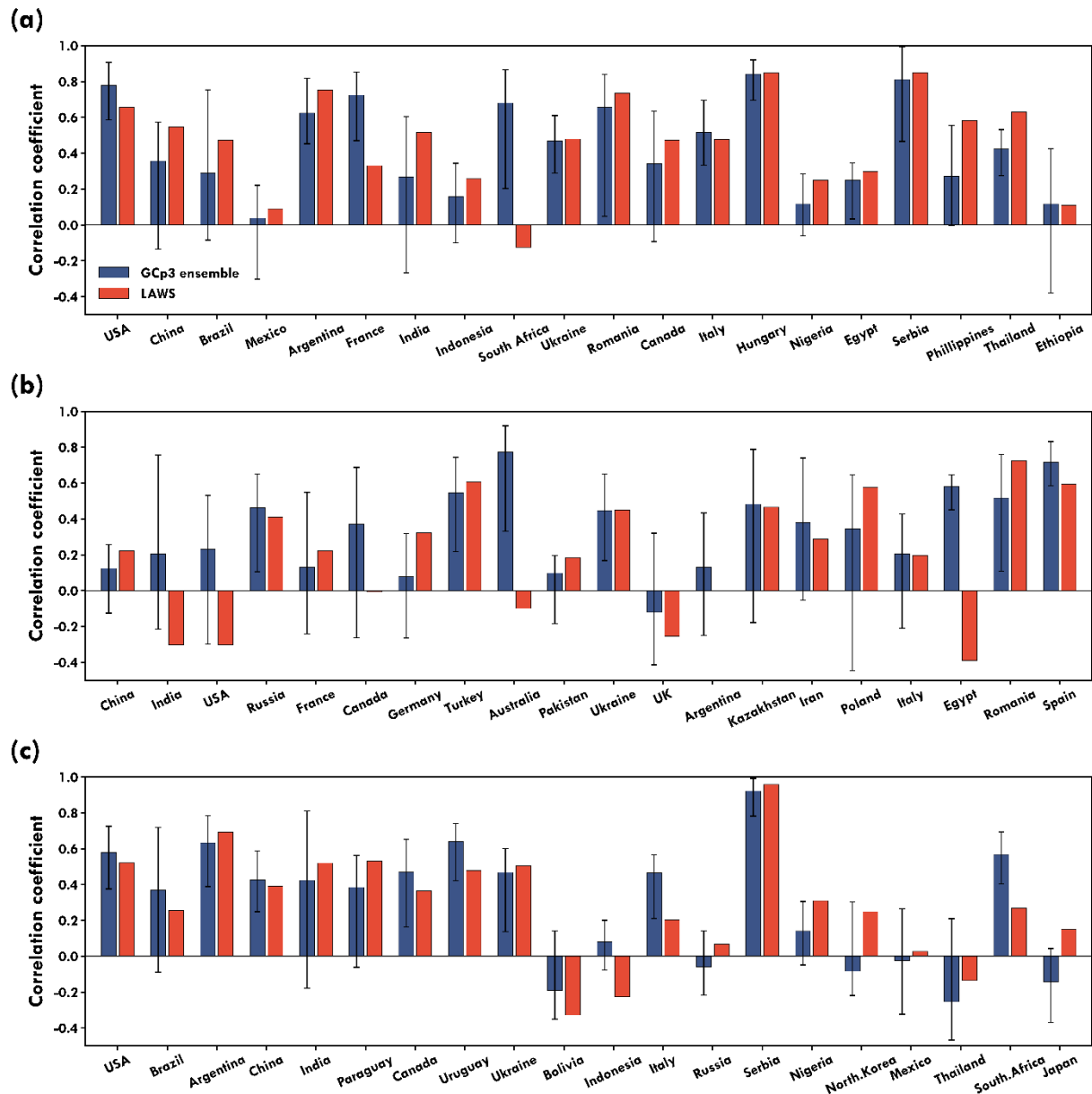


Figure 7. Comparison of Pearson correlation coefficients (R) between simulated and FAOSTAT yield anomalies for the top 20-producing countries of each crop: (a) maize, (b) wheat, and (c) soybean. Red bars represent the LAWS simulations from this study, while blue bars show the ensemble mean of the crop models evaluated by the GCp3 ensemble. Error bars indicate the minimum-to-maximum range across the GCp3 models.

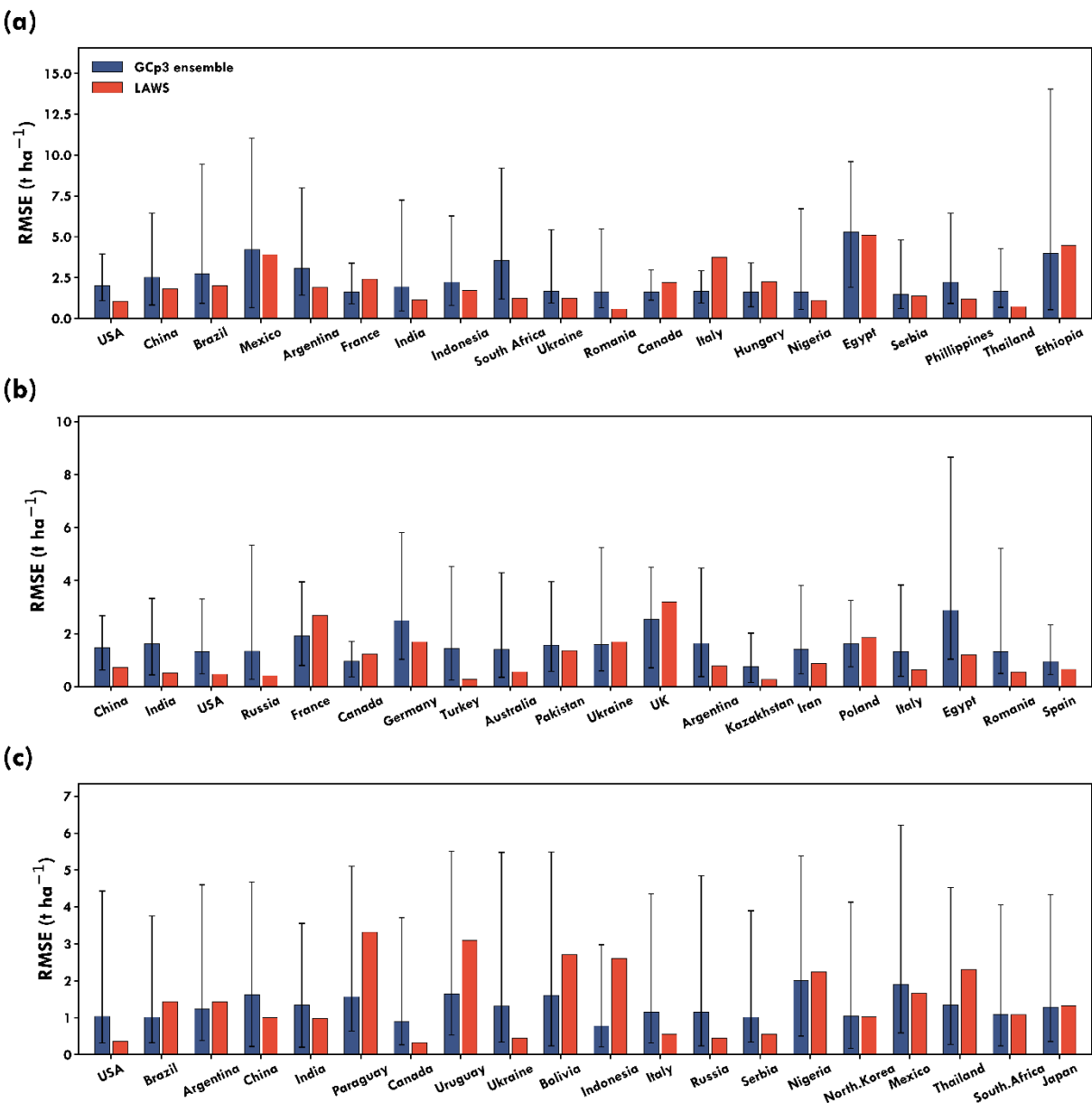


Figure 8. Comparison of root mean square error (RMSE) between simulated and FAOSTAT detrended annual yields during 1982–2008 for the top 20-producing countries of each crop: (a) maize, (b) wheat, and (c) soybean. Red bars represent the LAWS simulations from this study, while blue bars show the ensemble mean of the GCp3 crop models. Error bars indicate the minimum-to-maximum range across the GCp3 models.



3.3 Grid-cell level evaluation

Comparisons of interannual yield variability between the simulated yields and GDHY yields at the grid-cell level are shown in Fig. 9. Significant correlations ($p < 0.05$) covered 36.9 % of the harvested area for maize, 35.9 % for wheat, and 40.4 % for soybean. These proportions were within the range of the GCp3 ensemble (Fig. S6). For maize, significant correlations were mainly distributed in several major producing regions, including the eastern United States, central and southern Europe, the North China Plain, southern Brazil, eastern Argentina, southern Africa, and eastern Australia. For wheat, significant correlations were found across parts of North America, Europe, northern China, Central Asia, eastern Africa, southern Africa, and southeastern Australia. For soybean, significant correlations were mainly concentrated in the midwestern United States, northern China, the La Plata Plain, and parts of southern Africa. These results indicate that LAWS captured grid-cell interannual yield variability to some extent in major producing regions.

The spatial distributions of long-term mean yields simulated and GDHY yields are shown in Fig. 10. Compared with GDHY, LAWS reproduced the main contrast between low- and high-yielding regions in major production areas. The simulated yields captured several high-yielding regions, including the eastern United States, central and western Europe, and the North China Plain for maize; the Indo-Gangetic Plain and central and western Europe for wheat; and the United States and the La Plata Plain for soybean. However, regional biases remained. For example, LAWS underestimated yield in parts of northeastern China for maize and wheat, and did not fully reproduce high wheat yields in parts of Africa and the northern United States. In parts of the La Plata Plain and Africa, LAWS mainly overestimated soybean yields.

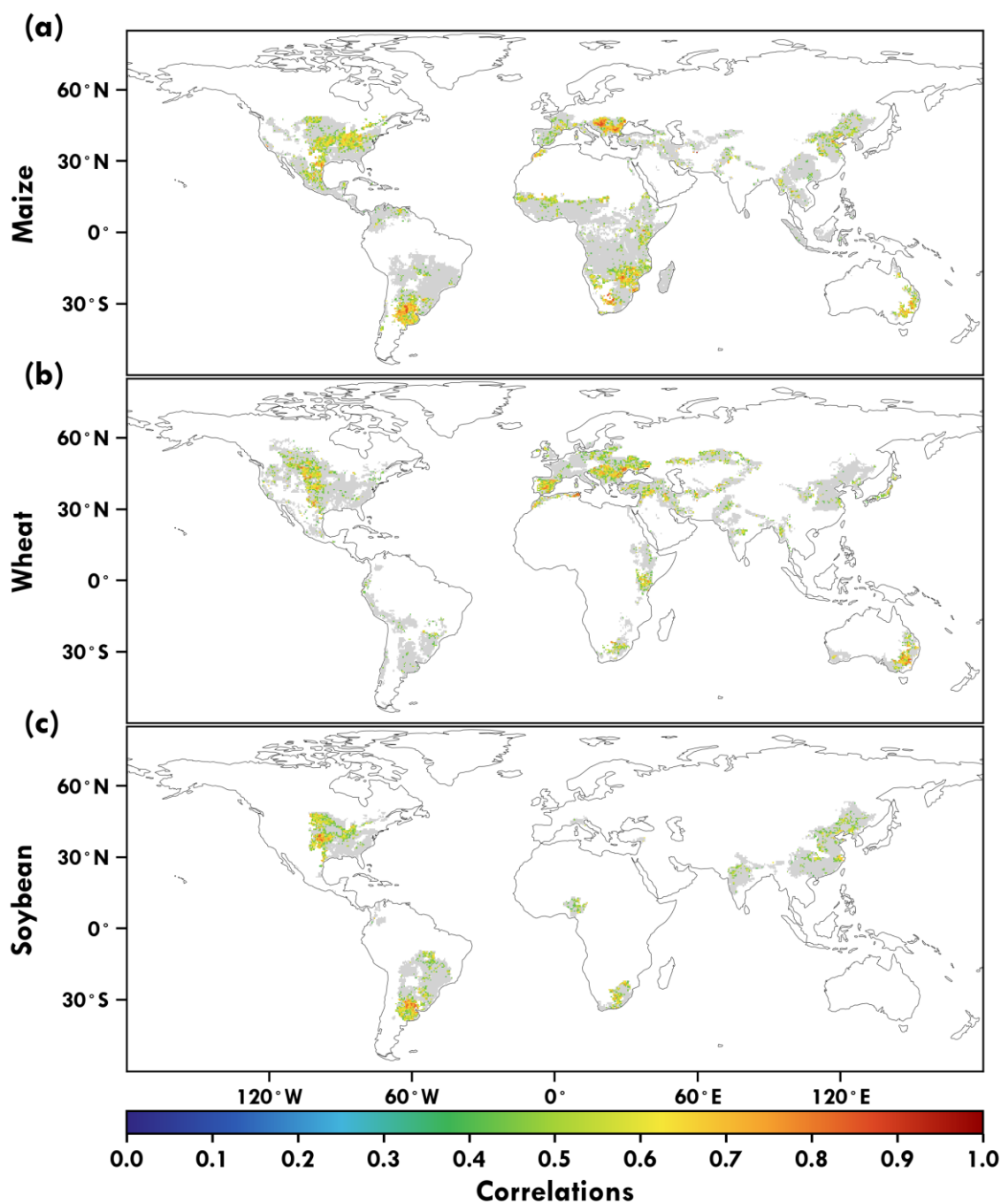


Figure 9. Correlation between simulated and GDHY yield anomalies. Maps show the significant positive coefficients between yield anomalies from LAWS and GDHY for (a) maize, (b) wheat, and (c) soybean over 1982–2008. Grey areas indicate grid cells with p values > 0.05 . White areas indicate grid cells where either simulated or GDHY yields are unavailable.

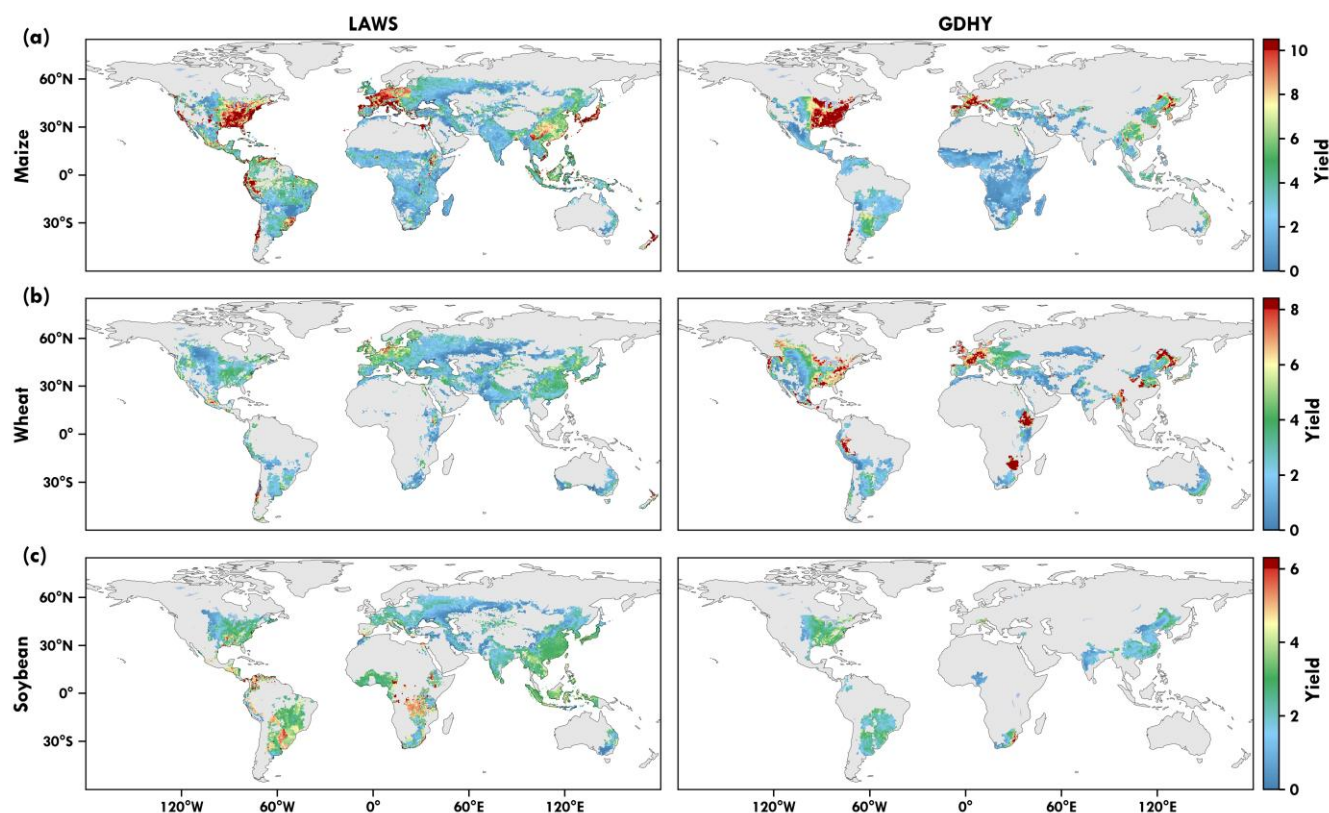


Figure 10. Comparison of simulated crop yield with GDHY yields. Maps show the spatial distribution of long-term mean yields for (a) maize, (b) wheat, and (c) soybean. The left column shows LAWS simulations, and the right column shows GDHY yields. Grey areas indicate grid cells with no data. Units are t ha^{-1} .

3.4 Case study to quantify the dependence of irrigated maize production on nonrenewable groundwater

To demonstrate the applicability of LAWS for food–water nexus studies, we conducted a case study to quantify the dependence of irrigated maize production on NRGW. This analysis requires a large-scale model that can quantify available surface water and groundwater resources and estimate the effects of irrigation water limitations on crop growth. We first examined whether LAWS produced a reasonable magnitude of irrigation withdrawals under the no-limit-withdrawal scenario. The annual mean global irrigation withdrawal simulated by LAWS during 1980–2010 was $2570 \text{ km}^3 \text{ yr}^{-1}$, including $1055 \text{ km}^3 \text{ yr}^{-1}$ from groundwater. These values fall within the ranges of previous estimates for total irrigation withdrawals ($2158\text{--}3185 \text{ km}^3 \text{ yr}^{-1}$; Table S3) and groundwater withdrawals ($465\text{--}1519 \text{ km}^3 \text{ yr}^{-1}$; Table S4).

We then quantified the share of irrigated maize yield supported by NRGW using paired simulations with and without NRGW abstraction (Fig. 11a). The results showed that NRGW supported varying shares of irrigated maize yield in several arid and irrigated regions, including the western United States, northern Mexico, the Middle East, Central Asia, the Indo-



Gangetic Plain, northern China, western South America, and southern Africa. In the most water-limited and irrigation-intensive regions, such as the Middle East, the Tigris–Euphrates basin, the Arabian Peninsula, Pakistan and northwestern India, parts of Central Asia, and parts of southern Africa, NRGW supported more than 50 % of irrigated maize yield.

We further selected one example grid cell located in an irrigated agricultural area along the Tigris River to illustrate the underlying crop–water responses (Fig. 11b–d). This example illustrates a situation in which surface water and RGW were accessible but could not fully meet irrigation demand in some years. When these renewable sources supplied most of the required irrigation water, little crop water stress occurred under either withdrawal scenario. However, their contribution declined substantially in years with limited water availability. In 2008, for example, surface water and RGW supplied only 38 % of irrigation withdrawals under the no-limit-withdrawal scenario, with the remaining 62 % supplied by NRGW (Fig. 11b). Without access to NRGW under the limited-withdrawal scenario, the resulting irrigation deficit caused the crop water stress to approach 0 during the growing season. This severe water stress reduced LAI and actual transpiration relative to the no-limit-withdrawal scenario (Fig. 11c and d).

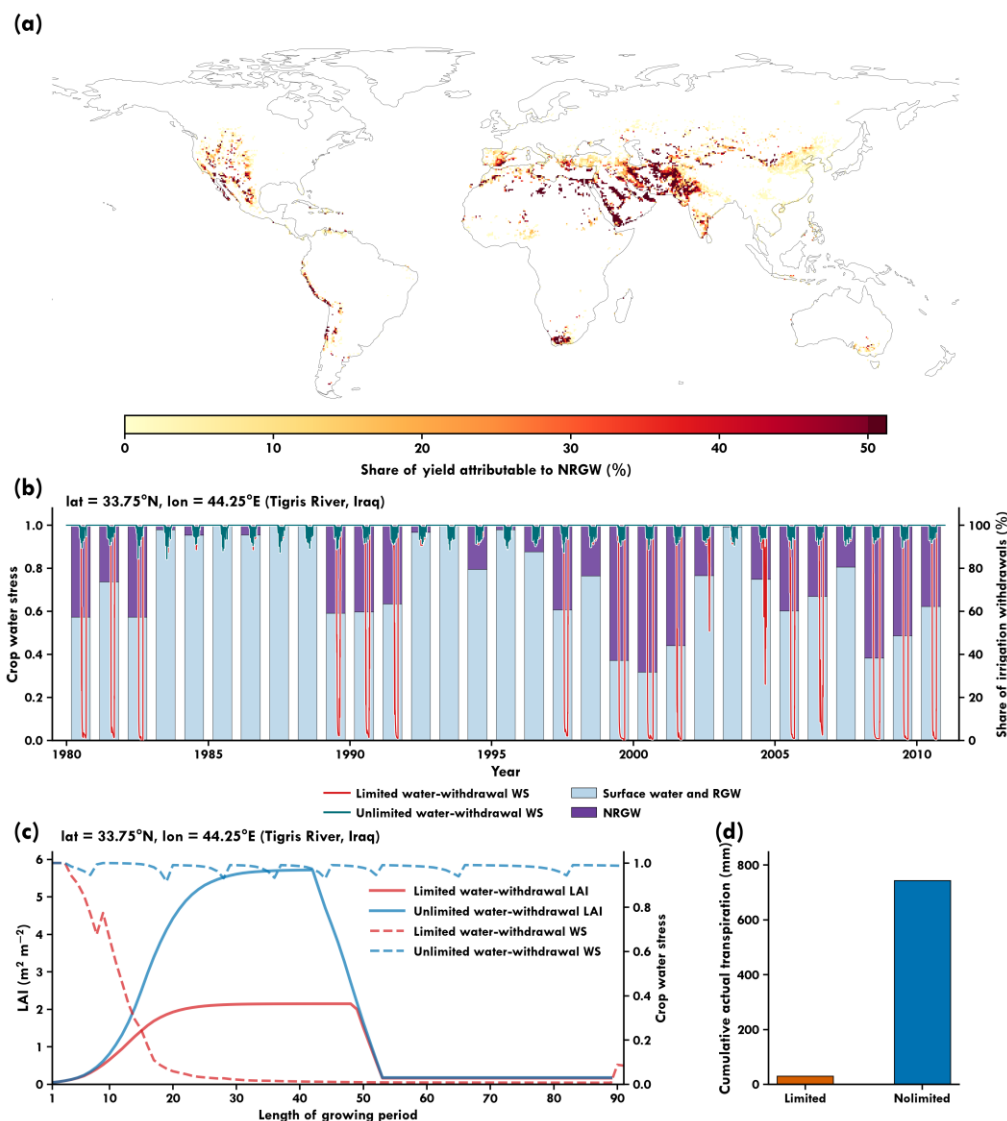


Figure 11. Contribution of nonrenewable groundwater (NRGW) to irrigated maize yield and example time series at a selected grid cell. (a) Spatial distribution of the share of irrigated maize yield supported by NRGW during 1980–2010. (b) Time series of crop water stress and irrigation water-source composition during the maize growing season at the selected grid cell (33.75° N, 44.25° E) during 1980–2010. Lines show crop water stress of irrigated maize under the limited-withdrawal and no-limit-withdrawal scenarios. Bars show the fractions of irrigation withdrawals supplied by surface water plus renewable groundwater and by NRGW from the no-limit-withdrawal scenario. Crop water-stress factor: 1 = no water stress and 0 = complete water limitation. (c, d) Example daily time series of leaf area index (solid line in c), crop water stress (dashed line in c) and cumulative actual transpiration during the 2008 growing season under the limited-withdrawal and no-limit-withdrawal scenarios.



4 Discussion

4.1 General performance of LAWS

LAWS was developed as a crop–hydrological modelling framework by integrating a dynamic agricultural module into CWatM. The module follows generic crop-growth processes and uses crop-specific parameters to represent different crop types, allowing flexible extension to other annual and perennial crops. Within this unified framework, crop growth and hydrological processes interact at a daily time step: crop development affects crop water use, while soil moisture and irrigation water availability constrain crop growth and biomass accumulation. This integrated crop–hydrological framework also enables LAWS to investigate broader interactions between agricultural production and water-resource systems, such as the effects of water allocation and competition on irrigation availability and crop production.

The site level evaluation showed that LAWS can reproduce the main seasonal dynamics of crop growth across different crops and regions under the default global parameterisation. This supports the applicability of LAWS to large-scale simulations of crop growth processes. However, discrepancies remained in the timing and magnitude of LAI and biomass development. For example, at Mead, the simulated soybean LAI followed the observed increasing trend, but the onset of LAI growth occurred earlier than observed. This timing bias is closely related to the heat-unit requirement for germination and early development (HUG in this study), which controls crop emergence; adjusting this parameter could therefore help better match the observed emergence timing. In addition to HUG, maximum LAI (LAIM in this study) and radiation use efficiency are also sensitive parameters for crop growth and have been widely used in crop model calibration (Fader et al., 2010; Deryng et al., 2011; Ai and Hanasaki, 2023). These parameters are often cultivar-dependent and can vary across regions. For example, the LAI simulation at Iowa could be improved by adjusting LAIM. However, such adjustment should be supported by long-term growing-season observations. Because only a limited number of growing seasons were available for each site, crop growth parameters were not calibrated against the site observations in this study.

For long-term mean yield, LAWS reasonably reproduced the spatial distribution of low- and high-yielding countries for maize and wheat, whereas the spatial agreement was weaker for soybean, with a tendency toward yield overestimation in many countries. Comparison with the GCp3 ensemble further showed that the country-level yield errors of LAWS were within the ensemble range for all top 20-producing countries and were lower than the ensemble mean in most countries for maize and wheat. This suggests that LAWS provides a reasonable representation of large-scale differences in mean crop yield comparable to that of latest global gridded crop models.

LAWS also showed moderate skill in capturing the interannual yield variability across varying spatial levels. Relative to the GCp3 ensemble, LAWS generally showed stronger performance at the global and national levels than at the grid-cell level, with its overall performance at the former two levels falling within the middle-to-upper range of the ensemble. At the grid-cell level, the harvested areas showing significantly correlations exceeded the ensemble mean only for soybean, but remained within the GCp3 range for all three crops. These results support the applicability of LAWS for large-scale assessments of crop production and its interactions with climate and water availability. Nevertheless, regional biases in mean



yield and interannual variability remained in both LAWS and the GCp3 models, highlighting persistent challenges in large-scale crop yield simulation (Koehler, 2020; Folberth et al., 2019). These discrepancies may partly reflect yield-determining processes that remain simplified or unrepresented, including pest and disease damage (Donatelli et al., 2017), responses to climate extremes (Heinicke et al., 2022), management, and technological progress (Licker et al., 2010). Incorporating these processes could improve the simulation of regional yield patterns and climate-related yield variability.

Overall, the multilevel evaluation indicates that LAWS is suitable for large-scale simulations of agricultural processes, with performance broadly comparable to state-of-the-art global crop models. More importantly, LAWS provides an open-source and unified framework in which crop growth and hydrological processes operate on common state variables and fluxes within the same daily calculation sequence. This structure facilitates further process-level development, such as incorporating crop nutrient dynamics, adaptive irrigation decisions, groundwater abstraction constraints, reservoir regulation, and environmental flow requirements. These extensions would allow LAWS to examine how changes in climate, water availability, and agricultural management propagate through crop water demand, water stress, yield, and hydrological systems, thereby supporting projections of the coupled responses of agricultural production and water resources under climate change.

4.2 Limitations

This study has several limitations in model evaluation. First, the site-level evaluation was affected by the scale mismatch between grid-cell simulations and site observations. LAWS was run at a spatial resolution of 30 arcmin, corresponding to approximately 50 km at the Equator, and each grid cell therefore represents average conditions over a large area. In contrast, the observations represent conditions in a single field or experimental site. Consequently, the elevation, meteorological forcing, soil properties, crop calendar, and water availability represented by the model may differ from the actual site conditions. These differences can affect the evaluation of simulated LAI and biomass, particularly when local management practices and microclimatic conditions deviate from the grid-cell averages. Second, the national- and grid-level yield evaluations were constrained by uncertainties in the available reference datasets. Although FAOSTAT provides a consistent basis for national-level comparisons, it does not represent within-country spatial heterogeneity, and some country-year values are estimated or imputed when official statistics are unavailable. Such estimations may not fully capture actual year-to-year yield fluctuations and can therefore affect the evaluation of climate-related yield variability. GDHY provides gridded yield estimates, but these data are not direct field observations and are affected by statistical downscaling and assumptions about input data. Therefore, the grid-cell level evaluation can also be affected by uncertainty in the reference dataset (Müller et al., 2017).

4.3 Future work

LAWS is intended to provide an open-source and modular crop-hydrological modelling framework that integrates comprehensive representations of agricultural and hydrological processes within a unified framework. Because LAWS was



developed directly within CWatM, existing CWatM developments for lateral groundwater flow (Guillaumot et al., 2022), glacier-sourced runoff (Hanus et al., 2024), and wastewater treatment and reuse (Fridman et al., 2025) provide a basis for
540 further extending the hydrological processes represented in LAWS. Incorporating these processes would broaden the applicability of LAWS for investigating crop production and water use under more diverse and complex hydrological conditions.

The current version of LAWS represents a first step toward this goal by linking crop growth, crop-specific water use, and hydrological processes within CWatM, providing a basis for further development of coupled agricultural and hydrological
545 processes, such as fertilisation and its associated effects on water quality. LAWS currently does not explicitly simulate fertilisation, plant nutrient uptake, or soil nutrient cycling. Nutrient availability, together with water management, is a major constraint on yield gaps and crop productivity (Mueller et al., 2012; Deryng et al., 2011). By altering crop growth and transpiration demand, nutrient availability and fertilisation can also influence crop water use and irrigation requirements (Jägermeyr et al., 2016). Incorporating these processes would improve the representation of agricultural management and
550 provide a basis for linking fertiliser-derived nutrient losses with surface runoff, drainage, groundwater flow, and river routing. This development would enable LAWS to jointly assess crop production, water use, and water-quality impacts under changing climate and agricultural management.

In this study, we evaluated the performance of LAWS in simulating crop growth dynamics and yield using a global parameter set without model calibration. In a coupled crop-hydrological model, parameters can affect both agricultural and
555 hydrological results through two-way feedbacks between crop growth and water availability (Zhang et al., 2026). Calibration against a single objective may improve one module while reducing the consistency of the coupled system. Previous studies have shown that relying on a single target variable, such as streamflow, may lead to acceptable performance for that variable while leaving evapotranspiration, groundwater storage, or irrigation demand poorly constrained (Rientjes et al., 2013; Koltsida and Kallioras, 2022). Therefore, developing a multi-objective calibration framework that simultaneously considers
560 yield, evapotranspiration, irrigation water use, soil moisture, and discharge is an important direction for future LAWS parameter calibration.

5 Conclusions

In this study, we developed LAWS, a process-based coupled crop–water model, by incorporating a new agricultural module into CWatM. The module simulates crop growth dynamics and crop-specific water use at a daily time step. Through its
565 coupling with hydrological processes, the coupled model represents two-way interactions between crop growth and the water cycle. The multilevel evaluation showed that LAWS reproduced the main seasonal dynamics of LAI and biomass, reasonably represented the spatial patterns of long-term mean yields, and captured interannual yield variability to some extent. The overall yield performance of LAWS was broadly comparable to that of the GCp3 ensemble. We further demonstrated the application of LAWS to food–water nexus analysis by quantifying the contribution of NRGW to irrigated
570 maize production, revealing strong dependence on NRGW in several arid and irrigation-intensive regions. By integrating



crop growth, hydrological processes, and human water management within a unified framework, LAWS provides a basis for investigating interactions among crop production, water availability, and water management under changing climate and water-use conditions.

Code and data availability

575 The LAWS code is publicly available in a GitHub repository (<https://github.com/Zhonghao2023/LAWS>). A frozen version used for this study can be found in Zenodo at <https://zenodo.org/records/22437730> (Fu, 2026b). The CWatM code is provided via a GitHub repository (<https://github.com/iiasa/CWatM>; last access: 13 August 2026), and the model version used for this study is available from <https://zenodo.org/records/10044318> (Burek et al., 2023). The input data and model setting file can be downloaded from <https://zenodo.org/records/22346142> (Fu, 2026a).

580 Author contributions

WL conceptualized the study. ZF developed the model. ZF and SY conducted simulations. ZF analysed the results and wrote the original draft. DF, MS, and PB provided critical expertise in CWatM. WL, TD and DM supervised this work. All authors reviewed and edited the manuscript.

Competing interests

585 The authors declare no competing interests.

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