European Journal of Agronomy 176 (2026) 128061

Contents lists available at ScienceDirect

European Journal of Agronomy

journal homepage: www.elsevier.com/locate/eja

Lentil and chickpea crop growth and yield prediction across Europe

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ARTICLE INFO

Keywords:
Agro-ecosystem model
Crop model
Parameter estimation
Grain legumes
MONICA

ABSTRACT

Lentil (*Lens culinaris M.*) and chickpea (*Cicer arietinum L.*) are valuable grain legumes that reduce dependency on synthetic fertilizers, enhance soil health, and diversify crop rotations, improving resilience to climate variability. However, their adoption in Europe remains limited due to irregular yields caused by biotic and abiotic stresses. Process-based soil-crop models can provide insights into the soil-plant-atmosphere dynamics of these legumes and support the development of innovative cropping systems.

This study presents the first species-specific parameterization of the agro-ecosystem model MONICA for lentil and chickpea in Europe addressing a critical gap in simulating the growth of minor crops. A recently proposed generic calibration protocol was adapted and applied to real multi-environment field data. Following this structured protocol, 27 crop-related parameters were calibrated using literature-derived values, direct measurements, and mathematical optimization.

Calibration utilized a unique multi-variable data from 28 site-year-management units (SYMU) for lentil and 24 for chickpea across diverse European climates along a latitudinal gradient. Evaluation utilized an independent dataset of grain yields encompassing numerous SYMU.

After calibration, MONICA successfully simulated phenology, aboveground biomass, plant nitrogen concentration, grain yield, plant height, leaf area, and soil moisture, achieving acceptable model efficiency (0.32 to 0.98) and low relative bias (−7% to 3%) for most variables. However, it underpredicted yield in high-performing SYMU and showed greater errors for dynamic variables. Improvements in simulating biomass partitioning, physiological maturity, and detailed soil data are needed to simulate grain yield more accurately for future climate change adaption studies.

This study provides a robust framework for parameterizing new crops and evaluating the agronomic performance of lentil and chickpea under diverse climatic scenarios, contributing to design sustainable cropping systems.

1. Introduction

Current cropping systems in Europe achieve high productivity through short and intensive crop rotations and a substantial reliance on synthetic inputs to sustain yields (Rega et al., 2020). Such intensive farming has contributed to pollution of soil, water, and air, and to a loss of biodiversity (e.g. Campbell et al., 2017). Introducing grain legumes into these systems can enhance their agronomic, socioeconomic, and environmental performance while providing important ecosystem services. In particular, using legumes for biological N fixation reduces the reliance on synthetic nitrogen fertilizers, which in turn lowers both direct and indirect greenhouse gas emissions and the risk of nitrate leaching (Plaza-Bonilla et al., 2017; Reckling et al., 2016); it enriches the soil with high-quality organic matter and facilitates soil nutrients' circulation and water retention (Stagnari et al., 2017).

However, many legumes are sensitive to water and temperature stress: drought during the reproductive stage can significantly reduce yields (Farooq et al., 2017), and heat stress can negatively affect seed set and grain filling (Sher et al., 2024). Additionally, N_2 fixation,

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https://doi.org/10.1016/j.eja.2026.128061
Received 26 February 2026; Accepted 26 February 2026

although often underappreciated, can be severely impaired by stresses such as drought, heat, anoxia, and high soil mineral nitrogen levels in the root zone (Lumactud et al., 2023). Moreover, legumes are vulnerable to pests, diseases, and weeds at different stages of their growth cycle (van Emden et al., 1988; Rubiales et al., 2014). The low marketable yield, low prices and the strong variability in legume yields are the primary reasons farmers hesitate to adopt legumes in their cropping systems (Meynard et al., 2017; Watson et al., 2017).

Among the various grain legumes, lentil (*Lens culinaris M.*) and chickpea (*Cicer arietinum L.*) stand out due to their adaptability to low-input systems in water limited areas and their high value for human consumption, making them ideal candidates for sustainable cropping systems, particularly in Mediterranean and semi-arid regions. Furthermore, they recently also experience increasing interest as candidate crops for cultivation across Central Europe (Divéky-Ertsey et al., 2022; Reif et al., 2020), with the aim to diversify the local cropping systems, making them economically more resilient against stressful climate events that occur more and more frequently under climate change.

The agronomic performance of lentil and chickpea is influenced by genotype, environmental and management factors, but so far it has been investigated only in a limited number of isolated field experiments (e.g. Frimpong et al., 2009; Devkota et al., 2021; Preiti et al., 2024). A process understanding is required to assess the performance across different climate zones, varieties and management practices. As conducting trial experiments in all environmental conditions is not feasible, dynamic, process-based models can help to predict and understand responses to environmental changes (Silva and Giller, 2020). Crop and agro-ecosystem models can help in understanding yield variability by simulating the effects of seasonal water and temperature stresses (Batchelor et al., 2002; Frieler et al., 2017). These models are valuable tools for diagnosing agronomic constraints and assessing the impacts of current and future climate variability. Furthermore, crop models allow for the estimation of key indicators that are difficult or expensive to measure in experimental plots, such as water drainage (Bruelle et al., 2017), carbon sequestration (He et al., 2017), CO_2 and N_2O emissions (Delandmeter et al., 2023; Dueri et al., 2023), N uptake, N use efficiency and nitrate leaching (Yin et al., 2020; Clarke et al., 2024).

MONICA (MOdel for NItrogen and Carbon dynamics in Agro-ecosystems) is a dynamic, process-based simulation model designed to predict crop growth, water use, nitrate leaching, and other environmental variables under different climate and management scenarios (Nendel et al., 2011). Originally developed to simulate systems that include typical Central European crops, MONICA is particularly well-suited for assessing the impacts of both climate change and land management practices on crop production (Nendel et al., 2014). MONICA has been widely applied in simulating yields and environmental effects across diverse agro-ecosystems, with proven adaptability for various crops (Asseng et al., 2013; Baum et al., 2016; Salo et al., 2016; Yin et al., 2017; Webber et al., 2018; Hampf et al., 2020; Falconnier et al., 2020). However, its application to grain legumes, which are critical for sustainable cropping systems, is primarily focused to soybean (Battisti et al., 2017a; Nendel et al., 2023; Kothari et al., 2022). Moreover, in the crop modeling community, only few crop models have been developed or adapted for lentil (Ghanem et al., 2015; Soltani et al., 2020; Jing et al., 2024) and chickpea (Singh and Virmani, 1996; Robertson et al., 2002; Soltani and Sinclair, 2011; Singh et al., 2014; Chen et al., 2016; Soltani et al., 2020; Mubvuma et al., 2021; Kherif et al., 2022). Those models have been adapted for lentil and chickpea but generally limited their calibration to production-related variables and/or to specific sites within similar climatic conditions. In contrast, we calibrated MONICA with multi-variable observations across diverse climatic environments.

Our primary objective was to calibrate the model at the species level, using a protocol recently proposed in the crop modeling community (Wallach et al., 2023), and to assess MONICA's performance in simulating key processes such as crop development, shoot biomass production, grain yield, nitrogen concentration in plant tissue, canopy growth, and soil water dynamic throughout the growing season and post-harvest under rainfed, low-input conditions typical of lentil and chickpea production in Europe. By doing so, we tested the hypothesis that the generic model, with its consistent formalism across crops, can effectively account for the specific traits of lentil and chickpea resulting in a robust calibration for these grain legumes. The second objective was to evaluate MONICA's ability to generate accurate predictions for an independent dataset and provide reliable agronomic insights into yield variability caused by abiotic stresses. We hypothesized that the model's representation of soil-crop interactions and its well-implemented process equations would enable accurate predictions of abiotic stress impacts.

2. Materials and methods

2.1. The MONICA agro-ecosystem model

The MONICA model (Nendel et al., 2011) was selected for its agro-environmental focus, crop genericity, and robustness in simulating nitrogen and carbon dynamics across different crops. Adapted from the HERMES model (Kersebaum, 2007), MONICA operates on a daily time step to simulate carbon, water, and nitrogen cycles within the soil-crop system.

MONICA describes crop phenology based on air temperature, day length, and water availability. Photosynthesis is simulated using the plant physiology module from ARCWHEAT1 (Mitchell et al., 1995) which employs a set of algorithms for calculating the maximum photosynthesis rate based on the ideas of Farquhar and von Caemmerer (1982) and Long (1991). It allows to simulate the effect of elevated atmospheric CO_2 concentrations on both the photosynthesis and the transpiration (Nendel et al., 2009). The Penman-Monteith equation for evapotranspiration (Allen et al., 1998) links photosynthesis and transpiration via the stomata. Temperature effects on various plant physiological processes in MONICA are represented using the Wang-Engel temperature function (Wang and Engel, 1998). Root growth follows an exponential distribution through the soil profile, and soil water dynamics are modeled using a capacity-based approach (Wegehenkel, 2000), with water exceeding field capacity moving downward through soil layers.

The model has been calibrated and tested for various crops, including wheat (Nendel et al., 2011, 2013; Asseng et al., 2013; Pirttioja et al., 2015; Dueri et al., 2022), maize (Nendel et al., 2011; Bassu et al., 2014; Kumudini et al., 2014; Durand et al., 2018; Falconnier et al., 2020; Kimball et al., 2023), rye (Nendel et al., 2011), barley (Nendel et al., 2011; Rötter et al., 2012; Tao et al., 2017), soybean (Battisti et al., 2017a,b; Kothari et al., 2022; Nendel et al., 2023; Kothari et al., 2024), potato (Nendel et al., 2011; Fleisher et al., 2017, 2021) and oil-seed rape (Nendel et al., 2011; Wang et al., 2022), among others. Input data required for simulation include soil characteristics, daily weather conditions (temperature, precipitation, solar radiation, humidity, and wind speed), and crop management practices such as sowing date, irrigation, fertilization, and initial soil water and nitrogen content. For lentil and chickpea, plant phenology is divided into seven phases: germination, leaf development, vegetative growth (side shoots and stem elongation), flowering, fruit development, physiological maturity, and senescence. Key cultivar-specific parameters include maximum photosynthetic assimilation rate, root characteristics, and biomass partitioning.

MONICA considers abiotic stresses such as water deficit, excessive heat, nitrogen limitation, and aeration deficit. Water deficits, indicated by a threshold ratio of actual to potential transpiration, reduce the photosynthesis rate of the growing crop, while low soil moisture hampers germination of the seeds. Excessive heat decreases ovule fertility during reproductive phases when temperatures exceed defined thresholds.

Table 1

Description of the Site-Year-Management Units in the calibration datasets for lentil. LAI: Leaf Area Index, PH: plant height, AGB: aboveground biomass, GY: grain yield, AGBNC: aboveground N concentration, SWC: soil water content over the entire profile, CP: crop phenology. Year refers to the year of harvest. Density is expressed in number of plants per m^2. Precipitation is expressed in mm and refers to the cumulated rainfall during the growing season.

Site	Year	Management and environment					Number of measurements						CP
		Cultivar	Density	Sowing date	Soil texture	Precipitation	LAI	PH	AGB	GY	AGBNC	SWC	
San Piero	2019	Robin	150	12 March	Loamy sand	257	0	0	1	1	0	0	☐
		Elsa	350	10 February	Silt loam	259	0	0	2	1	0	0	☐
	2020	Robin	150	5 March	Loamy sand	276	1	1	1	0	0	0	☑
	2021	Robin	150	25 February	Loamy sand	142	0	1	1	1	1	0	☑
		Elsa	350	5 February	Silt loam	140	0	0	2	1	0	0	☐
	2022	Robin	150	18 February	Sandy loam	203	0	0	0	1	0	0	☐
		Elsa	350	1 February	Sandy loam	243	3	4	4	1	0	0	☑
	2023	Elsa	150	18 October	Silt loam	937	3	7	4	1	0	0	☑
	2024	Elsa	150	31 January	Silt loam	851	2	7	2	1	0	4	☑
		Elsa	150	14 February	Loamy sand	782	1	3	2	1	0	3	☑
Udine	2021	Itaca	200	30 March	Silt loam	545	1	3	1	1	0	0	☑
	2022	Itaca	250	28 March	Loam	220	6	0	4	1	1	0	☑
	2023	Itaca	120	29 March	Loam	426	0	1	2	1	0	0	☑
Barrafranca	2000	Eston	180	30 December	Clay	382	0	0	0	1	0	0	☑
	2001	Eston	180	15 December	Clay	209	0	0	0	1	0	0	☑
Cava	2000	Eston	180	10 December	Clay	122	0	0	0	1	0	0	☑
	2001	Eston	180	14 January	Clay	105	0	0	0	1	0	0	☑
New-Eichenberg	2020	Anicia	200	23 April	Sandy loam	221	0	1	1	1	0	0	☑
	2021	Anicia	200	27 April	Sandy loam	256	0	1	1	1	0	5	☑
	2022	Anicia	300	22 April	Sandy loam	104	0	1	1	1	0	10	☑
Fahrenbach	2020	Anicia	200	23 April	Loamy clay	220	0	1	1	1	0	0	☑
	2021	Anicia	200	27 April	Loamy clay	286	0	1	1	1	0	7	☑
	2022	Anicia	300	22 April	Loamy clay	118	0	1	1	1	0	10	☑
Müncheberg	2020	Anicia	200	2 April	Loamy sand	159	0	1	1	1	0	0	☐
	2021	Anicia	200	8 April	Loamy sand	170	0	1	1	1	0	3	☐
	2022	Anicia	300	13 April	Loamy sand	99	0	1	1	1	0	12	☐
	2023	Anicia	200	15 April	Loamy sand	139	4	5	1	1	4	4	☑
	2024	Anicia	200	2 April	Loamy sand	189	5	4	3	1	2	3	☑
						Total	27	44	38	24	8	61	
						Coefficient of variation	0.35	0.26	0.21	0.30	0.08	0.32	

When nitrogen concentration in the plant tissue falls below the critical concentration, photosynthesis is also penalized. Finally, oxygen deficits in the rooted soil restrict water uptake, especially after prolonged periods of poor soil aeration.

In the case of legumes, MONICA represents biological nitrogen fixation using a generic crop-independent module that supplies part of the plant N demand through symbiotic fixation, while the remainder is taken up from mineral N in the soil. Potential N fixation is driven by carbon availability and constrained by abiotic stresses (e.g. drought, heat) and by soil mineral N, such that high soil N levels suppress fixation. In this study we retained MONICA's generic formulation of biological N fixation and specified the fraction of plant N demand met by fixation (*PartBiologicalNFixation*) for lentil and chickpea based on literature values (Table 3). We did not attempt a separate calibration of the N fixation process itself; instead, we evaluated the resulting N dynamics indirectly via plant N concentrations and grain yields.

2.2. Field experimental data

2.2.1. Calibration dataset

The calibration dataset was composed of Site-Year-Management Units (SYMU) representing a wide range of soil types, growing seasons, and management conditions. Data were drawn from publications and field experiments conducted at contrasting sites in Italy and Germany (Fig. 1): Barrafranca ($36^{\circ}50'N$, $14^{\circ}50'E$), Cava ($37^{\circ}22'N$, $14^{\circ}13'E$), San Piero a Grado ($43^{\circ}40'N$, $10^{\circ}20'E$), Udine ($46^{\circ}02'N$, $13^{\circ}13'E$), Fahrenbach ($49^{\circ}25'N$, $9^{\circ}09'E$), Neu-Eichenberg ($51^{\circ}23'N$, $9^{\circ}53'E$), Müncheberg ($52^{\circ}30'N$, $14^{\circ}08'E$) and Dedelow ($53^{\circ}21'N$, $13^{\circ}48'E$). The calibration dataset for lentil comprises 28 SYMU across eight years (2000–2001 & 2019–2024) and includes five cultivars (Table 1), whereas the chickpea calibration dataset consists of 24 SYMU spanning six years (2000–2001 & 2021–2024) and also involves five cultivars (Table 2). However, it is important to note that this is a non-orthogonal design, as not all sites or cultivars are represented in every year.

The lentil calibration dataset included five cultivars—Anicia (French), Elsa and Itaca (Italian), and Eston and Robin (Canadian). All are commercially available and showed similar phenology and yield potential, with thousand kernel weight (TKW) ranging from 30 to 45 g and maximum plant heights between 35 and 50 cm. They are all brown lentils, apart from Anicia which is a green lentil. The chickpea dataset included the Kabuli-type cultivars Cicerone, Maragià and Sultano (Italian) and Flamenco and Lambada (French), which are likewise commercially available and similar in phenology and yield potential, with TKW ranging from 300 to 450 g and maximum plant heights between 65 and 85 cm. Across the Italian and German trials, lentil and chickpea cultivars displayed comparable phenological and morphological behavior.

The cropping systems varied across experimental sites, including differences in system design (row spacing, crop density) and preceding crop in the rotation. However, all experiments followed low input management practices: no irrigation, mineral fertilization, or use of pesticides or herbicides (except in Dedelow for chickpea). Hand or mechanical (hoeing) weeding was performed, although yield reductions due to weeds were still observed in some cases. Plots affected by weed pressure were excluded from the calibration dataset; within each trial, only plots reported as not affected by weeds were retained, with the aim of characterizing crop performance under near-optimum field conditions. Irrigated treatments (3 SYMU for lentil and 4 SYMU for chickpea) were also included and pooled with non-irrigated treatments, because irrigation did not affect yield in the calibration experiments. This indicates that water limitation was likely not a major constraint and supports the use of these data as approximations of near-optimum conditions. The dataset also exhibited a wide range of sowing dates, spanning from late autumn to spring (Table 1). Detailed descriptions of the field experiments are available in the publications presenting the results of the experiments (Avola et al., 2018; Koskey et al., 2022; Lorenzetti et al., 2022, 2023; Leoni et al., 2023; Delle Vedove, 2024), while some data remain unpublished.

Developmental stages for lentil and chickpea were recorded (or inferred when exact stages were unavailable) in most SYMU. Despite their indeterminate growth habit, the BBCH scale (adapted from common bean; Feller et al., 1995) was used to define key phenological stages: (i)

Table 2
Description of the Site-Year-Management Units in the calibration datasets for chickpea. LAI: Leaf Area Index, PH: plant height, AGB: aboveground biomass, GY: grain yield, AGBNC: aboveground N conentration, SWC: soil water content over the entire profile, CP: crop phenology. Year refers to the year of harvest. Density is expressed in number of plant per m^2. Precipitation is expressed in mm and refers to the cumulated rainfall during the growing season.

Site	Year	Management and environment					Number of measurements						CP
		Cultivar	Density	Sowing date	Soil texture	Precipitation	LAI	PH	AGB	GY	AGBNC	SWC	
San Piero	2022	Sultano	60	10 March	Loamy sand	202	0	0	1	1	0	0	☑
	2023	Maragià	55	1 December	Silt loam	745	3	6	4	1	0	4	☑
		Sultano	60	22 February	Silt loam	381	0	6	2	1	0	0	☑
		Sultano	50	15 March	Silt loam	305	1	3	2	1	0	0	☑
	2024	Sultano	65	31 January	Silt loam	851	3	9	1	1	0	3	☑
		Lambada	65	21 February	Loamy sand	787	0	5	1	1	0	0	☑
		Sultano	55	9 April	Loamy sand	484	0	2	1	1	0	0	☑
Udine	2021	Sultano	50	30 March	Silt loam	568	3	3	2	1	2	0	☑
	2022	Sultano	50	28 March	Loam	237	24	0	12	4	8	6	☑
	2023	Sultano	65	17 March	Loam	727	0	5	2	1	0	0	☑
		Sultano	50	29 March	Loam	498	0	1	2	1	0	0	☑
	2024	Sultano	65	7 December	Loam	735	0	7	2	1	0	0	☑
		Sultano	65	21 February	Loam	641	0	6	2	1	0	0	☑
Barrafranca	2000	Sultano	60	10 January	Clay	412	0	0	0	1	0	0	☑
	2001	Sultano	60	18 December	Clay	266	0	0	0	1	0	0	☑
Cava	2000	Sultano	60	29 December	Clay	118	0	0	0	1	0	0	☑
	2001	Sultano	60	8 January	Clay	104	0	0	0	1	0	0	☑
Dedelow	2022	Cicerone	65	4 May	Clay	150	0	0	0	1	1	0	☑
	2023	Cicerone	65	19 April	Clay	195	0	0	0	1	0	0	☑
Müncheberg	2021	Cicerone	60	28 April	Loamy sand	244	0	0	0	1	1	1	☑
	2022	Cicerone	60	27 April	Loamy sand	108	0	0	0	1	1	1	☑
	2023	Maragià	60	18 April	Loamy sand	218	0	5	4	1	5	7	☑
		Cicerone	60	3 May	Loamy sand	207	0	0	0	1	1	1	☑
	2024	Flamenco	60	14 May	Loamy sand	253	3	4	2	1	1	2	☑
						Total	37	62	40	27	20	25	
						Coefficient of variation	0.28	0.31	0.29	0.18	0.05	0.34	

Table 3
Value of the default parameters updated from literature and available direct measurements for lentil (top) and chickpea (bottom).

	Parameter	Description	Value	Source
Lentil	*AssimilatePartitioningCoeff*$_{Root}$	Actual assimilate partitioning coefficient for roots by stage	[0.39, 0.28, 0.2, 0, 0, 0, 0]	Zakeri and Bueckert (2015), Jing et al. (2024)
	AssimilatePartitioningCoeff$_{Leaf}$	Actual assimilate partitioning coefficient for leaves by stage	[0.54, 0.54, 0.22, 0.3, 0.1, 0, 0]	Zakeri and Bueckert (2015), Jing et al. (2024)
	AssimilatePartitioningCoeff$_{Shoot}$	Actual assimilate partitioning coefficient for shoots by stage	[0.07, 0.18, 0.58, 0.67, 0.3, 0, 0]	Zakeri and Bueckert (2015), Jing et al. (2024)
	AssimilatePartitioningCoeff$_{Fruit}$	Actual assimilate partitioning coefficient for pods by stage	[0, 0, 0, 0.03, 0.6, 1, 0]	Zakeri and Bueckert (2015), Jing et al. (2024)
	BaseDayLength	Daylength required for assimilation by stage (h)	[0, 7.4, 7.4, 0, 0, 0, 0]	McKenzie and Hill (1989)
	BaseTemperature	Base temperature for assimilation by stage (°C)	[2.5, 2, 2, 2, 2, 2, 2]	Covell et al. (1986), Ghanem et al. (2015)
	CriticalTemperatureHeatStress	Critical temperature for heat stress (°C)	32	Delahunty et al. (2018)
	CropSpecificMaxRootingDepth	Maximum depth reached by the crop (m)	0.93	Fan et al. (2016)
	DayLengthRequirement	Day length required for maximum growth during by stage (h)	[0, 16, 16, 0, 0, 0, 0]	Summerfield et al. (1984)
	LT50cultivar	Temperature killing 50% of the plants (°C) (m)	—8.5	Murray et al. (1988)
	MaxCropHeight	Maximum canopy height reached by the crop (m)	0.5	Direct measurement
	MaximumTemperatureForAssimilation	Maximum temperature for assimilation (°C)	38	Sehgal et al. (2019)
	MinimumTemperatureForAssimilation	Minimum temperature for assimilation (°C)	2	Expert knowledge
	SpecificLeafArea	Specific leaf area by stage (m^2 kg^{-1})	[0.00069, 0.0012, 0.0014, 0.002, 0.0022, 0.0.0016, 0.0006]	Jing et al. (2024)
	StageAtMaxDiameter	Phenological stage at which canopy diameter is maximum	5	Direct measurement
	StageAtMaxHeight	Phenological stage at which canopy height is maximum	4	Direct measurement
	StageKcFactor	Light extinction coefficient by stage (°C d)	[0.3, 0.48, 0.85, 1.06, 0.82, 0.45, 0.35]	Jabow and Mahgoub (2017)
	StageTempSum	Temperature sum by stage (°C d)	[90, 360, 270, 300, 450, 160]	Tefera et al. (2022)
Chickpea	*AssimilatePartitioningCoeff*$_{Root}$	Actual assimilate partitioning coefficient for roots by stage	[0.39, 0.28, 0.2, 0, 0, 0, 0]	Soltani et al. (2006b), Vyshnavi et al. (2024)
	AssimilatePartitioningCoeff$_{Leaf}$	Actual assimilate partitioning coefficient for leaves by stage	[0.54, 0.54, 0.22, 0.3, 0.13, 0, 0]	Soltani et al. (2006b), Vyshnavi et al. (2024)
	AssimilatePartitioningCoeff$_{Shoot}$	Actual assimilate partitioning coefficient for shoots by stage	[0.07, 0.18, 0.58, 0.67, 0.27, 0, 0]	Soltani et al. (2006b), Vyshnavi et al. (2024)
	AssimilatePartitioningCoeff$_{Fruit}$	Actual assimilate partitioning coefficient for pods by stage	[0, 0, 0, 0.03, 0.6, 1, 0]	Soltani et al. (2006b), Vyshnavi et al. (2024)
	BaseDayLength	Daylength required for assimilation by stage (h)	[0, 4, 4, 0, 0, 0, 0]	Singh and Virmani (1996)
	BaseTemperature	Base temperature for assimilation by stage (°C)	[4.5, 4.5, 4.5, 4.5, 4,.5, 4.5, 4.5]	Soltani et al. (2006a)
	BeginSensitivePhaseHeatStress	Beginning of the time window for crop sensitivity to heat stress (°C d)	670	Kaushal et al. (2013)
	CropSpecificMaxRootingDepth	Maximum depth reached by the crop (m)	1.01	Fan et al. (2016)
	DayLengthRequirement	Day length required for maximum growth during by stage (h)	[0, 15, 15, 0, 0, 0, 0]	Ellis et al. (1994)
	EndSensitivePhaseHeatStress	End of the time window for crop sensitivity to heat stress (°C d)	1147	Kaushal et al. (2013)
	LT50cultivar	Temperature killing 50% of the plants (°C)	—4.5	Saghfi et al. (2013)
	LimitingTemperatureHeatStress	Maximum temperature for heat stress effect (°C)	38	Devasirvatham et al. (2015)
	MaxCropHeight	Maximum canopy height reached by the crop (m)	0.91	Direct measurement
	OptimumTemperatureForAssimilation	Optimum temperature for assimilation (°C)	26	Soltani et al. (2006a)
	PartBiologicalNFixation	Percentage of biological nitrogen fixed by the crop	0.6	Plett et al. (2021)
	SpecificLeafArea	Specific leaf area by stage (m^2 kg^{-1})	[0.00069, 0.00072, 0.00085, 0.00102, 0.00112, 0.0.0009, 0.0006]	Sinha et al. (2018)
	StageKcFactor	Light extinction coefficient by stage (°C d)	[0.4, 0.6, 0.7, 0.9, 1, 0.8, 0.35]	Garofalo et al. (2009)
	RootPenetrationRate	Plant-specific penetration rate of the root (m °C d)	0.003	Kashiwagi et al. (2015)

BBCH 09: emergence (50% of shoots emerged through the soil surface), (ii) BBCH 61: beginning of flowering (one flower bud visible on the main stem), and (iii) BBCH 89: harvest maturity (most pods golden-brown, seeds dry and hard). Soil water content was measured by 30 cm layers, with measurements taken 1 to 4 times per year depending on the SYMU (Table 1). Crop variables, such as Leaf Area Index (LAI), plant height, aboveground biomass, grain yield, and grain nitrogen content, were measured between 1 and 6 times per year, depending on the SYMU (Table 1). LAI was measured using both direct and indirect methods (e.g. SunScan Canopy Analysis System), with data harmonized accordingly. Plant height was recorded by measuring at least 10 plants in each plot, from soil level to the top of the canopy. Plant samples were hand harvested from 0.5 or 1 m^2 sampling areas by cutting at the soil surface. Aboveground biomass samples were dried at 50°C and weighed. At maturity, plants were harvested to determine grain yield. Both biomass and yield were finally converted into kg/ha. Aboveground biomass nitrogen concentrations were measured using the Dumas combustion method with a LECO-2000 analyzer (LECO, St. Joseph, MI, USA). The dataset exhibits considerable variability, with the mean coefficient of variation (CV) for each measured variable being significantly higher than what is typically observed in field experiments with wheat (13%, as reported by Taylor et al., 1999).

In a subset of SYMU, soil mineral N concentrations were also measured at a limited number of dates. However, bulk density was

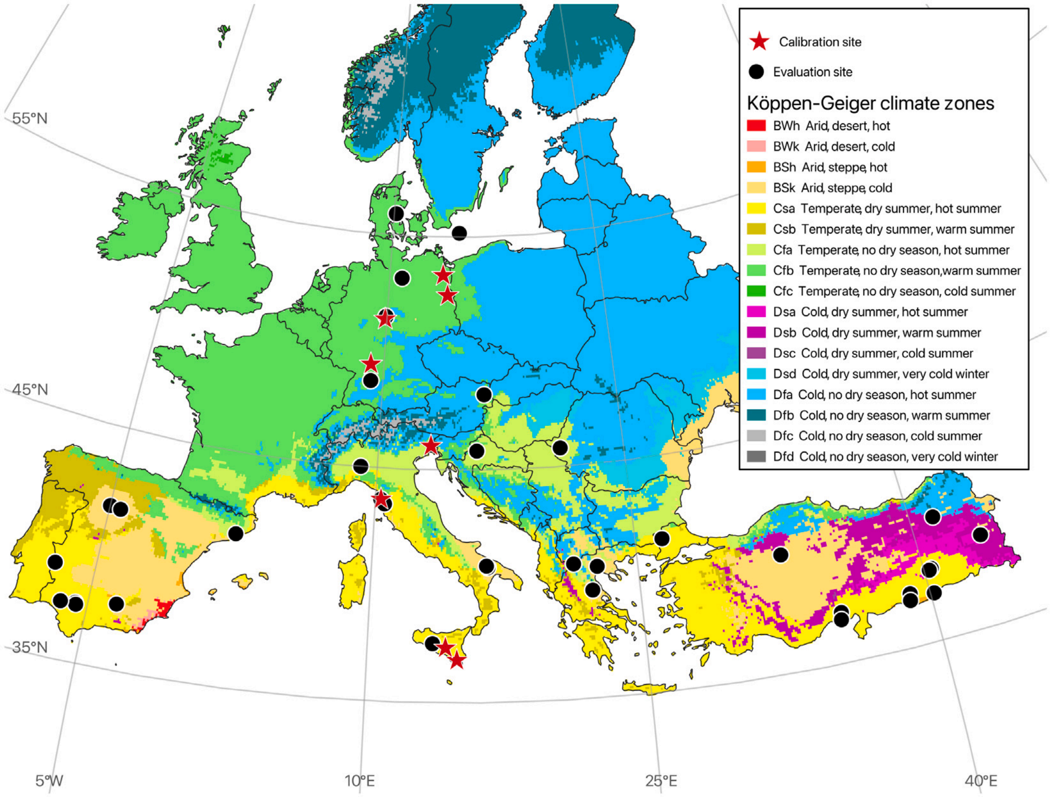

Fig. 1. Geographic distribution of experimental sites in the calibration and evaluation dataset, color-coded by Köppen-Geiger climate zones (Beck et al., 2023).

not available consistently across all sites and depths, which prevented us from converting these concentrations into reliable soil N stocks (kg N ha^{-1}) and from closing a full soil–plant nitrogen balance. For this reason, our evaluation of nitrogen dynamics focused on aboveground N concentrations rather than on explicit N fixation rates or soil N stock changes.

For each SYMU, basic initial soil data, including texture, pH, soil organic carbon and total nitrogen, were obtained from laboratory analyses, apart from the Fahrenbach, Neu-Eichenberg, Barrafranca, and Cava sites, where soil data were sourced from SoilGrids (de Sousa et al., 2020). From SoilGrids we also collected data about soil bulk density for all sites. Additional soil variables were included when available (e.g. C:N ratio, soil stone content) while others were calculated directly from the soil texture class (i.e. permanent wilting point and field capacity). All of this information was gathered and used as input parameters for soil in MONICA for each SYMU (see Supplementary Material for further information). Weather data for each SYMU, including temperature, precipitation, solar radiation, relative humidity, and wind speed, were collected from weather stations located either on-site or nearby the experimental fields, and were used as input climate data for the simulations.

According to Kersebaum et al. (2015), most of the SYMU utilized for model calibration are classified at a ‘silver’ level, with a few exceptions reaching the ‘gold’ level, where biomass and LAI were recorded multiple times throughout the season and differentiated by plant organs.

2.2.2. Evaluation dataset

The calibrated MONICA model for lentil and chickpea was used to predict grain yields across various regions in Europe (see Fig. 1). Data for evaluation were sourced from a recently published dataset on grain legume yields in Europe (Antichi et al., 2023), which includes information from both published scientific papers and unpublished experiments. The evaluation dataset comprises 47 SYMU for lentil and 56 SYMU for chickpea, spanning ten different European countries, not all of which were under low input management. The evaluation dataset reflects predominantly field-realistic production conditions and associated management variability, rather than near-optimum experimental conditions. SYMU that involved nitrogen fertilization or supplementary irrigation were also incorporated into the analysis, as the MONICA model is capable of simulating both nitrogen application and irrigation. Initial soil conditions were either retrieved directly from the source publications or, when unavailable, derived from SoilGrids (see Supplementary Material for further information). The weather data necessary for the simulations were obtained from the ERA5 reanalysis dataset (Hersbach et al., 2023).

2.3. Calibration protocol

The calibration process involved selecting the formalisms and corresponding parameters for simulating crop phenology, leaf area development, biomass accumulation, nitrogen and water uptake, plant height, and grain yield. The calibration of the MONICA model for lentil and chickpea followed the protocol recently proposed by Wallach et al. (2023), designed to incorporate all relevant observed variables while minimizing the risk of over-parameterization. However, when we applied this protocol to our real experimental data, it did not yield reliable calibrations, likely because of the high variability of the data and the absence of good prior parameter estimates, in contrast to the original study where the protocol was demonstrated on artificial data with starting values chosen close to the true optimum. To address this, we added a preliminary Monte Carlo exploration of the parameter space to identify plausible starting values, which improved the performance of the subsequent calibration.

The calibration process was structured into seven steps:

1. **Selection of default parameters**
   We began with the soybean parameter set, the most closely related species already available in MONICA (ZALF-RPM, 2025).

For lentil, we replaced as many soybean parameters as possible with values from the literature and used this as the default lentil parameter set for calibration. The optimized lentil parameters obtained from this calibration were then used as the starting point for chickpea calibration, and were further refined using chickpea-specific literature to derive the default chickpea parameterization.

2. **Mapping, definition and ordering of variable groups**
   We matched the observed variables from the calibration dataset with the ones that can be simulated in MONICA. These variables were grouped based on the biological processes they represent. Variables involved in strong feedbacks — i.e. cases where changing the parameters controlling a process leads to large changes in the variables associated with that process — were assigned to the same group. To limit feedback effects during calibration, the variable groups were ordered carefully according to the internal sequence of processes in MONICA. Because MONICA includes strong feedback mechanisms, we anticipated that parameter estimates for each group would need to be revisited and adjusted after all groups had been considered.
3. **Identification of major parameters**
   For each variable group, key crop parameters from the MONICA model were selected based on their consistent impact across different environments and their strong influence on model outputs, as identified by sensitivity analysis. With an expected low risk of over-parameterization, the selection was not restricted to just one key parameter per variable group, particularly in cases where multiple variables or in-season measurements were available. Default values, lower and upper bounds for each parameter were set using both physiological knowledge from the literature and expert insights.
4. **Identification of candidate parameters**
   We selected additional parameters to account for the variability observed across different environments after the major parameters were estimated. These candidate parameters were prioritized based on their importance in driving the processes behind each variable group.
5. **Initial parameter estimation (sequential approach)**
   In this step, each group of variables was handled individually, following the order defined in Step 2. The list of parameters for estimation was composed of the key parameters for each group, and they were estimated sequentially in the order of the variable groups. The Monte Carlo algorithm was used, which involved repeated random sampling of key parameters and assessing their performance within the simulation function. The parameter set that minimized the sum of squared error (SS), as defined in Section 2.4, was chosen as the final result for this stage and provided the starting point for the next step. This process was carried out using the SPOTPY package in Python (Houska et al., 2015).
6. **Final parameter estimation (simultaneous approach)**
   After calibrating each variable group separately in the previous step, all parameters were re-estimated simultaneously using the full dataset. This step helped mitigate feedback effects within the model. The objective function to be minimized was the sum of the relative root mean square error ($rRMSE$), as defined in Section 2.4, for each variable group, normalized by the error variance: $errVar = rRMSE/(n-p)$ where $rRMSE$ is the relative root mean square error for each group from Step 5, n is the number of data points, and p is the number of estimated parameters. For each parameter set, the corrected Akaike Information Criterion ($AICc$) was calculated, using the formula: $AICc = n\,ln[f + 2p + (2p(p+1))/(n-p-1)]$ where f is the objective function value, n is the number of data points, and p is the number of estimated parameters. Once all the major parameters were re-estimated, each candidate parameter was tentatively added to the list of parameters to be estimated. If estimating all parameters on the list (using 10 runs with different initial values) reduced the AICc below the previous lowest value, the candidate was retained. Otherwise, the candidate was removed, and its value reverted to the default.
7. **Goodness-of-fit validation**
   The goodness-of-fit metrics were calculated to assess model performance. These metrics were compared across simulations using the default parameter values, the parameters estimated in Step 5, and the re-estimated parameters from Step 6.

Due to the similarities in crop functioning and yield potential among the lentil and chickpea cultivars in our dataset, and the non-orthogonal design with an unbalanced representation of cultivars across sites and years, we did not differentiate parameters for individual cultivars. Instead, we calibrated one species-level parameter set per crop and applied it to all cultivars. MONICA, however, natively allows the definition of cultivar-specific genetic coefficients; the species-specific parameterization developed here is therefore intended as a transparent baseline that can be refined in future work once larger and more balanced multi-cultivar datasets become available. These species-level parameter sets represent effective near-optimum growing parameterizations, rather than genetic coefficients strictly defined for potential-yield environments.

After completing the calibration process and estimating the final parameter values, the optimized MONICA model was tested on the evaluation dataset to assess its ability to generalize.

2.4. Evaluation metrics

Model performance was evaluated both graphically and quantitatively by calculating the root mean square error (RMSE) and its relative value (rRMSE), the mean bias error (MBE) and its relative value (rMBE), and the index of agreement (IA):

$$SS = \sum (y_i - \hat{y}_i)^2 \tag{1}$$

$$MSE = \frac{SS}{n} \tag{2}$$

$$RMSE = \sqrt{MSE} \tag{3}$$

$$rRMSE = \frac{RMSE}{\bar{y}} \tag{4}$$

$$MBE = \frac{\frac{\sum (y_i - \hat{y}_i)}{n}}{\bar{y}} \tag{5}$$

$$IA = 1 - \frac{\sum_{i=1}^{n} |\hat{y}_i - y_i|}{2\sum_{i=1}^{n} |y_i - \bar{y}|} \tag{6}$$

where y_i is the observed and $\hat{y}_i$ the predicted value, n the number of observations and $\bar{y}$ the average of the observed values.

The rRMSE represents the relative prediction error of the model. The rMBE indicates whether the model overestimates or underestimates a particular variable and reflects both the magnitude and direction of the bias. The dimensionless IA was employed in this study to provide a comprehensive assessment of model performance. Originally introduced by Willmott (1981), the revised version proposed by Willmott et al. (2012) was applied here. The IA measures model efficiency, with values ranging from −1 to 1, where 1 signifies perfect agreement and −1 indicates no agreement. Its interpretation is similar to that of the coefficient of determination R^2 (proportion of variance explained), but the IA is a normalized metric and is less sensitive to outliers, making it a more robust indicator of model performance (Berghuijs et al., 2021).

Generally, model predictions are considered satisfactory when the IA value is greater than 0 and the rMBE is below 10%, as suggested by Beaudoin et al. (2008), which is close to the typical coefficient of variation (13% by Taylor et al. (1999)). However, due to the high variability in our dataset, we expected higher error rates.

3. Results

3.1. Calibration of lentil and chickpea

3.1.1. Selection of default parameters

Eighteen parameter values were updated from the literature for the calibration process (Table 3) both for lentil and chickpea. These legumes exhibit characteristics of both long-day and neutral-day plants, depending on the cultivar (Saint-Clair, 1972; Daba et al., 2016). Summerfield et al. (1989b) and Soltani et al. (2004) demonstrated that lentil and chickpea development is accelerated under long photoperiods, while showing only slight sensitivity to vernalization (Roberts et al., 1988; Summerfield et al., 1989a). Based on this, we activated the photoperiod response and deactivated the vernalization response in the model.

The *BaseDayLength* parameter, representing the photoperiod below which no development occurs, was set at 7.4 h for lentil and 4 h for chickpea, based on findings by McKenzie and Hill (1989) and Singh and Virmani (1996). An initial estimate for the photoperiod required for flowering (*DayLengthRequirement*) was derived from Summerfield et al. (1984) for lentil and from Ellis et al. (1994) for chickpea. The growing degree days required for lentil development (*StageTemperatureSum*) were initially estimated from Tefera et al. (2022). The base temperature for lentil development (*BaseTemperature*) was set at 2°C for all stages except emergence, for which Covell et al. (1986) suggested a different value. The base temperature for chickpea was set at 4.5 °C as suggested by Soltani et al. (2006a).

For the developmental-stage-dependent ratio of leaf area to leaf dry mass (*SpecificLeafArea*), we used initial estimates from Jing et al. (2024) for lentil and from Sinha et al. (2018) for chickpea. The crop light-extinction coefficient (*StageKcFactor*), the factor that relates the crop's potential evapotranspiration to a reference grass vegetation (Allen et al., 1998), was set between 0.3 and 1.06 depending on the lentil's growth stage, based on Jabow and Mahgoub (2017). Similarly, values for chickpea were derived from (Garofalo et al., 2009). The maximum rooting depth (*CropSpecificMaxRootDepth*) was set to 93 cm for lentil and to 101 cm for chickpea, following Fan et al. (2016), who found that the entirety of roots is contained within these depths. Kashiwagi et al. (2015) also provided a penetration rate of chickpea root through the soil.

For biomass partitioning, Zakeri and Bueckert (2015) found that more than 85% of lentil biomass is accumulated after flowering and is allocated to pods, stems, and leaves in a 58:26:10 ratio. These data, combined with those from Jing et al. (2024), allowed us to estimate the partitioning of assimilates during crop development (*AssimilatePartitioningCoeff*). Similarly, the work done by Soltani et al. (2006b) and Vyshnavi et al. (2024) allowed us to estimate the biomass partitioning coefficient for chickpea.

Lentil has an optimal temperature range of 18–30°C from flowering to maturity (Barghi et al., 2012), but it is highly susceptible to temperatures above 32°C during reproductive stages, which drastically limits yield (Delahunty et al., 2018). The maximum temperature for assimilation was derived from Sehgal et al. (2019), while the minimum temperature was set at 2°C, which is lower than that of soybean (5°C), as lentil is a cool-season pulse. Chickpea is also a cool-season pulse but appears to be less cold resistant than lentil, with optimal temperature range of 21–32 °C and an optimum temperature for assimilation set to 26 °C (Soltani et al., 2006a). Freezing tolerance data were obtained from Murray et al. (1988) and Saghfi et al. (2013). For chickpea, we identified initial estimates for the time window during which the crop is most sensitive to heat (Kaushal et al., 2013) and the percentage of nitrogen demand met through fixation (Plett et al., 2021). Additionally, several easily measurable parameters (e.g. *MaxCropHeight*) were directly obtained from field trials, ensuring alignment with observed data. The default MONICA parameters for lentil and chickpea updated from literature are summarized in Table 3.

3.1.2. Mapping, defining and ordering of variable groups

Table 4 summarizes the correspondence between observed calibration variables and MONICA's simulated outputs, including units. Emergence, flowering, and maturity dates were grouped under "phenology" and calibrated first, as they influence all subsequent processes.

Next, aboveground biomass and LAI were grouped as "crop and canopy growth" due to their interdependence. Grain yield, highly dependent on phenology and biomass growth, formed the third group. Nitrogen content followed, as it depends on biomass but has limited feedback on earlier variables.

To minimize feedback effects, remaining variables were calibrated in order of dependency. Soil water content, influenced by biomass and nitrogen, was calibrated last, along with plant height, which has minimal backward influence. Both variables are key to simulating evapotranspiration.

3.1.3. Identification of major and candidate parameters

We identified 20 major parameters (Table 5) based on variable group constraints and data availability, guided by previous MONICA sensitivity analyses (Specka et al., 2015, 2019). For phenology, we selected thermal time parameters (*StageTemperatureSum*) and added three others influencing effective temperature used for heat summation: the minimum temperature at which summation begins (*BaseTemperature*) and the required daily hours of light (*DaylengthRequirement*) coupled with the minimum hours of light at which summation begins (*BaseDayLength*). Remaining related parameters were designated as candidates (see Supplementary Material for further information).

In the crop and canopy growth group, major parameters included those governing photosynthesis (*MaxAssimilationRate*), respiration (*OrganGrowthRespiration* and *OrganMaintenanceRespiration*) and early-stage *SpecificLeafArea*. Candidate parameters included those related to initial crop biomass for roots and stems (*InitialOrganBiomass*), cold tolerance (*LT50cultivar*), and later-stage *SpecificLeafArea*.

For grain yield, in addition to overlapping growth and phenology parameters, we also included the thermal time window during which the crop and its reproductive organs are most sensitive to heat stress, defined by the parameters *BeginSensitivePhaseHeatStress* and *EndSensitivePhaseHeatStress*. The only candidate here was *yieldPercentage*, a proxy for harvest index.

In the plant N group, major parameters were those mainly driving the N concentration in the plant tissue (*NConcentrationPN*, *NConcentrationBO*) while we tested parameters driving N deficiency (*MinimumNConcentration*), the maximum concentration in the aboveground biomass (*NConcentrationAbovegroundBiomass*) and the ratio of maximum to critical N concentration in crop tissue (*luxuryNCoeff*), as candidate parameters.

For evapotranspiration, we defined mid-stage parameters that incorporate crop characteristics and the average effects of soil evaporation (*StageKcFactor*), along with parameters regulating crop height development (*CropHeightP1* and *CropHeightP2*), as major parameters. The remaining extinction coefficient parameters were tested as candidate parameters.

3.1.4. Parameters estimation and model agreement with data

Parameter estimation was conducted sequentially by variable group (Step 5), followed by simultaneous optimization (Step 6), as outlined in the calibration procedure. Table 6 summarizes the RMSE and rRMSE values for default and calibrated parameters.

For lentil, sequential calibration substantially reduced RMSE across most variables, particularly for physiological maturity, biomass, yield, nitrogen content, and plant height. The plant N group showed the strongest improvement, with rRMSE dropping from over 100% to 27.6%. While metrics for emergence, flowering, LAI, and soil moisture also improved, reductions were less pronounced. Simultaneous calibration further improved performance, especially for biomass, yield, and nitrogen, which recorded the lowest errors overall. Average rRMSE

Table 4

Measured and simulated variables, group definition and ordering of the calibration process.

Measured variable	Simulated value	Units	Variable group	Order of calibration
DOY of BBCH Stage 09	DOY at emergence	days	phenology	1
DOY of BBCH Stage 61	DOY at beginning of flowering	days	phenology	1
DOY of BBCH Stage 89	DOY at maturity	days	phenology	1
Biomass at various dates	AbBiom	kg/ha	crop and canopy growth	2
Leaf Area Index	LAI	m^2/m^2	crop and canopy growth	2
Grain Yield	Yield	kg/ha	grain yield	3
N in Biomass	AbBiomNc	$kg/ha\ (kg/ha)^{-1}$	plant N	4
Soil Moisture (VWC)	Mois (layers average)	m^3/m^3	evapotranspiration	5
Plant Height	Height	m	evapotranspiration	5

Table 5

Major parameters identified and described for each variable group, along with their default initial values and boundaries.

Variable group	Major Parameter	Default Value (bounds)	Short Explanation (units)
Phenology	$Tsum_0$	90 (60–150)	Temperature sum from sowing to emergence (°C d)
Phenology	$Tsum_2$	270 (95–420)	Temperature sum from beg. stem elongation to beg. flowering (°C d)
Phenology	$Tsum_4$	450 (90–600)	Temperature sum from end of flowering to beg. of pod filling (°C d)
Phenology	$BaseTemp_{early}$	2 (−2–4)	Base temperature for assimilation during early stages (°C)
Phenology	$BaseTemp_{late}$	2 (3–8)	Base temperature for assimilation during late stages (°C)
Phenology	*DaylengthRequirement*	16 (10–22)	Daylength required for maximum growth during leaf development and vegetative growth (h)
Phenology	*BaseDayLength*	7.4 (0–12)	Daylength required for assimilation during leaf development and vegetative growth (h)
Crop and canopy growth	*MaxAssimRate*	20 (3–100)	Plant-specific maximum CO_2 assimilation rate (kg CO_2 ha^{-1} d^{-1})
Crop and canopy growth	$OrganMaintenanceRespiration_{Leaf}$	0.03 (0.001–0.03)	Specific maintenance respiration of the leaves (kg m^2)
Crop and canopy growth	$OrganMaintenanceRespiration_{Shoot}$	0.015 (0.001–0.03)	Specific maintenance respiration of the shoot (kg m^2)
Crop and canopy growth	$SpecificLeafArea_1$	0.0012 (0.0005–0.03)	Specific leaf area to calculate leaf area index during leaf development (m^2 kg^{-1})
Crop and canopy growth	$SpecificLeafArea_2$	0.0014 (0.0005–0.03)	Specific leaf area to calculate leaf area index during vegetative growth (m^2 kg^{-1})
Grain Yield	*EndSensitivePhaseHeatStress*	500 (300–1000)	End of the time window for crop sensitivity to heat stress (°C d)
Grain Yield	*BeginSensitivePhaseHeatStress*	300 (0–780)	Beginning of the time window for crop sensitivity to heat stress (°C d)
Plant N	*NConcentrationPN*	3 (1–6)	Crop-specific N distribution coefficient
Plant N	*NConcentrationBO*	1 (0–5)	Crop-specific N distribution coefficient
Evapotranspiration	$StageKcFactor_3$	1.06 (0.8–1.3)	Crop-specific factor during flowering
Evapotranspiration	$StageKcFactor_4$	0.82 (0.7–1.2)	Crop-specific factor during pod filling
Evapotranspiration	*CropHeightP1*	6 (5–12)	Crop-specific height parameter
Evapotranspiration	*CropHeightP2*	0.5 (0.3–0.6)	Crop-specific height parameter

Table 6

Root mean squared error (RMSE) and relative root mean squared error (RRMSE) for the calibration data for lentil (top) and chickpea (bottom). The table shows RMSE and rRMSE for the default parameter values and after parameter estimation in steps 5 and 6, for each group variable. Highlighted in bold is the smaller value for each variable group.

			BBCH 09	BBCH 61	BBCH89	Biomass	LAI	Grain yield	N in biomass	Soil moisture	Height
Lentil	Default parameters value	*RMSE*	4.9 days	14.2 days	13.1 days	2870.1 kg ha^{-1}	1.44	1023.9 kg ha^{-1}	0.0290 kg N kg^{-1}	8.8%	0.14 m
		rRMSE	0.044	0.102	0.069	0.949	0.804	0.657	1.196	0.402	0.597
	After Step 5 (sequential)	*RMSE*	**3.7 days**	10.8 days	**7.5 days**	1740.9 kg ha^{-1}	1.21	766.09 kg ha^{-1}	0.0067 kg N kg^{-1}	**7.7%**	**0.08 m**
		rRMSE	**0.033**	0.078	**0.039**	0.576	0.676	0.492	0.276	**0.352**	**0.341**
	After Step 6 (simultaneous)	*RMSE*	4.4 days	**9.8 days**	11.5 days	**1349.0 kg ha^{-1}**	**1.16**	**512.5 kg ha^{-1}**	**0.0037 kg N kg^{-1}**	8.2%	0.08 m
		rRMSE	0.039	**0.070**	0.061	**0.446**	**0.628**	**0.329**	**0.177**	0.377	0.351
Chickpea	Default parameters value	*RMSE*	17.0 days	10.3 days	17.5 days	3536.5 kg ha^{-1}	2.08	1370.6 kg ha^{-1}	0.0046 kg N kg^{-1}	6.8%	0.14 m
		rRMSE	0.169	0.072	0.085	0.922	0.949	0.631	0.174	0.424	0.366
	After Step 5 (sequential)	*RMSE*	9.0 days	9.1 days	**12.1 days**	1903.2 kg ha^{-1}	1.13	1229 kg ha^{-1}	0.0037 kg N kg^{-1}	**6.3%**	0.12 m
		rRMSE	0.089	0.063	**0.058**	0.496	0.517	0.566	0.140	**0.391**	0.316
	After Step 6 (simultaneous)	*RMSE*	**7.1 days**	**8.0 days**	16.6 days	**1724.5 kg ha^{-1}**	**0.99**	**1155.2 kg ha^{-1}**	**0.0030 kg N kg^{-1}**	7.2%	**0.10 m**
		rRMSE	**0.070**	**0.056**	0.081	**0.450**	**0.445**	**0.507**	**0.112**	0.437	**0.267**

dropped by ~10% relative to Step 5, highlighting the importance of accounting for feedbacks among variables. In contrast, flowering and LAI showed marginal improvement (rRMSE reduce by less than 3%), and rRMSE slightly increased for emergence, maturity, soil moisture, and plant height. This may reflect the choice of the objective function, which emphasizes total rRMSE reduction, favoring parameters that affect more sensitive variables even at the cost of others.

For chickpea, simulations using default parameters (optimized lentil values plus those updated using literature data) already yielded rRMSE < 100% across all groups, with near-minimal errors for flowering, nitrogen content, soil moisture, and height. Sequential calibration further improved all metrics, with modest rRMSE reductions (1%–7%), except for biomass and LAI, which dropped by 43%. Maturity and soil moisture showed the lowest RMSEs. Simultaneous calibration reduced errors further, though it slightly worsened predictions for maturity and soil moisture. Feedback incorporation improved other variables, though less than in lentil, with a maximum rRMSE drop of 7%.

For lentil, 27 parameters (20 major, 7 candidate) were estimated in total (Table 7). Step 5 led to an average absolute change of 42% in parameter values relative to the default settings, particularly in phenology (38%) and canopy growth (48%). Grain yield and nitrogen parameters shifted 44% and 61%, while evapotranspiration changed only 18%. In Step 6, parameters changed their values by an average of 40%, with 7 candidate parameters accepted. Feedback effects were strongest in grain yield (up to 100% change from Step 5 to Step 6) and minimal in evapotranspiration (9%), reflecting the relative sensitivity of each group.

Regarding chickpea, the results differ somewhat from the lentil case, despite the same number of total parameters (27) being mathematically optimized (Table 7). Parameter changes after Step 5 averaged 41%, with the largest shift (79%) in the crop and canopy growth group, aligning with improved prediction accuracy. Other groups changed less (<34%), except nitrogen-related parameters (57%), which showed limited error reduction. Unlike lentil, simultaneous calibration caused a smaller average change (18%) in major parameters, indicating weaker feedback effects. The strongest feedback was again in crop and canopy growth (49%). Acceptance of nitrogen-related candidate parameters (*LuxuryNCoeff*, *NConcentrationAbovegroundBiomass*) improved nitrogen

Table 7
Parameter values estimated during the different calibration phases for lentil (top) and chickpea (bottom).

	Variable group	Estimated Parameter	Default Value	Value after Step 5 (sequential)	Value after Step 6 (simultaneous)
Lentil	Phenology	$Tsum_0$	90	111	149
	Phenology	$Tsum_2$	270	180	157
	Phenology	$Tsum_4$	450	420	397
	Phenology	$BaseTemp_{early}$	2	2.5	−0.8
	Phenology	$BaseTemp_{late}$	2	4.5	4.1
	Phenology	*DaylengthRequirement*	16.0	18.8	16.1
	Phenology	*BaseDayLength*	7.4	10.2	10.5
	Crop and canopy growth	*MaxAssimRate*	20	13.7	15.2
	Crop and canopy growth	$OrganMaintenanceRespiration_{Leaf}$	0.03	0.007	0.015
	Crop and canopy growth	$OrganMaintenanceRespiration_{Shoot}$	0.015	0.027	0.016
	Crop and canopy growth	$SpecificLeafArea_1$	0.0012	0.0017	0.0022
	Crop and canopy growth	$SpecificLeafArea_2$	0.0014	0.0016	0.0012
	Grain Yield	*BeginSensitivePhaseHeatStress*	300	259	6
	Grain Yield	*EndSensitivePhaseHeatStress*	500	421	827
	Plant N	*NConcentrationPN*	3	4.6	1.1
	Plant N	*NConcentrationBO*	1	1.7	2.2
	Evapotranspiration	$StageKcFactor_3$	0.85	1.14	1.22
	Evapotranspiration	$StageKcFactor_4$	1.02	0.89	1.18
	Evapotranspiration	*CropHeightP1*	6	5	5
	Evapotranspiration	*CropHeightP2*	0.5	0.55	0.55
	All groups	$Tsum_3$	300		103
	All groups	*yieldPercentage*	0.79		0.73
	All groups	*MinimumNConcentration*	0.005		0.0075
	All groups	$StageKcFactor_2$	0.85		0.77
	All groups	$StageKcFactor_5$	0.45		0.70
	All groups	$SpecificLeafArea_3$	0.002		0.0029
	All groups	$SpecificLeafArea_4$	0.0022		0.0006
Chickpea	Phenology	$Tsum_0$	149	134	134
	Phenology	$Tsum_2$	157	238	194
	Phenology	$Tsum_4$	397	435	505
	Phenology	$BaseTemp_{early}$	4.5	1.4	1.4
	Phenology	$BaseTemp_{late}$	4.5	7	3.1
	Phenology	*DaylengthRequirement*	15.0	20.3	19.9
	Phenology	*BaseDayLength*	4.0	4.2	4.0
	Crop and canopy growth	*MaxAssimRate*	15.2	13.5	13.6
	Crop and canopy growth	$OrganMaintenanceRespiration_{Leaf}$	0.015	0.0158	0.0158
	Crop and canopy growth	$OrganMaintenanceRespiration_{Shoot}$	0.016	0.0065	0.0162
	Crop and canopy growth	$SpecificLeafArea_1$	0.00072	0.0029	0.0022
	Crop and canopy growth	$SpecificLeafArea_2$	0.00085	0.0007	0.0012
	Grain Yield	*BeginSensitivePhaseHeatStress*	670	703	681
	Grain Yield	*EndSensitivePhaseHeatStress*	1147	1032	1032
	Plant N	*NConcentrationPN*	1.1	1.6	1.6
	Plant N	*NConcentrationBO*	2.2	0.7	0.7
	Evapotranspiration	$StageKcFactor_3$	0.9	1.14	0.9
	Evapotranspiration	$StageKcFactor_4$	1.0	1.06	1.06
	Evapotranspiration	*CropHeightP1*	5	4.65	4.65
	Evapotranspiration	*CropHeightP2*	0.55	0.45	0.45
	All groups	$Tsum_3$	103		125
	All groups	*yieldPercentage*	0.73		0.94
	All groups	*LT50cultivar*	1		1.07
	All groups	*LuxuryNCoeff*	−4.5		−0.2
	All groups	$StageKcFactor_2$	0.7		0.43
	All groups	$SpecificLeafArea_3$	0.00102		0.00208
	All groups	*NConcentrationAbovegroundBiomass*	0.060		0.068

predictions without altering major parameters values. Notably, different candidate parameters were selected for chickpea, though some key ones (e.g., *Tsum3*, *StageKcFactor2*, *SpecificLeafArea3*) were shared across crops.

3.1.5. Goodness-of-fit validation

Lentil. The calibration resulted in a satisfactory prediction of the dates for emergence, beginning of flowering, and physiological maturity. The relative bias was very low (0%–5%) with very good IA values (Fig. 2), highlighting the effectiveness of using photoperiodic and thermal time-course formalisms to calculate crop development. The highest prediction error within phenological dates, occurred for maturity, with an average deviation (RMSE) of 11.5 days, where the model tended to slightly anticipate the maturity date. Unlike flowering, where the model showed higher prediction errors for both early Sicilian and late German cultivars, no clear pattern of error distribution was observed for maturity across different cultivars.

Soil water content within the top 30 cm of the soil was reasonably well simulated by the model, with an IA value above 0.7 and a small relative bias. The model successfully captured the variation between very dry and very moist conditions, though it exhibited a relatively high prediction error (rRMSE of around 40%) (Fig. 2). A similar trend was

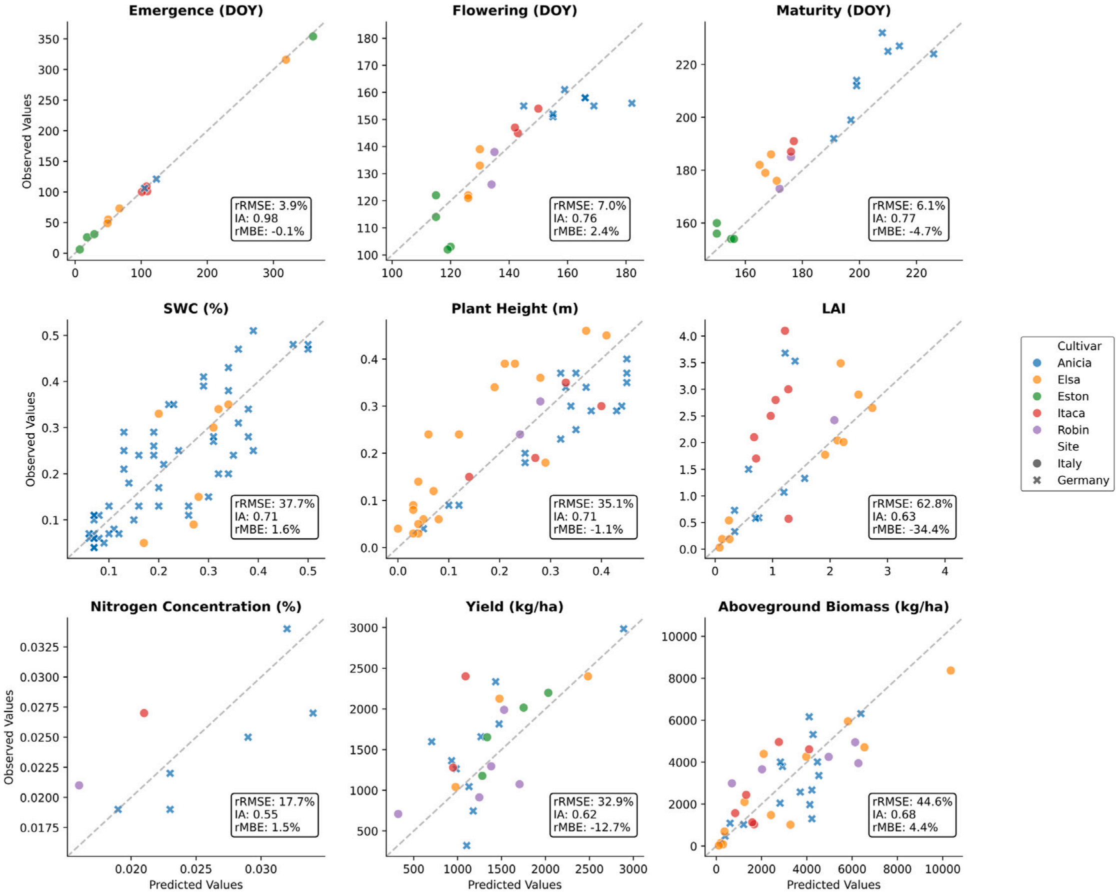

Fig. 2. Comparison of observed and MONICA-simulated phenology, soil water content (SWC), plant height, LAI, aboveground nitrogen concentration, grain yield, and aboveground biomass for the calibration dataset of lentil. rMBE represents the relative mean bias error, IA indicates the Index of Agreement, and rRMSE stands for the relative root mean square error. The dotted gray line represents the 1:1 line, with different symbols corresponding to different countries and different colors representing various cultivars.

observed in plant height predictions: the model displayed satisfactory efficiency and minimal bias, but the relative prediction error remained high. The model effectively predicted the height dynamics, from shorter plants during early stages to maximum heights later in the season. However, a noticeable challenge emerged in predicting final plant heights due to variations among cultivars, as the lentil parameters in the model were calibrated at the species level rather than for specific cultivars.

Regarding LAI values, the error metrics are the poorest among the simulated variable groups. There is a general underestimation, with an rMBE of around −35%, as the model consistently fails to capture the highest observed LAI values, never exceeding a simulated LAI of 3. Notably, the Itaca cultivar shows particularly high prediction errors, with its LAI consistently underestimated. This discrepancy may be attributed to differences in the methodology used to measure LAI in these experiments.

Observed grain yield varied widely across site-year-management conditions (ranging from 0.25 to 3.2 t ha^{-1}, Fig. 2), with considerable variability within each experiment as well (an average CV of 21%). The model efficiency was fairly good (IA = 0.62) for the calibration dataset, although it slightly underestimated yield values (rMBE = −12.7%). Although the rRMSE was relatively high, it was of the same order of magnitude as the CV of the observed data (30%, see Table 1), indicating that the error is consistent with the intrinsic variability of the system. In addition, the model successfully reproduced the full range of yield outcomes, capturing the entire spectrum of observed values.

Simulated aboveground biomass nitrogen concentration showed minimal bias (rMBE of 1.5%) and aligned well with observed values (rRMSE ~ 18%). However, despite the relatively low rRMSE, the model's efficiency was acceptable (IA = 0.55) due to the limited variability in the data, with N concentrations ranging only from 0.018% to 0.032%.

The predicted biomass showed good alignment with observations throughout the growing seasons (IA > 0.65 and bias below 5%). Despite this, the prediction error remained high (rRMSE of 45%), likely due to several factors that will be explored further in the discussion. Biomass at harvest varied significantly for lentil (between 1.0 and 8.5 t ha^{-1}), depending on site, year, and management (Fig. 2), and the model successfully captured this variability. It also accurately reproduced the biomass for the lentil cultivar with the longest growing period (winter-sown) in the calibration dataset.

Chickpea. The calibration achieved satisfactory predictions for the dates of emergence, beginning of flowering, and physiological maturity. The relative bias was low (less than 10%) with acceptable IA values (Fig. 3). However, the rRMSE values were generally higher compared to lentil, indicating that phenological stages are more challenging to predict in chickpea. The highest prediction error, in terms of RMSE, was observed for maturity, similar to lentil, with an average deviation of 16.6 days and a model agreement smaller than 0.7. The model consistently tended to slightly anticipate the maturity date across all cultivars and sites. Additionally, compared to lentil, the model showed less accuracy in capturing the emergence date, particularly for winter-sown SYMU. Soil moisture was simulated with an acceptable agreement (IA = 0.65). However, it showed a significant bias towards overestimating water content in the soil, a behavior not observed in

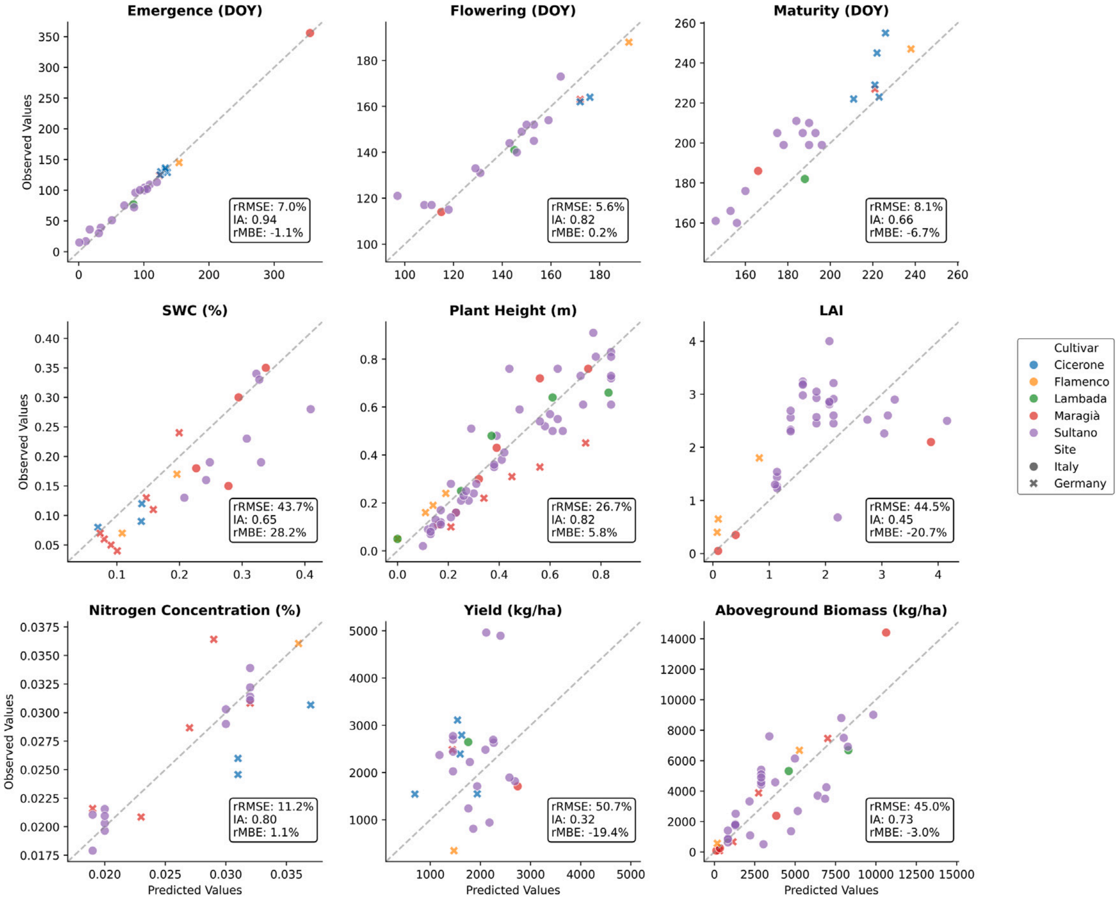

Fig. 3. Comparison of observed and MONICA-simulated phenology, soil water content (SWC), plant height, LAI, aboveground nitrogen concentration, grain yield, and aboveground biomass for the calibration dataset of chickpea. rMBE represents the relative mean bias error, IA indicates the Index of Agreement, and rRMSE stands for the relative root mean square error. The dotted gray line represents the 1:1 line, with different symbols corresponding to different countries and different colors representing various cultivars.

the lentil case. Similar to lentil, the model effectively captured the variability between very dry and very moist conditions, but it still exhibited a relatively high prediction error, with an rRMSE exceeding 40% (Fig. 3). In contrast, chickpea height was predicted more accurately than lentil height, demonstrating better model efficiency and lower prediction error, though with a slight overestimation. No clear trends were observed between cultivars and sites. Regarding LAI values, similar issues to those observed in lentil were present. There was a general underestimation, with an rMBE of approximately −21%. However, for chickpea, the model was able to simulate LAI values exceeding 3, although this occurred for the incorrect SYMU. In this case, the model's efficiency was low (IA < 0.5), and the prediction error was relatively high. Some cultivar-specific effects were evident, along with variations caused by different methods of measuring LAI within the same cultivar.

The simulated aboveground biomass nitrogen concentration exhibited minimal bias (rMBE of 1.1%) and closely matched the observed values, with an rRMSE of 11.2%. Unlike the lentil case, the model efficiency was good, successfully simulating even chickpea tissues with low nitrogen concentrations (<0.23%).

Observed grain yield exhibited substantial variability across SYMU, even more so than lentil, ranging from 0.34 to 4.9 t ha^{-1} (Fig. 3). For the calibration dataset, the model showed poor agreement between simulated and observed data (IA = 0.32), underestimating yield values with an rMBE of −19.4% and an average prediction error of 50.7%. Furthermore, the model was unable to capture the full range of observed yield values, as simulated values did not exceed 3 t ha^{-1}.

For aboveground biomass, the predictions were significantly better, showing strong alignment with observations throughout the growing season (IA > 0.5 and rMBE = 3%). However, the prediction error remained relatively high, with an rRMSE of 45%, similar to what was observed for lentil. As with lentil, biomass at harvest for chickpea varied substantially (3.5–14.4 t ha^{-1}) depending on site, year, and management practices (Fig. 3). The model effectively captured this variability, except for the exceptionally large Maragià biomass observed in early winter sowings.

3.2. Evaluation of lentil and chickpea

The model's performance in predicting grain yield shows moderate agreement with the observed values across the evaluation dataset (see Fig. 4), with very similar results both for lentil and chickpea. The index of agreement was fairly good (IA = 0.66 both for lentil and chickpea), but there is still considerable room for refinement. The relative RMSE (rRMSE = 55.1% and 43.3% respectively for lentil and chickpea) highlights the high variability in prediction accuracy across different environments, indicating that the model struggles to consistently capture the complexity of yield outcomes under various conditions.

The relative mean bias error (rMBE = −17.1% and −17.6% respectively for lentil and chickpea) shows that the model systematically underestimates grain yield, with most of the simulated values falling below the observed ones, particularly for higher yields. This underestimation is more pronounced in certain countries, such as Turkey, Romania and Greece, where higher yields were observed but poorly

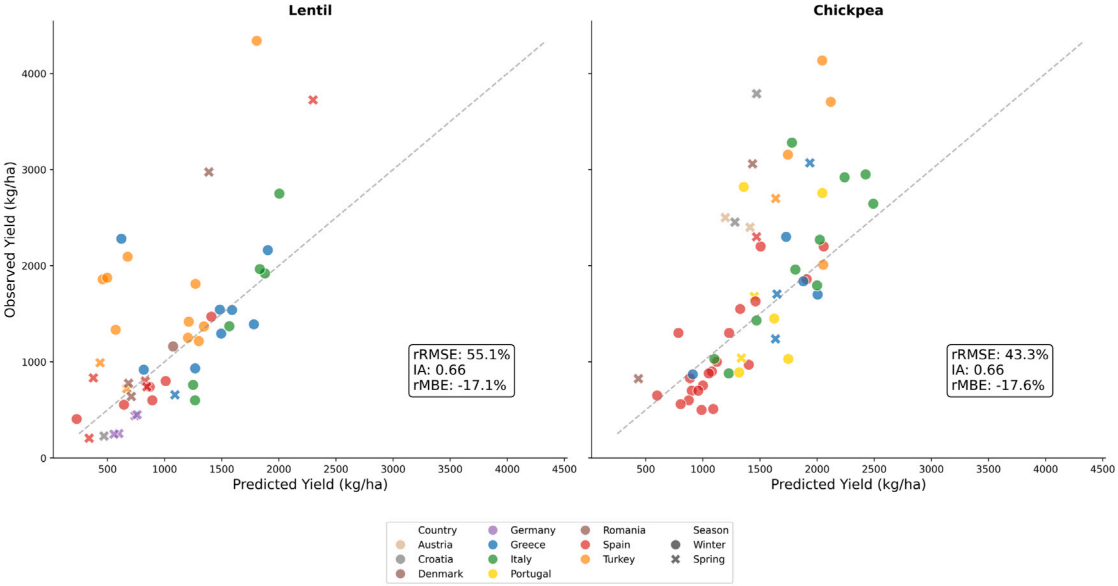

Fig. 4. Comparison of observed versus MONICA-simulated grain yield for the evaluation dataset for lentil and chickpea. rMBE (relative mean bias error) quantifies the systematic bias of the model, IA (index of agreement) measures how much the model improves on a simple mean-based prediction, while rRMSE (relative root mean square error) quantifies the size of the prediction error. The dotted gray line represents the 1:1 reference line (ideal prediction). Colors indicate different countries, while symbols differentiate between sowing seasons (Winter and Spring).

predicted by the model. The discrepancy could be attributed to environmental or management factors that were either not fully captured by the model inputs or not adequately parameterized.

The lower or comparable rRMSE values in the calibration data relative to the evaluation data for both lentil and chickpea suggest that over-parameterization is not a concern.

When comparing the rRMSE values for lentil and chickpea in the evaluation dataset, chickpea exhibits smaller errors. This is likely due to the greater number of SYMU available in the chickpea evaluation dataset, which also has a lower coefficient of variation compared to the evaluation dataset for lentil.

Despite the relatively high error metrics, the model successfully captures the general trend of yield variability across the different countries and environments. However, the significant underestimation in certain cases points to the need for further refinement, particularly for higher-yielding scenarios, which may involve enhancing the model's sensitivity to local management practices or specific environmental conditions.

4. Discussion

The calibration of the MONICA model for lentil and chickpea successfully demonstrates its adaptability to new legume species. This is notable, as adapting generic crop models to entirely new crops has received limited attention, with rare examples like the work of Falconnier et al. (2019) on faba bean using pea parameters as a base and Wimalasiri et al. (2021) applying a sugar cane model to hemp. Most crop models focus on cultivar-specific calibrations (Jégo et al., 2010; He et al., 2017; Casadebaig et al., 2020), having species-specific parameters already calibrated, but our work shows that MONICA can generalize to entirely new species when combined with literature-based parameters and a structured calibration protocol.

By implementing the protocol proposed by Wallach et al. (2023), which uniquely integrates multiple variable groups and uses the Akaike Information Criterion (AIC) for model selection, we optimized key parameters and reduced the risk of over-parameterization. This approach allowed us to effectively estimate key parameters, combining literature values with a precise mathematical optimization for those parameters that could not be directly measured. Uncalibrated parameters retained their default values, but in our work, we conducted an extensive literature review to identify a robust set of parameters (18 parameters per species). This careful selection process highlights the importance of choosing appropriate default values, an often-overlooked yet critical step in model calibration, to ensure the model's accuracy and relevance (He et al., 2017).

One of the unique contributions of our work lies in the fact that we applied the Wallach et al. (2023) protocol to real-world data, which, to the best of our knowledge, had not been attempted previously. This provided valuable insights into its limitations and how it could be improved. We found that using a broader optimization method (Monte Carlo) before refining with AIC helped achieve near-optimal parameter estimates. This approach diverges slightly from the strict AIC-driven methodology outlined by Wallach et al. (2023) but proved essential in converging towards parameters that minimized prediction errors. Furthermore, the sequential calibration of variable groups, as seen in other studies (Pasley et al., 2022; Jha et al., 2022), was useful to reduce errors. However, when strong feedback mechanisms were present, simultaneous calibration across multiple groups, as suggested by Guillaume et al. (2011), resulted in more accurate predictions, particularly for variables such as yield and biomass.

Unlike the findings of Wallach et al. (2023), we observed substantial variation in parameter values during simultaneous calibration, highlighting the importance of this step when feedback effects between variable groups are strong. This process led to significant improvements in the overall model performance and showed the need for simultaneous calibration, especially when dealing with complex interactions between crop growth processes.

The MONICA model, as adapted here, proved robust across a variety of environmental conditions and management practices, as evidenced by its ability to simulate key agronomic variables like phenology and aboveground biomass. Simulation of grain yield showed weaknesses of the model to reproduce observed data especially for lentil and chickpea under high-yielding conditions above 2 t/ha. These findings are consistent with the model's previous adaptations for other crops such as soybean (Battisti et al., 2017a,b), wheat, barley, and maize (Kostkov et al., 2021). Although the model performed decently in simulating lentil and chickpea yields, its precision did not match the levels reported in studies that considered fewer variables or dealt with lower observed variability (Jing et al., 2024). This limitation is less likely due to issues with the cultivar-specific parameterization itself and more indicative of challenges in accurately reproducing phenological maturity, particularly in high-yielding site-years. This aligns with findings from other legume modeling efforts, such as those by Ghanem et al. (2015) and Tefera et al. (2022), but underscores the need for additional data and refined parameterization approaches to enhance the model's accuracy.

An other key innovation of this paper lies in the dataset utilized. Few studies have incorporated such a wide range of latitudinal values (spanning from 36° to 53° parallels) as we did in our calibration dataset. Additionally, the evaluation dataset represents a groundbreaking application of the recently published European grain legume dataset (Antichi et al., 2023) for modeling purposes. This dataset, when further explored and combined with other available data sources, provides a valuable tool for the crop modeling community, enhancing the potential for more accurate simulations and broader applications.

A limitation of our study is that the calibration dataset does not represent classical potential-yield environments in the strict sense. Rather, the calibration dataset was filtered to approximate near-optimum field conditions (by excluding weed-affected plots and observing weeds pressure is more limiting than water for these crops). Thus, although the retained calibration data were relatively close to agronomic optimum under realistic field management, they do not correspond to fully stress-free, highly controlled experiments specifically designed to characterize potential yield. Such datasets are difficult to obtain for lentil and chickpea at field scale in Europe, especially across multiple sites and years. In addition, we did not estimate cultivar-specific parameters. This was a deliberate choice rather than a technical constraint: the calibration dataset combined several cultivars in a non-orthogonal design, with unbalanced representation across years, sites and measured variables, which did not provide the numerosity and replication required for robust genotype-specific calibration. At the same time, the cultivars used in Italy and Germany showed very similar phenology and morphology across environments, which supported treating lentil and chickpea at the species level. Our primary goal was therefore not to derive genetic coefficients that strictly reflect potential yield, but to obtain species-specific parameterizations that allow MONICA to emulate field-scale growth and yield patterns under the conditions in which these crops are most commonly cultivated. We acknowledge that this species-level approach entails some loss of cultivar-level detail and contributes to clustering of traits, as also noted by Wright et al. (2021), and that cultivar-specific calibration, though labor-intensive, can reduce prediction errors and would likely improve model accuracy in our case (Kersebaum et al., 2015; Grassini et al., 2015). MONICA already supports cultivar-specific genetic coefficients, and staged workflows similar to ours have been implemented for soybean (Nendel et al., 2023), where a species-specific parameterization is subsequently refined for cultivar groups. In future work, multi-environment, well-watered and completely weed-free trials, combined with methods to streamline cultivar calibration (Mongiano et al., 2019), would be highly valuable to better disentangle genotypic potential from stress effects and to further refine the physiological plausibility of model parameters.

In terms of error sources, inconsistencies in measurement methods for key variables like LAI and phenology contributed to prediction discrepancies. LAI, in particular, is prone to errors due to differences in direct and indirect measurement methods, as previously noted by Klingler et al. (2020). Moreover, the use of different phenological scales across experiments — some following Erskine et al. (1990) while others using the BBCH scale (Feller et al., 1995) — added further variability, affecting the accuracy of phenological predictions. Although we excluded most data points whose values were clearly affected by biotic stressors, it is possible that some observations with low levels of biotic stress remained in the dataset and may have subtly influenced model performance.

Another significant source of error stems from uncertainties in soil data, particularly in cases where in-situ measurements were unavailable. As noted by Grassini et al. (2015), precise soil characterization is essential for reliable crop simulations, and the quality of input data significantly affects model outcomes (Kersebaum et al., 2015). In several sites, field capacity and permanent wilting point — crucial soil parameters for simulations — were not accurately estimated. This issue was especially pronounced in the evaluation dataset, where soil data carried greater uncertainties. Additionally, a third source of error in the evaluation dataset came from missing management details (see Supplementary Material for further information), such as sowing and harvesting dates, which further affected model performance.

Errors in phenological predictions, particularly concerning physiological maturity, contributed to yield underestimation, especially in colder climates such as the high-altitude sites of continental Turkey, where the modeled temperature accumulation was insufficient to reach maturity. Even minor inaccuracies in phenological stages can lead to significant yield discrepancies (Lu et al., 2022), as delays in reaching maturity disrupt the allocation of aboveground biomass to grain production. This highlights the critical need for improving phenological modeling, particularly in regions with extreme climatic conditions.

A major limitation of this study is that nitrogen dynamics were only partially explored. While legumes are particularly valued for their capacity to fix atmospheric N_2, we did not explicitly calibrate or validate the biological N fixation module in MONICA. In our simulations, N fixation was represented using the model's generic legume module, with the fraction of plant N demand met by fixation specified from the literature, and the calibration targeted only aboveground N concentrations. Studies on other legumes have shown that explicitly calibrating N fixation and soil N uptake can improve model performances (e.g. Falconnier et al., 2019; Chen et al., 2016), and we consider this an important next step for lentil and chickpea in MONICA. Nevertheless, the good agreement between simulated and observed plant N concentrations and the generally realistic yield levels suggest that, under the conditions studied here, the current representation of N fixation is adequate to sustain crop growth, even if the underlying N fluxes remain to be evaluated in detail.

Despite these limitations, the final parameter values for lentil and chickpea were physiologically consistent with literature findings. For lentil, classification as a long-day, cool-season species (Summerfield et al., 1989b; Ferguson and Erskine, 2001) was explicitly represented through dynamic base-temperature and photoperiod (daylength) functions in the model. The simulated timing of phenological stages and overall growth duration showed good agreement with values reported by Tefera et al. (2022) and Venugopalan et al. (2021), supporting the adequacy of the resulting parameterization.

Our study contributes valuable insights into the potential impact of climate change on legume productivity. While much attention has been given to cereals like wheat and maize in Europe (e.g. Bindi and Olesen, 2011; Semenov et al., 2014; Trnka et al., 2015; Webber et al., 2018), research on legumes remains limited. The calibrated MONICA model now offers an important tool for assessing how legume crops might respond to increased drought-induced stress, a critical factor given the current projections for future climate in Europe. By distinguishing between winter and spring sowing, the model is well-positioned to test adaptation strategies such as shifts in sowing dates (Donatelli et al., 2015). Moreover, other adaptation strategies, like water-efficient rotations (Kollas et al., 2015), residue management (Faye et al., 2023), and intercropping (Yu et al., 2024), can be further explored using this model.

5. Conclusions

We conclude that the MONICA model, calibrated for lentil and chickpea, demonstrates strong potential as a tool for simulating key agronomic processes such as phenology, biomass accumulation, and nitrogen dynamics under varying environmental and management conditions. This study successfully addressed our primary objective by evaluating the ability of the model to represent the specific traits of lentil and chickpea through a structured calibration protocol. The results confirm that MONICA can generalize to new legume species with reasonable accuracy, although improvements are needed to better capture high-yielding site-years and variables measured using different methodologies (e.g. LAI) or strongly influenced by site-specific conditions (e.g soil water content).

While the model performed well in capturing broad trends of yield variability, systematic underestimations in certain environments suggest that refinements in phenological modeling, the inclusion of more detailed site-specific data and a better representation of soil health dynamics are needed to improve accuracy. Further refinement of cultivar-specific traits could also improve the accuracy of the model and its predictive capability. Despite these challenges, MONICA proved capable of providing meaningful insights into the impact of environmental stresses on lentil and chickpea productivity.

Future efforts should focus on expanding the calibration dataset, refining cultivar-specific traits, and enhancing the representation of critical processes such as nitrogen fixation. These developments will further enhance the model's utility in supporting sustainable legume cropping systems under varying climatic and management scenarios.

CRediT authorship contribution statement

A. Triacca: Conceptualization, Data curation, Methodology, Writing – original draft, Visualization, Formal analysis. **G. Nerucci:** Data curation, Writing – review & editing. **F. Leoni:** Data curation, Writing – review & editing. **S. Carlesi:** Methodology, Supervision, Writing – review & editing, Conceptualization. **M. Reckling:** Data curation, Funding acquisition, Writing – review & editing. **B. Horneburg:** Funding acquisition, Data curation. **M.S. Rahman:** Data curation. **A.C. Moonen:** Funding acquisition, Supervision, Writing – review & editing. **C. Nendel:** Conceptualization, Investigation, Methodology, Software, Supervision, Writing – review & editing.

Funding

We thank the German Federal Ministry of Agriculture, Food and Regional Identity (BMLEH) for funding the projects LinSel (Selection of lentil genotypes suited for sustainable cropping systems) and CiLaKlima (Genetic screening of chickpeas and grass peas; grant number 2820EPS028) and the EU for funding VALPRO Path and LegumES through the Horizon Europe research and innovation program (grant agreement No. 101059824 and 101135512). This study was supported by the LEG-ITA project, funded by the European Union – NextGeneration EU Mission 4, component 1, project number 2022MR7KJ9, CUP numbers G53D23004240006 and J53D23010280006. For the Udine calibration data we acknowledge the support of the Smart Protein project, funded by the European Union's Horizon 2020 Research and Innovation Programme (grand agrement No. 862957). A.T. and G.N. receive a study grant from the PhD Programme in Agrobiodiversity at Sant'Anna School of Advanced Studies, Pisa, Italy.

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.

Acknowledgments

The authors would like to thank the staff for running field experiments and collecting the soil and crop data. In Italy, our special thanks go to Gilbert Koskey, the technicians of the Institute of Plant Sciences of the Sant'Anna School of Advanced Studies in Pisa, and of the Research Centre for Agro-Environmental Research "Enrico Avanzi" of the University of Pisa for the technical support and to Daniel Marusig and Gemini Delle Vedove for providing highly relevant data for the calibration. We also extend our gratitude to Damaride Argenio for her motivational support and assistance in organizing the data. In Germany, we thank the staff of the research stations of ZALF in Müncheberg and Dedelow for managing and weeding the trial, and Gunhild Rosner, Kathleen Karges and Christoph Möller for the crop and soil monitoring.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eja.2026.128061.

Data availability

Data will be made available on request.

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