



Introducing Crop Heat Stress in the Community Land Model v5

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Abstract. Extreme heat can cause great harm to crop production, but the effects on grain yield are not always represented in global land surface models. In this study, new functions are introduced in the Community Land Model v5 (CLM5) to account for heat stress effects induced by heatwaves (3 days) that can result in crop yield losses by looking at vegetation temperature and a regionally-varying temperature trigger on a global scale. Two different heat stress implementations are tested, both targeted to affect the reproductive stage of the growing season. In the first method, heat stress accelerates senescence of Leaf Area Index (LAI), and in the second, heat stress directly reduces carbon allocation to grains for yield. The resulting impact on yield for the different experiments is then evaluated for the crops wheat, maize, rice and soybean for the years 1985-2014. We show the added value of using vegetation temperature to distinguish effects between irrigated and rainfed crops. In addition, we highlight the need for using critical thresholds that are not static over the globe, but take into account the regional climate. Both methods capture heat stress during specific events, but since the heat stress implementations only affect the reproductive crop stage, the potential of an evaluation with reference data becomes limited as the exact timing of the simulated growing season becomes another crucial modeling factor. Comparing the two different implementation methods, the heat stress impact on accelerated LAI senescence had a larger impact in the tropics and subtropics, whereas reducing the carbon allocation to grains for yield had a stronger impact in higher latitudes. The findings of this study advance crop sensitivity to climatic heat extremes in global land surface models.

1 Introduction

Heat plays an important role in global food security. It has been highlighted by the United Nations as "one of the most serious and acute hazards facing agriculture around the globe" (FAO and WMO, 2026). Several studies have reported on the negative impact of warming temperatures and temperature extremes on global crop yields (Hu et al., 2024; Vogel et al., 2019; Zhao et al., 2017). As the impact of heatwaves on food systems will only increase in both frequency and magnitude (Battisti and Naylor, 2009; Martinez-Villalobos et al., 2025), it is essential to better understand how food systems are and will be affected in the future, which requires an accurate representation of crop responses to temperature extremes in global models.



In this regard, current state-of-the-art global gridded crop models struggle to meet the criteria to accurately represent climate extremes on crop yields (Nóia Júnior et al., 2025). Two studies that evaluated several global gridded crop models (a combination of upscaled crop models and land surface models) conclude that while most models were able to capture reduced yields from drought and heat events for different crops, the magnitude of the impact on yield was often too low (Schewe et al., 2019; Heinicke et al., 2022). In addition, Müller et al. (2017) showed a low internal agreement between individual models, revealing a much larger problem of uncertainties and inconsistencies in global gridded crop models.

These findings confirm the general understanding that agricultural systems are notoriously difficult to model at the global level. This can be broadly attributed to two reasons. The first being the highly variable impact of heat stress on crop production, as it depends on many factors. Crops naturally have a strong temperature-dependent physiology, in which photosynthetic activity is optimal within a specific temperature range which varies per crop species and cultivar. But when crops are exposed to elevated temperatures, either for a short intense period or a prolonged period of time, crop mechanisms can become damaged (Fahad et al., 2017; Rezaei et al., 2015; Webber et al., 2022). Sensitivity to heat stress additionally varies throughout the growing season, with mechanisms around the reproductive stage, such as flowering and pod set, being especially vulnerable (Arshad et al., 2017; Liu et al., 2016; Siebers et al., 2015; Poudel et al., 2023; Webber et al., 2022). A meta-analysis considering >120 published studies revealed yield losses due to heat stress during the reproductive stage of around 33-48%, rising to 65% when heat and drought stress occurred simultaneously (Cohen et al., 2021). But the reported yield impacts also showed a large distribution, ranging from +20% to -100% for heat stress alone (Cohen et al., 2021). These findings highlight the complexity of stress effects in crops.

A second factor complicating crop heat stress representation in models is that agricultural systems are not purely natural systems, but instead have a strong socio-economic component (Renting et al., 2009; Urruty et al., 2016). In field-scale crop models, information on spatiotemporal variability in crop species, cultivar and management practices is often provided or measured, and high accuracy in model output can be achieved. But at the global level, models are generally run at coarse spatial resolutions (0.25-2°), in which many different crop responses are lumped into a single signal. When looking at heat stress, this introduces some additional challenges, the first being that this low spatial resolution can average out local anomalous events. Short intense periods of extreme heat in small regions are therefore not captured. Another factor is the modeled magnitude of heat impact, which in reality is often a combination of different factors. Despite these challenges, efforts on improving land surface models (LSMs) and climate models continue, due to their unique capability of interconnecting energy, water, and biogeochemical processes at the land surface to the deeper soil layers and the atmosphere. Additionally, Earth system models (whereby LSMs are coupled to atmosphere, ocean and ice sheet models) can provide insights into future impacts under different climate scenarios. Hence, by improving global crop simulations in Earth system models, we can get a more comprehensive understanding of the interactions between global climatic changes and cropping systems.

In this study, the objective is to globally capture crop heat stress, for the first time, in the Community Land Model, version 5 (CLM5). CLM is the land model component of the Community Earth System Model (Lawrence et al., 2018, 2019), a key climate model for simulating Earth system processes and contributor to climate projections as part of the Coupled Model Intercomparison Project (Eyring et al., 2016). Levis (2014) highlighted the need for considering crop heat stress in CLM5 during



the crop's sensitive stages, as the model's simulated yield estimates often unrealistically increase under different warming scenarios, even when excluding the CO₂ fertilization effect.

60 To achieve this objective, new functions are introduced in the CLM5 crop module (Git release tag ctsm5.2.019) to trigger heat stress and keep track of heat stress intensity during the most sensitive CLM5 crop stage: the reproductive grain fill stage. The aim of these functions is to capture spatial and temporal distributions of historical heat stress events at the global level, with an emphasis on large regional impacts on agriculture. The aim is to capture effect of heat stress lasting for several days (i.e. heatwaves), as opposed to heat-shock events, which are more intense heat events that last for several minutes to several
65 hours (Jagadish et al., 2021). The motivations of model development choices are built on existing literature and available global spatial datasets. Implemented crop heat stress impacts are explained in the methods section 2.2, and the heat stress function is explained in 2.2.2. The experimental set up, including evaluation of the model implementations in terms of impact and accuracy, is explained in section 2.3, after which the results are presented and discussed in section 3. The findings of the study are aimed at progressing research on heat stress implementations on crops to consider more realistic impacts on crop yield,
70 both historically and for scenario projections. In section 4, an evaluation of the potential for heat stress representation in CLM5 is outlined.

2 Methods

2.1 Existing CLM5 crop module

CLM5 in BGC-Crop mode can simulate transient crop cover and management, including irrigation and fertilization (Lom-
75 bardozzi et al., 2020). The crop module is based on the prognostic crop module of the Agro-Ecosystem Integrated Biosphere Simulator (Agro-IBIS) (Kucharik and Brye, 2003). Crop physiological processes are constrained by environmental factors, including temperature. This is done by (i) defined crop growth stages in thermal time (growing degree-days) and (ii) the photosynthetic activity rate, which peaks at an optimum temperature, which for C₄ crops is about 10°C higher than C₃ crops (Bonan et al., 2011). C₃ and C₄ plants differ in photosynthesis processes, where for C₃ plants optimal photosynthesis temperatures
80 acclimate based on a 10-day running mean temperature, thereby shifting throughout the season, between 11-30°C (Lombardozi et al., 2015). In addition, drought stress is considered as plant hydraulic stress, which can originate from dry soils and dry atmospheric conditions (Kennedy et al., 2019). CLM5 considers four crop growth stages: planting, leaf emergence (vegetative stage), grain fill (reproductive stage), and maturity (harvest). The model considers eight actively managed crop functional types (CFTs)—temperate soybean, tropical soybean, temperate corn, tropical corn, spring wheat, cotton, rice, and sugarcane— which
85 have specific phenological parameters. Apart from the actively managed CFTs, CLM5 contains many non-actively managed CFTs that use parameter settings of one of these eight active CFTs. An important parameter is the growing degree-days until maturity, GDD_{mat} (°C day), which defines the thermal time from planting to harvest and is based on the 2 m air temperature (Lawrence et al., 2018; Lombardozi et al., 2020). During each crop stage, carbon and nitrogen are allocated to specific pools according to calculated C:N ratios, which are controlled by CFT-specific parameters and change over the growing season after
90 entering a new crop stage. The definitions of the four crop stages are briefly explained below and visualized in Fig. 2.



Crop stage I: planting The planting date depends on several temperature-based conditions within a CFT-specific planting window. Planting occurs on the last day of the sowing window if these conditions are not met. The planting window for CFTs in the Southern Hemisphere is shifted 6 months later compared to the Northern Hemisphere.

Crop stage II: leaf emergence Emergence is initialized once the base temperature of the soil is exceeded. At the first time step of leaf emergence, carbon pools for stems, leaves and roots are activated. Naturally, during this stage the leaf area index (LAI; $\text{m}^2 \text{m}^{-2}$) starts to grow.

Crop stage III: grain fill Grain filling starts either when maximum LAI is reached or when GDD is around 50% of GDD_{mat} . At the start of this phase, a new pool for grain production is created. This phase marks the onset of leaf senescence, in which LAI starts to decline.

Crop stage IV: maturity Harvest is assumed to occur at the time step at which 100% of GDD_{mat} is reached. Part of the grain carbon is used for seed carbon for the upcoming growing season, while the remaining grain carbon is considered for harvest.

Crop types are simulated separately from natural vegetation on managed land units, in which irrigated and rainfed CFTs have independent soil columns. Present day cropland and crop type areas are derived from the MIRCA2000 dataset (Portmann et al., (2010)) and extrapolated through time using the Land Use Harmonization 2 (LUH2; Hurtt et al., 2020) dataset available through the Land Use Model Intercomparison Project (LUMIP; Lawrence et al., 2016). Further details on the CLM5 model and its components are explained in Lawrence et al. (2018).

2.2 Implementing heat stress impacts on crops in CLM5

In this study, two different methods are tested in which heat stress can impact crop processes. The first focuses on accelerated LAI senescence (method 1; LAI) and the second on reduced carbon allocation to reproductive grains (method 2: REP). The heat stress itself is described by a function which is based on a temperature trigger, i.e. the initiation of heat stress, and the stress intensity, which increases with increasing temperatures. The focus is on elevated temperatures that last for several days (i.e. heatwaves), while heat shock events are not considered. Heat-shock events are difficult to capture accurately at this scale and resolution and plants can develop a protection against heat shock (Jagadish et al., 2021), which makes it hard to implement. Because two crop impact methods are considered (LAI and REP), the heat stress function needs to be parameterized in parallel for the two methods. An overview of all heat stress components can be seen in Fig. 1, and the individual processes are outlined in the dedicated subsections.

2.2.1 Impact

Crops are most sensitive to heat during the reproductive stage (flowering and grain filling), in which a combination of processes can be impacted, such as reductions in pod set, grain number, size, quality, shortening in grain filling duration, and accelerated leaf senescence (Arshad et al., 2017; Liu et al., 2016; Webber et al., 2022). Because of these many different effects that interplay during heat stress, there are different approaches to represent heat stress crop models. In (upscaled) field-scale process-based crop models, crop responses to heat stress are either modeled to affect photosynthesis, flowering stage, accelerated leaf

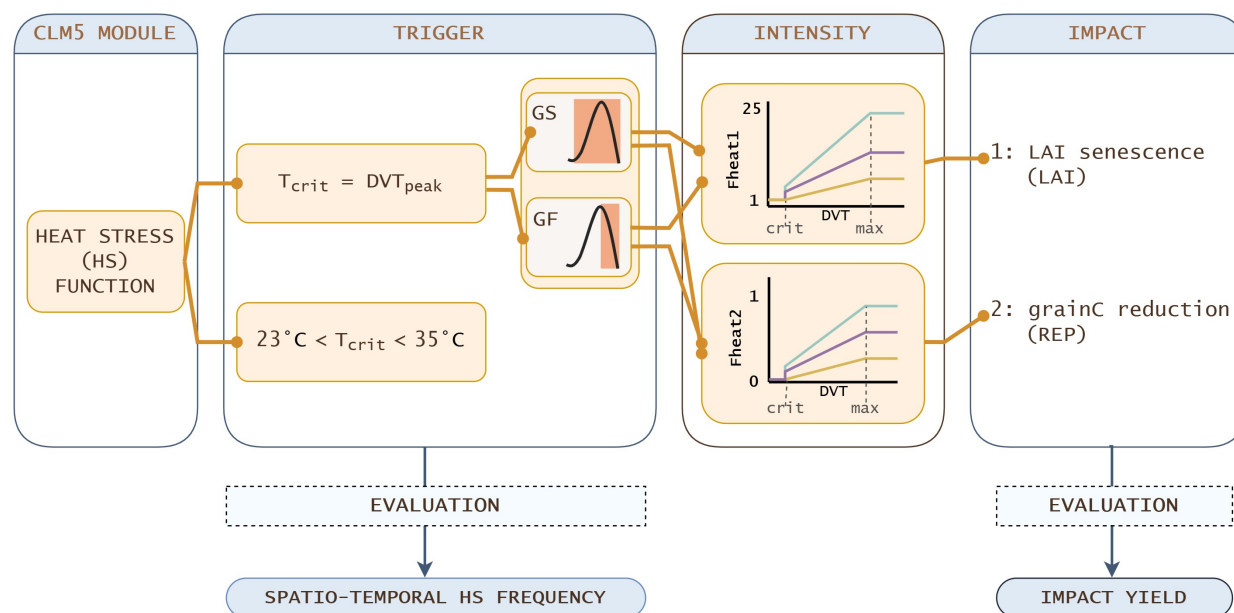


Figure 1. Schematic overview of the experimental set up. The CLM5 heat stress implementation is tested in terms of high temperature trigger, of which the experiments with constant values of T_{crit} were abandoned after evaluation. The DVT_{peak} were used for the final batch of experiments using two different methods; 1) accelerated LAI senescence and 2) retranslocation of grainC to rootC. Both the heat stress trigger and impact were evaluated with external datasets.

senescence, grain yield, or a combination of these (Bassu et al., 2014; Wang et al., 2017). In this study, two separate methods
 125 are developed based on existing techniques in established crop models and evaluated to assess the impact on the CLM5 crop
 module. Both these methods will affect the most heat sensitive crop stage—grain fill. Note that flowering is not a separate crop
 stage in CLM5 and will therefore not be specifically considered in this study. As shown in Fig. 2, in the first method, the heat
 stress factor is applied to accelerate LAI senescence, thereby reducing the grain-filling period which can result in lower yields.
 In the second approach, the crop phenology is not affected, but instead the grain production is directly reduced once heat stress
 130 is triggered. This is done by reallocating the fraction of carbon and nitrogen for grain production to other parts of the plant.

Method 1

In CLM5, LAI senescence in crops is initialized at the start of the grain fill phase, as the inverse of background litterfall. In
 the first method, heat stress is represented by a multiplicative factor >1 onto litterfall. The introduction of the heat stress factor
 (F_{heat1}) in this function causes accelerated LAI senescence once heat stress is triggered. Because LAI senescence is computed
 135 at every timestep, the duration of heat stress plays an important role on the final impact.

Method 2

In CLM5, the allocation fractions of the available carbon (C), and indirectly nitrogen (N), are divided over different parts of
 the plant in allocation pools, whereby the demand of C and N are linked through C:N ratios specific for each plant component
 (leaf, stems, fine roots) and crop stage. The portion of C allocated to the grains is calculated during the grain fill stage as the



total C allocation, i.e. 1, minus the sum of allocation fractions from the other pools, as shown in Eq. 2. In this approach, the carbon allocation fraction to the grain pool is reduced once heat stress is triggered by introducing a loss allocation pool (a_{loss} ; Eq. 1) which increases when heat stress intensity increases. This a_{loss} pool redirects the carbon allocation fraction from the grain pool to the fine roots (Eq. 2), similar to Peng et al. (2018). This method was included as a secondary approach, to account for the direct influence of heat stress on reproductive mechanisms that are not represented by phenology traits, such as reduced pod setting or grain development.

$$a_{loss_i} = (1 - a_{froot_i} - a_{livestem_i} - a_{leaf_i}) * F_{heat2_i}, \quad (1)$$

$$a_{repr_i} = 1 - (a_{froot_i} + a_{loss_i}) - a_{livestem_i} - a_{leaf_i} \quad (2)$$

where i is the simulated timestep; F_{heat2_i} is the heat stress factor at timestep i ranging between 0 (=no stress) and 1 (full stress); a_{repr} , a_{froot} , $a_{livestem}$, a_{leaf} , are the carbon allocation fractions to reproductive, fine root, live stem and leaf pools respectively; and a_{loss} is the newly-defined carbon loss pool.

2.2.2 Heat stress factor

The heat stress factor (F_{heat}) is defined by adopting the strategy of similar large-scale crop heat stress studies in which the intensity of stress is described using a simple linear function between a critical onset temperature threshold (T_{crit} ; °C) and a maximum temperature threshold (T_{max}), after which full heat stress is applied (Challinor et al., 2005; Deryng et al., 2014; Lucia Martin et al., 2025; Teixeira et al., 2013). Both methods use the same linear function, but with different values of the maximum heat stress factor, Fx_{heat} , where Fx_{heat1} for method 1 does not have an upper limit, but with method 2, Fx_{heat2} cannot exceed 1. Note that also the onset of heat stress is different between the two methods (1 for method 1 and 0 for method 2). Heat stress will only occur when T_{crit} is exceeded for three consecutive days; i.e. the first day in which heat stress is effectively applied equals the fourth day that T_{crit} is exceeded. F_{heat} has an onset value, x , for the first day of effective heat stress regardless of the temperature on that day, which is 20% of Fx_{heat} . Since Fx_{heat} is the defining parameter of the function for heat stress magnitude, a group of experiments are done with different values for $Fx = x_{heat}$ for both methods, further explained in section 2.3. After the first day of effective heat stress, F_{heat} depends on its position on the linear slope, where the slope steepness is defined by the difference between T_{crit} and T_{max} , as shown in Eq. 3.

$$F_{heat,i} = \begin{cases} F_0, & \text{if } T_i < T_{crit} \\ x + (Fx_{heat} - x) * \left(\frac{T_i - T_{crit}}{T_{max} - T_{crit}} \right), & \text{if } T_{crit} \leq T_i \leq T_{max} \\ Fx_{heat}, & \text{if } T_i > T_{max} \end{cases} \quad (3)$$

Where F_0 is no heat stress, Fx_{heat} maximum heat stress, T_i the mean daytime temperature on day i , and x the onset value on the first day of heat stress or when $T_i = T_{crit}$.

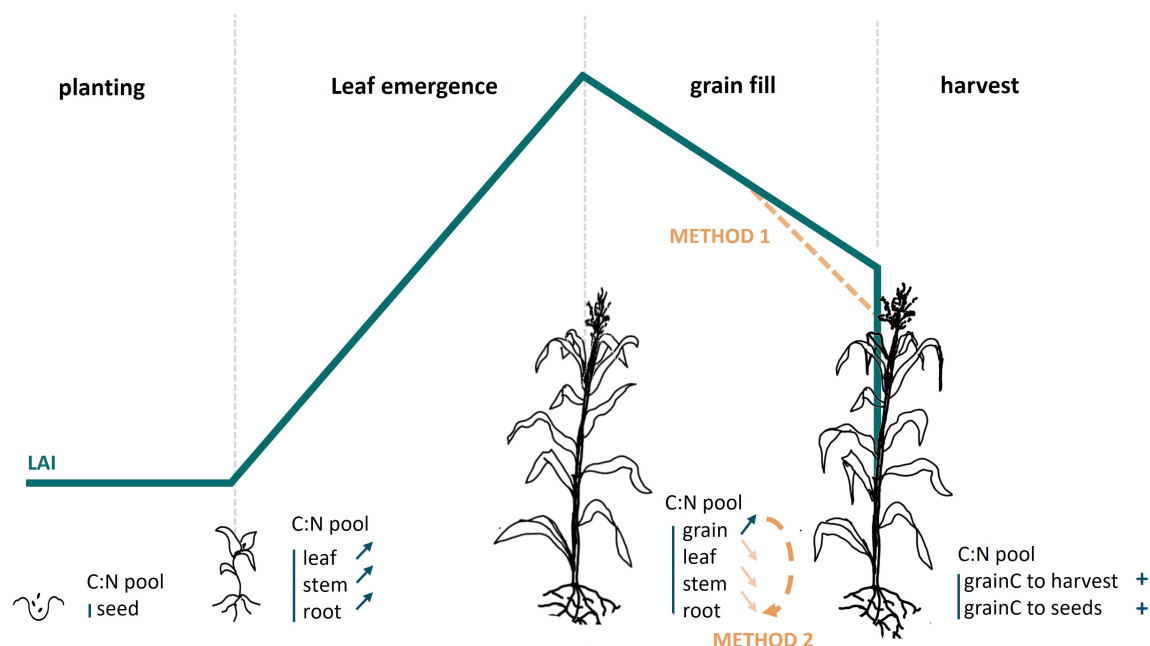


Figure 2. Schematic overview of crop development in CLM5, including the four crop stages and the carbon (C) allocation pools (leaf, stem, fine roots, grain) for each crop stage. The relation between C and N, C:N, varies between crop stage and pool and is also dependent on availability of soil N. Arrows up indicate that uptakes are increasing, while arrows down indicate a decline. The + signs in the harvest stage represent the grain carbon at the end of the crop season divided between food harvest and seeds for the new season of the crop. A schematic representation of LAI is presented with the green line and the two methods (Method 1: accelerated LAI senescence (LAI) and Method 2: reduced allocation to reproductive grains (REP)) for impacting the heat stress on the crop development are indicated in orange.

2.2.3 Vegetation temperature

For this study, heat stress is tracked using the mean daytime vegetation temperature (*DVT*)—i.e., the vegetation temperature averaged over daytime hours. This means that the number of hours varies over season and latitude. The average over the daytime hours was selected to capture persistent anomalous temperatures during a day, as opposed to short-term heat shock events, for which a maximum temperature would be more suitable.

Vegetation temperature is considered to be a more direct measure of crop heat stress compared to 2-meter (m) air temperature, as it considers the actual incoming radiation at the leaf level contributing to warming (Webber et al., 2016). During mid-summer, leaf warming from shortwave radiation is high, causing the leaf temperature to be higher than the surrounding air temperature (Jagadish et al., 2021). Siebert et al. (2014) found that air temperatures were up to 7°C lower than rye canopy temperatures at 0.5 m height in Germany, and only when 0.2 m canopy temperatures were used could the heat stress effects be reproduced. In addition, canopy temperatures consider the plants' capability of self-cooling through transpiration, which



differentiates heat stress effects on rainfed versus irrigated crops in water-limited environments. By not considering vegetation temperature, the effects of this management practice in global climate studies is ignored (Siebert et al., 2017).

180 CLM5 calculates vegetation temperature as part of the sensible heat balance by solving the Newton-Raphson iteration over vegetated surfaces, as shown in equation 4:

$$-S_v + L_v(T_v) + H_v(T_v) + \lambda E_v(T_v) = 0 \quad (4)$$

where T_v is vegetation leaf temperature, S_v and L_v are the solar radiation and the net longwave radiation absorbed by vegetation, respectively; H_v and λE_v are the sensible and latent heat fluxes from vegetation, respectively; and λ is the latent heat of
185 vaporization, with a value of $2.501 \times 10^6 \text{ J kg}^{-1}$. For further details on the calculation procedure, the reader is kindly referred to chapter 2.5 of the CLM5 technical note (Lawrence et al., 2018).

To ensure that CLM5 modeled T_v falls within reliable ranges, an evaluation was done against satellite-based land surface temperature (LST) from ESA's Climate Change Initiative (CCI). This was done by comparing monthly modeled skin temperature ($TSKIN$), which is highly correlated to T_v (Fig. B1) with ESA-CCI LST. The evaluation is described in Appendix B.

190 2.2.4 Heat stress trigger and intensity

T_{crit} is a fundamental parameter of the heat stress function, but the definition for T_{crit} lacks consistency in literature. For example, Deryng et al. (2014) summarizes T_{crit} values from nine different studies, which for wheat varied between 22–27°C, while other studies reported much higher critical temperatures for wheat, around 34°C (Lobell et al., 2012; Heinicke et al., 2022; Zhao et al., 2019). These inconsistencies in literature are based on a two-fold problem. First of all, crop sensitivity to
195 heat is not constant over the growing season, but varies per crop stage (Poudel et al., 2023; Luo, 2011). The second issue is the lack of consideration of regionally-varying crop cultivars and their specific heat tolerance, which is flagged as a major limitation in global crop modeling studies by Gbегbelegbe et al. (2017) and Kachapur et al. (2023). Gbегbelegbe et al. (2017) therefore argues for crop representation that is parameterized based on the environment within which crop types contain relatively homogeneous cultivars due to climatological and ecological similarities.

200 Two approaches were tested to define the minimum and maximum temperatures for heat stress. In the first approach, experiments were run with different combinations of T_{crit} (23–35°C) and T_{max} (45–50°C). These values remained constant over space and between CFTs. In the second approach, the definition for T_{crit} was based on variations in regional growing season climates with associated crop cultivars. This was done by keeping track of the highest value of the daytime mean vegetation temperature (i.e. only considering daylight hours), and is referred to as the *peak vegetation daytime temperature*, i.e. DVT_{peak} . This was tested in two separate ways, i) by tracking DVT_{peak} during the entire growing season, and ii) by only
205 tracking DVT_{peak} during the grain fill stage. For both approaches, DVT_{peak} was tracked for the first five simulated growing seasons for each individual CFT (1980–1985). From the second growing season on, the DVT_{peak} was compared at harvest timestep to the DVT_{peak} of the previous year, in which only the lowest of the two values was saved. This means that, out of the five growing seasons, T_{crit} is based on the CFT-specific peak daytime vegetation temperature which occurred at least once
210 every year. Note that the onset of a heat stress event requires three consecutive days in which T_{crit} is exceeded, and only during



the grain fill stage. To keep the thresholds of T_{crit} and T_{max} within realistic boundaries for this second approach, minimum and maximum values of DVT_{crit} are set at 23°C and 45°C, respectively. This DVT_{peak} approach was designed to include the local climate in defining the temperature threshold while minimizing the impact on the model computation time and memory. As the values of T_{crit} in this approach vary spatially, so should T_{max} . Colder, temperate climates have a larger variability in seasonal temperature, while growing seasons are longer to achieve the growing-degree-days to maturity (GDD_{mat}) compared to the subtropics and tropics (see Appendix C). This means that the warmest temperatures are often reached within a specific window during the year. For the climates in the subtropics and tropics, DVT_{peak} temperatures are less variable over the growing season, while for some warm climates temperatures can easily reach the absolute crop tolerance of 45-50°C (Appendix C). In this study, the range between T_{crit} and T_{max} is assumed largest in cold-climate growing seasons and narrows with increasing temperature, as shown in Fig. 3. Warmer growing-season climates have a steeper slope between minimum and maximum heat stress compared to temperate regions. The maximum possible value for T_{max} was assumed here at 49°C, meaning that above this threshold, full stress would be applied regardless of location or CFT.

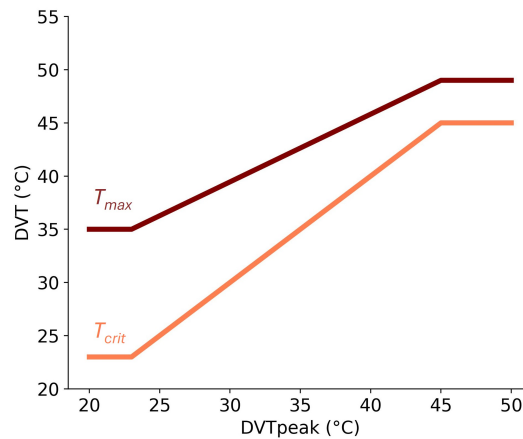


Figure 3. Heat stress threshold values of DVT for T_{crit} (orange) and T_{max} (dark red) per DVT_{peak} value, as implemented in the heat stress function of Eq. 3.

2.2.5 Heat stress crop module workflow

The heat stress functions are described in a new module `CropHeatStress.F90`, and tested in a working version of CLM5 (CTSM Development Team, 2024), with git release tag `ctsm5.2.019`. The new module contains three main functions related to heat stress occurrence, duration and intensity.

The heat stress factor is initialized with zero impact—i.e., $F_{heat} = F_0$ (method 1, $F_0 = 1$; method 2, $F_0 = 0$). Only when conditions of steps 1 (tracking) and 2 (onset) are met does F_{heat} increase. The steps are as follows:

- 1. Tracking:** The crop vegetation temperature (DVT) is checked at the end of each day during the crop growing season.



230 **2. Onset:** a Heatwave (HW) can be *true* or *false* and is initialized as *false* (no HW). The onset of a HW (i.e. HW= *true*) occurs when the number of consecutive days in which DVT exceeds T_{crit} is three.

3. Duration: When conditions for tracking (1) and onset (2) are met, heat stress is initiated, meaning that F_{heat} will start to impact LAI senescence (method 1) or carbon allocation (method 2), depending on the experiment. The magnitude of F_{heat} is defined by the linear function shown in Eq. 3. F_{heat} and HW days are tracked throughout the entire growing season for
235 each crop type, but can only affect the third crop stage (between grain fill and harvest), i.e. the leaf senescence mechanism or carbon to grain allocation mechanism.

4. Reset: When DVT falls below DVT_{crit} , the HW days will be reset to 0 and F_{heat} will be set to its initial value again (i.e., no heat stress).

2.3 Experimental set-up

240 The experiments were run at a spatial resolution of 1.9° latitude x 2.5° longitude for the period of 1980-2014. Each experiment and the control run used an initial file that was based on an 1850 initial conditions file and ran up to the year 1980. From the 35-year simulation period, the first five years served to compute DVT_{peak} . The results were therefore only analyzed for the years 1985-2014. CLM5 was run in historical mode, considering transient crops. The land surface and land use changes (e.g. crop cover) in CLM5 are derived from LUH2 (Hurtt et al., 2020). The default reanalysis data of the Global Soil Wetness Project,
245 phase 3 v1 (GSWP3v1) were used to force the meteorology (Dirmeyer et al., 1999, 2006; Kim, 2017). Implementations affect all crops, but only four actively-managed crops were evaluated: maize (temperate and tropical), wheat, soybean (temperate and tropical) and rice. Heat-stress intensity increases with temperature, while impacts will be more significant as the heat stress prolongs.

For each method, six experiments were done, considering two different processes - calculation of DVT_{peak} and magnitude
250 of $F_{x_{heat}}$ - that affect the applied heat stress, and can be seen in Table 1. The LAI1-LAI6 experiments refer to method 1 and REP1-REP6 refer to method 2. The first process is DVT_{peak} , which defines the value for T_{crit} based on the peak temperature tracked over five seasons. In the first three experiments, DVT_{peak} is tracked during the entire crop growing season (*GS*) while in the last three experiments, DVT_{peak} is tracked only during the crucial grain fill stage (*GF*). So for *GF* the value for DVT_{peak} is tracked only during the part of the growing season during which the heat stress is considered. Note that a range of
255 absolute values (23°C - 35°C) for T_{crit} were also tested for both methods, but these experiments produced unrealistic results, which are outlined in section 3.1, so analysis focuses primarily on the DVT_{peak} method of calculating T_{crit} .

The second tested process in the experiments concerns the magnitude of applied heat stress, $F_{x_{heat}}$. The linear heat stress function of section 2.2.4 is applied to both methods, but as the two methods vary in the way heat stress impacts the crop, i.e. accelerated LAI senescence or reduced grainC allocation, the magnitude of the applied stress must be tested separately as well.
260 For method 1 (LAI senescence) the multiplication factor of heat stress implies that F_{heat} must be larger than 1, but does not have an upper limit. For the second method (reproductive carbon to grain allocation), possible values of F_{heat} are between 0 and 1 (inclusive). For each of the two methods, a group of experiments were held with three different values for $F_{x_{heat}}$, and



therefore various degrees of heat stress magnitude. For method 2, a maximum value for Fx_{heat} is set to 0.9 to always allow some carbon to go to the grain pool.

Table 1. Parameter values used in the sensitivity experiments.

Method 1: LAI experiments			Method 2: REP experiments		
Experiment	DVT_{peak}	Fx_{heat}	Experiment	DVT_{peak}	Fx_{heat}
LAI1	GS	5	REP1	GS	0.3
LAI2	GS	15	REP2	GS	0.6
LAI3	GS	25	REP3	GS	0.9
LAI4	GF	5	REP4	GF	0.3
LAI5	GF	15	REP5	GF	0.6
LAI6	GF	25	REP6	GF	0.9

265 2.4 Model evaluation

2.4.1 Evaluation data

ESA-CCI Land Surface Temperature

Land surface temperature (LST ; K) was used for evaluation of modeled skin temperature $TSKIN$ from the ESA-CCI Moderate Resolution Imaging Spectroradiometer (MODIS) on Earth Observing System – Terra version 3.0, which is available for
270 the years 2000–2014 (Ghent et al., 2022). This dataset provides LST at spatial resolutions of 0.01° , which were rescaled to match the CLM5 resolution using area-weighted averaging with the Climate Data Operator tool (CDO; Schulzweida, 2023). Only gridcells that include at least 5% cropland and are 100% land were considered. In addition, only data in which temperatures were at least 278.15 K (5°C) for both datasets were included, to exclude the effect of frozen soils and snow. Finally, to minimize the effect of bare soils, the data were filtered to include only months in which modeled LAI was above 0.2. There
275 was no filtering on quality flags. The LST data were provided for daytime (10 a.m.) and nighttime (10 p.m.) separately. These were averaged to obtain the mean LST for the $TSKIN$ analysis in Appendix B.

The same regridded LST dataset was used to assess the anomalous monthly temperature during years in which heat stress was triggered in section 3.1. For this analysis, daytime LST was used, as it is more consistent with the modeled daytime vegetation temperature (DVT). For this evaluation, the number of years in which simulated heat stress was triggered at least 5
280 days in the month were identified and for these years the monthly LST anomalies were evaluated, over the period of 2000–2014, divided over standard deviation (i.e. the Z score). If for a specific year more than one month was identified as heat-stressed, the mean LST anomaly was taken over those months to represent the monthly anomaly of that year. Note that simulated heat-stress can only occur during the simulated grain fill stage.

Downscaled FAO gridded yield dataset

285 Yield simulations for heat-stressed years were compared against global annual statistics from the FAO, which includes har-



vested area, production and yield, at country level, starting at 1961. To allow for a gridded spatial analysis, the dataset from Lombardo et al. (2020) was used, in which the country-level FAOSTAT data were downscaled using the observed crop distribution and yield data from Earthstat (<http://www.earthstat.org/harvested-area-yield-175-crops>). This dataset contains 10-km spatial resolution production, harvest and yield data for 175 crop types for the year 2000 (Monfreda et al., 2008). The Earthstat-FAO dataset was available at 0.9° spatial resolution and needed to be aggregated to the modeled 1.9x2.5°, which was done with the remapping tool of the CDO software, which considers area-weighted aggregation. The yield was derived by first computing the sum of the crop production and area over the aggregated new gridcell, and then dividing the production over the area per crop. An important adjustment was done for crops in the Southern Hemisphere, where growing seasons for these crops can overlap the new year. A problem with reference annual yield data is that recorded harvest might relate to the sowing year instead of the harvest year, while CLM5 records the harvest in the year where maturity is reached. Additionally, simulated crop growing seasons contain a significant uncertainty, and the end of season might not always match the reality. Crops in which the simulated end of the growing season commonly overlaps into the new year were therefore identified. If the CLM5 grain fill stage occurred at the start of a new calendar year, between January 1 and February 28 and shifting the FAO yield a year up gave an improved Pearson yield correlation of $R > 0.3$, the shifted FAO yield data was used. The areas in which this was applied are indicated in the resulting maps for transparency.

2.4.2 Yield evaluation

The simulated yield (t ha^{-1}) was derived using the annual grain carbon to food output (GRAINC_TO_FOOD_ANN, $\text{gC m}^{-2} \text{yr}^{-1}$) and the conversion method described by Rabin et al. (2023). This conversion assumes the harvestable food grain carbon to be 45% of the total dry weight (Monfreda et al., 2008), a harvest efficiency of 85% (Kucharik and Brye, 2003), and a conversion from dry to wet biomass considering crop-specific dry matter fractions. Since the Earthstat-FAO yield data does not distinguish between irrigated and rainfed crops, the CLM5 irrigated and rainfed CFT yields for the same gridcell had to be merged. This was done by first calculating the CFT-specific production using the crop area map and dividing the sum of production per crop over the crop area sum. Only data with a presence of at least 10 years for both the simulated and reference dataset were considered. One thing to note is that in this version of CLM5, all wheat is planted as spring wheat. This can create additional bias between simulated and reference wheat yields in regions where winter wheat dominates.

The focus of this study is on extreme temperature events, requiring the differentiation between anomalous and non-anomalous growing seasons in terms of temperature. The GSWP3v1 reanalysis forcings were used to assign days in which the maximum air temperature T_x exceeded the 95th percentile, as computed using the temperature climatology between 1985-2014, with a 5-day moving window. Anomalous temperatures were masked on a minimum value of 28°C and on occurrence during the heat stress-affected grain fill crop stage in CLM5. This was done to analyze the impact of the crop heat stress implementations and exclude the effect of discrepancies between simulated and actual growing seasons. The final temperature mask considers anomalous temperatures (95th percentile) that would occur for at least 5 consecutive days during the grain fill stage, in combination with negative yield anomalies of the reference Earthstat-FAO dataset. In the results, temporal comparisons between

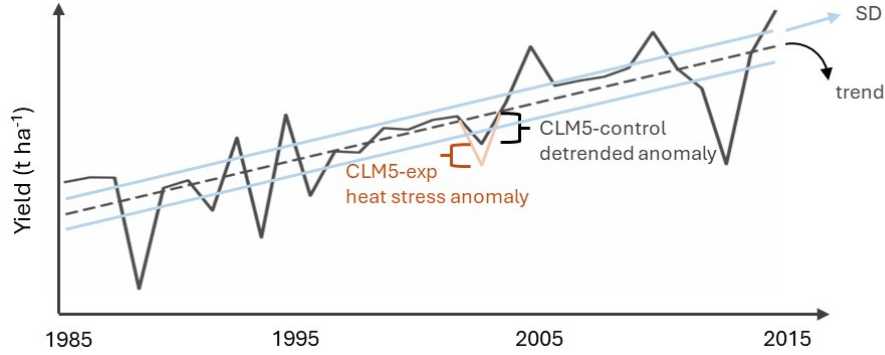


Figure 4. Meaning of different yield terms explained. The solid black line shows the actual yield values and the yield trend is indicated as a hatched line. Detrended yield anomalies are the difference between the absolute yield and the trend for that year. The black caption shows the meaning of 'detrended anomaly', referring to the difference between the control run and trend. The orange caption shows the meaning of difference in yield (Δ yield), between the control run and the experiment considering heat stress impacts. The standard deviation (SD) is used to obtain standardized yield anomalies in Eq. 7, as it normalizes the peaky behavior of the crop yields which can be more extreme for the reference or the model.

experiments and reference yield include this mask. For figures showing yield data for specific years, this temperature mask was not applied, but instead locations are indicated where this condition holds using area hatching. Performance metrics, such as Pearson's correlation (R) or root mean square difference (RMSD), of which the equations can be found in Appendix A, always consider all years.

Throughout the analysis, different yield terms are used of which an explanation is given in Fig. 4. The absolute yield difference ($t\ ha^{-1}$) refers to the difference between the experiment and the CLM5-control run, which was needed to assess the impact of the individual experiments on the modeled yield. The relative yield difference is calculated as the absolute yield difference divided by the control yield ($\Delta Y_{exp}; \%$), following Eq. 5

$$\Delta Y_{exp,i} = \frac{Y_{exp,i} - Y_{control,i}}{Y_{control,i}} \times 100\%, \quad (5)$$

where $Y_{exp,i}$ is the yield for year i and $Y_{control,i}$ is the yield in the control run for the same year.

The yield analysis focuses on anomalies rather than absolute yield data. To compare the CLM5 run with Earthstat-FAO yield anomalies, the standardized detrended yield anomalies (SYA; Eq. 7) were computed. This was done by first detrending the yields, as can be seen in Eq. 6, to exclude long-term effects, by fitting a polynomial function of two degrees, which was preferred over a linear function after some reference yield trends showed a decline for some years, followed by a steady increase. The detrended standardized anomalies were then computed by dividing the detrended anomaly over the temporal standard deviation (SD) of the residuals (after subtracting the yield). This was needed to harmonize the magnitude of temporal



variability between simulated and reference yield. By normalizing over the SD, it becomes clear how anomalous a year was compared to other years.

$$residual_i = yield_i - trend_i \quad (6)$$

$$SYA_i = \frac{residual_i - \overline{residuals}}{SD_{residuals}} \quad (7)$$

where $residual_i$ is the detrended yield residual (anomaly) for year i used to derive SYA_i for the same year, in which the mean of the residuals ($\overline{residuals}$) is subtracted from $residual_i$ over time, which should be nearly 0. In statistical terms, SYA equals the Z score. $SD_{residuals}$ is the standard deviation of the residuals over time.

3 Results

3.1 Triggered crop heat stress

Figure 5 shows the number of years in which a heat stress event was triggered during the grain fill stage over our 30-year period under three different definitions for T_{crit} : first by an absolute threshold of $DVT = 30^\circ\text{C}$ (DVT_{30} ; Fig.5a), and two based on peak vegetation temperature DVT_{peak} , in which T_{crit} is specific for the climate and CFT, as described in section 2.2.4. In Fig. 5b, DVT_{peak} was tracked during the entire growing season (DVT_{peakGS}), whereas in Fig. 5c, it was only tracked during the grain fill stage (DVT_{peakGF}). Figure 5a highlights the problem of using a single temperature threshold for all climates. For subtropical and tropical regions, a heat stress was triggered every year, while in temperate climate regions (North America, Europe, Russia, and northeast Asia) this T_{crit} threshold heat stress is simulated to occur 1-5 years out of 30, or none of the years in the uppermost latitudes. When changing T_{crit} to different constants of DVT in the range of $23\text{--}35^\circ\text{C}$ (not shown), this problem remained, only the boundary between all-year occurrences and no-year occurrences would shift north or south, depending on lower or higher T_{crit} values. Figure 6 shows the median (a) and maximum (b) duration of heat stress events for different locations, grouped per heat stress frequency over the simulation period. For the experiment with a constant T_{crit} threshold of 30°C , we see that the group where heat stress occurs (almost) every year also contains the largest number of heat-stressed days—for some regions even the entire grain fill duration—which would lead to extreme heat stress impacts on yield every year.

Using DVT_{peak} to define T_{crit} (Fig. 5b & c) reduces the number of triggered years significantly over the domains that were triggered each year in Fig. 5a, most notably in the Global South and lower- to mid-latitudes. In the high-latitude domains, for which constant T_{crit} simulated no heat-stressed years, heat stress becomes triggered in the frequency of 1-5 times out of 30 years. For DVT_{peakGS} , the majority of heat stress frequencies remain below 6, with higher-frequency hotspot regions in Mexico, the western USA, and southwestern Asia. The Southern Hemisphere now contains an opposite pattern, in which many regions in Africa and South America have no triggered heat stress events during the entire simulation period. This is most

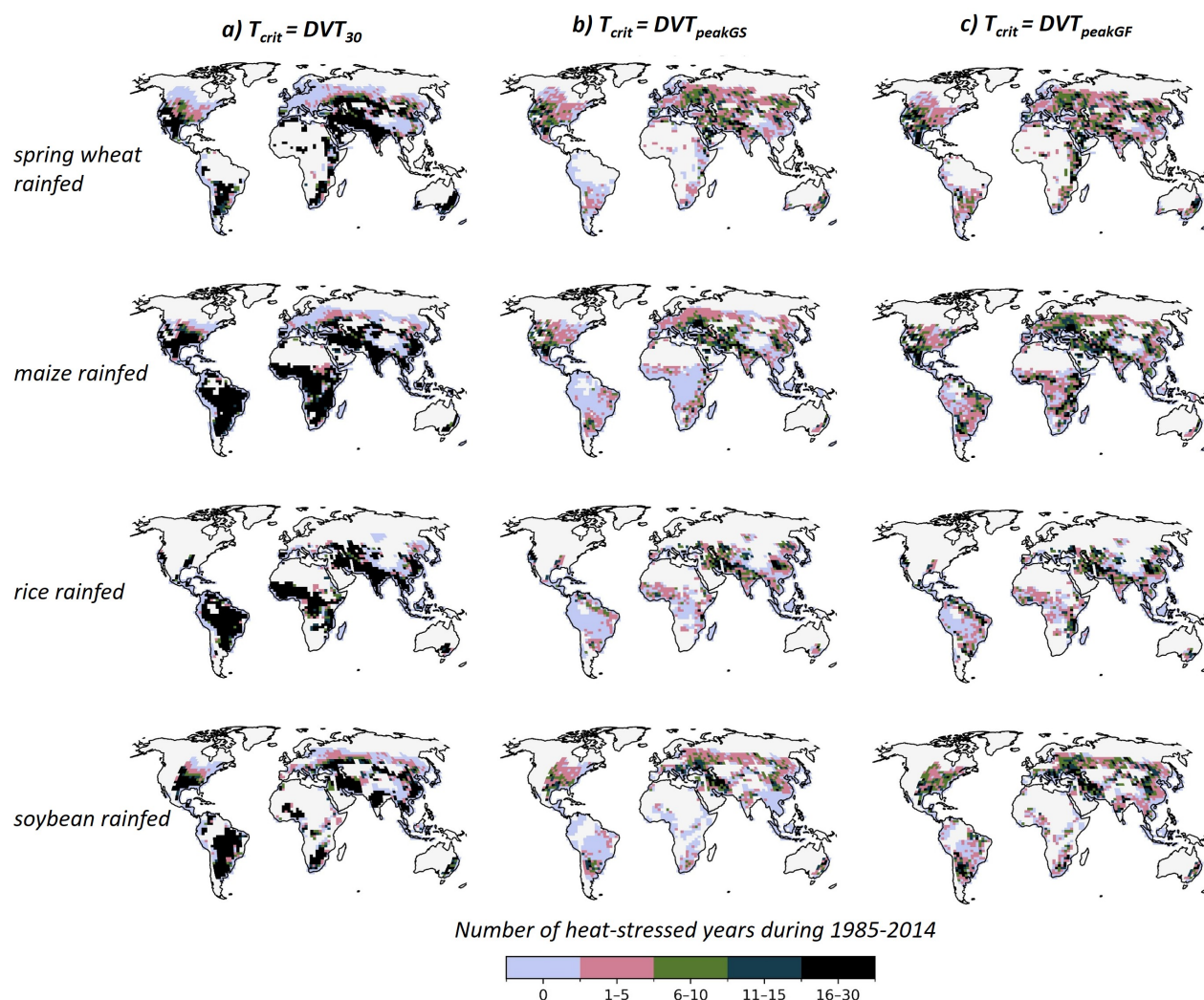


Figure 5. Simulated frequency of heat-stressed year occurrences for rainfed crops, in which a heat stress event was initiated for more than one day during the grain-fill crop stage, during a 30-year period (1985-2014) for the rainfed crops spring wheat, maize, rice and soybean (rows) and for three different T_{crit} values a) 30°C , b) DVT_{peakGS} and c) DVT_{peakGF} . White areas show no crop grown, light blue areas indicate the crop is cultivated but there were no heat-stressed years simulated for the entire period, and black areas show that heat stress was triggered for every simulated year. Note the unequal bins for the number of years on the colorbar.

likely related to temperature peaks occurring in an earlier growing season stage, leaving the grain fill phase mostly unaffected. This becomes more clear when we compare Fig. 5b and c, in which the DVT_{peakGF} results in more occurrences of heat stress in those same regions. With DVT_{peakGF} this also results in an overestimation of heat stress event occurrences, such as the western Sahel, southeastern Africa, and some regions in northeastern and southern South America. Overall, heat stress frequencies



increase, as can be seen by the increase in green and black areas compared to DVT_{peakGS} over all continents and for each
 370 crop. In terms of heat stress duration (Fig. 6), simulated periods in regions with heat stress occurrences of less than 20 out of
 30 years commonly have no more than ten days of heat stress, while this duration increases with each HW frequency group,
 indicating that for regions where heatwave frequency is overestimated, the duration is often overestimated as well. This increase
 is more visible for the maximum number of heat-stressed days per location (Fig. 6b). There is no strong difference in number
 of heat-stressed days between experiments with DVT_{peakGS} and DVT_{peakGF} . Both DVT_{peak} methods show a reduction in heat
 375 stress days for all categories compared to the constant T_{crit} threshold of 30°C, even during an unrealistically high heat stress
 frequency of >20 years.

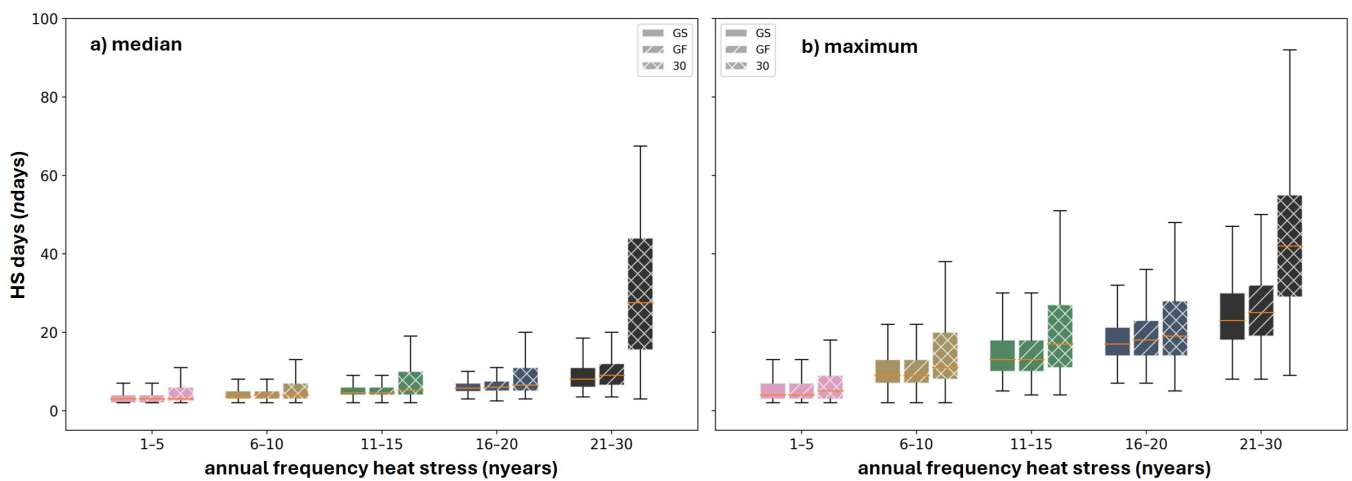


Figure 6. a) Median and b) maximum amount of heat-stressed days per growing season, grouped per frequency of heat-stressed year occurrences in years over the 30-year simulation period of 1985-2014, for three different settings for T_{crit} : T_{crit} of 30°C ("30"), T_{crit} of DVT_{peakGS} ("GS"), and T_{crit} of DVT_{peakGF} ("GF"). Note the difference in number of years of the categories on the x-axis.

Figure 7 shows the LST-CCI temperature anomalies for the years in which simulated heat stress was triggered for at least
 five days within a calendar month, following the same T_{crit} thresholds as in Fig. 5. Note that in the model implementation,
 initiation of heat stress requires at least three sequential days of T_{crit} to be exceeded. The resulting anomalies are calculated
 380 over the period 2000-2014. Since for DVT_{30} , most locations in the Global South experience heat stress every year in the
 simulation, the LST-CCI SD anomalies are naturally close to 0°C (Fig. 7a). High positive LST anomalies of more than 6°C
 correspond to the few domains in the Northern Hemisphere for which heat stress frequencies were simulated between 1–6 out
 of 30 years. The other two experiments show an increase in positive LST anomalies, most notably for the Northern Hemisphere.
 The mid- and low-latitude regions become only slightly more positive. The strongest positive anomalies are visible in Eurasia
 385 for maize and soybean of +4°C. Rice shows no strong anomalies for any global threshold, but increase for a small region in
 southern North America (> 4°C)(Fig. 7b) and (Fig. 7c). There are also regions in sub-Saharan Africa and west Asia which
 remain close to 0°C. This matches with overestimation of heat stress event occurrences, as can be seen in Fig. 5, indicating that



it likely also resembles more the mean LST anomaly instead of outliers. This effect likely comes from very high vegetation temperatures during the entire growing season due the warm climates of those regions, in combination with the mean growing season temperature being around the upper limit of T_{crit} that was set at 45°C (Appendix C).

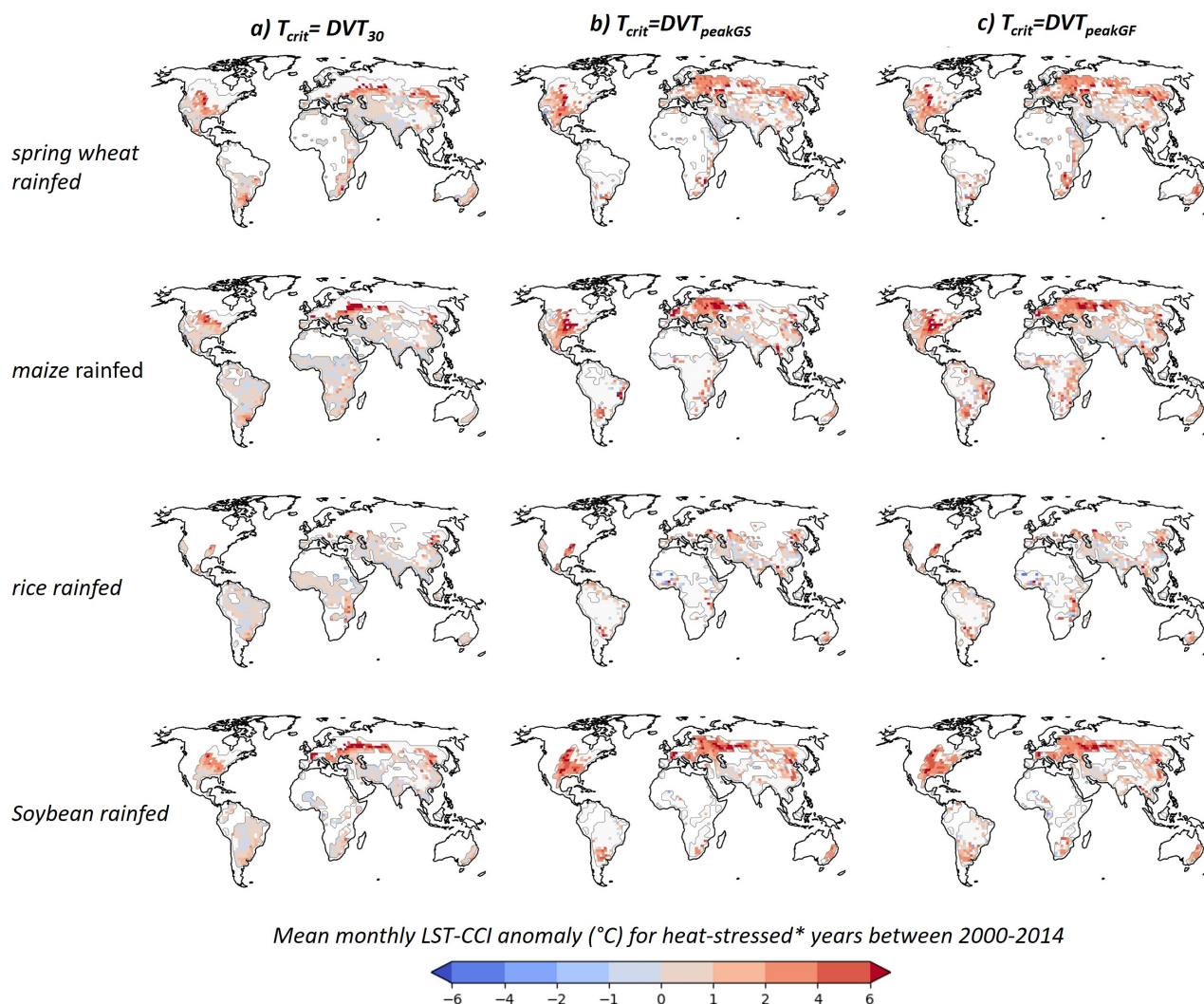


Figure 7. Mean $LST - CCI$ anomalies in (°C) for years in which at least one month experienced modeled heat stress of more than five days in the calendar month and during the grain-fill crop stage of rainfed crops, calculated between the years 2000 and 2014. The experiments presented in Fig. 5. The inland contour-lines in the maps show the crop area extent, which contain a light off-white color in case of no data.
*Note that the threshold number of five heat-stressed days in a month was used here, since the reference LST-CCI data is in monthly means.

Since the T_{crit} threshold is specific to the plant type, not only different crop types but also rainfed and irrigated CFTs of the same crop have their individual thresholds. Figure 8 shows the difference in number of heat-stress occurrences between



rainfed and irrigated crops for the same location, where zero differences between rainfed and irrigated heat-stressed years have been excluded. The largest difference can be observed for the method where T_{crit} is the same between irrigated and rainfed crops, which highlights the cooling effect of irrigation on DVT temperatures during warm periods in line with the effects on air temperature (Thiery et al., 2017, 2020; Yao et al., 2025). As opposed to the constant T_{crit} , for the DVT_{peak} experiments the T_{crit} value is no longer equal between irrigated and rainfed crops, but based on historical vegetation temperatures, which are usually lower in warm season for irrigated crops compared to the rainfed crop for the same location. The effect between irrigated and rainfed crops therefore reduces. Despite the fact that the DVT_{peak} threshold for irrigated crops still show overall reduced heat stress occurrences, for some cases there are more heat-stressed years simulated in irrigated crops than rainfed crops. This is most notable for maize and in the West Sahel (not shown).

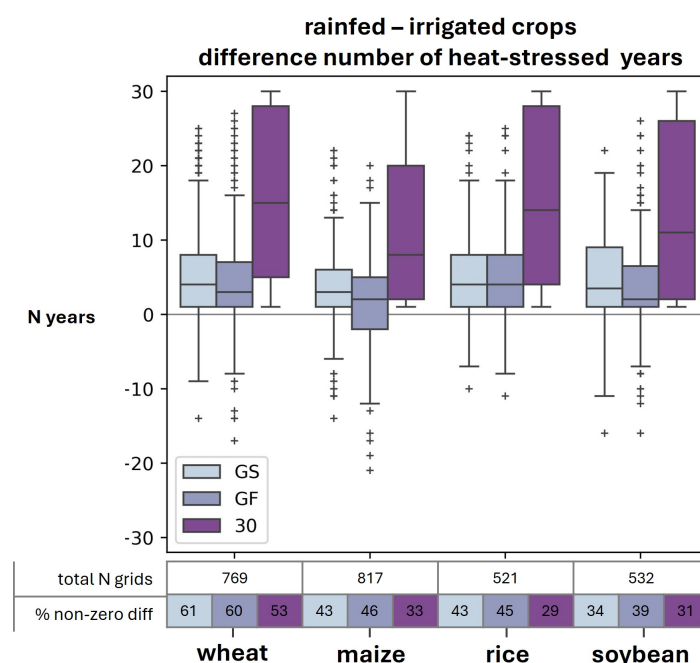


Figure 8. Non-zero differences in heat-stressed years between rainfed and irrigated crops, in number of years over the total simulation period (30 years), for the same experiments as in Fig. 6. Plus signs (+) show outliers. The table below shows the total number of locations (gridcells) in which rainfed and irrigated crop co-occur and the percentage of those pixels in which the difference between rainfed and irrigated heat-stressed years are not zero (valid gridcells used in boxplots).



3.2 Yield

3.2.1 Model accuracy

The 12 different experiments (Table 1) of the two different heat stress impact methods—accelerating LAI (LAI) and reducing the reproductive carbon to grain allocation (REP)—were evaluated in terms of impact relative to the CLM5-control run. To get a better understanding of the impacts in warm years and compare the model to reference data, the Earthstat-FAO yield data and experiment modeled yield were filtered on years with anomalously warm maximum daily air temperature during the grain fill stage (95th percentile), while also containing negative Earthstat-FAO yield anomalies. This was necessary for two reasons: (i) to highlight the impact on yield during the "extreme" years that are of most interest, and (ii) the implemented changes can only impact yield during the grain fill stage. An analysis considering all years would reduce the impact of the implementations strongly for the majority of locations, making seemingly no significant difference. The change in Pearson's correlation coefficient (ΔR) for example for maize between the SYA for all years of the experiments and the control run with Earthstat-FAO data, remained within ± 0.01 for 55-97% of the pixels (not shown), with the higher impact experiments (e.g., 3 and 6) causing larger differences. Similarly, between 63% and 98% of pixels contained an SYA $\Delta RMSD \leq 0.01$ considering all experiments (not shown). This doesn't mean that there were no significant changes in R or RMSD, as can be seen in Appendix D and E. Especially for maize, R and RMSD improved mostly over the Northern Hemisphere. For the LAI experiments, some areas in the Southern Hemisphere improved, whereas for other areas performance deteriorated, most notably in central Africa. For experiment REP6, there are also some stronger changes in wheat in west Asia. For REP6, the smallest changes are found for soybean, whereas for LAI6, wheat and rice were minimally impacted (see Appendix D and E).

Figure 9 shows the relative difference in yield from the CLM5-control run for the anomalous warm years for which the reference SYA Earthstat-FAO data is negative, i.e. lower than normal yields. The differences in SYA between the CLM5-control run and Earthstat-FAO are shown on the outer right plots. The evaluation with CLM5-control show that the mean simulated wheat for these years are in good agreement with the reference data, but the range in SYA for individual locations is still between 2 and -2, in which the CLM5-control shows less negative impact on yield anomalies in Europe but a more strong negative impact on yield anomalies in North America and Asia, for the selected years. The largest differences between the CLM5-control run and Earthstat-FAO data are found in maize and rice crops. The relative yield difference between the experiments and the control run clearly reflect the variation in applied maximum heat stress, where the most clear impacts are seen in LAI6 and REP6. For maize, the LAI experiments simulate stronger yield reduction in South America than in the Northern Hemisphere, while for the REP experiments, the largest impacts are found in Europe. Similarly, the impacts on rice are most notably in South America for the LAI experiments with some outliers, while for the REP experiments mostly Asia is impacted. The yield impact on rice is overall stronger for the LAI experiments. The SYA difference plots between CLM5-control and Earthstat-FAO do not show a clear regional pattern in overestimated SYA, whereas the impacts from the experiments are more strongly grouped by region. The experiments of the first method seem to have more impact in Asia and Europe, whereas for the second method, there is a substantially stronger impact on yield reduction for Europe. The largest impact for the experiments of method 1 is on soybean in East Asia and North America, whereas for method 2 this is on maize in

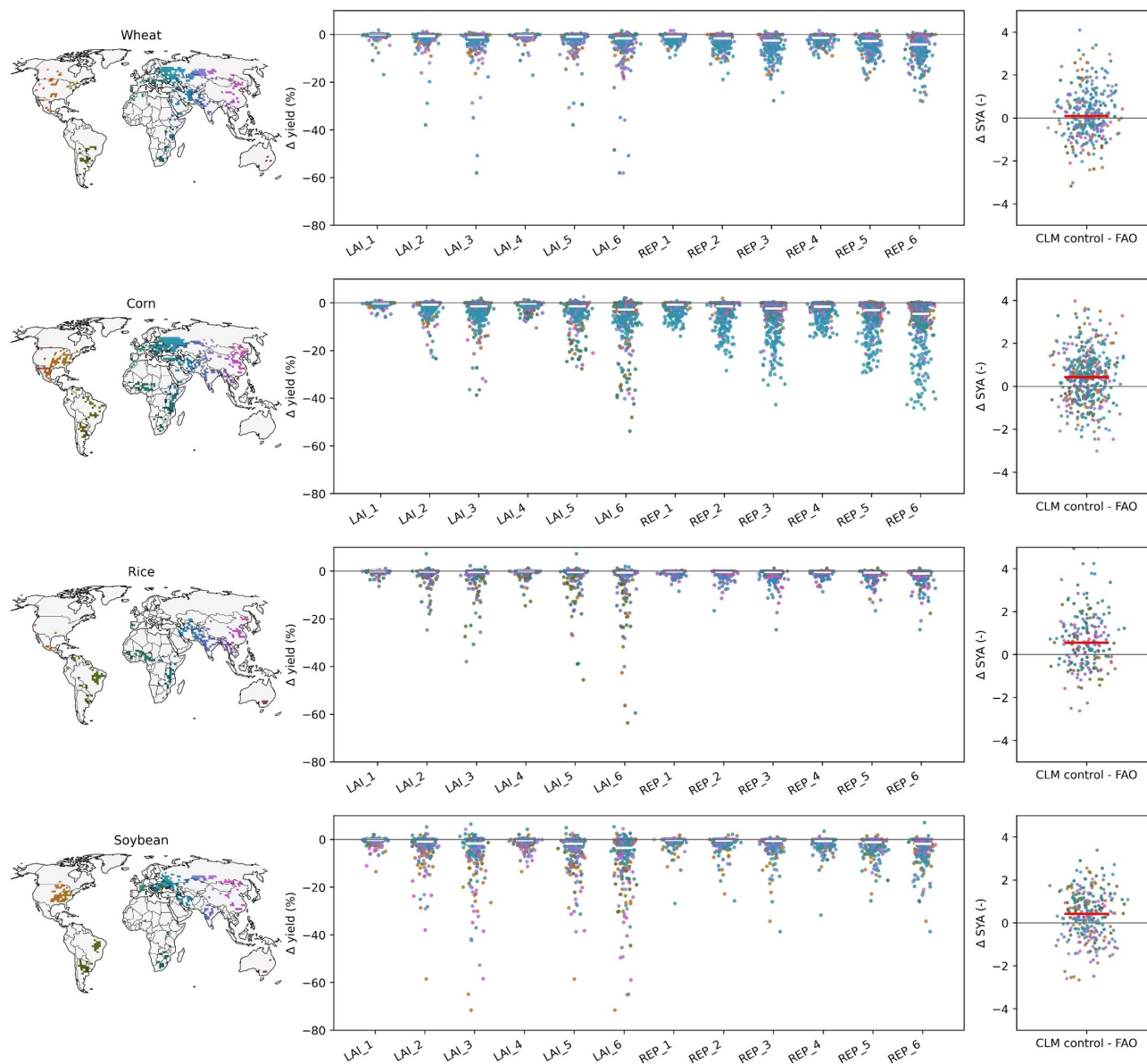


Figure 9. Mean relative yield difference plots (%) between each CLM5 experiment and CLM5-control run for anomalous warm years (air temperature in the 95th percentile for five consecutive days) during the grain fill stage that coincide with negative SYA (-) values of Earthstat-FAO data for these years. The right boxplots show the mean difference in SYA (-) between these filtered years. The colors indicate the location as shown on the maps on the left.

Northern Eurasia. For method 2, there is a clear difference between reduced yields for maize compared the other crops, whereas for the LAI experiments, all crops contain some extreme impacts. For the experiments of method 2, the impacts on rice and



soybean are lower compared to the LAI experiments. For each crop and experiment, there are some positive yield differences, which indicates that for some years and locations, the experiments simulate higher yields with the heat stress implementations compared to the CLM5-control run.

3.2.2 Heat stress impacts

To better understand how the two methods perform for specific events, we focus on years during which severe heatwaves occurred that significantly affected crop production. Figure 10 shows the SYA for CLM5-control and Earthstat-FAO for the European heatwave of 2003 and the Russian heatwave of 2010. The relative yield differences for experiments LAI5 and REP5 with the CLM5-control run are shown on the left panels, to highlight the areas with the most significant impact compared to CLM5-control. The two panels on the right show the SYA for the CLM5-control run and the Earthstat-FAO reference yield dataset. In the summer of 2003, a severe compound heat and drought event took place, in which maize and wheat yield anomalies in southern Europe exceeded -4 standard deviations (Ciais et al., 2005). For the Earthstat-FAO data, the computed anomalies exceed -3 standard deviations in central and western Europe, where for maize, negative SYA also reached below -4 standard deviations. The CLM5-control run shows reduced yields over mainland Europe, which represents the combined effect of drought stress and temperature-based crop phenology (GDD-based growing season and photosynthetic activity). The affected areas generally overlap the Earthstat-FAO negative yield anomalies, but the magnitude is more variable and underestimated, especially for maize. The yield differences from the experiments of both methods shows zero to limited impact for wheat over central Europe. This is because the heatwave event did not take place during the simulated grain fill phase, as can be seen by the lack of hatched areas in Fig. 10. This mismatch in growing season may originate from the fact the growing season is strongly determined by growing degree-days, which can cause strong inter-annual variability in temperate climate regions. A model development study by Boas et al. (2021) over agricultural sites in Germany and Belgium confirmed occasional mismatches in CLM5 wheat simulations. When we look at the maize crop, we do see changes over a few hatched areas, which are minimal for method 1 but notable for method 2. In REP5, some areas have lower yields compared to CLM5-control, which were originally not showing negative SYA, indicating that some heat-affected areas are not captured by the existing effects in the model. The timeseries in these locations show that the LAI5 barely reduced absolute yield, while the REP5 experiment shows indeed a stronger decline for maize in 2003 and other years in the time series (1994, 1997, 2006, 2013).

The Russian heatwave in the summer of 2010 was a unique event, in which a flash drought in late May and early June was followed up by anomalously warm temperatures in August (Christian et al., 2020; Hunt et al., 2021). As the primary crop grown in Russia (Lioubimtseva et al., 2013), both winter and spring wheat production were especially hit in western Russia due to the timing of the drought occurred right around the wheat flowering period, causing reductions up to over 80% in the most severely hit regions, compared to the 2008-2009 growing season (Hunt et al., 2021). Despite the fact that maize is not as widely grown as wheat in western Russia, the impact was severe for all grain production, which was reduced by a third as a consequence of the event (Lioubimtseva et al., 2013).

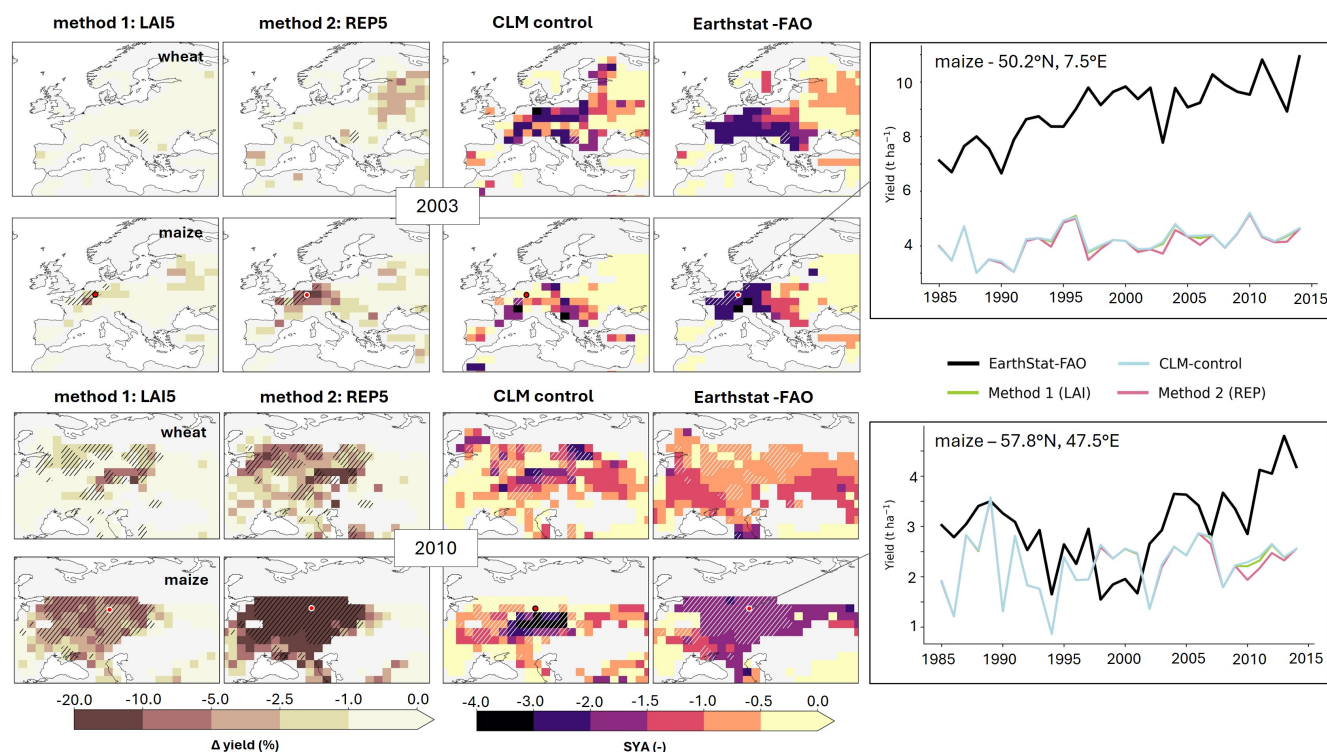


Figure 10. Yield results for two specific heat-stressed years in the Northern Hemisphere, i.e. 2003 and 2010 and for the crops wheat and maize. Images on the left: normalized relative yield difference (%), between experiment 5 for method 1 and method 2 and the CLM5-control run. Images on the right: SYA (-) for the CLM5-control run and the reference dataset of Earthstat-FAO. For both events a timeseries is shown for maize with the absolute yields of all four datasets. Location is indicated on the maps. Hatched areas show where for that year the maximum air temperature was in the 95th percentile for at least 5 days during the grain fill phase.



The Earthstat-FAO reference data for the year 2010 show indeed large-scale negative anomalies for wheat, but the magnitude of the SYA is not as strong as for maize. The CLM5-control run shows some strongly impacted regions for both crops, but with a smaller extent compared to the reference data. Relative yield impacts in experiments LAI5 and REP5 show stronger yield reductions for maize, especially for method 2. Similarly to the 2003 European heatwave, some regions that did not contain negative SYA in CLM5-control are affected with the heat stress implementation for both methods. However, there are also several regions showing strongly negative SYA for CLM5-control that are additionally impacted by the heat stress implementation.

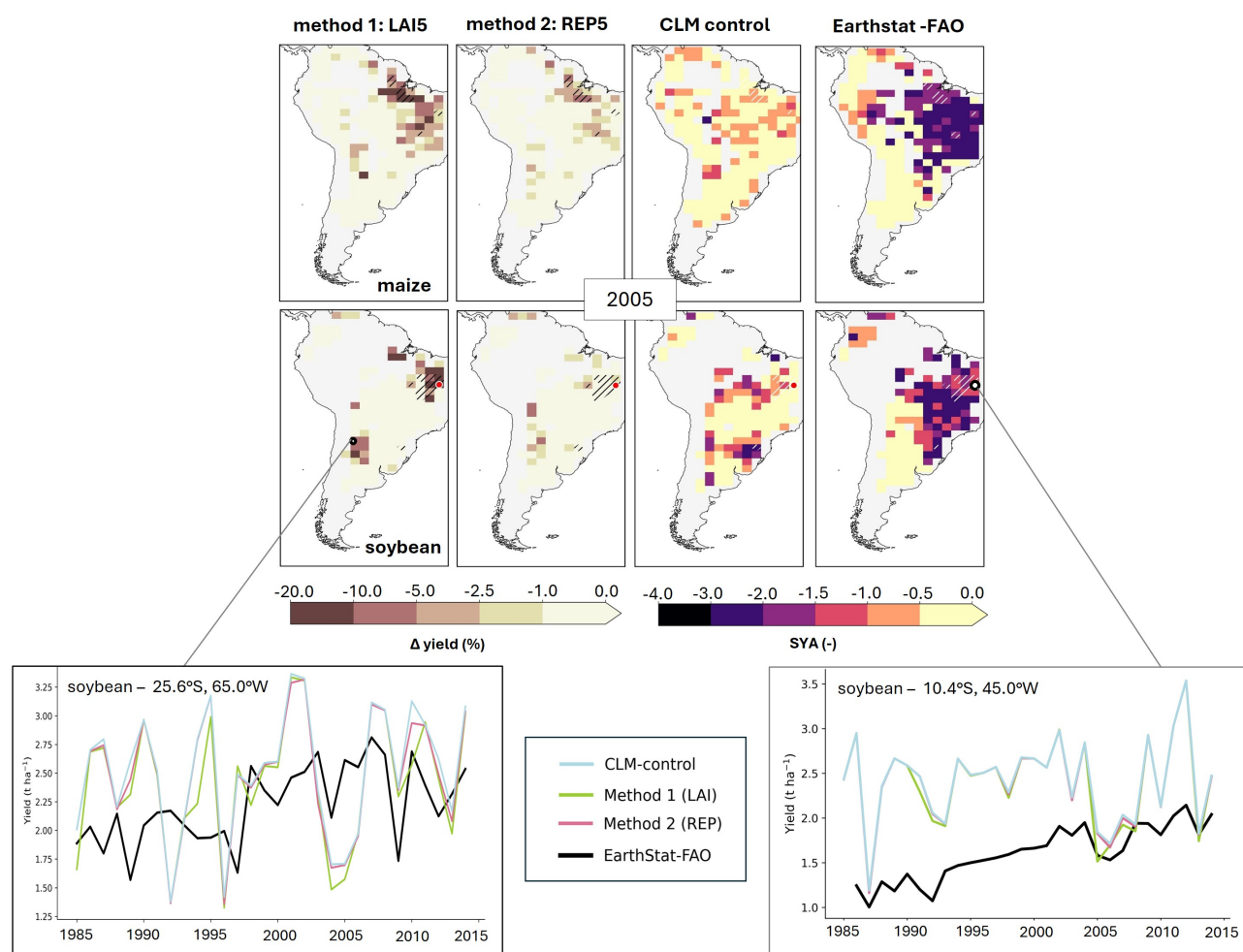


Figure 11. Same as Fig. 10, but for the year 2005 in South America, for the crops maize and soybean. Hatched areas show where for that year the maximum air temperature was in the 95th percentile for at least 5 consecutive days. Time series are shown for location 25.6°S and 65°W and 10.4°S and 45°W.



480 To zoom in on the impacts of a different climatological region, Fig. 11, shows the same maps as Fig. 10, but over South America for the year 2005. South America, especially Brazil, was hit by three consecutive drought years between 2003 and 2005, resulting in significant yield reductions (Ferreira et al., 2024). In 2005, a prolonged drought in combination with high temperatures elevated the pressure on crop production. Soybean losses in Brazil were estimated to be 75%, during a period in which canopy temperatures were 7°C above ideal conditions (Gusso et al., 2014). Figure 11 reflects the negative yield anomalies for soybean in South America of 2005 with SYA reaching lower than -4 standard deviations below the mean. These losses are not very well reflected in the CLM5-control simulations. There are also only a few regions in which anomalous air temperatures overlapped the CLM5 grain fill phase of these crops, indicating also a likely mismatch in growing season and limited potential impact by the heat stress implementations. There is a shift in impact between the two methods compared to the Northern Hemisphere, in which the LAI5 experiment shows stronger reductions relative to the REP5 experiment. The time series plot for location 10.4°S and 45°W in Fig. 11 shows a decline in yield for the CLM5-control run, and with experiment LAI5, the yield reduces further due to the heat stress impacts. For REP5, no clear impact is seen for this year. The SYA for this location is more negative for the Earthstat-FAO data (between -1.5 and -2.0 standard deviations below the mean) compared to CLM5-control (between -0.5 and 1.0 standard deviations below the mean). This effect between experiments is not specific for this location or year. A time series in Argentina (25.6°S and 65°W) for example shows a difference in impact between experiments as well, where for LAI5 yield reductions are more pronounced than for REP5.

4 Discussion

In this study, a new crop heat stress module was introduced in CLM5 and globally evaluated for four different crops. The results showed the impact of different components of the heat stress implementation on the crop representation. First of all, the definition of T_{crit} is a crucial parameter, which cannot be used as a global constant, even per crop, but also needs to represent the different agro-climatological zones. While the TV_{peak} analysis shows improvement compared to a constant value for T_{crit} , direct implementation is probably challenging because of the high dependency on the starting date of the simulation, which represents the climate of that period. This can be an advantage or a disadvantage, depending on the purpose. A threshold that is strongly defined by climatology of the first simulation years will be significantly different for simulations in other decades. Considering the change in environment over longer timescales, a shifting value for T_{crit} , in which the cultivated crops are more adjusted to their climatological zones, would be more realistic as opposed to assuming the same variety from decades earlier. If time-constant thresholds are preferred, this could be realized by including the spatially-varying parameters as model input maps, in which the CFT-specific temperature thresholds can be based on historical temperature records, agro-ecological zones and if possible, information on common crop varieties within each region. When the focus is on climate projections, transient T_{crit} values could be linked to the characteristics deciding agro-ecological zones (e.g. climatology, soil characteristics, aridity index) for different crops in literature, such as Dadras et al. (2023), which would then automatically shift in a changing climate. Despite the improvements with a spatially-varying threshold for T_{crit} , some areas were targeted by heat stress with a very high frequency, which increased when TV_{peak} was only tracked during the grain fill period. However, tracking during



the entire growing season resulted in large regions in Africa and South America in which no heat-wave events were simulated for any crop. This indicated that the warmest periods over these regions generally occur before the simulated grain fill phase. The R (Appendix D) and RMSD (Appendix E) maps of the REP6 and LAI6 experiments showed that for some regions in the Global South the performance in SYA simulations improved, whereas for other regions (central Africa and central South America), performance went down compared to the reference SYA. Due to the growing season commonly overlapping into the new year and the fact that actual planting date in these climates are more commonly linked to rainfall season instead of temperature (which is the basis for the CLM growing season stages), evaluations are extra challenging over these regions. This is combined with known inaccuracies of CLM5 simulated growing seasons and crop parameterizations (Rabin et al., 2023). In this regard, the sowing windows of later versions of CTSM (from 5.3 on) have been improved and could potentially show better results. Additionally, obtaining long-term consistent high quality evaluation data remains a challenge, especially over the Global South, where records are more sparse.

Apart from the T_{crit} threshold value, the use of canopy temperatures instead of air temperatures to define heat stress is a relatively new approach compared to existing large-scale crop heat studies. A major advantage of this approach is the differentiation between rainfed and irrigated crops in terms of heat stress sensitivity. However, when basing the critical temperature threshold on the CFT, it would be more realistic to keep the critical temperature values between rainfed and irrigated CFTs equal. The yield evaluation showed that the CLM5 control run for some regions did not contain negative anomalous yields, whereas adding the heat stress representation caused negative anomalous yields, matching the yield anomalies of the reference data. For other regions, the CLM5 control run already simulated negative yield anomalies due to hydraulic stress and high temperature limitations mostly in the form of crop phenology and physiology (GDD, photosynthesis) and became more negative after the heat stress implementations. The question therefore remains whether additive stress responses are appropriate representations of compound stress events. The impacts become stronger in warmer climates that generally already produce lower yields compared to temperate regions, and when both heat and drought stress occur, this might result in too much yield reduction.

The impact of heat stress on crops was tested with two different methods. The acceleration of LAI senescence results in a more indirect approach and had a stronger impact on yields in the Global South compared to the direct reduction in carbon to food grains, which caused more yield reductions in the Northern Hemisphere. This difference could originate from the difference in absolute LAI and subsequent yield between these regions. In regions where the maximum LAI reaches low values in general, the accelerated senescence could have a much stronger impact.

Some regions saw an increase in yield, which mostly occurred after strong heat-related yield reduction in the previous year. This effect was visible for both methods, but did not occur for the exact same years. An important part of the different implementations are its effect on the phenology, not only yield. By changing the plant processes, both the carbon and nitrogen cycles are affected. Appendix F and G show the differences in NPP and LAI for wheat and maize in experiments LAI5 and REP5. The focus of these maps is on the difference where the experiment shows higher values compared to the control run. We see that for both methods, NPP and LAI are (minimally) impacted, but that method 1's LAI and NPP values show generally larger differences from the control run compared to method 2. A possible explanation for this could be that moving more leaf carbon



and nitrogen to the soil litter, instead of retranslocating it to the grains, adds more soil nutrients for the subsequent growing season. For method 2, changes in the cycle of carbon and nitrogen are primarily caused by relocating C and N from the grains
550 to the roots, causing the root litter to increase in the soil and also providing more soil carbon and nitrogen that would otherwise be used for food consumption, which in CLM5 is simulated as a slow release into the atmosphere over the subsequent year (Lawrence et al., 2018). Additionally, there could be a secondary effect—by increasing the root C and N, the roots become larger and could take up more nutrients. However, the results show that during heat stress events, the reducing effect on the C of the grain is greater than the increase in roots. It should be noted that during the grain fill stage, less C and N are going into
555 the live stem, leaf, and root pools, as the plant is slowly deteriorating. While the reallocation of the carbon to fine roots was necessary to keep the carbon balance within the plant intact, it does not represent an actual crop response to heat. In reality, the allocation of carbon to grains does not change, but is used inefficiently, which may be better represented by increased respiration. However, the REP experiments did seem to slightly outperform the LAI experiments, therefore it could have more potential for implementation, especially if the implementation considers respiration of the lost carbon instead of reallocation,
560 thereby minimally changing the carbon cycle.

The yield in the Southern Hemisphere was especially impacted by method 1, where some regions with simulated impact caused reduced yields every year. The ΔR (Fig. D1) and $\Delta RSMD$ (Fig. E1) maps also showed that some areas, especially for maize in central Africa, did not improve with method 2. For method 2, directly impacting the grain production resulted in some improvements compared to the Earthstat-FAO dataset in the Northern Hemisphere for maize and in China for rice, but showed
565 limited impacts for wheat and soybean. This could also be related to the different simulated vs actual growing season, which is common issue with CLM5, for some regions and crops, like India (Kangari et al., 2025). Comparing the two different methods, reducing the carbon to grain showed slightly better improvements globally. Combining method 1 and 2 could also be tested in future research, in which the different methods could affect the crop at different times. In several studies, the grain production is specifically targeted during the flowering period and not the entire grain fill period (Challinor et al., 2005; Lucia Martin et al.,
570 2025; Teixeira et al., 2013). This approach was not adopted here, not only because CLM5 does not represent a flowering period, but also because the flowering period is relatively short, e.g. around two weeks, which would make the correct timing of the crop stages more crucial and difficult to evaluate. But with future improvements of CLM5, different heat stress impacts during flowering and grain filling could be considered, as was done by Peng et al. (2018) for maize at some specific locations. Other opportunities to improve heat stress representation are testing other heat stress functions, such as an exponential function, and
575 considering not only the daytime vegetation temperature, but also increased nighttime temperature and the ratio of day and night temperature, as these have proven to reduce plant functioning and yield (Jagadish et al., 2015; Narayanan et al., 2015; Saini et al., 2023).

Apart from the challenges and opportunities in the model framework, the evaluation of the implementation is equally important. The yield evaluation product that was used here is based on national yield statistics from the Food and Agriculture
580 Organization, which is the main source of annual global level yields with long historical records of multiple decades. These records are not perfect and are additionally processed from national level to a gridded map, which increases uncertainty. New crop yield datasets are being published, often with the aid of satellite data (Iizumi and Sakai, 2020; Tang et al., 2024), but they



all make use of the same FAOSTAT national yield data. In addition to the data record itself, extracting from that record specific heat-impacted events is very challenging, and other factors will always contribute to the yield anomalies. It remains unclear to what extent farm-level decisions on management, pests, and diseases are contributing to the total yield signal in national statistics. In addition, apart from heat waves occurring during the reproductive stage, there might have been other crop-damaging processes that took place earlier in the growing season. An option would be to combine yield data with extreme events from databases, such as the Emergency Events Database (EM-DAT) or Wikimpacts (Li et al., 2026). A common limitation of these data records is, however, large spatial data gaps (Jones et al., 2023).

Apart from the above-mentioned challenges in crop heat stress modeling, the simple model implementations from this study proved able to (i) identify specific heatwave events, and (ii) impact crop yields over regions that were previously not showing negative anomalies by CLM5.

5 Conclusions

In this study, functions to account for crop heat stress were introduced in the Community Land Model v5 (CLM5) and evaluated globally for the first time for four different crops, combining tropical and temperate CFTs for maize and soybean, using two different methods and a batch of parameterization experiments. In the first method, LAI senescence was accelerated causing reduced yield in tropical climate regions. In the second method, the allocation of carbon to grains was reduced, which showed to have a stronger impact on the Northern Hemisphere. Different critical threshold values for temperature were tested to define the onset of heat stress, which showed that regionally varying thresholds are necessary to accurately represent crop variety. In addition, using the vegetation temperature instead of 2m air temperature resulted in different impacts between rainfed and irrigated crops for the same location.

The evaluation showed the most impacts on maize, with improvements in standardized yield anomalies (SYA) in the Northern Hemisphere. The impacts were smaller for wheat and rice. The evaluation for specific years proved that large scale heatwave events could be captured by the implementations. To define which approach is most optimal to impact crops by heat effects, the different set-ups are to be compared in regional case studies with varying climates in future research. On the broad topic of heat stress implementations in globally gridded crop models, this study highlighted the relevance of using vegetation temperature to distinguish effects of high temperatures on irrigated vs non-irrigated crops and the use of region-specific temperature thresholds for crop heat stress as opposed to a single threshold over the globe.

Code availability. The CTSM5.2 open source code was used with git release tag 5.2.019 (CTSM Development Team, 2024). The new model code from this study is available on Github, at https://github.com/ShannonRoos/CTSM5.2_CropHeatStress and archived on Zenodo, at <https://doi.org/10.5281/zenodo.22664312> (de Roos, 2026a). The CLM5 bash execution script and Python postprocessing/visualization scripts are available on Zenodo as well, at <https://doi.org/10.5281/zenodo.22672865> (de Roos, 2026b).



Appendix A: Performance metrics

Performance metrics were computed (i) to compare modeled skin temperature to satellite-based surface temperature and (ii) compare modeled yield for different experiments with FAO standardized yield anomalies, for all years and for between CLM experiments and reference data.

Equations for root mean square difference (RMSD):

$$\text{RMSD} = \sqrt{\frac{1}{n} \sum_{t=1}^n (\text{CLM}_t - Y_t)^2} \quad (\text{A1})$$

Where N is the number of observations and Y is the reference dataset (*ESA – CCI LST* or *FAO SYA*).

Equation for Pearson's correlation (R):

$$r = \frac{\sum_{t=1}^n (\text{CLM}_{\text{exp}_t} - \overline{\text{CLM}_{\text{exp}}}) (Y_t - \bar{Y})}{\sqrt{\sum_{t=1}^n (\text{CLM}_{\text{exp}_t} - \overline{\text{CLM}_{\text{exp}}})^2} \sqrt{\sum_{t=1}^n (Y_t - \bar{Y})^2}} \quad (\text{A2})$$



Appendix B: Modeled *TSKIN* evaluation with ESA-CCI MODIS LST

CLM5 computes *TV* for each individual CFT, which allows for crop-specific heat stress. The accuracy of modeled *TV* cannot be directly verified, as there are no observational (crop-specific) *TV* datasets available. We therefore made use of the modeled skin temperature (*TSKIN*), i.e. the effective outgoing radiative temperature of the land surface, which is closely related to *TV* as can be seen in Fig. B1. Correlations between *TV* and *TSKIN* are especially close with high vegetation cover, as the influence of the soil becomes less significant (not shown). *TSKIN* can be directly compared to the satellite-based land surface temperature, *LST* from the ESA-CCI MODIS. It should be noted that the modeled *TSKIN* is based on the energy balance calculations of both ground and vegetation, and therefore influenced by the transient land cover maps that are used as model input.

The evaluation in Fig. B2 of months in which the simulated LAI was higher than 0.3, shows strong Pearson correlations (*R*) and anomaly correlations (in which the monthly means have been subtracted from the monthly data) for most of the Northern Hemisphere, which reduce at lower latitudes, but are still considered acceptable, as anomaly correlations are often still above 0.4, and RMSE values remain below 4 K. A likely contributing factor for reduced correlations at lower latitudes is the increased interference from clouds, as the ESA-CCI MODIS data has not been filtered on quality flags.

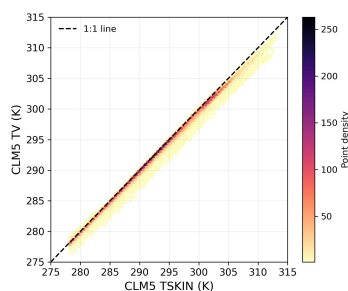


Figure B1. relation of modeled monthly vegetation temperature and skin temperature in CLM5 for the years 2000-2014.

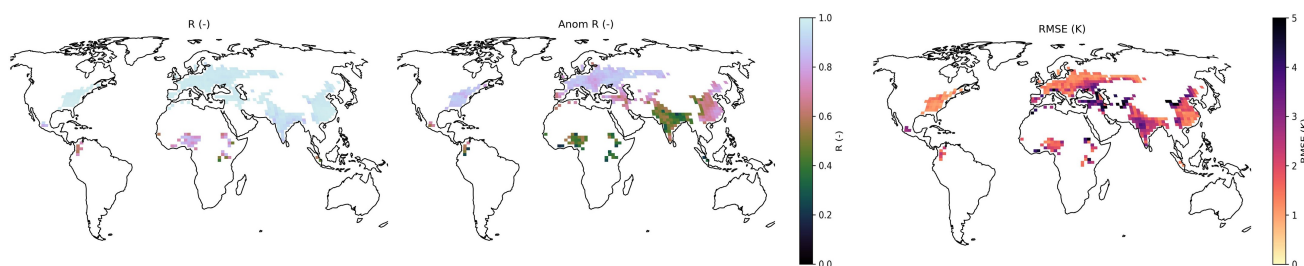


Figure B2. Evaluation of correlation (*R*; -) anomaly correlation (anom *R*; -) and root mean square difference (RMSD; K) between monthly modeled skin temperature (K) and monthly ESA-CCI MODIS LST.



Appendix C: Mean crop temperatures

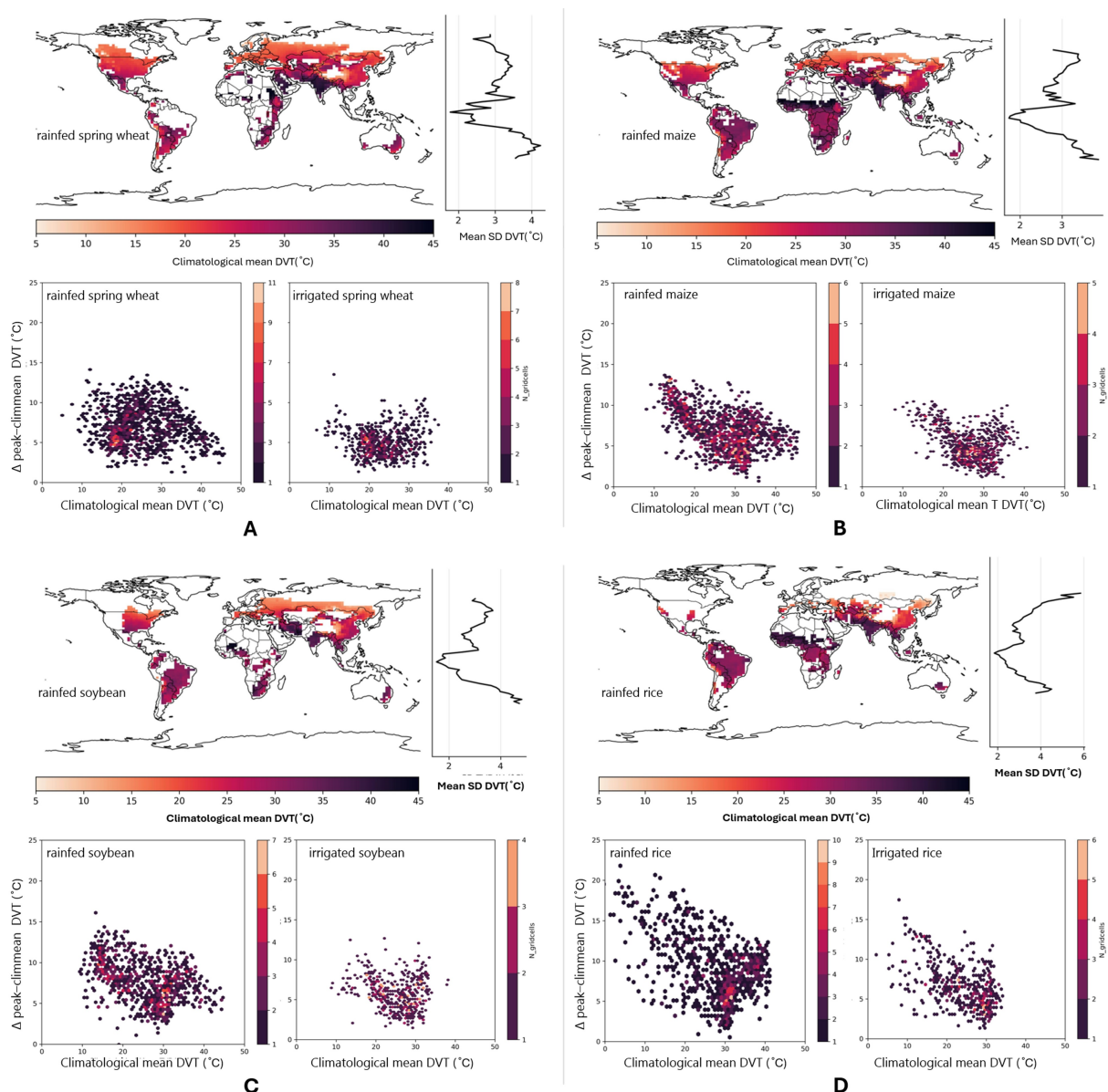


Figure C1. Modeled climatological mean of vegetation daytime temperature (DVT; °C), during the crop growing season for a) spring wheat, b) maize, c) soybean and d) rice. The scatterplots show the relationship between the climatological mean of the different locations on the x-axis, and on the y-axis, the difference peak vegetation temperature and the climatological mean. The map shows the rainfed crops, scatterplots are shown for rainfed and irrigated crop.



Appendix D: R SYA metrics experiment 6

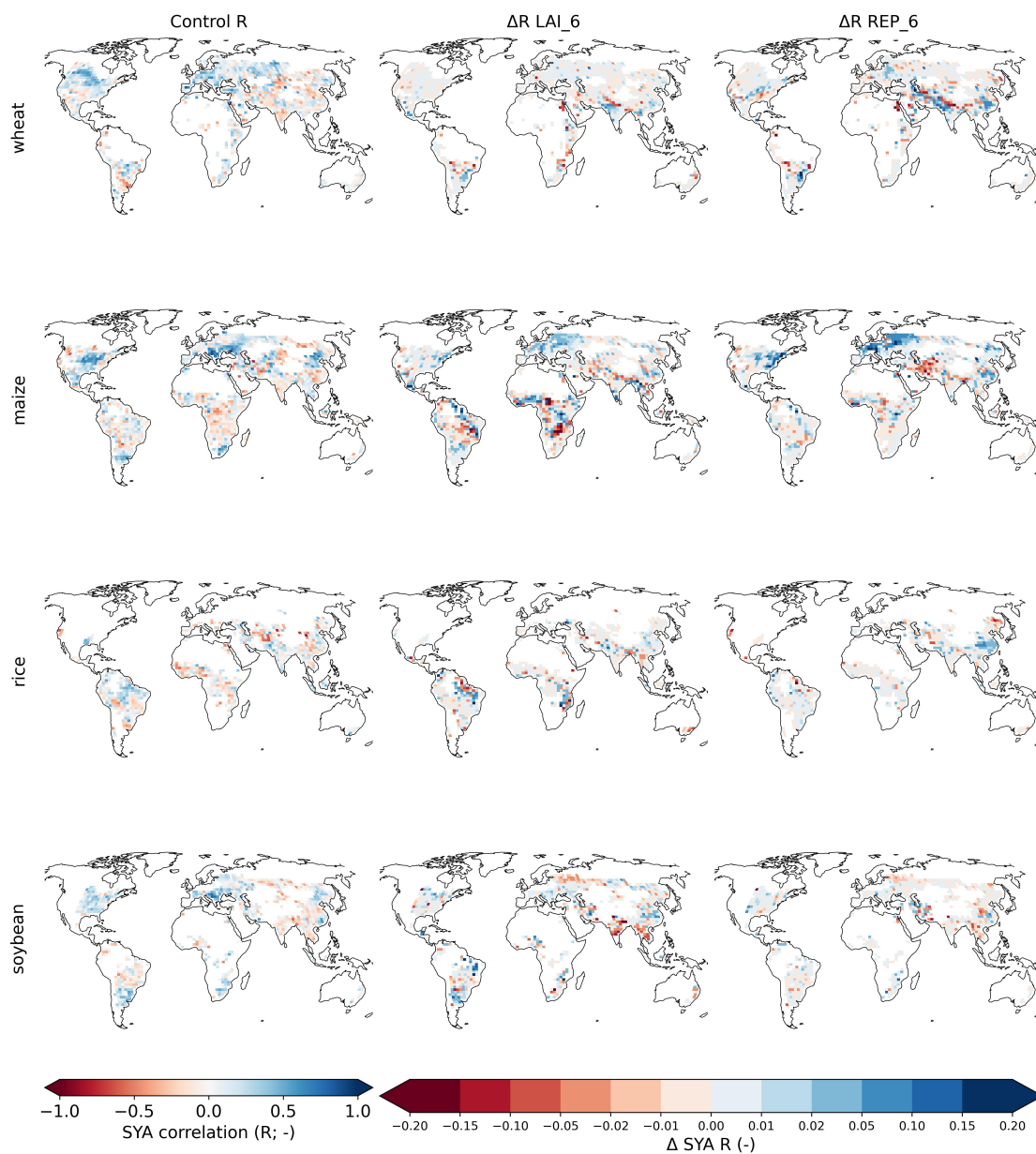


Figure D1. Left: Pearson correlations between simulated SYA of CLM5-control and Earthstat-FAO SYA ($R_{control}$). Right: R differences between experiment LAI6 or REP6 with Earthstat-FAO (R_{exp}), and $R_{control}$, where $\Delta R = R_{exp} - R_{control}$.



Appendix E: RMSD SYA metrics experiment 6

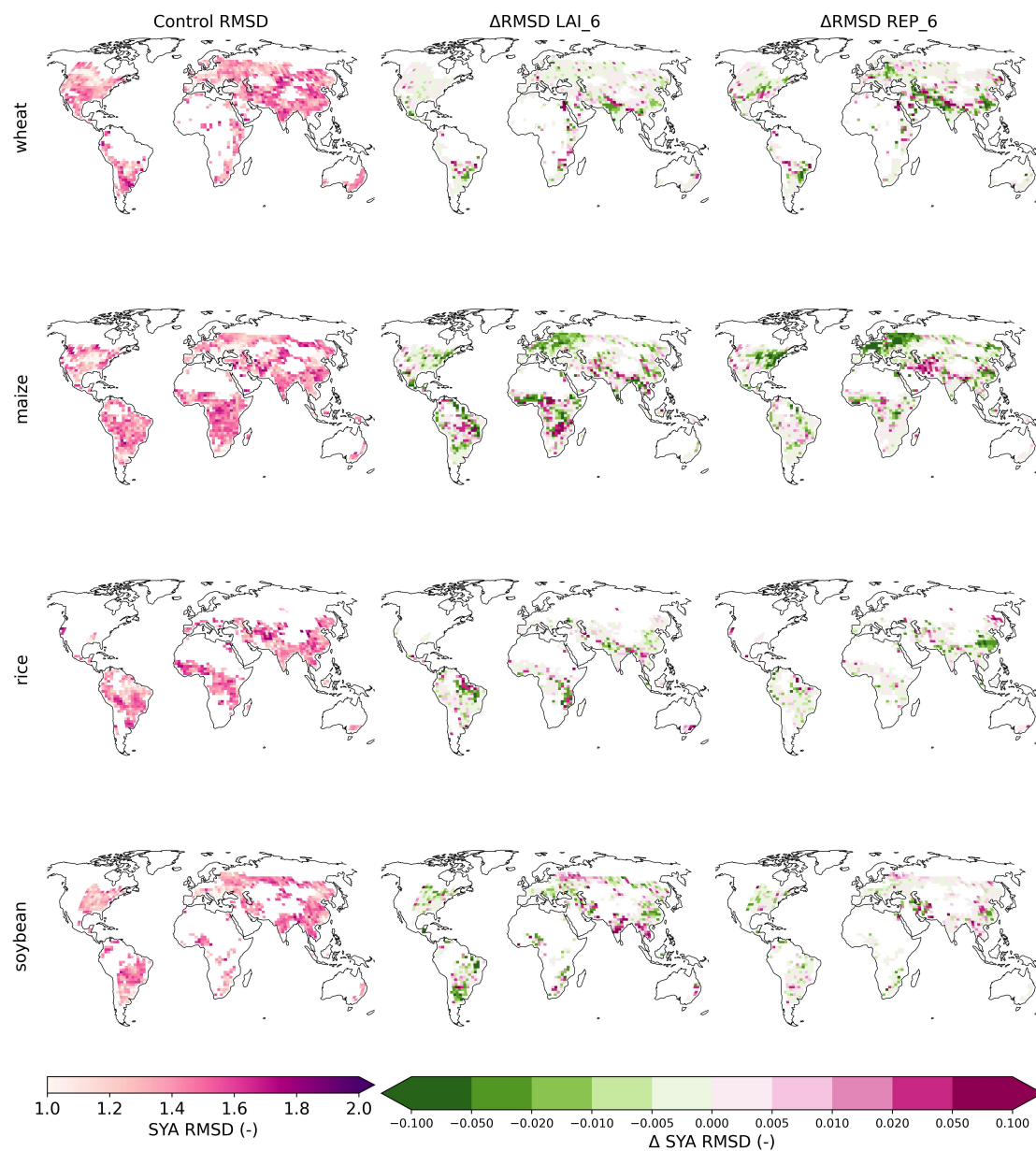


Figure E1. Left: Root mean square difference between simulated SYA of CLM5-control and Earthstat-FAO SYA ($RMSD_{control}$). Right: $RMSD$ differences between experiment LAI6 or REP6 with Earthstat-FAO data ($RMSD_{exp}$), and $RMSD_{control}$, where $\Delta RMSD = RMSD_{exp} - RMSD_{control}$.



Appendix F: NPP difference maps between experiment and CLM-control

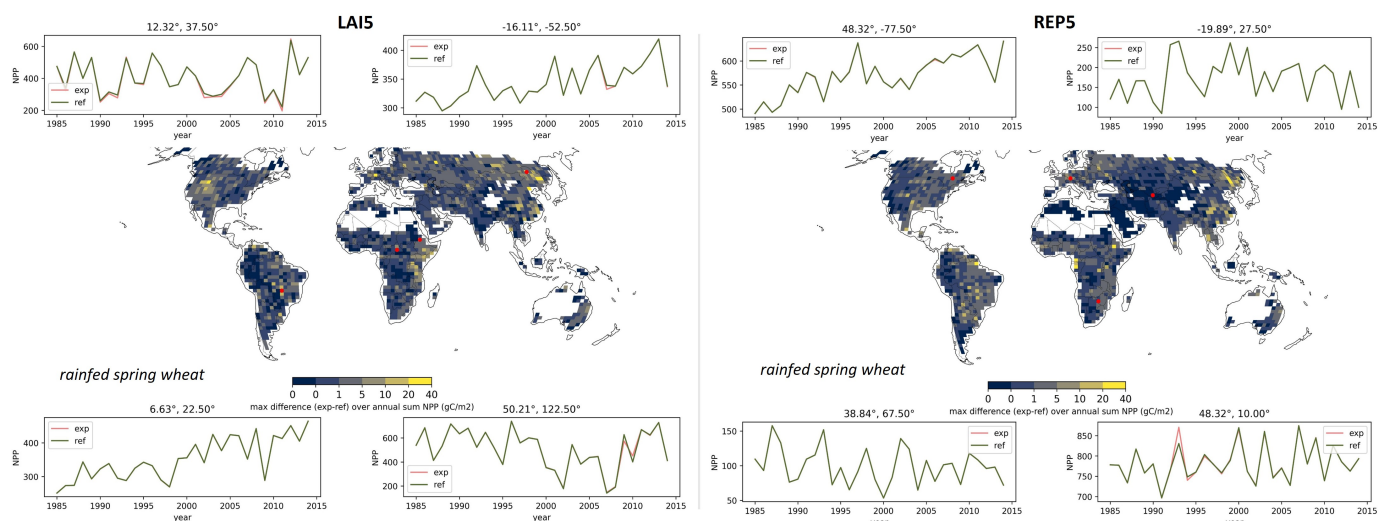


Figure F1. The maps show the maximum difference (experiment- control) in the simulated annual sum of Net Primary Production (NPP; gC m^{-2}) for rainfed spring wheat for LAI5 on the left and REP5 on the right. Each map contains four locations with time series of annual NPP sums of the experiment run (exp, LAI5 or REP5) in pink and the CLM-control run (ref) in green.

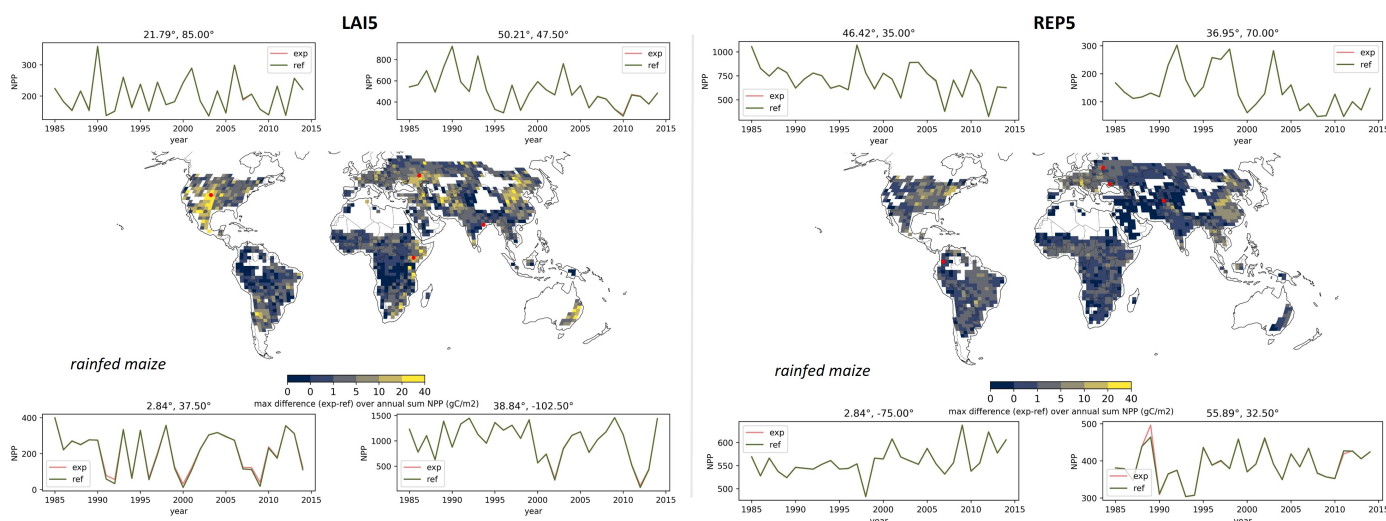


Figure F2. Same as Fig. F1 but for rainfed maize.



640 Appendix G: LAI difference maps between experiment and CLM-control

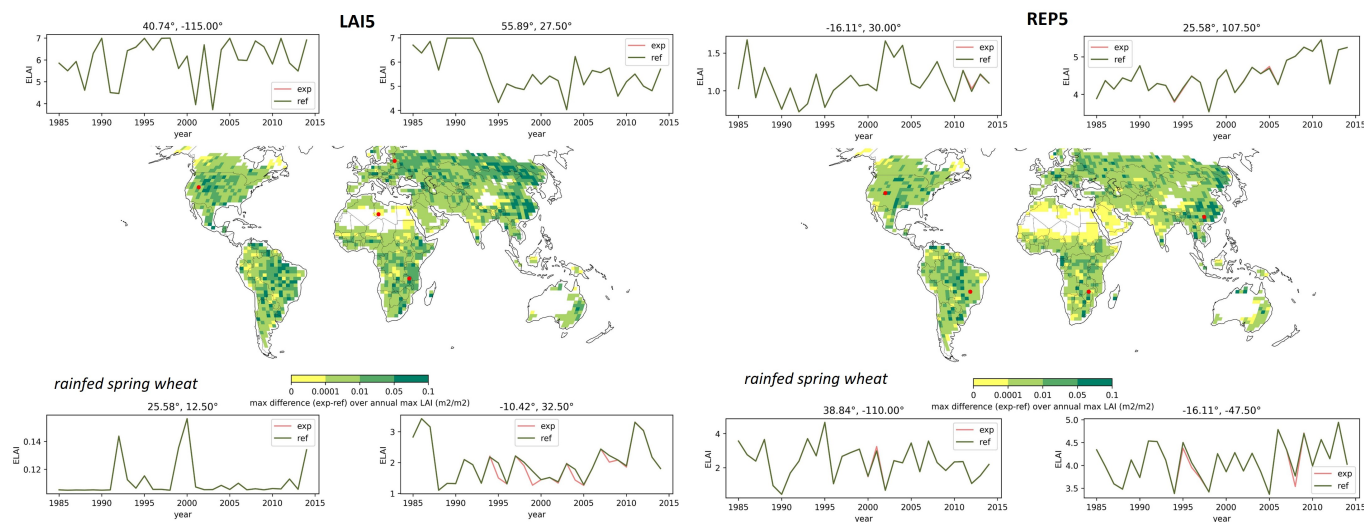


Figure G1. The maps show the maximum difference (experiment- control) in the simulated annual maximum LAI (m^2m^{-2}) for rainfed spring wheat for LAI5 on the left and REP5 on the right. Each map contains four locations with time series of annual maximum LAI of the experiment run (exp, LAI5 or REP5) in pink and the CLM-control run (ref) in green.

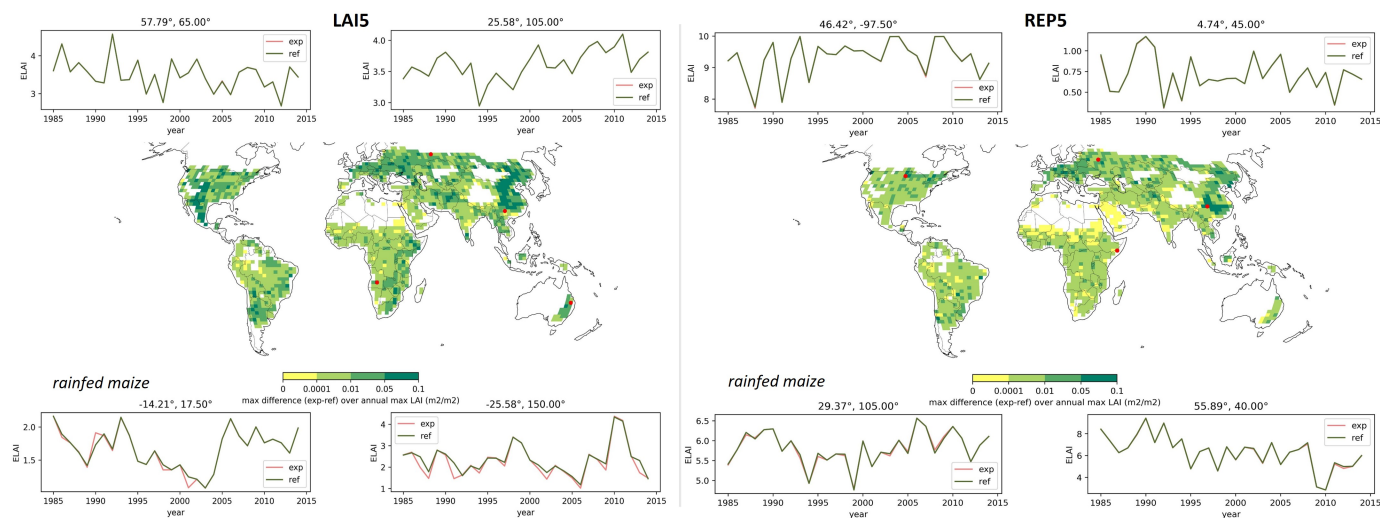


Figure G2. Same as Fig. G1 but for rainfed maize.



Author contributions. All authors contributed to conceptualization of the research. WT acquired the funding. SDR and SR wrote the heat stress model code in CLM5. SDR set up the experimental design with help from WT and SR. SDR performed the research analysis and visualization. DL provided resources for analysis. SDR wrote the paper and all authors contributed.

Competing interests. At least one of the (co-)authors is a member of the editorial board of Geoscientific Model Development. The authors
645 declare no other competing interests.

Acknowledgements. The authors would like to acknowledge the Belgian Science and Policy Office (BELSPO), for funding the research under the CropWaves STEREOIV project (grant No:SR/00/412). WT acknowledges funding from the European Research Council (ERC) under the European Union's Horizon Framework research and innovation programme (grant agreement No 101124572; ERC Consolidator Grant 'LACRIMA') and the European Union's Horizon Europe programme (grant agreement No. 101295156; 'FUTURA' project). DLL was
650 supported by National Science Foundation DISES Award 2409246 and the U.S. Department of Agriculture NIFA Award 2021-0455.

The CESM project is supported primarily by the National Science Foundation (NSF). This material is based upon work supported by the NSF National Center for Atmospheric Research, which is a major facility sponsored by the NSF under Cooperative Agreement 1852977. Computing and data storage resources on the Derecho (doi:10.5065/qx9a-pg09) supercomputer was provided by the Computational and Information Systems Laboratory (CISL, 2023) at the National Center for Atmospheric Research (NCAR). Postprocessing was done on
655 the Hortense supercomputer from the Flemish Supercomputer Center (VSC), Belgium, under the Storage4Climate project, funded by the Research Foundation - Flanders (FWO) and the Flemish Government.

We would also like to thank the steering committee members of the CropWaves project, Chiara Corbari, Jonas Jägermeyr, Juan M. Lopez, and Han Su, for their feedback on the project. SdR would especially like to thank the Land Modeling Working Group at NCAR, as they have been very helpful and encouraging during the conception of the research and welcoming during the visit at the institute.



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