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Modelling crop yield in a wheat–soybean relay intercropping system: A simple routine in capturing competition for light

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ABSTRACT

Moving from sole cropping to intercropping is a transformative change in agriculture, contributing to several ecosystem services. However, modelling intercropping is challenging due to intensive parameterisation, complex calibration, and experiment scarcity. To facilitate future understanding, design and adaptation of intercropping, it is therefore necessary to develop simple modelling routines capable of simulating essential features. In this paper, we integrated a light competition module requiring four parameters into MONICA, a generic agro-ecosystem model, with the goal of simulating a wheat–soybean relay-row intercropping system. We tested three calibration approaches using data from two years of field experiments located in Müncheberg, Germany: sole cropping-based calibration, intercropping-based calibration and a default calibration method that incorporates both systems. Under both irrigated and rainfed conditions, MONICA successfully reproduced the aboveground biomass and yield of sole crops from field experiments, with $\mathrm{RMSE_A}$ ranging from 0.64 t $\mathrm{ha^{-1}}$ to 2.74 t $\mathrm{ha^{-1}}$ and $\mathrm{RMSE_Y}$ ranging from 0.003 t $\mathrm{ha^{-1}}$ to 0.47 t $\mathrm{ha^{-1}}$. By taking light competition into account, the modified MONICA was able to simulate interactive performance in relay-row intercropping. Generally, MONICA overestimated the aboveground biomass and yield across the three calibration strategies, and simulations for wheat were more accurate than those for soybean. However, a comparison among the calibration strategies revealed that the intercropping-based strategy outperformed the others. It significantly improved the model efficiency for soybean yield in intercropping, increasing the Index of Agreement from 0.27 to 0.73, and it decreased the Mean Bias Error for yield by up to 76%. Our results demonstrate the feasibility of using a model that is simple in both calibration and inputs, yet detailed enough to simulate the complex aboveground light competition of intercropping. Additionally, they underscore the significance of cropping system specific calibration, highlighting the importance of calibrating crop performance specifically for intercropping in order to capture genotype-by-environment interactions.

1. Introduction

Due to the development of intensive agriculture, sole cropping has become the dominant system for crop production, leading to agriculture and landscape simplification (Gámez-Virués et al., 2015), and reductions in yield stability and environmental sustainability (Tigchelaar et al., 2018). Furthermore, climate change is exacerbating this situation (Arora, 2019). Out of all abiotic and biotic stressors, increases in temperature cause the most direct negative impacts on crop productivity. Every degree of elevated average global temperature causes global wheat yields to fall by 6% (Asseng et al., 2015; Zhao et al., 2017). Agro-biodiversity loss, as a consequence of intensive agriculture, has become better known (Haughey et al., 2018). The long-term selection of a limited number of favorable traits in crops has decreased the diversity of crop environmental responses to adverse weather in the past 5 to 15 years (Kahiluoto et al., 2019). This agro-biodiversity loss degrades ecosystem functions and, consequently, ecosystem services (Dardonville et al., 2022; Nyström et al., 2019). Agro-biodiversity loss hampers the restoration of soil fertility (Furey and Tilman, 2021), weakens resilience to climate extremes (Hutchison et al., 2018) and undermines biological resistance to abiotic stresses such as pests (Rusch et al., 2016) and diseases (Gaba et al., 2015). Given the tremendous adverse effects of

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agriculture intensification, calls for transformation and reformation of agriculture towards diversified cropping systems have become more urgent (Rigal et al., 2023).

Intercropping plays an important role in cropping system diversification. Intercropping refers to the simultaneous growth of multiple crop species or genotypes within the same field (Himmelstein et al., 2017; Martin-Guay et al., 2018). Benefits include increases in yield and quality potential (Dhima et al., 2014), resource-use efficiency and availability (Garrity et al., 2010; Mao et al., 2012; Xia et al., 2013) and pest, disease and weed self-regulation abilities (Florence et al., 2019; Vidal et al., 2017; Zeller et al., 2012). Intercropping can be categorised into three major types according to their morphological and phenological complexity. Type 1 intercropping systems consist of intercrops that share similar phenology and morphology. Type 2 systems are composed crop components with similar phenology but deviating morphology, while Type 3 systems feature intercrops that vary in both phenology and morphology (Gaudio et al., 2019). Alternatively, intercropping systems can be divided by their spatial arrangement. Here, strip intercropping denotes the growing of two or more species in wide strips, which are usually determined by the width of agricultural machinery, allowing separate crop management, but less interaction between species compared to row intercropping. Row intercropping entails growing crop species in narrow rows, often with 1 to 3 decimetres. Mixed intercropping, on the other hand, is defined by species randomly arranged in the field with no regular spatial pattern (Xu et al., 2020). Cereal-legume intercrops have been the most extensively investigated combination. Wheat–soybean relay-row intercropping systems have been tested in the Americas and China. In Europe, they are still poorly investigated, but considered a promising option (Lamichhane et al., 2023). With the wheat-soybean relay-row intercropping, a farmer plants soybean into a wheat crop that was established earlier (often in the previous autumn), which represents both Type 3 and row intercropping. Relay-row intercropping creates closer plant–plant interaction than strip intercropping but at different phenological stages. This system has demonstrated its potential in a field experiment in the south-eastern Pampas of Argentina, where the intercropping system overyielded sole cropping by 58% (Caviglia et al., 2011).

Intercropping can significantly improve resource capture and utilisation through resource sharing, niche complementarity, and facilitation (Brooker et al., 2015; Cardinale et al., 2012). In wheat–soybean relay intercropping, the fraction of the annual photosynthetically active radiation (PAR) capture increased from 0.24 to 0.44, as a result of the longer overall growing season and the varying canopy (Caviglia et al., 2004). In contrast to light, which often satisfies demand, water resources are usually not sufficient. Thus, it is remarkable that water capture in wheat–soybean relay intercrops was 93% higher than that of sole wheat and 68% higher than that of sole soybean (Caviglia et al., 2004). Contrasting phenologies create a temporal niche in the early growing phase for intercrops, and thus the asynchronous peak-resource demand minimises the adverse competition effects (Li et al., 2013). Furthermore, integrating a nitrogen-fixing plant such as soybean via intercropping can lead to higher crop yields and protein content in the cereal grain (Li et al., 2009; Lithourgidis et al., 2007; Nyawade et al., 2020).

While a meta-analysis of 126 intercropping-related studies highlighted the fact that intercropping increased gross energy production by 38% and gross income by 33% on average (Martin-Guay et al., 2018), the advantages of intercropping over sole cropping are not absolute (Brooker et al., 2015; Gaudio et al., 2019). The higher system complexity compared to sole crops constrains research, and experimentation on relay-row intercropping in Europe remains scarce (Hufnagel et al., 2020). Moreover, labour intensity hinders the widespread adoption of intercropping. More empirical studies are needed to help understand the mechanisms behind intercropping's success which could facilitate the adoption of the system despite its inherent complexity (Casagrande et al., 2017). In this study, we employed wheat–soybean relay-row intercropping as an example. Its spatiotemporal niche makes the use of machinery in the sowing and harvesting of mixed crops possible, cutting labour costs (Lamichhane et al., 2023). These machines are similar to those farmers would use for each of the sole crops (cereal drills for wheat and direct sowing machines for soybean), so in most cases, no further investment would be required on the part of the farmer except for specific devices to be installed on the combine harvester to harvest the wheat above the still-growing soybean crop.

Crop models have been widely used as tools for understanding processes and exploring the compound interactions among crops (Jeuffroy et al., 2014). Nevertheless, most models have been developed for sole cropping (Wallor et al., 2018). Moreover, for most existing intercropping models, competition for light is the primary concern, as crop production depends mainly on the amount of photosynthetic active radiation (PAR) intercepted (Gaudio et al., 2019). Three methods are commonly used to simulate intercropping canopy competition for light. The simplest of these is the Horizontal Homogeneous Canopy (HHC) model, which is derived from a model for the sole crop context (Monteith, 1965). The modelled canopy comprises two species instead of one and is divided into two layers according to the plant height difference between intercropped species (Tsubo et al., 2005). The PAR intercepted by the upper layer (the taller species) and in the lower layer (the shorter species) is calculated. Several existing models employ this method, including APSIM (Holzworth et al., 2014) and CROPSYST (Stöckle et al., 2003). The second method is the stripe-canopy model, elaborating on the block structure and the spatial arrangement, which allows a description of the intercrop planting configuration. This has been implemented in the M3 (Berghuijs et al., 2020) and SWAP models (Pinto et al., 2019). The third method is functional-structural plant modelling (FSPM), which accounts for system dynamics at the organ level through a sophisticated description of the 3D structure of the intercropping system (Evers et al., 2019; Vos et al., 2010). Trade-offs between model simplicity and functionality need to be balanced when integrating these approaches into simulations of intercropping systems.

When attempting to apply a monoculture-specific crop model to intercropping systems, challenges arise because genotype-specific traits might exhibit different phenotypic expressions under crop–crop interactions (Ajal et al., 2022; Pelech et al., 2023). Generally, fixed parameters after calibration are applied for one genotype under all conditions, which we refer to as default calibration in this paper. However, this potentially ignores the genotype-by-environment effect (G × E). With the awareness that using two sets of parameters for one genotype in different conditions is not common in modelling studies, we first compared the model simulation using a fixed parameter set that fits both intercrop and sole crop conditions (DC) with parameter sets calibrated specifically to sole cropping (SC) and intercropping (IC) data.

This research aims to a) enhance our understanding of essential physiological processes in intercropping systems and b) demonstrate how crop-growth dynamics in these systems can be represented in crop models. Toward these goals, a simple intercropping module has been developed and integrated into the Model for Nitrogen and Carbon in Agroecosystems (MONICA) (Nendel et al., 2011). This module is designed to assess whether considering light competition between wheat and soybean in relay-row intercropping can lead to accurate yield estimations under both rainfed and irrigated conditions. Furthermore, we assess the impact of different calibration strategies on the accuracy of model simulations for intercropping system. The evaluated strategies include both system-specific calibrations and a general calibration approach that combines data from both systems.

2. Materials and methods

2.1. Field experiment

A two-year, relay-row winter wheat–soybean intercropping experiment was conducted at the Müncheberg, Germany experimental site (52°31’N, 07°38’E) during the 2020/2021 and 2021/2022 growing seasons. The long-term annual precipitation sum was 531 mm. The mean air temperature was 8.5 °C. Two winter wheat cultivars, Moschus and RGT Reform (hereafter Reform), and one soybean cultivar, Merlin (maturity group 000), were used.

The study treatments included wheat–soybean relay-row intercropping, sole wheat, and sole soybean under rainfed and irrigated regimes (Supplementary Fig. 1). The experiment followed a split-plot approach with six replicates in a randomised complete block design. Each plot was 3 m in width and 8 m in length. The row distances for sole wheat and sole soybean were 12.5 cm and 50 cm, respectively. Soybean was cultivated between double rows of wheat in intercropping, also with a spacing of 50 cm for soybean. Site characteristics and field management are listed in Table 1. Irrigation targeted the demand of soybean. To prevent crop failure from severe drought, water was exceptionally applied to the rainfed plots on June 16th, 24th, and 28th in the 2020/2021 growing season, the irrigated plots still received more water (Table 1). Crops were managed conventionally (Supplementary Table 1).

Measurement of crop growth variables, including leaf area index, plant height and total aboveground biomass took place throughout the growing season. We used a sampling area of 12 m^2 for each plot to define the final grain yield when the crops reached their physiological maturity. Harvesting was conducted using a combine harvester with a unique header designed for intercropping (Flexxifinger). We used a linear quantum sensor (Li-Cor, Lincoln, NE, USA) to measure light interception at the ground, at the mid-canopy profile and at the top of the canopies development stages were recorded based on the BBCH scale (Meier, 2018). Aboveground biomass was sampled from 1 m^2 from the central rows of each plot (considering marginal effects), and separated into leaves, stems and spikes (pods). Soil moisture (in %) was measured by soil moisture sensor in topsoil (7 cm). We also measured soil bulk densities and inorganic nitrogen contents from three soil layers (0–30 cm, 30–60 cm, and 60–90 cm) in August, separately sampled from three replicate soil cores (Supplementary Table 2).

2.2. Model description and development

MONICA (Nendel et al., 2011) is a process-based simulation model for nitrogen and carbon dynamics in agroecosystems adapted from the HERMES model (Kersebaum, 2007). Biomass accumulation in MONICA follows the approach developed by Goudriaan and Van Laar (1978). It describes the daily totals of gross CO_2 assimilation using a set of differential equations for both closed and non-closed canopies. Dry matter production is calculated based on the photosynthesis–light response with a set of saturation levels of photosynthesis, where the actual crop photosynthesis rate is proportional to the saturation level. The optimum temperature for photosynthesis and the base temperature for each phenological stage of every crop component were determined based on previous modelling experiments conducted in Germany (Asseng et al., 2013; Nendel et al., 2013; Battisti et al., 2017; Kothari et al., 2022a, 2022b; Nendel et al., 2023) (Webber, et al., 2018a,2018b) (Supplementary Table 3). The model describes the daily crop photosynthesis under clear and overcast skies, classifying crop leaves into “sunlit” and “shaded” to account for unequal light distribution. This allows the fraction of interception (F) to be determined (Eq. 1), where the light extinction coefficient is fixed at 0.8. By multiplying the fraction of light interception and defining crop photosynthesis under clear and overcast skies, the model gives the overall photosynthesis of a non-closed canopy. For a closed canopy, the daily total is the multiplied product of day length, maximum photosynthesis and leaf area index (LAI).

Table 1
Site characteristics and field management information in 2020/2021 and 2021/2022.

Year	2020/2021	2021/2022
Soil texture	St3[a]	St3
Sand content	72%	68%
Clay content	20%	24%
Silt content	8%	8%
Sowing date, wheat	18 November 2020	14 October 2021
Sowing date, soybean	6 May 2021	29 April 2022
Harvest date, wheat	11 August 2021	21 July 2022
Harvest date, soybean	27 October 2021	17 October 2022
Amount of irrigation	120 mm / 50 mm	230 mm

a. Soil texture according to the KA5 (Eckelmann et al., 2005) Soil Texture Classification System. St3 refers to medium clayey sand

$$F = 1 - e^{-0.8 \times \mathrm{LAI}} \tag{1}$$

The effects of water deficit, heat, nitrogen deficiency and aeration deficit are also included in the model, reducing the estimations of biomass growth and yield formation. The model also considers data recorded at daily intervals on soil temperature, moisture, organic matter turnover, nutrient uptake and transport for the effect of these variables on soil conditions. MONICA thus requires crop and soil parameters, crop management information and weather data for calculation (Nendel et al., 2011). This study implemented the HHC sub-model described by Tsubo and Walker (2002) to couple with MONICA (Fig. 1) to represent the intercropping systems. To describe the wheat–soybean relay-row intercropping system, we divided the canopy into two layers according to the height difference between the two species. In this study, winter wheat was the taller species and soybean was the shorter species. However, since soybean may exceed the height of wheat in lateral stages, this definition will change over time. Therefore, in the model description, we refer to the taller species and shorter species to avoid conflicts. The upper canopy layer only consists of the taller species. The understory layer compose of the shorter species and the lower part of the taller species, as follows:

$$\eta = \frac{PH_S}{PH_T} \tag{2}$$

$$LAI_{T1} = (1 - \eta) \times LAI_T \tag{3}$$

$$LAI_{T2} = \eta \times LAI_T \tag{4}$$

η is the ratio between the plant height of the shorter species and the taller species. LAI_T is the total leaf area index (LAI) of the taller species. PH_S and PH_T are the plant heights of tall and short crops, respectively. Then LAI_{T1} is the LAI of the taller species in the upper layer canopy, while LAI_{T2} is the LAI of the taller species in the lower layer. Thus, the fraction of intercepted photosynthetically active radiation of the upper layer (F_{T1}) is defined as:

$$F_{T1} = 1 - e^{-k_T \times LAI_{T1}} \tag{5}$$

Therefore the PAR intercepted by the upper layer of the taller crop (I_{T1}) is the total available PAR multiply the F_{T1}:

$$I_{T1} = I_0 \times F_{T1} \tag{6}$$

where k_T is the light extinction coefficient of the taller species derived from the field experiment. The fraction of the intercepted PAR by the taller species and the shorter species in the second layer (F_{T2} and F_S) is described as follows:

$$F_{T2} = \frac{k_T \times LAI_{T2}}{k_T \times LAI_{T2} + k_s \times LAI_s} \times \left(1 - e^{-k_T \times LAI_{T2} - k_s \times LAI_s}\right) \tag{7}$$

$$F_s = \frac{k_s \times LAI_s}{k_T \times LAI_{T2} + k_s \times LAI_s} \times \left(1 - e^{-k_T \times LAI_{T2} - k_s \times LAI_s}\right) \tag{8}$$

Since the total light reaching the lower layer is constrained by the first layer of taller plants, we calculated the actual PAR interception by the lower layer as follows:

$$I_{T2} = I_0 \times (1 - F_{T1}) \times F_{T2} \tag{9}$$

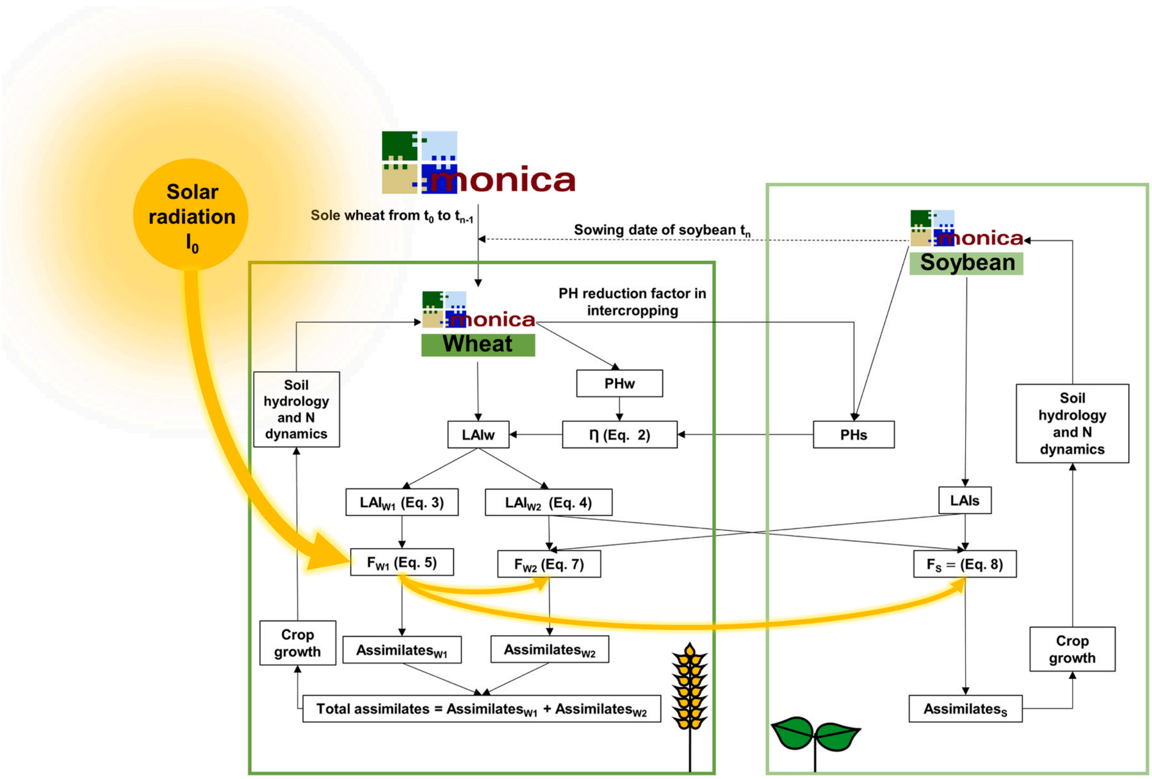

Fig. 1. Concept map of an intercropping version of the MONICA agro-ecosystem model, which combines two instances of MONICA using a shared canopy approach. PH refers to plant height, F is the fraction of light interception of soybean (F_S) and wheat in the upper (F_{W1}) and lower layers (F_{W2}), and η is the ratio of soybean plant height to wheat plant height.

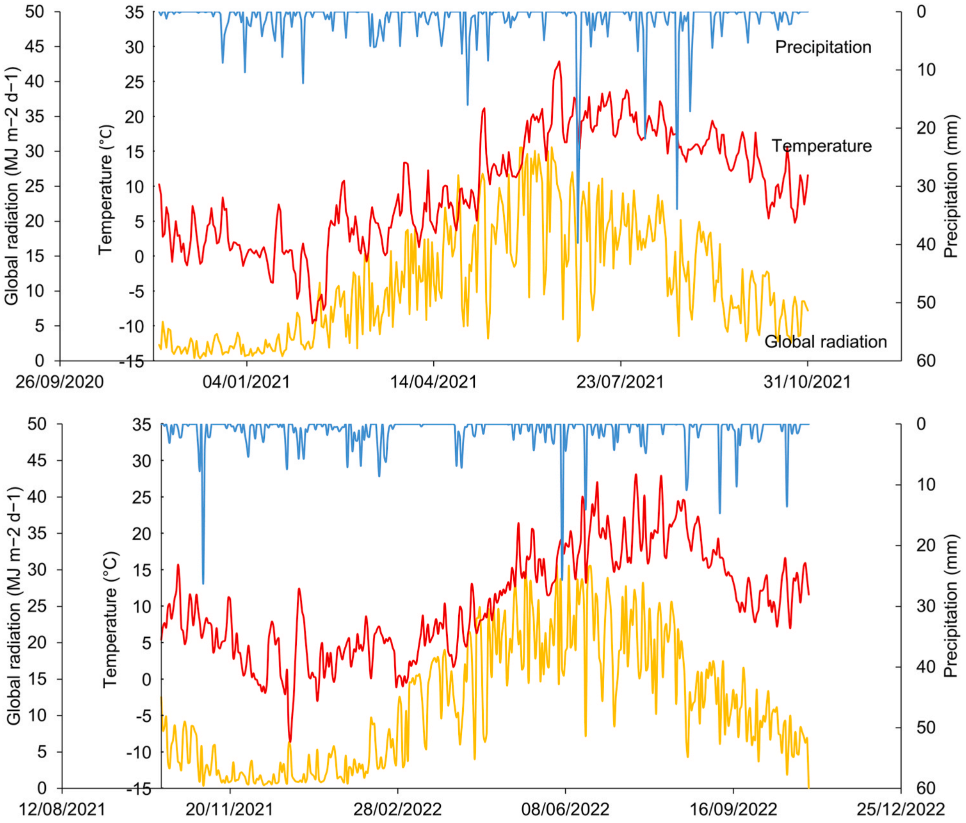

Fig. 2. Daily rainfall (blue), temperature (red) and global radiation (yellow) during 2020/2021 and 2021/2022 in Müncheberg, Germany.

$$I_s = I_0 \times (1 - F_{T1}) \times F_s \tag{10}$$

The light extinction coefficient (k) was species-specific, derived from the LAI and light interception measured from field experiments, with 0.681 for wheat and 0.612 for soybean.

2.3. Model inputs

As mentioned before, MONICA requires climate, soil, crop, and management information as inputs. Climate input data includes daily solar radiation, temperature, precipitation, relative humidity and wind speed. Weather data was acquired from a climate station in Müncheberg (52.51°N, 14.12°E), located at 0.8 km distance from the experimental site (Fig. 2). Soil input requires the thickness of each layer, the type of soil according to the German KA5 Soil Texture Classification System (Eckelmann et al., 2005), or alternatively, the percentages of sand silt and clay or permanent wilting point, field capacity and saturation, and bulk density ('Supplementary Table 2). Management data encompasses sowing and harvest dates, irrigation level and timing, and nitrogen application dates and amounts.

2.4. Calibration and validation

We used the experimental data for 2020/2021 to calibrate the model. The calibration procedure was initiated by adjusting the phenological stage-dependent cumulative temperature sum to fit the observed developmental stages. Next, based on the observed biomass, LAI and yield in both rainfed and irrigated conditions, we automatically adjusted the root penetration rate and organ yield percentage of fruit to obtain the smallest root mean square error (RMSE) between observations and simulations. Since MONICA already has default parameters for winter wheat and soybean established from prior experiments with German cultivars, our study focused solely on the minimum parameters. Based on observations in different cropping systems, we determined three calibration strategies for each cultivar in intercropping system: calibration based on respective sole-cropping observations (SC), calibration based solely on intercropping observations (IC), and calibration by pooling data from both sole-cropping and intercropping conditions (DC) (Supplementary Table 4). The selected parameters include the root penetration rate, which indicates the cultivar's sensitivity to drought, the temperature sums required for seven different phenological stages, which indicate developmental characteristics, and the ratio of shell/pod to actual grain, referred to as the yield percentage (Supplementary Table 4). The selection of parameters were based on the extensive experience with MONICA model from previous studies (Nendel et al., 2023) and comprehensive sensitivity analysis of the model (Specka et al., 2015; Specka et al., 2019). Supplementary Fig. 2 and 3 show calibration results from all three approaches for soybean (var. Merlin) and winter wheat (vars. Moschus and Reform) during sole cropping and intercropping, under both irrigated and rainfed conditions. To evaluate the performance of our new modeling module, data from the second year of a field experiment were used (2021/2022). Nevertheless, since a considerable portion of the intercropping treatments were affected by an abundance of weeds (as illustrated in the supplementary Fig. 4), three of the six replications were omitted from the analysis of the second year's data when computing the performance metrics of the model.

2.5. Evaluation of model performance

The mean bias error (MBE) calculates the average difference between simulated and observed values. It serves as an evaluation metric that quantifies bias, providing a concise overview of the overall direction of deviation for the target variable (Willmott and Matsuura, 2005). The primary advantages of MBE are its simplicity in calculation and interpretation. A positive value indicates an overestimation, while a negative value signifies an underestimation. Since MBE can be misleading when positive and negative errors offset each other, root mean square error (RMSE) is used to represent the absolute error. The RMSE is the square root of the mean squared difference between the simulations and measurements. Its unit is consistent with the variable of interest (Hodson, 2022). In conjunction with RMSE and MBE, the dimensionless index of agreement (IA) was used here offering a complete picture of model performance. The IA, first proposed by Willmott (1981), is a criterion for model efficiency, ranging from 0 to 1, with 1 indicating perfect agreement and 0 indicating no agreement. It is a normalized measure whose interpretation is similar to coefficient of determination (R^2), but more robust with being less sensitive to outliers (Berghuijs et al., 2021).

$$MBE = \frac{1}{N}\sum_{i=1}^{N}\left(\widehat{Yi} - Yi\right) \tag{11}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(Yi - \widehat{Yi}\right)^2} \tag{12}$$

$$IA = \frac{\sum_{i=1}^{N}\left(Yi - \widehat{Yi}\right)^2}{\sum_{i=1}^{N}\left(\left|\widehat{Yi} - \overline{Y}\right| + \left|Yi - \overline{Y}\right|\right)^2} \tag{13}$$

Here, Y_i is the observation of aboveground biomass (AGB), LAI and grain yield, and $\hat{Y}_i$ is the corresponding simulation. $\overline{Y}$ is the mean of observations, where N is the total number of observations.

3. Results

3.1. Model validation for aboveground biomass over the growing period

Validation in sole crops demonstrated satisfactory predictions for both wheat and soybean, especially for yield (Fig. 3). The root mean square error of yield ($RMSE_Y$) for both species was small, with the lowest being found in rainfed winter wheat var. Reform, which was 0.003 t ha^{-1} (mean = 5.63 t ha^{-1}), and the highest in irrigated winter wheat var. Moschus, which was 0.47 t ha^{-1} (mean = 5.88 t ha^{-1}). The $RMSE_Y$ of soybean var. Merlin under rainfed and irrigated condition were small, with rainfed conditions showing a lower $RMSE_Y$ of 0.005 t ha^{-1} (mean = 0.54 t ha^{-1}). On the other hand, MONICA overestimated AGB. The model overestimated the soybean AGB in irrigated conditions, while slightly overestimating it under rainfed conditions. For wheat, the overestimation was pronounced in Moschus under rainfed conditions. For Moschus under irrigation and Reform under both conditions, the AGB prediction agreed with observations.

The three calibration methods demonstrated different levels of accuracy for AGB simulation, with the most notable being an overestimation for soybeans in the rainfed treatment (Fig. 4). However, the MONICA model accurately captured the suppression effect on soybeans when intercropped, driven by the different wheat cultivars. For instance, the IC calibration simulated Merlin's AGB under irrigated conditions, which was 0.7 t ha^{-1} lower when intercropped with Moschus as opposed to when intercropped with Reform (Fig. 4). The IC approach yielded the most accurate AGB simulations for two cultivars of wheat and soybean under both water regimes, while in irrigated conditions SC provided the best prediction for soybeans intercropped with Reform (Fig. 4). All calibration approaches were able to discern the differences between irrigated and rainfed conditions in the simulation of AGB. For soybean Merlin, the variation between calibration methods was minimal when intercropped with Reform under rainfed condition. For Moschus, both the DC and SC calibration approaches resulted in a 3 t ha^{-1} overestimation of AGB. In contrast, the IC approach demonstrated strong potential for accurately detecting AGB in the cultivar. For Reform, the SC method yielded the highest AGB simulations, whereas the IC method yielded the lowest, and AGB was better captured under rainfed

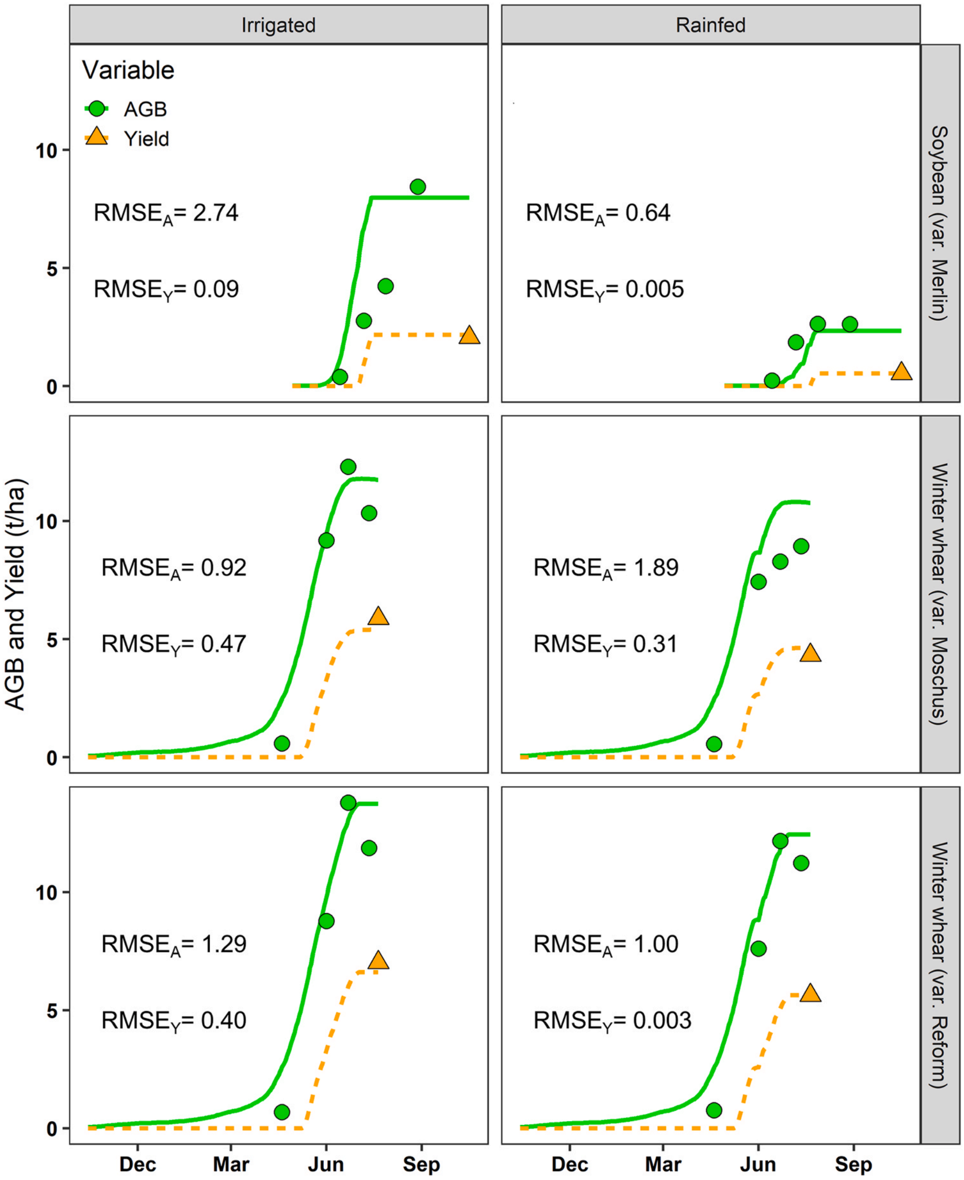

Fig. 3. Validation of the aboveground biomass (AGB) and yield for sole soybean var. Merlin, winter wheat var. Moschus and winter wheat var. Reform, based on the calibration for sole cropping under irrigated and rainfed regimes. Observations from the 2021/2022 field experiments are presented as green dots. Lines represent the simulated variables: green solid line = AGB; orange dashed line = yield. The RMSEs of species were calculated for each variable across water regimes.

conditions (Fig. 4).

3.2. *Model evaluation for aboveground biomass and yield*

Overall, the model simulations were more accurate for the yield and AGB of intercropped wheat than for intercropped soybean. The IC calibration produced the best model predictions for wheat and soybean, compared to the SC and DC approaches. The SC-based calibration demonstrated suitable model efficiency for the AGB of intercropped Moschus (IA = 0.87) and Reform (IA = 0.91) (Table 2). However, it largely overestimated the AGB of the intercropped Moschus, with an MBE of 2.52 t ha^{-1} (Table 2). The model also overestimated the AGB of the intercropped Reform, but with a lower MBE of 2.37 t ha^{-1} (Table 2). The AGB of intercropped soybeans was poorly represented by the SC method, with an IA value of 0.42 (Table 2). The IC method outperformed both the SC and DC methods, exhibiting a smaller RMSE and MBE and a higher IA (0.65) for soybean (Table 2). The MBE of the intercropped Moschus aboveground biomass using the IC method was 4% that of the simulations based on the SC calibration (Table 2). Intercropped specific calibration also improved the IA, increasing it from 0.87 to 0.99 (Table 2). The IC performed consistently well in yield estimation and achieved the lowest MBE for all species compared to SC and DC. The SC model overestimated Reform yield the most, with an MBE of 1.97 t ha^{-1}. The Moschus yield predicted by IC exhibited the smallest overestimation of 0.003 t ha^{-1} (Table 2). Using the IC approach, the MBE of the Merlin yield decreased by 76% compared to the SC approach, 95% for Reform and 99% for Moschus (Table 2). Nevertheless, the RMSE and IA values of yield should be read with caution due to the small sample size.

4. Discussion

4.1. *Aboveground biomass and yield simulations*

Our new modelling approach employing IC calibration calculated fairly low soybean AGB and yield, but still overestimated these amounts compared to on-site measurements. Possible causes of the overestimation of soybean AGB and yield were weed infestation and intensified drought in the experiments. In this study, the wheat–soybean

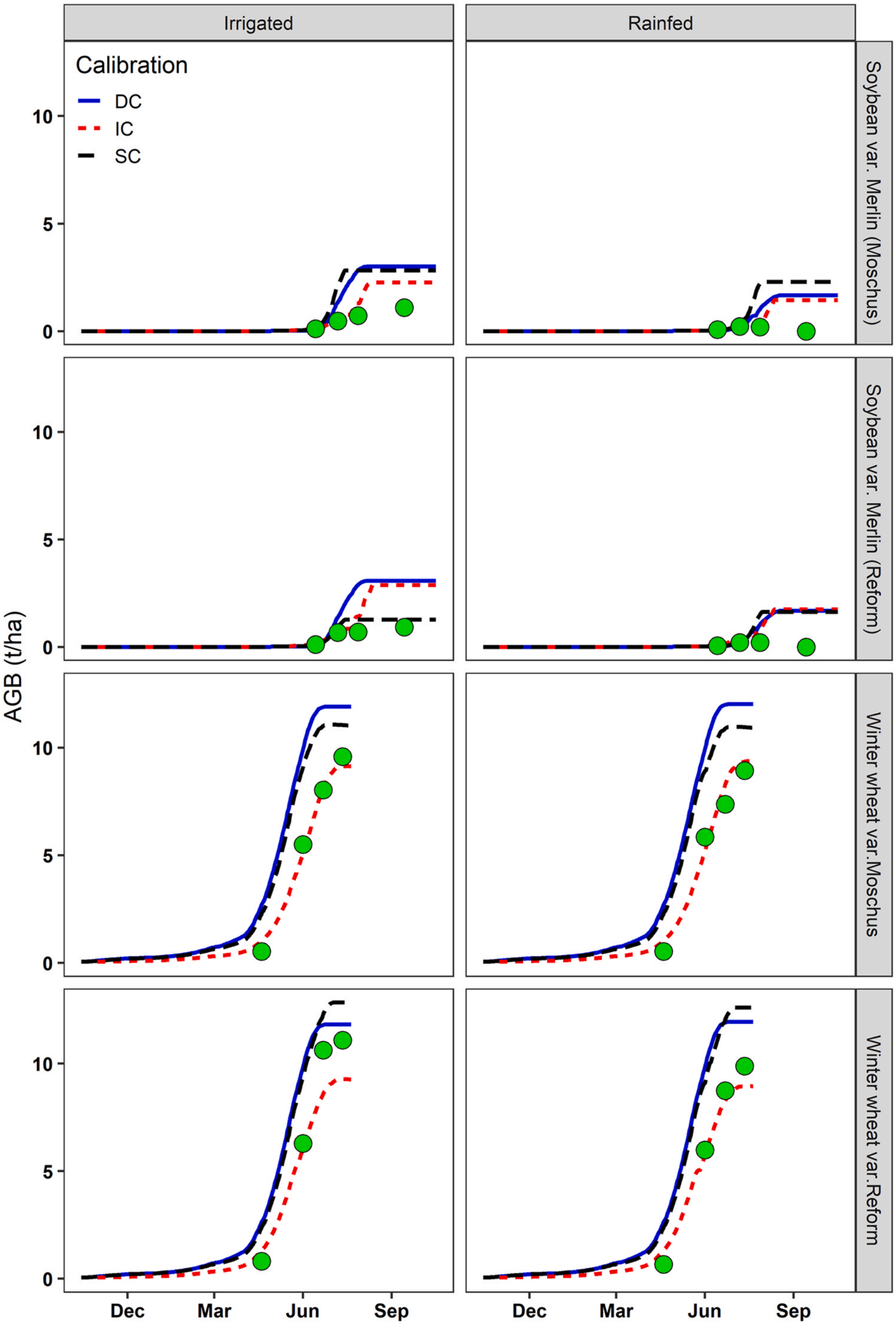

Fig. 4. Validation results of aboveground biomass (AGB) for intercropped winter wheat var. Moschus + soybean var. Merlin, and winter wheat var. Reform + soybean var. Merlin, with three calibration options under irrigated and rainfed regimes. Observations from the 2021/2022 field experiments are presented as green dots. Lines represent the simulations, with the blue solid line = default calibration (DC); red dashed line = intercropping-based calibration (IC); and black dashed line = sole cropping-based calibration (SC).

relay-row system suffered from significant weed infestation (Supplementary Fig. 5). The higher weed infestation is against the intend effect of reducing weeds, which has been observed in other studies. A case study of maize-soybean relay-row intercropping showed a decrease in weed biomass of up to 61% compared to of that sole crops (Su et al., 2018). In addition, experiments with soybean–buckwheat relay-stripe intercropping also reported effective weed suppression (Biszczak et al., 2020). The reasons for higher weed infestation (Supplementary Fig. 5) in our study are diverse, relate to the dry climate and management. Leoni (2022) pointed out the importance of selecting legume species and varieties with certain traits for weed management when using cereal–legume relay-row intercropping. Legume species and varieties that suffer from competition with wheat, may increase weed infestation especially during the late phase when wheat has been harvested. The spacing between wheat rows also plays a crucial role in managing weeds. Due to the temporal niche between the component crops, the relay-row arrangement led to a later or no canopy closure compared to sole cropping and reduced weed suppression. Management of weeds at

Table 2
Comparison of simulated and observed aboveground biomass (AGB) and yield of winter wheat var. Moschus, winter wheat var. Reform and soybean var. Merlin in the intercropping system from a 2021/2022 field experiment, with calibrations based on sole cropping (SC), intercropping (IC) or both (DC).

	Calibration method	AGB			Yield		
		RMSE	MBE	IA	RMSE	MBE	IA
		t ha^{-1}	t ha^{-1}		t ha^{-1}	t ha^{-1}	
Intercrop winter wheat var. Moschus	DC	3.49	3.35	0.80	0.73	0.61	0.45
	SC	2.65	2.52	0.87	1.65	1.61	0.31
	IC	0.54	0.11	0.99	0.31	0.003	0.49
Intercrop winter wheat var. Reform	DC	2.53	2.30	0.90	0.85	0.22	0.28
	SC	2.48	2.37	0.91	1.97	1.85	0.44
	IC	1.07	-0.56	0.98	0.77	0.10	0.23
Intercrop soybean var. Merlin	DC	1.56	0.85	0.61	0.67	0.67	0.41
	SC	1.23	0.79	0.42	0.68	0.60	0.27
	IC	0.82	0.48	0.65	0.23	0.16	0.73

such a late growing stage is difficult in practice and requires adapted machinery (Lamichhane et al., 2023). Weeds become additional resource competitors for soybeans as they absorb and transpire water, which exacerbates the drought stress experienced by soybeans. Presumably, this intensification leads to a transition into terminal drought, completely eliminating soybean AGB and, consequently, yield. Given that most crop models have not incorporated biotic stressors (Antle et al., 2017), they consequently fail to capture AGB and yield losses due to the contemporaneous presence of weeds. MONICA uses a field-condition modifier parameter to consider any yield-reducing factors that are not explicitly represented through biophysical processes in the model. Such non-explicit, yield-reducing factors may include pest and disease effects, improper management, the application of growth-regulating herbicides, and stem lodging. Thus, in principle, the yield reduction induced by weeds can be reproduced in MONICA by properly calibrating this modifier to increase the model's accuracy. Data on weed infestation from more years and sites is needed for such an additional calibration effort.

The synergistic interaction of heat and drought was another potential reason for reducing the soybean yield and biomass in intercropping. Stressors interact with each other when they simultaneously occur, and these interactions could be additive, antagonistic or synergistic (Rillig et al., 2021; Zandalinas and Mittler, 2022). Heat and drought in this context may interact synergistically, where the adverse effects of these combined stressors exceed the sum of heat and drought stress applied individually (Suzuki et al., 2014). Individual drought stress or heat stress has been extensively discussed in the literature. Drought decreases leaf area expansion and transpiration (Jefferies and Mackerron, 1993), and also reduces the grain number, grain yield and grain N yield (Rajala et al., 2011). Whereas heat exposure mainly affects grain number (Talukder et al., 2014), constrains photosynthetic capacity, accelerates leaf senescence (Harding et al., 1990), and consequently reduces grain yield (Farooq et al., 2011). Drought exposure causes stomata closure when heat exposure occurs simultaneously and canopy temperature is 3 °C higher than that of crops exposed only to heat without drought (Rizhsky et al., 2002). This obviously increases water demand, and thus intensifies stresses. One study on barley showed that drought also reduced grain weight by 20%, high temperature reduced it by 5%, the combination of drought and heat, however, caused a 30% reduction, which is clearly larger than the sum of the parts (Savin and Nicolas, 1996). While present models generally consider multiple abiotic stresses to have an additive effect, the synergistic and antagonistic effects of combined stresses have been poorly documented or discussed in model studies (Webber, et al., 2018a,2018b). Between the juvenile phase and harvest of our soybean crop, precipitation in the calibration year (2020/2021) was 89% higher than the validation year (2021/2022), which was 180 and 95 mm, respectively. Meanwhile, the average temperature of the validation year was 2 °C higher than the calibration year, with nine days of temperature higher than 25 °C (Fig. 2). Although MONICA was able to reproduce the crop growth as affected by drought or heat, the soybean plants potentially suffered from the synergistic effects of drought and heat as has been shown by Elsalahy and Reckling (2022) for the same site in 2020 and 2021. This effect was beyond the model's capability, and therefore the decreased soybean biomass and yield were not well simulated.

An exception to the generally overestimated results is the SC irrigated Merlin intercropped with Reform, which was predicted accurately (Fig. 4). Yet, this does not necessarily qualify the SC as the best calibration, since the specific calibration resulted in a substantial overestimation of AGB for the winter wheat variety Reform. Vigorous crops have higher competitiveness and weed suppression ability (Aharon et al., 2021), which means a higher suppression on the later sown species in intercropping system. Our model captured the higher suppression effect, and the corresponding response of soybean under the suppression, but it also stresses that the results of intercropping simulation should be interpreted cautiously due to crop-crop interactions (Juste et al., 2021).

Overall, the intercrop version of MONICA simulated a higher AGB in intercropped wheat than in wheat as a sole crop while also modelling a drastic decrease in soybean AGB. This is reasonable in a relay-row system, as the soybean plants are shaded by the coexisting wheat plants, which primarily intercept light (Lamichhane et al., 2023). This outcome highlights the ability of the model to simulate the interactive behaviour between two species with contrasting morphological and phenological traits. Despite the uncertainties from weed infestation and combined heat and drought stresses, the new model demonstrated significant potential for assessing wheat productivity in intercropping under varying water availability.

4.2. *Calibration strategies*

The original MONICA program was developed for sole cropping in rotation and has since been parameterised and tested for a range of crops across environments and management strategies, including wheat (Asseng et al., 2013; Dueri et al., 2022; Nendel et al., 2013; Pirttioja et al., 2015) and soybean (Battisti et al., 2017; Kothari et al., 2022a, 2022b; Nendel et al., 2023). These previous parameterisations can be directly applied in adapting the model to intercropping. Only a few parameters were targeted (Supplementary Table 4) when new cultivars were introduced, minimising the parameterisation requirement.

In the calibration exercise, the SC calibration yielded simulations that corresponded closely with the observations for wheat and soybean (Supplementary Figs 2 & 3) sole crops, and the validation for sole crops (Fig. 3) confirmed that the original MONICA is still a well-performing tool for predicting the growth and yield formation for crops in sole cropping. In intercrop validation with the SC parameters, while the intercropped wheat AGB showed high model efficiency (Table 2), the poor predictions regarding soybean indicated that the SC approach overlooked more complex ecological processes in intercrops (Juste et al., 2021). The DC approach, which was calibrated for both sole and intercropping conditions, showed a slightly better model agreement in intercropped soybeans. The IC captured the characteristics of relay-row intercrops sufficiently well compared to SC and DC. Unlike the standard calibration in other studies, where parameters are assumed to be constant in any environment (Rincent et al., 2019), IC also considers genotype–environment interactions indirectly. In relay-row intercropping, the later-sown crops were suppressed by the dominant crop in the early phase and recovery growth commenced after the dominant crop's harvest (Tanveer et al., 2017). However, species with lower resilience to shading are likely to perform poorly in the recovery phase and in the end cannot reach the genetic potential of the cultivar (Fan et al., 2018).

In the new version of MONICA, where LAI is a function of plant height differentiation of the component crops (Fig. 1), plant height plays a crucial role in biomass and yield simulation. Given the fact that we found a remarkable decrease in soybean plant height in the intercropping system (Supplementary Fig. 6), it seems risky to calibrate models only according to the observed growth patterns of crops growing in sole cropping. Moreover, severe shading on the soybean plants altered the microclimate and postponed soybean development in the 2020/2021 field experiment and consequently led to a delay in flowering and maturity in the intercropped soybean (Supplementary Table 5). IC enabled us to capture the morphological and phenological changes generated from these different patterns and altered microclimate, which thus led to the best results in this study. The comparison among different calibrations demonstrated that in intercrops with large temporal niches, the simulation of the dominant crop was generally satisfactory. Attention needs to be drawn to the later-sown crop calibration, particularly when a crop growth model with a fixed set of parameters is used. This implies the significance of incorporating the genotype (G) × environment (E) perspective into ecological modelling.

4.3. Limitations and outlook

The MONICA model is suitable for simulating wheat–soybean relay-row intercrops when factors such as machinery and plant protection are maintained at optimal levels. AGB and yield in the current relay-row design were estimated with acceptable accuracy. Management in relay row intercropping requires anticipation by farmers, and the new intercropping MONICA can aid in the optimisation of sowing dates and the selection of suitable cultivars for intercrops. Further research still needs to examine simulating crop growth under water deficit conditions, as the new modifications to the model overestimate AGB and yield under rainfed conditions. To better capture intercropping under water-deficit conditions, it would be useful to have a modified root module that could account for competition for belowground resources and the different exploitation strategies of different species, and thus describe water competition between component crops and the resulting growth detriments. However, one key aspect of MONICA is its minimal calibration requirement, and good root models with adequate complexity to fit in this structure are scarce. Balancing the simplicity of the model with essential features and the uncertainties generated by an integrated root model depends on the specific research interest (Li et al., 2015; Wang et al., 2023). The extent to which an added root module could improve the current model for relay-row intercropping deserves further exploration.

Similar to the model adaptations of APSIM or STICS to intercropping, MONICA has demonstrated acceptable agreement in crop phenology and growth (Kherif et al., 2022; Wu et al., 2023). Crop phenology simulation, in most crop models, responds to air temperature and sometimes water deficit, but in a simpler way. For relay-row intercropping in temperate regions such as Europe, sometimes relayed crops cannot accumulate as many thermal units as their respective sole-cropped variant and unsatisfactorily mature due to shading and microclimate change (Leoni et al., 2022). An inaccurate estimation of later-sown crops phenology might, therefore, bear risks in an escape from abiotic stressors, resulting in an overestimation of crop growth. Improving the phenology model, introducing more dynamic responses to climate factors, and incorporating microclimates to further model accountability would be helpful. Using air temperature in crop models instead of canopy temperature may introduce biases in simulating crop growth and development processes, especially under drought conditions (Siebert et al., 2014). For accurate canopy temperature modelling, it is essential to establish a standardized field measurement procedure (specifying the target organ and section of the canopy profile) and find a balance between model complexity, computational power demands, and data needs for calibration (Webber et al., 2016, 2018).

Our calibrated routine has yielded promising results for row intercropping. However, the generalization of this model to other intercropping systems, such as strip intercropping or mixed cropping (with two or more species in a row), should be approached with caution. For instance, the advantages of strip systems are often due to interactions between species in the border rows. Therefore, system-specific modules, like the quasi-Bayesian approach developed by Wu et al. (2021) for APSIM, should be considered for these systems.

Specific calibration for an intercropping system can partly account for changes in the growth parameters of wheat and soybean, which are driven by interspecific interactions. However, to more systematically address these interactions and the mechanisms that remain unknown resulting from crop-crop interactions, a hybrid model that couples a data-driven approach with a process-based model would be most suitable. Previous hybrid models of this type have been reported to provide higher accuracy in predicting maize and soybean yields (Chang et al., 2023; Corrales et al., 2022). Eventually, the mechanisms behind plant–plant interactions need to be explainable and interpretable. Therefore, a long-term future option would be to incorporate knowledge from individual-based modelling, which more specifically characterises and quantifies the plasticity of a cultivar, thus facilitating crop growth models and increasing our comprehension of intercrops.

5. Conclusions

In this study, we developed a less parameter-intensive intercropping module and incorporated it into the minimally parameterised, process-based MONICA crop model. We then tested three calibration strategies, using this adapted model to simulate wheat–soybean relay-row intercropping. Our results demonstrate that by accounting for light competition between wheat and soybean in relay-row intercropping, the model generates acceptably precise yield and AGB predictions. In this sense, when we applied optimal condition, it was not necessary to make the model overly complex. When crops suffer from multiple, simultaneous stresses, however, they require further consideration, and a model should be developed to capture these synchronous stresses. The comparison among the three calibration approaches quantitatively highlighted the significance of cropping system specific calibration for modelling intercropping systems, with IC outperforming SC and DC in both yield and AGB estimation. However, there is still room for improvement in enhancing crop phenology simulation and understanding genotype-by-environment (G × E) interactions in intercropping. Systematic experiments investigating G × E interactions with a large genotype panel would help to test crop plasticity in intercropping systems.

Overall, we piloted various calibration strategies to broaden the scope of genotype × environment perspectives in crop modelling. Despite the uncertainties and challenges posed by weed infestation and the synergistic effects of drought and heat, this study endorses intercropping-enhanced MONICA as a crucial step in bridging computer simulations and field experiments, thus helping stakeholders move toward more diversified and sustainable agriculture. Our results pave the way for MONICA's users to focus on modelling crop system diversification while maintaining the program's minimal parameterisation and calibration features. With MONICA's capabilities for landscape modelling, simulations on extensive spatial-temporal scales can investigate the long-term effect of intercropping under climate change, and further explore intercropping's potential to transform intensive agriculture.

CRediT authorship contribution statement

Nendel Claas: Methodology, Supervision, Writing – review & editing. **Thompson Jennifer B.:** Data curation, Validation, Writing – review & editing. **Reckling Moritz:** Data curation, Methodology, Writing – review & editing. **Yu Jing:** Formal analysis, Methodology, Validation,

Visualization, Writing – original draft. **Rezaei Ehsan Eyshi:** Conceptualization, Investigation, Methodology, Supervision, Writing – review & editing.

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.eja.2023.127067.

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