Ideotype definition to adapt legumes to climate change: A case study for field pea in Northern Italy.

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Primary research article

Abstract

One of the key strategies to alleviate negative impacts of climate change on crop production is the development of new cultivars better adapted to the conditions expected in the future. Despite the role of legumes as protein sources, medium- and long-term strategies currently debated mainly focus on agricultural policies and on improved management practices, whereas ideotyping studies using climate projections are scarcely reported. The objective of this study was to define pea ideotypes improved for yield and irrigation water productivity targeting current climate and four future projections centred on 2040, resulting from the combination of two General Circulation Models (HadGEM2 and GISS-ES) and two Representative Concentration Pathways (RCP4.5 and RCP8.5). The STICS model was used, with the default pea parameterization refined using data from two years of dedicated field experiments. Ideotypes were defined by combining STICS and the E-FAST sensitivity analysis method focusing on model parameters representing traits on which breeding programs are ongoing. Results showed that climate change is expected to decrease the productivity of current pea cultivars (up to -12.6%), and that increasing irrigation (to cope with the expected less favourable rainfall distribution) would not avoid yield losses. The proposed ideotypes, characterized by a shorter vegetative phase and by increased tolerance to high temperature, performed better than current varieties, providing higher yields (+4.5%) and reduced water consumption (-20%). For the first time, we demonstrated the suitability of STICS for ideotyping purposes and used a simulation model to define pea breeding strategies targeting future climate conditions.

Keywords:

Adaptation strategies; ideotyping; *Pisum sativum*; sensitivity analysis; STICS.

1. Introduction

Climate change is considered one of the major threats to agricultural productions worldwide and its implications for food security are rising to alarming levels (IPCC 2014). Global food demand in 2050 is projected to increase by at least 60 percent above 2006 levels because of population and income growth, in a context where urbanization is exacerbating the competition for soil, water and energy between countryside and cities (FAO 2016). The interaction between warmer temperatures, changes in rainfall distribution and frequency and intensity of extreme weather events is expected to impact agriculture in different ways, ranging from increase in yields and arable lands in some regions to the aggravation of food security issues in already vulnerable areas (Parry et al. 2004). In case of negative impacts, adaptation strategies are needed to reduce the extent of projected yield losses and, in the medium-long term, one of the most promising one is the development of new varieties better adapted to the forecasted agro-climatic conditions.

Given their capability to interpret genotype (G) × environment (E) × management (M) interactions, process-based crop models are increasingly used to support breeding programs via the definition or evaluation of plant types suited for specific conditions (Martre et al. 2015), including those resulting from future climate projections (e.g., Tao et al. 2017). Indeed, under the assumption of a close relationship between plant traits and model parameters (Casadebaig et al. 2016), process-based crop models can be used to define and test new ideotypes (corresponding to combinations of model parameters) more suited for future conditions (Paleari et al. 2017a), thus reducing costs and time needed to develop new cultivars. However, some plant traits are represented in the available crop models in a coarse way (Messina et al. 2018) and plant responses to some abiotic stressors are poorly formalized (Rötter et al. 2018). While new models are being developed explicitly to support breeding (e.g., Paleari et al. 2017b), the choice of the crop model to use and of the traits to consider should thus be carried out carefully. In particular, the analysis should be restricted to the traits actually represented by one or more model parameters (Paleari et al., 2017a).

While the development of model-aided ideotypes to support breeding programs is gradually becoming more popular for cereals (e.g., Peng et al. 2008), empirical breeding methodologies such as ‘selection for yield’ (yield-driven selection, without considering functional traits leading to genotype performance) or ‘default elimination’ (correcting morphophysiological imperfections or quality-related features) (Donald 1968) are still the most adopted for legumes. Despite being successful in selecting most productive cultivars in current agro-environmental contexts, those methodologies could be not enough to define plant types suited to the climate conditions expected in the future. Under these conditions, indeed, the improvement of complex traits involved with phenology or water stress tolerance could be crucial (Bahl 2015).

The interest in legumes, motivated by their health, economic and environmental value, is increasing (FAO 2016). In EU-28, dry legumes harvested area increased by 64.7% between 2013 and 2015, with field pea playing a key role, with more than one third (34.2%) of the total grain legumes area (ec.europa.eu/eurostat). To support the rising interest in legumes, studies on the evaluation of the impacts of climate change over those crops are ongoing (e.g., Anwar et al. 2015), as well as on the development of new breeding strategies to effectively derive improved cultivars, especially for resistance/tolerance to biotic and abiotic stressors (Mousavi-Derazmahalleh et al. 2019).

Among legumes, field pea (*Pisum sativum* L.) is highly sensitive to climatic conditions during the crop cycle, with pea yields being markedly influenced by drought and high temperatures during the phase of grain formation (Guilioni et al. 2003). Despite studies were published on the use of crop models to assist pea varietal selection for specific growing conditions (e.g., Jeuffroy et al. 2012), analyses involving crop models for defining pea ideotypes under climate change scenarios are not available.

The objective of this study was to perform a crop model-based analysis to derive field pea ideotypes for both current climate and future projections. As a case study, the focus was on Northern Italy. The potential benefits deriving from the adoption of the proposed ideotypes were quantified in terms of changes in productivity and irrigation water use efficiency compared to current cultivars.

2. Materials and methods

2.1. Breeding targets and crop model

The first step of the analysis was to identify the morphological and physiological traits on which breeders are currently focusing to improve the productive performance of field pea. In this light, selecting a crop model whose parameters have the most direct link to the plant traits of interest is of primary importance to increase the feasibility of *in silico* ideotypes (Paleari et al. 2017a). The model was thus selected according to its capability (i) to simulate the crop of interest and (ii) to properly take into account key plant traits via parameters representing as closely as possible the traits. The analysis led to identify the model STICS (Brisson et al. 2002) as the most suitable for the objective of the study, given its reliability for reproducing field pea growth and development (e.g., Corre-Hellou et al. 2009) and the close relationships between model parameters and traits of interest. In particular, six plant traits of potential interest for field pea breeding were selected for the study based on a dedicated literature search, which correspond to nine STICS parameters (Table 1).

STICS is a generic crop model that simulates on a daily basis crop growth and development, as well as soil and crop water, carbon and nitrogen budgets. Its flexibility allowed the adoption of the model for a variety of crops with determinate and indeterminate growth habit, the latter being simulated by accounting for trophic interactions between different cohorts of fruits. Crop development is derived as a function of thermal time, estimated based on daily mean crop temperature and the parameters base, optimal and critical temperature, and modulated by photoperiod sensitivity, vernalisation requirements and drought stress. Leaf area index (LAI, -) is simulated as a function of crop development and the crop responses to temperature, plant density, nitrogen and water stress. Radiation interception within the canopy depends on light extinction coefficient and LAI (Beer's law analogy), as well as on presence of pods that also contributes to light harvesting. Aboveground biomass accumulation is estimated using a photosynthesis approach based on radiation use efficiency (RUE), with the maximum radiation use efficiency modulated by temperature limitation, radiation excess, drought stress, nutrient availability and atmospheric CO_2 concentration (parameter ALPHACO_2, in this study set to 1.2 as from model documentation). Yield is derived via a dynamic harvest index, which increases linearly during grain filling (Brisson et al. 2002). Further details on model algorithms can be found in the seminal literature (Brisson et al., 1998) and in the model documentation (Brisson et al., 2009).

Trait	Relevance for breeding	Parameter	Units	Parameter description	Mean	Source
Cold tolerance	McPhee 2003; Shafiq et al., 2012; Mayer and Badaruddin, 2001; Sadras et al., 2012	tgmin	°C	Minimum temperature for germination and emergence	4	This study (calibration)
		tdebgel	°C	Temperature at the beginning of frost action	-4	STICS documentation
Heat tolerance	Vocanson and Jeuffroy 2008; Guilioni et al., 2003; Sadras et al., 2012	teoptbis	°C	End of thermal optimal plateau for net photosynthesis	25	This study (calibration)
		temax	°C	Maximum temperature for net photosynthesis	32	This study (calibration)
Root flooding sensitivity	Vozáry, et al. 2012	sensanox	-	Anoxia sensitivity	0.1	This study (calibration)
Drought tolerance	McPhee 2003 Sadras et al., 2012	sensrsec	-	Root sensitivity to drought	0.4	STICS documentation
Plant height	Tar'an, et al. 2003	hautmax	m	Maximum plant height	0.65	STICS documentation
Early development and maturity	Vocanson and Jeuffroy 2008; Tayeh et al., 2015; Weller and Ortega, 2015	stlevamf	°C-days	Thermal time between emergence and end of juvenile phase	300	This study (calibration)
		stlevdrp	°C-days	Thermal time between emergence and onset of fruit filling	700	This study (calibration)

Table 1. Traits included in the ideotyping study because of interest for pea breeding and corresponding STICS parameters.

2.2. Model parameterization

Data to adapt STICS default parameters to Italian pea cultivars were collected on seven field trials between 2016 and 2017. The experimental fields were distributed in five locations across the Emilia-Romagna region, which was selected as representative of the conditions explored by the crop in Northern Italy. Sowing dates per site were 13 March 2017 in Alseno (44.92° N, 9.96° E; soil: clay, USDA texture classification), 2 April 2016 in Jolanda di Savoia (44.88° N, 11.98° E; soil: clay), 16 April 2016 and 23 March 2017 in San Rocco al Porto (45.08° N, 9.69° E; soil: silt loam), 13 and 15 April 2016 in San Pietro in Trento (44.32° N, 12.08° E; soil: sandy loam in one field, sandy clay in the other), and 15 March 2017 in Bagnolo (44.93° N, 9.94° E; soil: clay). Soil organic matter ranged between 1.6% (Alseno) to 2.2% (San Pietro in Trento). More details on soil properties are reported in Table S1. All the field experiments were located in the Po river alluvial plain, mostly characterized by deep soils that – together with heavy textures – guarantee good water reserves. Sowing dates in the experimental fields reflected standard practices in the region, and they were immediately after the spring rainfall peak typical of northern Italy. This allowed initializing the simulations with soil water content at field capacity for model calibration/validation and for the ideotyping experiments. Different weather conditions (source: Regional Agency for Environmental Protection, ARPAE) characterized the pea season in the different combinations site × sowing date, especially for precipitations, which ranged between 145 and 285 mm (total rainfall over the growing season, which lasted on average 75 days). According to the management practices of the study area, in case of scarce precipitations sprinkle irrigation was applied. Cultivars Waverex (San Pietro in Trento, sowing date: 13 April 2016) and Wolf (all other experiments) were grown, selected since they are the most cultivated in the study area and among those suggested by the Regional product specification. Field management allowed keeping the fields weed-, disease- and pest-free, with optimal water and nutrients supply. The aim of the study was indeed to analyse the impact of climate variations on productivity and on changes in water requirements that would be needed to maintain the crop under unlimiting conditions for water, as they currently are. Parameter calibration was performed using data collected on the crops sown on 15 April 2016 in San Pietro in Trento, 16 April 2016 and 23 March 2017 in San Rocco al Porto, and 15 March 2017 in Bagnolo, whereas remaining datasets were used for validation. The number of observations (single measurements) used for calibration and validation was 56 and 40, respectively.

Field measurements were carried out at four development stages, as described in the Biologische Bundesanstalt, bundessortenamt und CHemische industrie (BBCH) scale for pea (Feller et al. 1995): leaf development (BBCH code 17), flowering (BBCH code 64), development of fruits (BBCH code 73), and fully ripe (BBCH code 89). To account for in-field variability, data were collected in three random points at each sampling event. For biomass determination, twenty plants for each point were sampled and divided into stems, leaves, flowers and fruits, and dried at 105°C until constant weight. For the 2017 experiments, LAI, specific leaf area (SLA, $m^2\ kg^{-1}$), canopy height and the number of branches, leaves, flowers and pods per plant were also determined at each measuring point and for each measuring date. LAI was estimated by using the PocketLAI smart-app (Confalonieri et al., 2013), whereas SLA was derived by digitalizing sampled leaves and calculating the leaf area to dry mass ratio.

The refinement of STICS parameters for Italian pea cultivars was carried out manually using a trial-and-error approach, targeting the highest agreement between observed and simulated values of yield, LAI, aboveground biomass, and biomass of the different organs (stems, leaves and pods). The agreement between measured and simulated values was quantified using mean absolute error (MAE), relative root mean square error (RRMSE), Nash and Sutcliffe modelling efficiency (EF), coefficient of residual mass (CRM) (Table 2), and R^2. Overall, the calibration led to modify the values of 33 out of 258 crop parameters.

Agreement metric	**Equation**	**Range and optimum**
Mean absolute error (MAE; Jørgensen et al., 1986)	$\mathrm{MAE} = \frac{\sum_{i=1}^{n} \lvert Y_i - X_i \rvert}{n}$	From 0 (optimum) to +∞
Relative root mean square error (RRMSE; Jørgensen et al., 1986)	$\mathrm{RRMSE} = 100 \cdot \frac{\sqrt{\frac{\sum_{i=1}^{n} (Y_i - X_i)^2}{n}}}{\overline{X}}$	From 0 (optimum) to +∞
Modelling efficiency (EF; Nash and Sutcliffe, 1970)	$\mathrm{EF} = 1 - \frac{\sum_{i=1}^{n} (Y_i - X_i)^2}{\sum_{i=1}^{n} (X_i - \overline{X})^2}$	From -∞ to 1 (optimum)

Coefficient of residual mass (CRM; Loague and Green, 1991)	$\mathrm{CRM} = 1 - \frac{\sum_{i=1}^{n} \overline{Y}}{\sum_{i=1}^{n} \overline{X}}$	From -∞ to + ∞; optimum: 0. Negative values indicate model overestimation, positive values underestimation

Table 2. Agreement metrics used for model evaluation (Y, predicted values; X, observed values; n, number of observations).

2.3. Definition of ideotypes and evaluation as compared to current cultivars

The analysis of the 1986-2005 weather data in the region suggested to perform the ideotyping study for two sites, centered in Piacenza (45.05° N, 9.70° E; site A hereafter) and Ravenna (44.42° N, 12.18° E; site B), considered as representative of the range of the conditions explored by pea in the study area. Site A is drier, with average temperature during the pea season close to the optimum for the crop, whereas site B is warmer and rainier. Ideotypes were defined for both current climate (1986-2005 baseline; derived from the European Centre for Medium-Range Weather Forecasts; ECMWF) and future scenarios. To handle the uncertainty in future climate projections, four 20-year timeframes centred on 2040 were derived for each site by considering (i) two Representative Concentration Pathways (RCPs) – RCP4.5 and RCP8.5 (IPCC's Fifth Assessment Report AR5, IPCC 2014) – which represent potential pathways of greenhouse gas (GHG) emissions and atmospheric concentration for the 21th century, and (ii) two General Circulation Models (GCMs) – HadGEM2, (Hadley Centre, UK, Collins et al., 2011) and GISS-ES (NASA, Schmidt et al., 2006) – which provide climate projections at global scale accounting for variations in GHGs concentrations. RCP4.5 is considered an optimistic scenario, with CO_2-equivalent stabilized at about 650 ppm in 2100, whereas RCP8.5 derives from the hypothesis of no specific climate mitigation targets, with about 1370 ppm CO_2-equivalent in 2100 (IPCC 2014). Downscaling for both baseline and future climate projections was carried out with the stochastic weather generator LarsWG5 (Semenov and Barrow 1997). After comparing the four forecasted climatic scenarios (resulting from the combination of two GCMs × two RCPs) in terms of temperatures and rainfall amount and distribution, we selected for the ideotyping study the two combinations RCP × GCM characterized by the largest differences in the thermal and pluviometric regimes: RCP4.5-GISS-ES and RCP8.5-HadGEM2 (Figure 1).

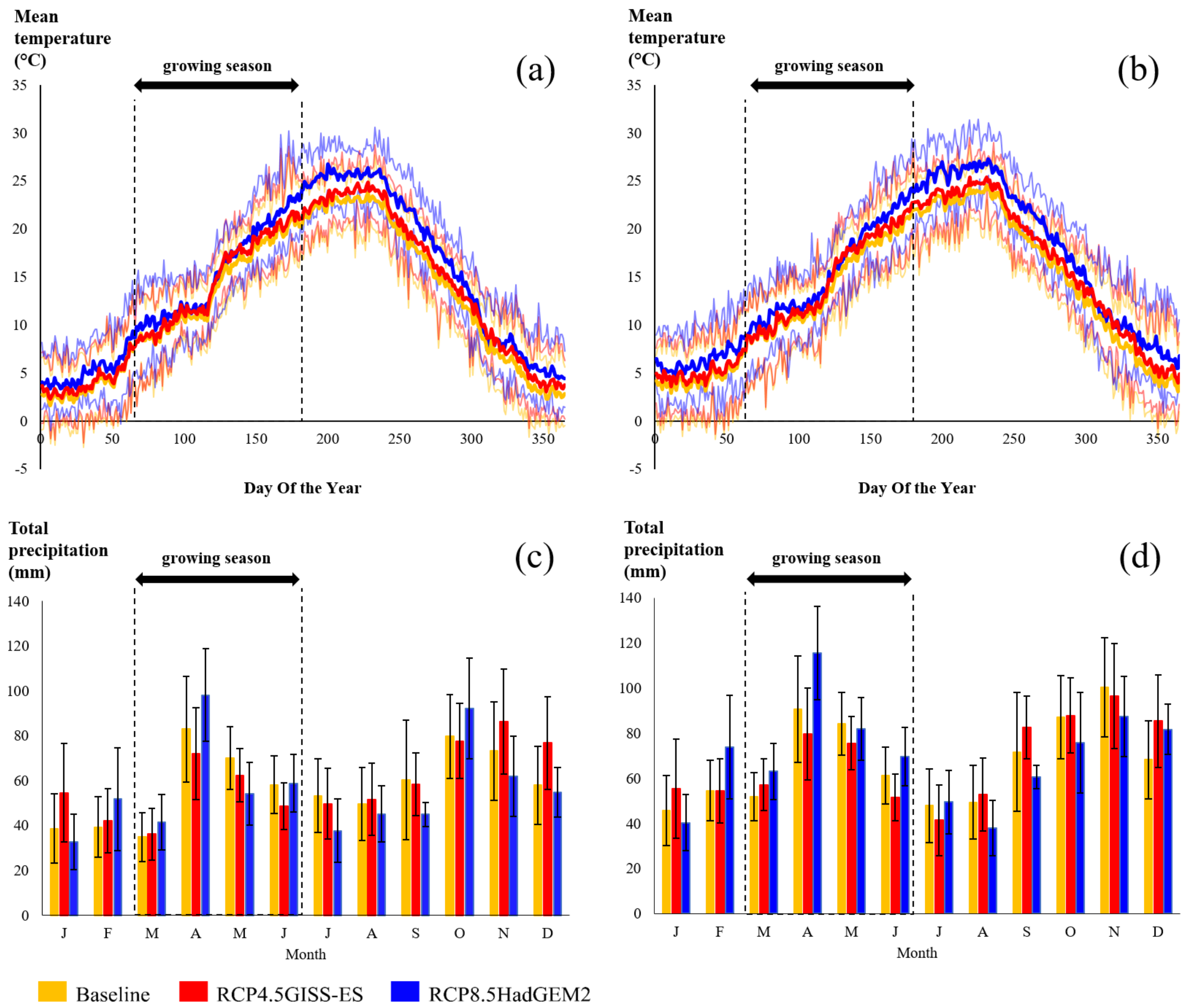

Figure 1. Comparison between the daily mean temperature (a, b) and the monthly cumulative precipitation (c, d) of the baseline scenario (yellow) and of the two 2040 climate scenarios used in the study: RCP4.5-GISS-ES (red) and RCP8.5-HadGEM2 (blue). For temperatures, solid lines refer to the 20-year average (1986-2005 for the baseline, 20 years centered in 2040 for future projections); thin lines refer to the lowest and the highest value of the series. For precipitations, the bars represent the 20-year mean of monthly cumulative precipitation. Panel (a, c): Piacenza (site A), panel (b, d): Ravenna (site B). The arrows provide information on the main growing season for the crop in the study area.

Parameter hyperspace was explored to identify key traits for field pea improvement using global sensitivity analysis techniques (Martre et al. 2015) and the parameter distributions reported in Table 1. Given available parameter values retrieved from literature and from the field experiments carried out during this study did not allow to define robust distributions, we assumed all distributions being normal, with standard deviation equal to the 5% of the mean of available values (Table 1) according to Richter et al. (2010). Although this approach could underestimate the variability available in current pea cultivars for some traits, it reduces the risk of proposing ideotypes that cannot be realized in vivo.

The variance-based global sensitivity analysis method Extended Fourier Amplitude Sensitivity Test (E-FAST; Saltelli et al. 1999) was used. For each parameter, E-FAST allows the estimation of first- and total-order effects, the latter including the amount of output variance explained by the interactions of the parameter with all the others. For each combination site × climate scenario, the sample size for the sensitivity analysis was set to 2600, calculated as the product of the number of factors (10), the number of repetitions of the sampling scheme (4), and the sample size for each repetition (65). The number of factors was the number of parameters analysed plus a *dummy* factor used to quantify method default-error threshold. In fact, given that the *dummy* factor cannot affect the model output – because it is not used in the simulations – the value of its SA metric represents the basal error of the SA method. Model parameters with sensitivity indices below this threshold were considered as not relevant and thus not included in the ideotype design. This sample size was considered the minimum one to guarantee an adequate exploration of the parameter hyperspace while avoiding inefficiencies caused by the symmetry properties of trigonometric functions used by the method (Saltelli et al. 1999). The total number of 1-season simulations was 312000. To account for both productivity and yield stability across years, sensitivity indices were calculated on the composite output shown in Eq. 1:

$$Y_{index} = \left[\left(\frac{Y_i}{Y_{MAX}}\right) \cdot 0.7\right] + \left[\left(1 - \frac{CV_i}{CV_{MAX}}\right) \cdot 0.3\right] \qquad \text{Eq. 1}$$

where Y_i and CV_i are the mean and the coefficient of variation of the yield values simulated with the combination of parameters *i* for the 20 season of each climate scenario; Y_{MAX} and CV_{MAX} are mean and coefficient of variation corresponding to the combination of parameters that achieved the maximum values for the metrics. Y_{index} was also used to rank the combinations of parameters and – for each combination site × RCP × GCM – to define the ideotype as represented by the means of parameter values of the best 1% combinations. The efficient exploration of the parameter hyperspace achieved with the SA sampling design can indeed be used to derive context-specific-ideotype (Paleari et al. 2017a), specifying the extent and the direction of the improvement suggested for each trait. By considering the mean of multiple top-ranked combinations, this approach has also the advantage of reducing the effect of potential local minima in the parameters space on the in vivo realizability of ideotypes.

The potential benefits deriving from the adoption of the designed ideotypes as compared to current pea cultivars were evaluated, for both current climate and climate change projections, in terms of percentage variation of yield, irrigation water requirements, and irrigation water-productivity. Aboveground biomass (AGB, t ha^{-1}), yield stability, and cycle length (days) were also evaluated.

The agreement between parameter rankings (the first parameter being the one with the highest total order effect) obtained for different environmental conditions was evaluated using the Top-Down Concordance Coefficient (TDCC, Iman and Conover 1987; Eq. 2), where TDCC values equal to 1 indicate perfect agreement.

$$TDCC = \frac{\sum_{i=1}^{k}\left[\sum_{j=1}^{nSA} ss(SM_{ij})\right]^2 - nSA^2 \cdot k}{nSA^2\left[k - \sum_{i=1}^{k}\frac{1}{i}\right]} \qquad \text{Eq. 2}$$

where *nSA* is the number of sensitivity analysis replicates; SM_{ij} the sensitivity measure of the parameter *Xi* and the replicate *Rj*; $ss(SM_{ij}) = \sum_{i=r(SM_{ij})}^{k} 1/i$ is the Savage score (Savage, 1956) calculated for all parameters *Xi* and replicates *Rj*, and $r(SM_{ij})$ the rank assigned to the sensitivity measure of the replicate *Rj*.

In particular, TDCC was calculated within climate scenarios (thus comparing rankings obtained for the two sites) and within site (comparing rankings obtained for different climate scenarios). TDCC was finally used to estimate the plasticity of the STICS model (Confalonieri et al. 2012), quantifying the model aptitude to change the sensitivity to parameters while changing the conditions explored (Eq. 3):

$$L = TDCC \cdot e^{(\sigma_{SAM} - 1)} \qquad \text{Eq. 3}$$

where σ_{SAM} is the normalized difference between cumulated rainfall and reference evapotranspiration during the crop season. *L* varies from 0 to about 1.51, with highest plasticity at 0.

The sensitivity analysis (i.e., sampling the parameters hyperspace and estimating SA metrics) was conducted using the software SIMLAB (Tarantola and Becker, 2016), whereas a dedicated VBA software was developed for generating the configuration files (.usms) and the plant files (one for each combination of parameters) required to run STICS in batch. SIMLAB is freely available at https://ec.europa.eu/jrc/en/samo/simlab; the VBA code is available for the Authors upon request.

3. Results

3.1. Model parameterization

The parameterization allowed obtaining a good agreement between observed and simulated values for all state variables (Fig. 2, Table 3). For the calibration datasets, EF (modelling efficiency; min: -∞, max and optimum: 1) was largely positive for both LAI and biomass-related state variables (mean EF equal to 0.75). The satisfactory behavior of the model was confirmed by the other agreement metrics, with R^2 always higher than 0.70, mean RRMSE equal to 40.2, and CRM equal to 0.14 on average.

The good agreement between measured and simulated values was confirmed during validation, with mean RRMSE equal to 30.4, R^2 equal to 0.75 on average (higher than 0.70 for four out of five biomass-related variables), and mean EF equal to 0.62. Similarly to what observed for the calibration datasets, model over- and under-estimation were limited, with average CRM values equal to +0.06.

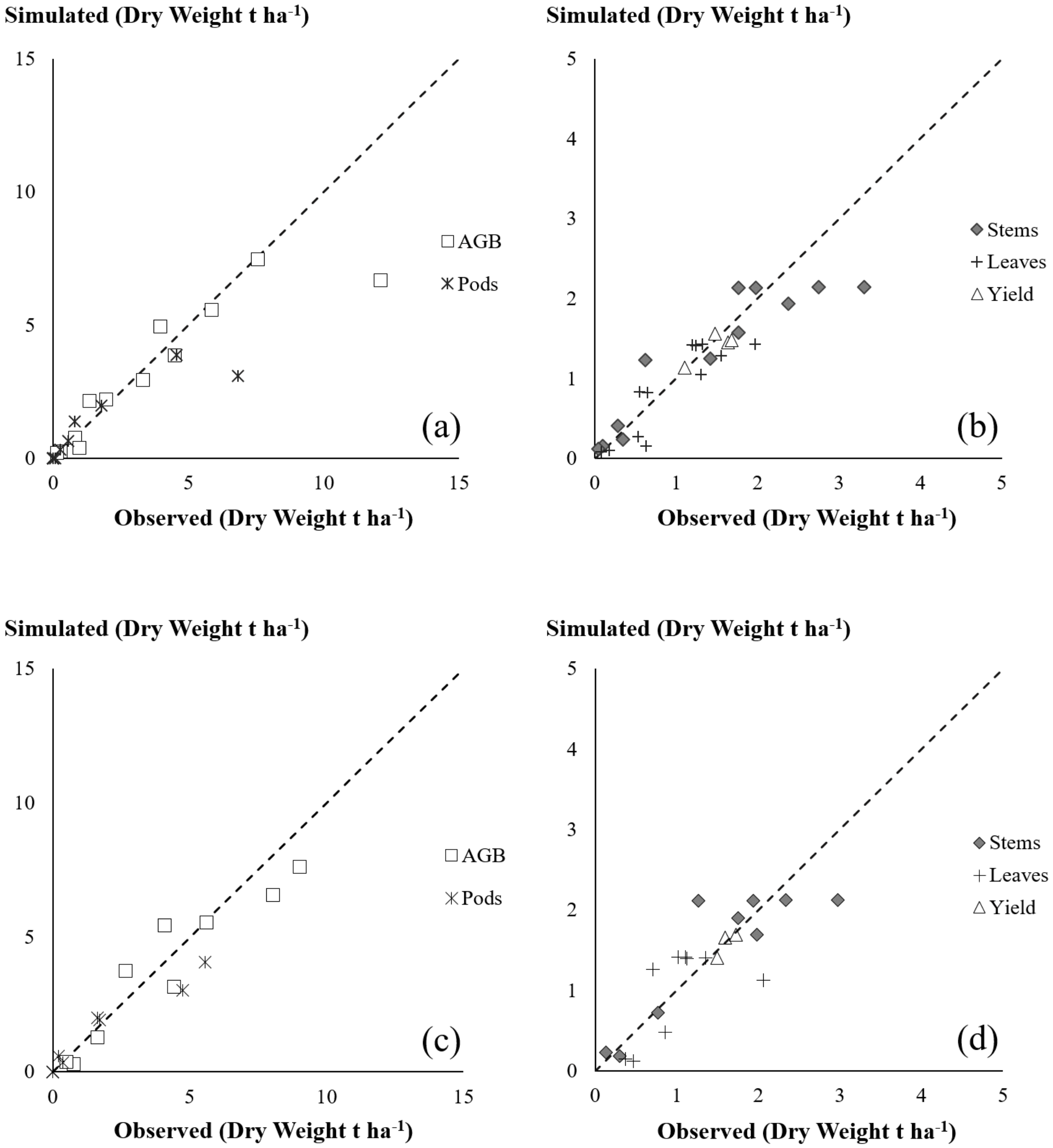

Figure 2. Agreement between measured and simulated biomass values for different plant organs for the calibration (a, b) and validation (c, d) datasets. Dotted lines refer to perfect agreement. For yield (b and d panel), only one sampling point (harvest) was available for each dataset.

Activity	Variable	MAE	RRMSE (%)	EF	CRM	R^2	*p*-value
Calibration	Yield (t ha^{-1})	0.12	9.67	0.61	0.04	0.70	n.s
	LAI (-)	0.56	33.44	0.85	0.28	0.99	**
	AGB (t ha^{-1})	0.79	45.75	0.77	0.12	0.82	***
	Leaf biomass (t ha^{-1})	0.24	29.71	0.75	0.08	0.78	***
	Stem biomass (t ha^{-1})	0.34	33.1	0.81	0.08	0.84	***
	Pod biomass (t ha^{-1})	0.45	89.59	0.72	0.24	0.83	***
Validation	Yield (t ha^{-1})	0.06	4.26	0.49	0.01	0.77	n.s.
	AGB (t ha^{-1})	0.85	24.7	0.88	0.07	0.89	***
	Leaf biomass (t ha^{-1})	0.39	44.73	0.11	0.03	0.37	n.s.
	Stem biomass (t ha^{-1})	0.31	28.83	0.77	0.02	0.77	**
	Pod biomass (t ha^{-1})	0.47	49.42	0.85	0.16	0.94	***

*Table 3. Agreement between observed and simulated values for the calibration and validation datasets. MAE: mean absolute error; RRMSE: relative root mean square error; EF: modelling efficiency; CRM: coefficient of residual mass; R^2: coefficient of determination of the regression between measured and simulated values. See Table 2 for a detailed description of these metrics. All biomass-related variables refer to dry weight. **: p-value <0.01; ***: p-value <0.001; n.s.: not significant. P-values (F-test) represent the significance of the linear regression between observed and simulated values to which the R^2 refer to.*

3.2. Ideotypes improved for productivity and irrigation water use efficiency

The ideotypes are presented and discussed in terms of percentage variation of parameter values as compared to the parameter values characterizing the current cultivars (Fig. 3). The absolute values of the nine parameters defining the ideotypes are reported in Table S2.

Sensitivity analysis results (Fig. 3a, b) revealed the relevance of all the parameters presented in Table 1, being their total effects always higher than the one calculated for the *dummy* factor.

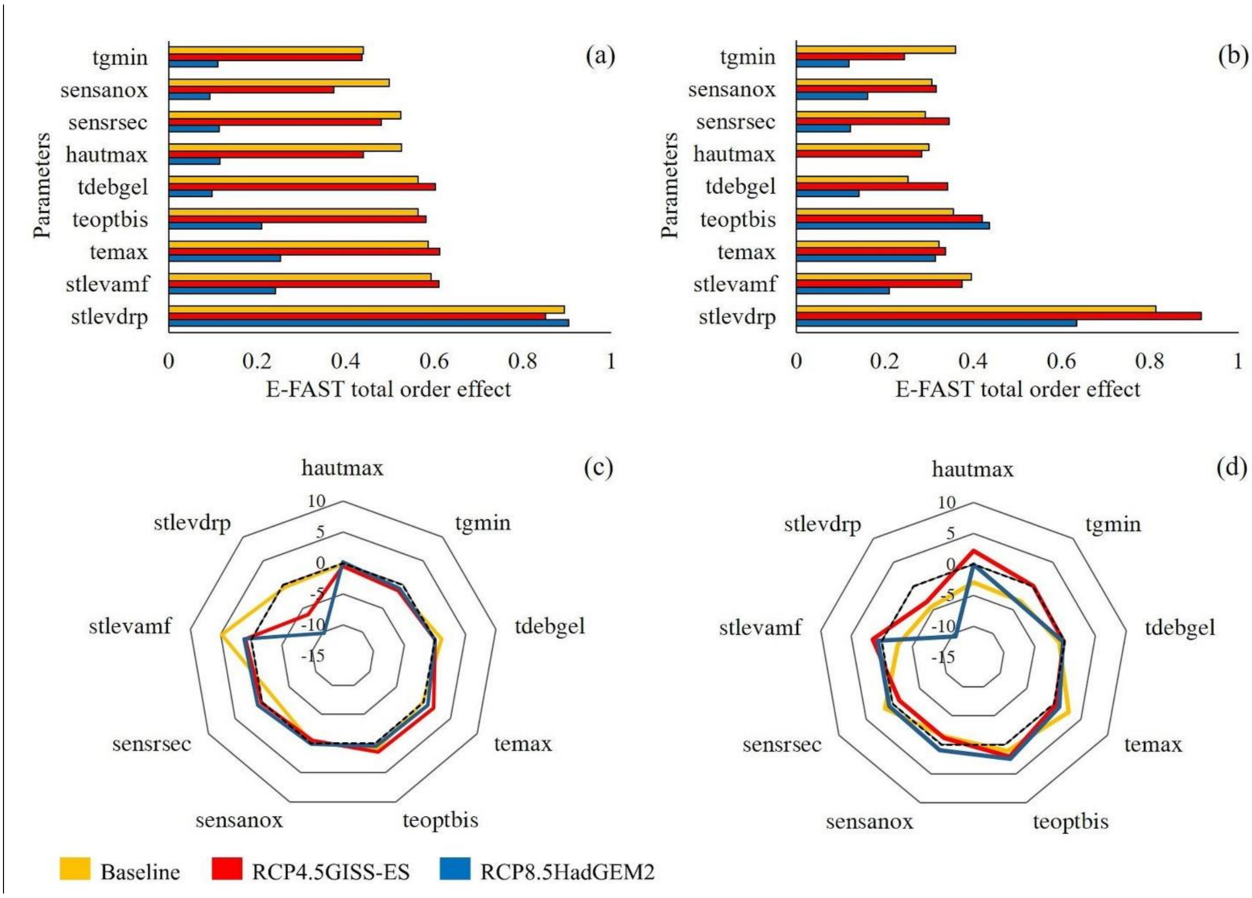

Figure 3. Sensitivity analysis results (a and b) and ideotype profiles (c and d) for the two sites (a and c refers to site A; b and d to site B) and the three climate scenarios analyzed (yellow refers to the baseline; red to RCP4.5-GISS-ES; blue to RCP8.5-HadGEM2). Sensitivity analysis results are presented as E-FAST total order effects. Ideotype profiles are represented as percentage variation of parameter values with respect to the parameter values for current genotypes (for which the reference is the dotted line). Hautmax: maximum plant height; tgmin: minimum temperature for germination and emergence; tdebgel: threshold temperature for frost damage; teoptbis and temax: optimum and maximum temperature for growth; sensanox: root sensitivity to anoxia; sensrsec: root sensitivity to drought; stlevamf: thermal time to end the vegetative phase; stlevdrp: thermal time to start fruit filling. Details on parameter description are available in Table 1.

For the baseline scenario, the ideotype presented minor differences compared to existing cultivars both in terms of variation in parameter values and productive performances (e.g., for yield, less than 2.5% in site A, less than 4.0% in the site B), indicating that available genotypes are well suited for the climatic conditions they are currently exploring. However, for site A (yellow series in Fig. 3c), the longer juvenile phase of the ideotype (stlevamf: +4.8%) allowed an overall increase in photosynthetic area and, consequently, higher photosynthetic rates and yields. The ideotype defined for the same scenario (baseline) in site B (Fig. 3d), instead, was characterized by a shorter cycle compared to existing cultivars (stlevamf: -2.7%; stlevdrp: -4.4%) and by a higher tolerance to high temperatures (teoptbis: +1%; temax: + 2.7%).

Similar results were obtained for the two sites for the RCP4.5-GISS-ES scenario (red series in Figs. 3c, 3d), with ideotypes characterized by wider optimal temperature range (teoptbis*:* +1.5% and teoptbis: +2.1% for site A and B, respectively) and by higher tolerance to abiotic stressors as compared to current cultivars. The main feature of the two ideotypes defined by targeting the RCP4.5-GISS-ES scenario is nevertheless a reduction of the thermal time needed to complete the vegetative phase (stlevdrp: -6.3% and -3.4% for site A and B, respectively), allowing an earlier flowering with respect to current cultivars. Also the ideotypes defined for the RCP8.5-HadGEM2 scenario (blue series in Figs. 3c, 3d) were characterized by shorter vegetative phases (stlevdrp: -10.17% and -10.6% for site A and B, respectively), which allowed earlier flowering and limited the exposure to the combined effect of heat and drought in the last part of the season. Indeed, the pronounced earliness required for the ideotypes turns into just minor changes in the optimal temperature (teoptbis: +0.78% and +2.4% for site A and B, respectively), and no variation for traits involved with tolerance to water stress.

The profile of the ideotypes described above refers to the mean of the 1% top-ranked parameter combinations (see Materials and methods). The varibility observed around those values was limited, with an average coefficient of variation equal to 3%.

3.3. Potential benefits from the adoption of the ideotypes under climate change scenarios

Simulation results showed that climate change will have a negative impact on current field pea cultivars, since average projected yield variations compared to the baseline were around -6% in both sites for the RCP4.5-GISS-ES scenario, and equal to -12.6% and -8.3% for site A and B, respectively, for RCP8.5-HadGEM2 (Fig 4a). The simulated average dry yield over the 20-year baseline was equal to 1.58 t DM ha^{-1} for site A and 1.40 t DM ha^{-1} for site B (corresponding to about 6.3 t ha^{-1} and 5.6 t ha^{-1} of fresh weight). Water requirements are also expected to increase (from 5% to 22%, Fig 4b) leading the overall productivity of irrigation water to decline of more than 20% (Fig 4c). Compared to the productivity simulated for current cultivars under the different climate change projections, ideotypes would assure – under the same conditions – yield increases ranging from +5.4% to +7.2% for site A and from +2.0% to +3.4% for site B (Fig. 4d), whereas the reduction in water requirements would vary between -11.0% and -35.5% in site A, and between -2.2% and -31.0% in site B (Fig. 4e). This led to water-productivity values that range from 5.8% (site B, RCP4.5-GISS-ES) to 66% (site A, RCP8.5-HadGEM2) higher than the values simulated for current genotypes and climatic conditions (Fig. 4f).

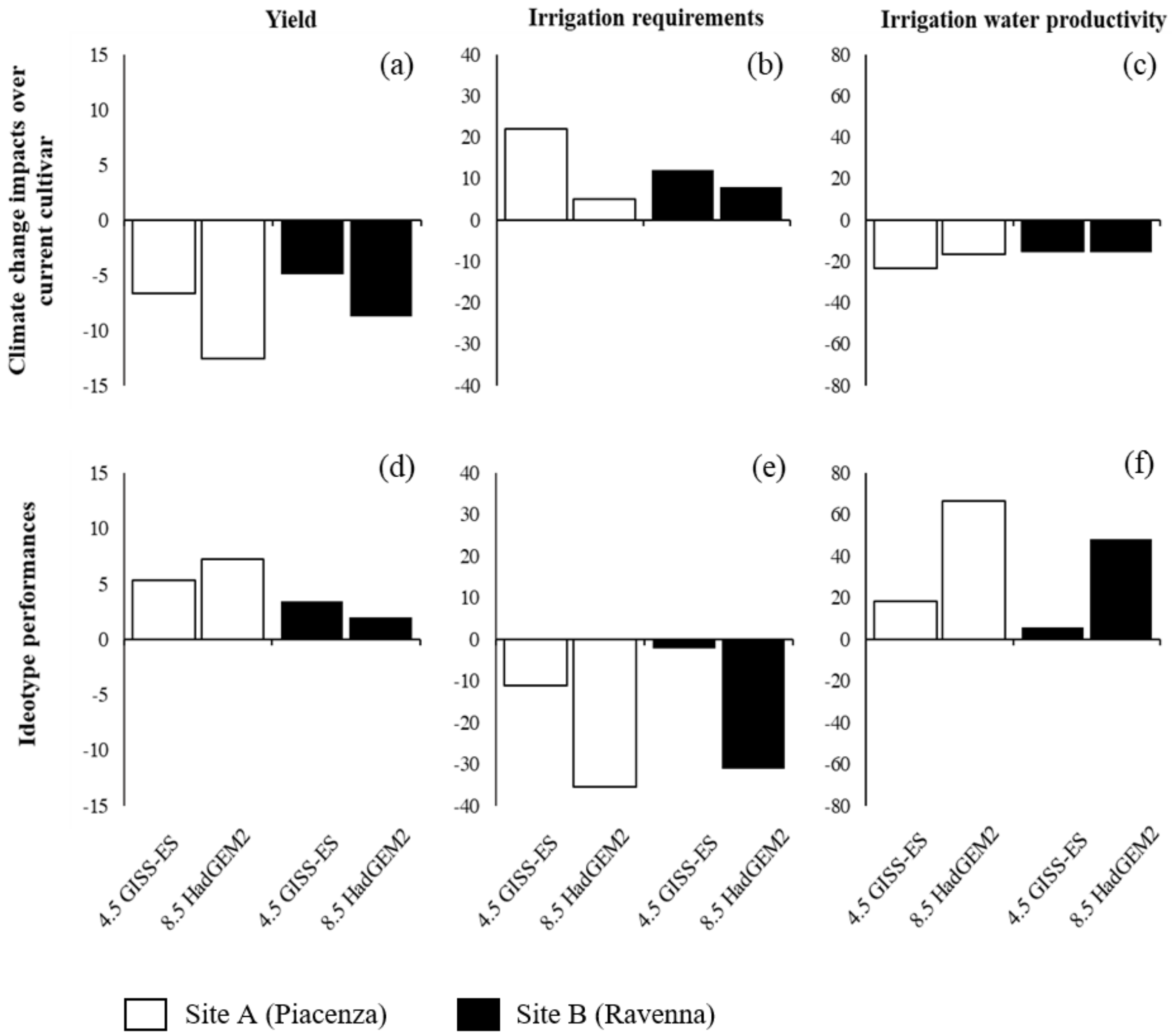

Figure 4. Climate change impacts on field pea in Northern Italy: a, b and c refer to the impacts simulated for current cultivars (percentage variation as compared to the baseline); d, e and f to the performances (percentage variation) of the defined ideotypes in comparison to the current cultivars simulated in each forecasted climate scenarios (4.5-GISS-ES: RCP4.5 generated with the general circulation model GISS-ES; 8.5-HadGEM2: RCP8.5 generated with the general circulation model HadGEM2). Light and dark bars refer to site A and B, respectively.

4. Discussion

The results obtained for the calibration and validation datasets are consistent with what reported by Coucheney et al. (2015), who evaluated the performance of the STICS model using a dataset covering different crops and a variety of environmental and management conditions, in turn confirming the reliability of the parameterization developed in this study.

Sensitivity analysis results showed large variability, especially when different climate scenarios were considered (Figs. 3a, 3b). TDCC values (Top-Down Concordance Coefficient, indicating agreement between rankings) revealed significant differences (p-value>0.05) between parameter rankings resulting from sensitivity analysis experiments run using baseline climate and future projections, in turn confirming the importance of considering climate change scenarios for model-based ideotyping analysis. Moreover, this demonstrated the STICS suitability for the identification of climate-zone-specific ideotypes – i.e., optimal combination of parameter values (representing simple traits) for target conditions (Tao et al. 2017) – because of its capability of changing the sensitivity to parameters while changing the conditions of application. Indeed, despite the overall variability in the conditions explored was not large (coefficient of variation of SAM across the six combinations site × climate scenario was equal to 0.04), STICS showed a value of plasticity (L = 0.30), similar to that estimated for the WOFOST model in a comparative study, where the model was regarded as the most plastic (Confalonieri et al. 2012).

Concerning the differences between the ideotypes defined for different agro-climatic contexts (Fig. 3), in the baseline scenario the ideotype defined targeting site B was characterized by a shorter cycle and higher tolerance to heat as compared to that identified in site A. This is due to higher daily mean temperature in the first site, with maximum temperature frequently exceeding the optimal threshold for field pea, especially in the last part of the growing season. In this context, reducing the length of the cycle would allow to avoid heat stress and related yield losses (Guilioni et al. 2003). Moreover, the ideotypes were characterized by an improved adaptation to low temperatures during germination and emergence, which allows a faster establishment of the crop (parameter tgmin). Together with an improved adaptation to high temperatures during grain filling, this allowed the ideotype to achieve higher growth rates over the entire season, thus counterbalancing the negative trade-offs of a shorter cycle. This is in line with the results of Sadras et al. (2012), who highlighted that an enhanced growth rate during the early crop stages and the capability of maintaining high photosynthetic rates during pod setting and filling are key traits for field pea breeding in case of environments characterized by terminal heat and drought stress. Thermal conditions were instead within the optimal range for the crop (18-25 °C) in site A, which led to an ideotype with slightly increased duration of the vegetative phase to take advantage of higher photosynthetic area, in line with experimental results reported by Tagliapietra et al. (2018) for soybean (*Glycine max L. Merr*).

While differences between the ideotypes defined for the two sites were marked for the baseline scenario, the site effect was less clear when future climate projections were considered (Figs. 3c, 3d). Indeed, regardless of the site, the results obtained for future climatic scenarios agreed in defining ideotypes characterized by an increased tolerance to high temperature and by a shorter cycle, mainly to limit the possible negative impacts of unfavorable rainfall distribution and thermal extremes during the pod set and filling phase. As already discussed for the ideotypes defined for the baseline condition, the improved adaptation to warmer conditions and to sub-optimal temperatures during germination and emergence allowed the ideotypes to reach higher growth rates, thus improving yield performance even with a shorter cycle. Moreover, the earliness of the ideotypes allows them to better take advantage of spring precipitations (Fig. 1). This turns into lower irrigation requirements, despite comparable values of cumulative evapotranspiration and higher yields than current cultivar under the same conditions (Table S3).

Overall, ideotyping results are coherent with what reported by Mousavi-Derazmahalleh et al. (2019) in their review about available genomic resources to adapt legumes to climate change, in turn supporting the usefulness and the feasibility of the breeding targets we are proposing. These authors indeed identified phenology and heat tolerance as important target traits for future legumes breeding, showing how several tools and methods, as well as genetic resources, are available to successfully pursue these objectives.

The hypothesis of a low suitability of current field pea genotypes for the conditions expected in the mid-term in Northern Italy is confirmed by the evaluation of climate change impacts on current cultivars in the study area, which showed a marked reduction in productivity and an increase in irrigation requirements (Figs 4a and 4b). In agreement with what reported by Bénézit et al. (2017), our results suggest that, for field pea, the advantages given by the increased CO_2 availability are more than counterbalanced by the negative effects caused by raising temperatures and drought stress. Yield losses observed under future climate projections for the current genotypes were mainly related with the marked temperature increase in the second half of the cycle, which coincides with the pod set and filling phase (Fig. 1). High temperatures are known to be detrimental for pea yield, by negatively affecting both seed formation and plant growth rate (e.g., Lecoeur and Guilioni, 2010; Guilioni et al., 2003). The projected thermal anomalies are particularly evident for the RCP8.5-HadGEM2 scenario, in which pea showed indeed the worst yield performance (Fig. 4a).

The adoption of the ideotypes defined in this study would markedly increase the system productivity under climate change scenarios, by reducing both yield losses (Fig. 4d) and water requirements (Fig. 4e). In a context characterized by the exacerbation of the conflicts for water use between countryside and urban areas, the forecasted raise in irrigation requirements (Figs. 4b and 4e) highlights the importance of increasing water use efficiency, either by improving irrigation techniques or by developing new genotypes with reduced water demand.

5. Conclusions

This study confirmed the suitability of the generic crop model STICS to successfully reproduce field pea growth and development under different climatic and management conditions. Moreover, we demonstrated for the first time that STICS, combined with global sensitivity analysis techniques, can be successfully used for ideotyping purposes, identifying critical traits for improving productivity and water use efficiency under current conditions and future climate projections. This is partly due to the high plasticity of the model, which allows its use for the definition of climate-zone-specific ideotypes (Tao et al. 2017; Paleari et al. 2017a).

Regardless of the scenario considered, our results showed how climate change is expected to have a negative impact on field pea productions in Northern Italy, thus confirming the relevance of breeding programs targeting the adaptation of field pea features to the conditions forecasted in the medium-term. In particular, our analysis led to identify crop earliness as the most important trait for increasing yield and irrigation water productivity, given it allows to partly escape the unfavorable conditions otherwise experienced by the crop in the last part of the cycle. To a smaller extent, also traits involved with heat tolerance resulted important for defining the ideotypes.

Further studies will focus on extending the analysis to other traits, for instance those related to resistance to diseases, given that biotic stressors are also of primary concern within legumes breeding programs. This will require to couple the STICS model to a plant disease one (Caubel et al. 2017). Another factor that could reduce the uncertainty of this kind of analysis is the use of parameter distributions tailored on the germplasm involved in specific breeding programs instead of generic distribution for the species, in order to fully exploit the potential of the available genetic resources.

Acknowledgments

This project was partly funded by the Emilia Romagna Region (FEASR PSR 2014-2020 sottomisura 16.1.01, domanda 5004939).

Declaration of conflict of interest

The authors declare that they have no conflicts of interest.

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