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Full length article

A model-based decision support framework to optimize cultivar recommendation. A case study on *Pisum sativum* L.

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ABSTRACT

Cultivar recommendation is a crucial decision-making process for successful cropping seasons. Crop models can effectively support the identification of suitable cultivars for a given context, as they allow the exploration of a wide range of agro-climatic conditions that would be difficult to capture with multi-environment trials. In this study, a framework for cultivar recommendation based on the integration of crop models with ideotyping techniques is applied to pea (*Pisum sativum* L.) in the Emilia-Romagna region, Northern Italy. Eighteen agro-climatic contexts were identified by considering the two main sowing windows and regional climate and soil data. Statistical distributions of seven functional traits related to phenology, canopy architecture, biomass partitioning, and photosynthetic efficiency were derived for 20 commercial pea cultivars and used to run a variance-based sensitivity analysis of the STICS crop model for each agro-climatic context. Model parameters corresponding to the seven functional traits were used as sensitivity analysis inputs, with a composite function accounting for both yield and its stability as the target output. Sensitivity analysis results were used to design pea ideotypes for each agro-climatic context, and the similarity between the phenotypic profiles of commercial cultivars and those of ideotypes was evaluated using the Euclidean distance weighted by the sensitivity index. Spatially distributed recommendations based on context-specific, similarity-based cultivar rankings were derived. A clear change in cultivar rankings was found across agro-climatic contexts, highlighting the need to explicitly analyse G×E × M interactions. The simple methodology used to derive the cultivar phenotypic profiles and the process-based modelling approach allow the framework to be easily extended to different sowing times, newly released cultivars, or different crops, all of which are key features for transferring the framework to operational farming contexts. While the preliminary evaluation of the recommendations provided by the system supports its potential reliability, further validation through multi-environment trials is required before full deployment at the operational level.

1. Introduction

Cultivar recommendation is a key factor in increasing crop resilience and ensuring yield stability of cropping systems. Identifying the most suitable cultivar for a given agro-climatic context requires a careful analysis of genotype (G) × environment (E) × management (M) interactions (Cooper et al., 2021), as phenotypic plasticity can markedly affect the performance of the same genotype across different conditions (Nicotra et al., 2010). Casadebaig et al. (2022) demonstrated, for sunflower, that optimizing cultivar choice can influence yield stability as much as the genetic improvement itself, especially in areas with a strong interannual variability in weather conditions. Besides climate and soil factors, crop management practices such as sowing date, irrigation, fertilization, and plant density also play a key role in increasing yields and their stability. Simulation studies on pea (Jeuffroy et al., 2012; Colbach et al., 2022) highlighted that interactions between cultivar characteristics and management practices can lead to substantial differences in yield, emphasizing the need to jointly optimizing cultivar choice and crop management to maximize productivity (Jeuffroy et al., 2012; Colbach et al., 2022).

Crop simulation models are increasingly used to support multi-environment trials to increase the number of genotypes under evaluation and to extend the analysis of their performance across a wide range of conditions, with clear advantages in terms of costs and time (Chenu et al., 2013; Jeuffroy et al., 2014; Cooper et al., 2021). However, a key issue in spatially-distributed model-based analyses, especially for

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rainfed systems, is the spatial resolution of environmental characterization (E $\times$ M). Casadebaig et al. (2022) underlined the need to identify a trade-off between the performance of high-resolution systems (which requires detailed and updated information on climate, soil, and management) and the transferability of decision support tools to operational contexts.

Another key issue in existing approaches for model-based cultivar recommendation is the collection of datasets for the genotype-specific calibration of model parameters. These datasets should include the evaluation of the cultivars of interest in a wide range of conditions, which means multiple sites and seasons (Casadebaig et al., 2016; Verma et al., 2023). This is needed to minimize the risk of including in parameter values site- or seasons-specific factors, whereas they should only include information on morphological and physiological features of the genotypes (Confalonieri et al., 2012). While crucial for ensuring the reliability of model outcomes, the need for genotype-specific model calibration makes the analysis resource-intensive, thereby limiting the pool of genotypes under evaluation and increasing the information required whenever a new cultivar is released. New emerging approaches to evaluate G$\times$E $\times$ M interactions and support cultivar recommendation also demand extensive datasets to produce reliable results. Among these, machine learning (ML) techniques have recently gained attention for their ability to handle large and complex datasets. However, despite their predictive power, ML approaches suffer from limited interpretability and high data requirements, which limits their transferability to operational farming conditions (Zhang et al., 2023).

To overcome these limitations, Paleari et al. (2020) proposed an approach for cultivar recommendation that does not require the collection of datasets from experiments carried out in multiple sites and seasons. The approach is based on (i) agro-climatic zonation (considering climate, soil, and management information), (ii) the in silico design of ideal crop types (ideotypes, i.e., combinations of morpho-physiological traits optimizing crop performance, Martre et al., 2015) for each agro-climatic context and for specific purposes (e.g., in this study, improving yield and its stability across seasons), and (iii) similarity analyses between ideotypes and the phenotypic profiles of commercial cultivars. Because phenotypic profiles (i.e., combinations of cultivar-specific values for multiple phenotypic traits) are not derived at the level of performance traits (e.g., yield), but at the level of functional traits corresponding to genotype-specific model parameters (e.g., stage-dependent specific leaf area under unstressed conditions; Colbach et al., 2022), data can be collected at a single site over a single season. In contrast to performance traits, functional traits are only slightly affected by environmental and management factors (Violle et al., 2007). However, the evaluation of the approach by Paleari et al. (2020) was conducted on bean, an irrigated crop planted within a relatively narrow sowing window (from mid-April to mid-May), thereby limiting the diversity of conditions considered in the evaluation of the cultivar recommendation approach.

The objective of this study was assessing the suitability of the Paleari et al. (2020) approach for providing end-users (e.g., agronomists, farm advisors, and farmers) with cultivar recommendations to maximize yield and its stability across seasons for field pea (*Pisum sativum* L.) in Northern Italy. This crop plays a key role in the preserved vegetables market and, as it is mainly grown under rainfed conditions with staggered sowing dates from late winter to late spring to ensure a constant supply to processing plants, is subject to a large variability in growing conditions that contribute to yield instability. This study extends the preliminary analysis by Paleari et al. (2022) where cultivar recommendation for pea was based solely on phenology.

2. Materials and methods

The approach adopted in this study follows the methodology proposed by Paleari et al. (2020). The analysis was articulated in the following steps: (i) agroclimatic zonation of the study area considering climate, soil, and management factors; (ii) characterization of available germplasm for key functional traits via field measurements, (iii) sensitivity analysis and model-based ideotype design for each agro-climatic context, using as inputs model parameters corresponding to the functional traits of interest and their germplasm-specific statistical distributions, and a composite function accounting for both yield and its stability as the target output, (iv) evaluation of the similarity between commercial cultivars and ideotypes to provide context-specific cultivar recommendations.

2.1. Agro-climatic zonation

The study focused on the Emilia-Romagna region, one of the most relevant pea cultivation areas in Italy (ISTAT, 2025). A characterization of the target area in terms of climate, soil and management factors was carried out to account for the spatial variability in agro-meteorological conditions, as described below. The zonation focused on plain areas where pea is grown. Concerning management, only sowing time was considered because it is the management factor with the largest variability in the study area: the crop is mainly rainfed, not stressed by limited nutrient availability (also because of symbiotic N fixation), and sown at standard density. Also, biotic stress-free conditions are ensured through the integrated use of agrochemicals and mechanical weeding. Two sowing dates were compared (February 1st and April 1st for early and late cultivation, respectively), which were considered to be representative of the full range of sowing times across the region (Paleari et al., 2022). For each sowing date, the Synthetic AgroMeteorological indicator (SAM; normalized difference between cumulated rainfall and reference evapotranspiration during the crop season, negative values indicate dry conditions; Confalonieri et al., 2010) was calculated by using the 5 km-resolution, 10-year gridded weather dataset (2009–2018) of the Regional Agency for Prevention, Environment and Energy of Emilia-Romagna (ARPAE; Antolini et al., 2016). Synthetic AgroMeteorological indicator values at the centroids of the grid cells were used to cluster them into six homogenous climatic contexts, three for early sowings and three for late sowings (Fig. 1). Given that the SAM index ranges from -1 to $+1$, a threshold of 0.25 was used to discriminate between humid (SAM$>$ 0.25), mildly humid ($0.25 \leq$ SAM <0), and dry climates (SAM$<$0) in early sowings. For late sowings, an additional threshold of -0.1 was applied to better discriminate drought levels due to the drier conditions during the crop cycle. Regional soil texture data (https://geo.regione.emilia-romagna.it/geocatalogo/) were analysed to derive a soil zonation based on three classes (Al Majou et al., 2008): fine (clay content $>$35% and sand content $<$65%), coarse (clay content $<$17.5% and sand content $>$65%), and medium (otherwise). The intersection of the climate zonation (accounting for the two sowing windows) and soil zonation allowed identification of 18 homogenous agro-climatic contexts representative of variability in pea growing conditions in the target area.

2.2. The crop model

The crop model STICS (Brisson et al., 2009) was used for its suitability for simulating legume species in the study area (Paleari et al., 2020), including pea (Ravasi et al., 2020), and for its plasticity (i.e., different responsiveness to input factors while changing the conditions explored), the latter being a key feature for properly reproducing G$\times$E $\times$ M interactions (Confalonieri et al., 2012). This crop model simulates crop growth and development, as well as soil water, N, and carbon dynamics, with a daily time step, accounting for interactions between soil, crop, atmosphere and management practices. Crop development is simulated based on thermal time accumulation using a triangular response function defined by the parameters base, optimum, and maximum temperature, with an option to account for the photoperiodic response. Biomass accumulation is simulated using a net photosynthesis approach based on radiation use efficiency, whereas the

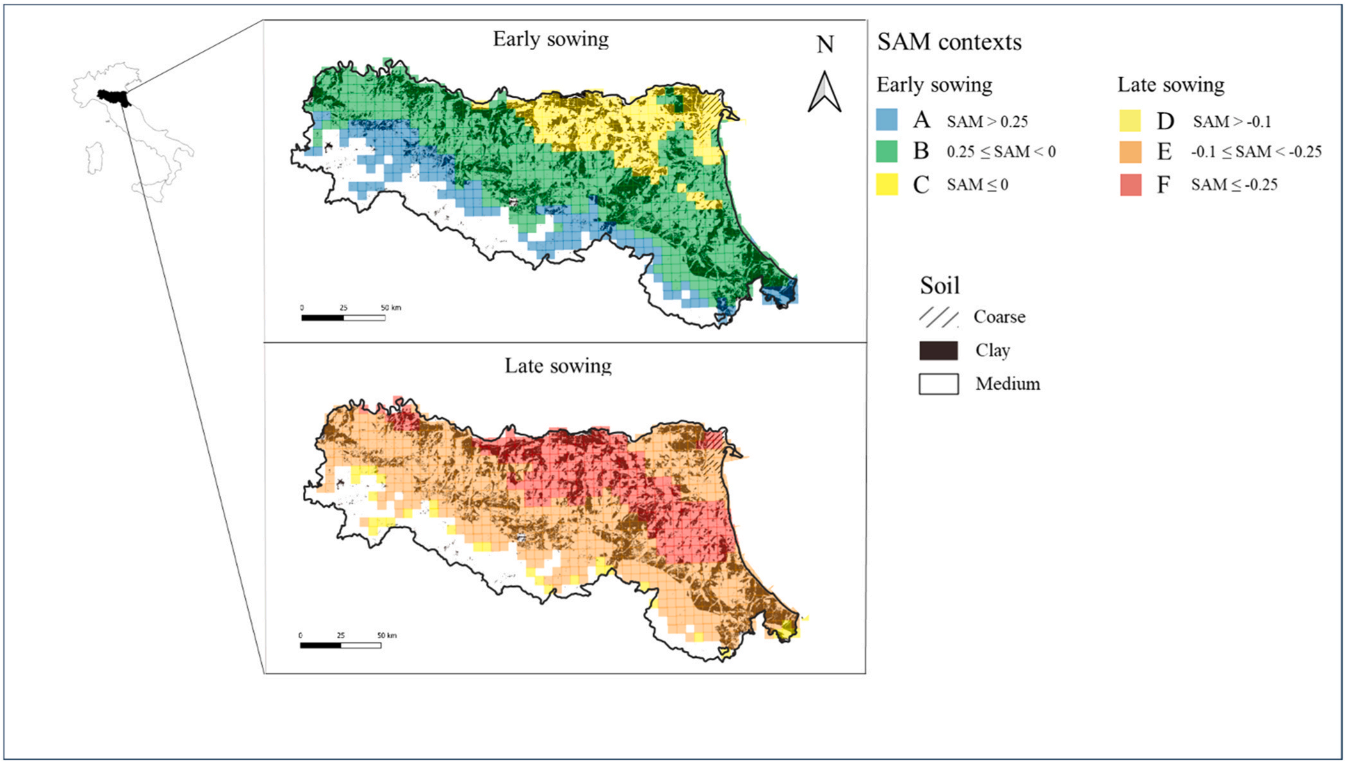

Fig. 1. Agro-climatic zonation of the pea cultivation area in the Emilia-Romagna region based on (i) the Synthetic AgroMeteorological (SAM; normalized difference between cumulated rainfall and reference evapotranspiration during the crop cycle; negative values indicates dry conditions) for early and late sowings, and (ii) soil texture, with the three soil classes referring, respectively, to fine (clay >35% and sand <65%), coarse (clay <17.5% and sand >65%), and medium (otherwise) soils (Al Majou et al., 2008).

amount of photosynthetically active radiation (PAR) intercepted by the canopy is estimated according to the Lambert-Beer law as a function of leaf area index (LAI) and the parameter light extinction coefficient. Daily aboveground biomass accumulation is modulated by temperature and stress factors (water and nitrogen deficit, heat, and waterlogging). Photosynthates are then allocated to the different plant organs via dynamic partitioning coefficients that vary according to the crop development stage and the simulated source–sink balance of the plant. For indeterminate plants, the model simulates the competition between vegetative and reproductive sinks. Further details on the STICS model are available in the literature (e.g., Brisson et al., 2003; 2009).

The STICS parameterization for pea developed by Ravasi et al. (2020) was used, who evaluated the model against independent observations collected in multiple locations and seasons in the same study area. Results from that study highlighted good prediction capabilities, especially for yield, the target variable used in this study. In that case, the mean absolute error for validation datasets was equal to 0.06 Mg ha^{-1}and the relative root mean square error was close to 4% (Ravasi et al., 2020).

2.3. Field experiments

A dedicated field trial was carried out in Lagosanto (44.45° N, 12.09° E, Ferrara province) to characterize twenty commercial pea cultivars in terms of functional traits related to phenology, canopy structure, biomass partitioning, and photosynthetic efficiency. The cultivars (Table S1) were sown on March 16th 2023 in 8 m × 1.65 m plots in a completely randomized block design with three replicates and a standard sowing density of 120 plants m^{-2}. The field was kept under optimal nutritional conditions with irrigation and fertilization, and crop management allowed keeping the field weed- and pest-free through the integrated use of agrochemicals and mechanical weeding. During the experiment, seven functional plant traits corresponding to STICS parameters were determined (Table 1). To ensure transferability and usability of the proposed framework, functional trait selection was carried out in collaboration with technical experts and agronomists from food-processing industries involved in the pea value chain in the region. The primary criterion for selecting functional traits was to characterize cultivar phenotypic profiles using a limited number of measurable traits that represent the main physiological processes involved in yield formation (Table 1). This strategy was adopted to reduce the effort and data requirements associated with extending the framework to newly released cultivars. Selected traits were also chosen based on their ease of estimation from either (i) variables routinely measured in cultivar evaluation trials (e.g., phenology) or (ii) traits that can be assessed using simple and user-friendly tools (e.g., leaf area index estimated with indirect methods, e.g., PocketLAI smart-app, Confalonieri et al., 2013). The selected functional traits were measured under standardized, non-limiting conditions to maximize the expression of genotypic differences and minimize environmental effects. Therefore, they were considered suitable descriptors of cultivar phenotypic profiles within the proposed framework.

Concerning the traits involved with phenology, emergence (stage 09 of the BBCH scale for pea; Meier, 2001), first pod (BBCH 70) and maturity (BBCH 88) dates were recorded. The three STICS parameters related with thermal time requirements from sowing to germination (*stpltger*; °C-day), from emergence to first pod (*stlevdrp*; °C-day) and from first pod to maturity (*dureefruit*; °C-day) were derived by phenological observations, the response functions to temperature (air temperature after emergence, soil temperature before) of the STICS model and the parameters base (*tdmin*; °C) and maximum (*tdmax*; °C) temperature for development derived for the same cultivars by Paleari et al. (2022). Soil temperature was predicted by the STICS soil module, which simulates soil thermal dynamics based on weather conditions, canopy characteristics, and soil properties. The simulated soil temperature was then used as the environmental driver for thermal time calculations before

Table 1
Traits estimated for the 20 commercial pea cultivars involved in the field trials, their statistical distributions and related STICS parameters. All traits were normally distributed so the mean and the standard deviation are reported in brackets.

Process	Trait	Parameter (*Acronym*)	Unit	Distribution	Coefficient of variation (%)
Photosynthesis	Radiation Use Efficiency	Maximum radiation use efficiency during the grain filling phase (*efcroirepro*)	g MJ^{-1}	Normal (3.54, 0.4)	11.3
Partitioning	Proportion of pericarp relative to the total weight of the fruit	Proportion of pericarp out of the total weight of the fruit (*envfruit*)	g g^{-1}	Normal (0.36, 0.10)	27.8
Canopy architecture	Maximum plant height	Maximum plant height (*hautmax*)	m	Normal (0.64, 0.11)	17.2
	Light extinction coefficient	Extinction coefficient for solar radiation (*extin*)	unitless	Normal (0.79, 0.14)	17.7
Phenological development	Thermal time to germination	Cumulative thermal time allowing germination (*stpltger*)	°C-day	Normal (26.9, 5.78)	21.5
	Thermal time to first pod	Cumulative thermal time from emergence to the onset of filling of harvested organs (*stlevdrp*)	°C-day	Normal (467.8, 78.18)	16.7
	Thermal time to the physiological maturity	Cumulative thermal time of a fruit at the setting stage to the physiological maturity (*dureefruit*)	°C-day	Normal (325.3, 25.9)	8

emergence, in accordance with model equations.

Before harvest, dry aboveground biomass (AGB, Mg ha $^{-1}$) and yield (Mg ha $^{-1}$) were quantified by sampling a 9.5 m^2 area (a 20 cm-buffer at plot perimeter were discarded to avoid border effects, leading to a sampled area of 7.60 m × 1.25 m) and oven-drying the plants until constant weight, which was verified by weighting periodically the samples to confirm the complete removal of residual moisture. Plant height, seed and pod dry biomass, and light extinction coefficient were also estimated. The former was measured with a ruler on five points per plot. Pods and seeds were collected from six plants per plot, oven-dried until constant weight, and weighted to calculate the proportion of pericarp out of the total weight of the fruit (parameter *envfruit*, g g^{-1}, Table 1*)*. Leaf Area Index (m^2 m^{-2}) was estimated (three times during the season) by using the PocketLAI smart-app (Confalonieri et al., 2013) with five measurement replicates per plot. The parameter light extinction coefficient (*extin*, unitless) was derived at first pod stage (BBCH 70) by inverting the Lambert-Beer's law (Ross, 1981) (Eq. 1):

$$extin = -\frac{\ln\left(\frac{PAR\ below}{PAR\ above}\right)}{LAI} \tag{1}$$

where PAR above and below is the photosynthetically active radiation (μmol m^{-2} s^{-1}) measured with the AccuPAR LP−80 ceptometer (Decagon, Pullman, WA, USA) above (one measure replicate) and below the canopy (three measure replicates).

Under unstressed conditions, STICS simulates daily biomass accumulation as a function of the intercepted solar radiation (in turn depending on LAI and light extinction coefficient) and of radiation use efficiency (i.e., net photosynthetic rate for unit of solar radiation intercepted, g MJ^{-1}). The latter varies across phenological stages (juvenile, vegetative, and reproductive) that correspond, respectively, to the parameters *efcroijuv*, *efcroiveg* and *efcroirepro* (g MJ^{-1}, Table 1). Based on the relationships among these parameters determined for pea by Ravasi et al. (2020) and using the light extinction coefficient values measured during the field trial, the cultivar-specific values of the three parameters involved with radiation use efficiency were derived via manual calibration by targeting the best agreement between simulated and observed aboveground biomass (RRMSE = 5.1%) at maturity. In particular, at each iteration of the calibration, *efcroirepro* was changed (trial-and-error), whereas *efcroijuv* and *efcroiveg* were derived from the value of *efcroirepro* to preserve the ratio among the three parameters determined by Ravasi et al. (2020). At each iteration, model performance was evaluated against the observed aboveground biomass until no further improvement in RRMSE was achieved.

2.4. Model-aided cultivar recommendation

Statistical distributions of the functional traits corresponding to the seven crop model parameters (Table 1) were derived using values estimated on the 20 commercial cultivars involved in the field trial. These distributions were used together with global sensitivity analysis techniques (Extended Fourier Amplitude Sensitivity Test, E-FAST; Saltelli et al., 1999) and the crop model STICS to identify key traits and trait values for improving crop performance under each of the identified 18 agro-climatic contexts. All other parameters representing plant morpho-physiological features were kept constant according to the parameterisation of Ravasi et al. (2020).

Variance-based sensitivity analysis methods quantify the relevance of input factors (in this study parameters corresponding to plant functional traits) by decomposing the total variance of model output into terms of increasing dimension (partial variances) that represents the contribution of each parameter alone (first order effect), or in interaction with others (second order in case of pairs of parameters, third order in case of triplets, etc.). In particular, the E-FAST method explores the parameter space using frequency-based sampling, where each input parameter is assigned a unique sampling frequency and all parameters are varied simultaneously along a sinusoidal trajectory through the parameter space. The sampling procedure is repeated multiple times, each with a different starting point of the search curve. This sensitivity method provides only the first and total order effects, the latter representing the contribution of a parameter in interaction with all the others (Homma and Saltelli, 1996). This allows the method to explore the parameter space in a very efficient way. The E-FAST method was parameterized according to Confalonieri et al. (2010), leading to 1743 parameter combinations (the closest to 250 × number of parameters among the possible sample sizes), representing hypothetical, virtual genotypes. A truncation of 10% was applied to observed functional trait distributions, to avoid sampling unlikely values and improve the coherence between ideotypes and available cultivars. Correlations among parameters were not included in the study, as no significant correlations were found among the functional traits considered. Yield and yield stability were evaluated for each combination through 10-year simulations (10 independent 1-year-long simulations from 2009 to 2018) and combined in a synthetic score (Y_{index}; Eq. 2, Ravasi et al., 2020):

$$Y_{index} = \left[\left(\frac{Y_i}{Y_{\max}}\right) \bullet 0.7\right] + \left[\left(1 - \frac{CV_i}{CV_{\max}}\right) \bullet 0.3\right] \tag{2}$$

where Y_i is the mean yield (calculated over the 10 years) of a given parameter combination in a specific environment, and $Y_{\max}$ is the highest mean yield among all parameter combinations in the same environment.

Similarly, CV_i represents the coefficient of variation associated with the same parameter combination in the same environment, and $CV_{\max}$ is the highest coefficient of variation observed among all parameter combinations in that environment. The different weights used for yield (0.7) and yield stability (0.3) were defined based on expert opinion, derived from interactions with technicians from one of the biggest European companies for preserved food (Ravasi et al., 2020).

For each agro-climatic context, an ideotype (i.e., ideal cultivar for that context) was then derived by averaging parameter values of the best 1% of combinations ranked according to the Y_{index}, to improve the reliability of ideotype profiles by minimizing the effect of potential local minima in the parameter hyperspace (Paleari et al., 2017). The values averaged showed a small variability around the mean (~ 2% for traits with highest impact on model output). Ideotypes were then used to derive similarity-based rankings of the 20 cultivars under the assumption that the cultivar with trait values closest to those of the ideotypes is the one expected to perform better under the environmental and management conditions that characterize each of the 18 contexts. The similarity was estimated using the similarity index (*IDI*, Eq. 3) based on the weighted Euclidean distance method proposed by Carvalho et al. (2002) for index-based selection and adapted to in silico analysis by Paleari et al. (2020):

$$IDI_i = \sqrt{\frac{1}{n} \times \sum_{j=1}^{n} \left(y_{ij} - vo_j\right)^2} \tag{3}$$

where y_{ij} is the standardised transformed phenotypic value of the i_{th} cultivar for the j_{th} trait and vo_j is the standardised optimal value of the j_{th} trait (i.e., that of the ideotype, Eq. 5). The transformed phenotypic value is the measured phenotypic value with a penalization in case the trait value falls outside the optimal range (the range of the corresponding parameter in the best 1% of combinations used to determine the ideotype). The transformation is achieved by adding to the measured trait the difference between the optimum value of the j_{th} trait (i.e., that of the ideotype, VO_j) and the lower (LI_j) or the upper (LS_j) limit of the optimum range in case of measured values above LS_j or below LI_j, respectively, thus increasing the distance between the measured trait value and the optimal one. Both the transformed and the optimal phenotypic value are then standardised to allow simultaneous analysis of traits with different units, and weighted by the relevance of the trait on the overall performance (i.e., the sensitivity total order effect of the corresponding parameter, Eq. 4 and eq. 5). Therefore, the trait with a major impact on the objective function has a higher weight on the evaluation of the similarity:

$$y_{ij} = \sqrt{a_j} \times \frac{Y_{ij}}{s(Y_j)} \tag{4}$$

$$vo_{ij} = \sqrt{a_j} \times \frac{VO_j}{s(Y_j)} \tag{5}$$

Where $s(Y_j)$ is the standard deviation of the transformed phenotypic value (Y_j) for all the genotypes analysed, and a_j is the total order sensitivity index of the parameter corresponding to the j_{th} trait. Full details about the procedure for similarity index estimates can be found in Paleari et al. (2020).

The reliability of the cultivar rankings obtained was evaluated through comparison with the results of independent field experiments carried out in 2021 in the study area (Codigoro, Ferrara province; 44.86 °N, 12.17 °E), which aimed at comparing commercial pea cultivars. The crop was sown in early spring on a sandy soil, with a dry climate characterising that season. For all the cultivars, crop management allowed keeping the field weed- and pest-free, with unlimiting conditions for nutrients. At harvest, grain yield was measured and used to rank cultivars.

3. Results

3.1. Environmental characterization

The study area is characterized by different climate patterns between early and late pea sowing periods (Fig. 1). The values of the SAM index (Synthetic AgroMeteorological indicator, Confalonieri et al., 2010) were mostly positive in case of early sowing (February – April) and largely negative in the case of late sowing (April – June). This trend highlights a substantial shift in both temperature and precipitation at the beginning in April across the study area. For early sowing, SAM index values ranged from values close to 0 (indicating a balance between rainfall and evapotranspiration) to markedly humid conditions (SAM values higher than 0.25, indicating rainfall in excess of evapotranspiration demand). Under late sowing, a large variability in terms of water availability was found, with values close to 0 in some areas (class SAM C and D, Fig. 1) and markedly dry conditions in others (SAM values lower than - 0.25 for class F).

3.2. Cultivar characterization for functional traits

All traits were normally distributed (Table 1, Table S2), but variability differed among traits across the 20 cultivars (Fig. S1, Table 1). The proportion of pericarp relative to the maximum weight of the fruit (*envfruit*) showed the largest heterogeneity across cultivars, as highlighted by the coefficient of variation (CV, %, Table 1). In contrast, the least variable trait was the thermal time needed to reach physiological maturity. The other two phenological parameters (*stpltger* and *stlevdrp*) showed instead more variability (Table 1).

3.3. Traits relevance across agro-climatic conditions

The sensitivity analyses highlighted that the trait with the largest influence on yield and its stability was the thermal time from emergence to first pod, which was ranked first in 15 out of the 18 agro-climatic contexts and explained most of the variability in Y_{index} (Fig. S2). This trait played a key role in early sowing contexts, where it consistently explained the largest part of the output variability. The only exception was observed in the climatic context D, i.e., the least dry among the late-sowing contexts (SAM close to 0, Fig. 1), where the radiation use efficiency at the reproductive stage was ranked first among the traits in terms of its contribution to variability in yield performance. This trait emerged as the second most relevant in most contexts, particularly for late sowing. From the third rank onward, the contribution of individual traits decreased markedly, with sensitivity indices dropping to very low values. Nonetheless, a consistent pattern was observed for the thermal time to physiological maturity, which was generally ranked third across most contexts, with the highest sensitivity analysis index values in context D. While the impact of climate-related variability was clear, the effect of soil type under the same climatic conditions was negligible (Fig. S2), with very low differences in the sensitivity analysis results obtained for different soil types. This can also be clearly seen in the variability in performance across the 1743 virtual genotypes among which ideotypes were selected (Fig. S3).

Results of the ideotype design (Fig. 2) highlighted that the variability in agro-climatic conditions did not affect the main ideotype structure, with differences among ideotypes mainly related to the suggested extent of trait variation (%) as compared to current cultivars (trait mean value, Table 1). Earlier first pod appearance would be beneficial for yield and yield stability across all contexts, with a reduction of the trait thermal time to first pod (corresponding to parameter *stlevdrp*) that reached 19.3% compared with the mean value of the 20 commercial cultivars (Fig. 2). This was confirmed by the negative correlation observed between yield and its stability (Y_{index}) and days from sowing to first flower across all environments (Pearson correlation coefficient, *r*, equal to −0.86, on average), and between Y_{index} and thermal time to first pod (*r*

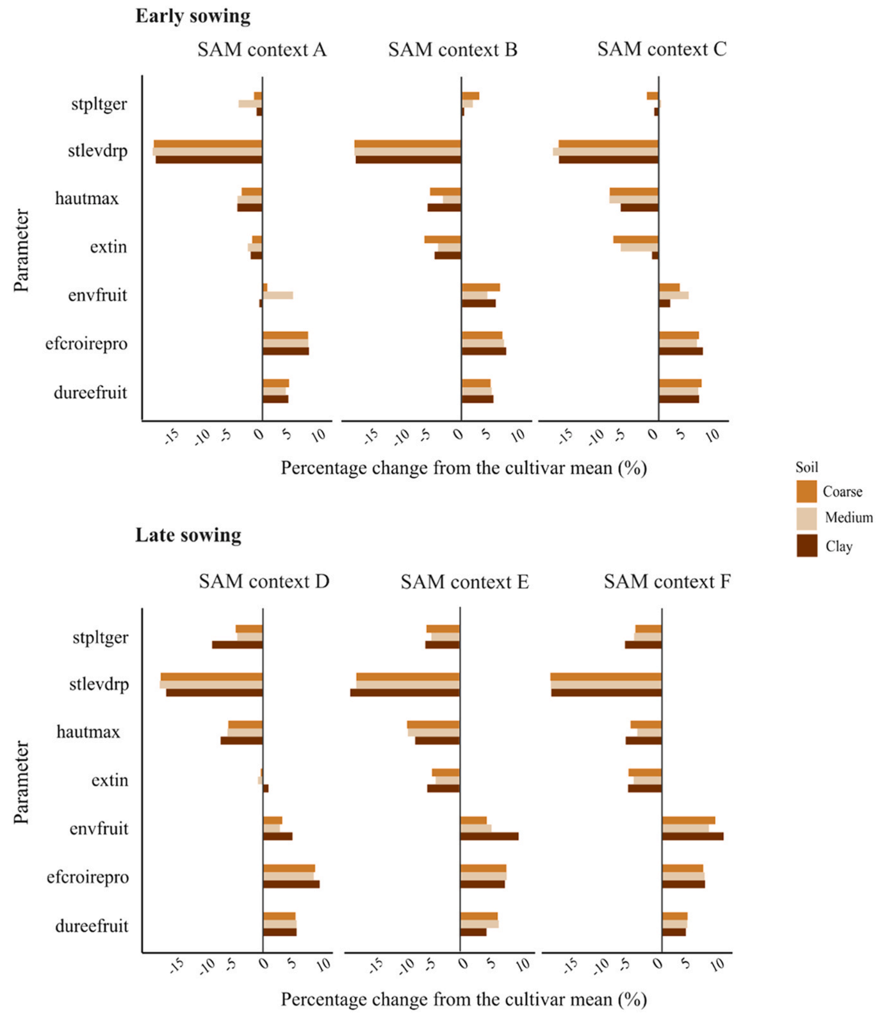

Fig. 2. Ideotype profiles (suggested variation of each trait as compared to the 20 commercial cultivars distribution mean reported in Table 1) for each agro-climatic context. Panels refer to classes of the Synthetic Agroclimatic Indicator (SAM, Confalonieri et al., 2010), while the different shades of brown indicate different soil types (dark, medium, and light brown bars refer to clay, coarse, and medium soils, respectively).

equal to −0.87, on average). The second key feature of the ideotypes concerned radiation use efficiency during grain filling (parameter *efcroirepro*), for which ideotypes showed, on average, values 7.9% higher than current cultivars (Table 1). This was supported by the positive correlation found between radiation use efficiency and biomass accumulation across agro-climatic contexts (average *r* value equal to 0.88). However, a progressive reduction of the increase for this trait was found while moving towards drier conditions, likely due to the fact that the crop is not irrigated and increasing productivity would expose the crop to higher water stress. A longer grain filling phase would be beneficial too, as underlined by the increased thermal time requirements from first pod to physiological maturity (parameter *dureefruit*), although with some variability across the explored conditions (suggested increase ranged between +7% and +4.4%). This, combined with an earlier first pod appearance, would extend the grain filling duration without affecting the harvest time, a crucial point to avoid unfavourably high temperature during grain filling. Time to germination (parameter *stpltger*) was generally shorter in the ideotypes (3.9% reduction, on average), to allow a quick crop establishment and subsequent early canopy development. The variability among soil types was larger for this trait, probably because of the effect of soil texture on soil temperature that directly affects the germination process. As compared to the 20 commercial cultivars, ideotypes also displayed a lower light extinction coefficient (−4.1% on average) and a shorter plant height (−6.2% on average). While the former is related with improving the light penetration through the canopy, the benefits related with the latter deal with the effects of plant height on the water balance (Brisson et al., 2009). Additional details on the ideotype main traits are reported in Table S3 and Table S4, while a summary of the ideotypes' main features is reported in Table S5.

3.4. Cultivar recommendation

The analysis of the similarity between the ideotypes and 20 commercial cultivars led to rank the latter according to their suitability to the context-specific agro-climatic and management conditions, with the higher similarity corresponding to the lowest value of the ideotype similarity index (IDI). An example of the rankings obtained for two diverging agro-climatic contexts is shown in Fig. 3, whereas all ranking plots are shown in Figs. S4 and S5.

While some cultivars proved to be a sound choice regardless of the conditions, others highlighted clear G×E × M effects (Fig. 4). As an example, cv. Romago was always among the top-five cultivars both for early and late sowings, revealing its potential for broad-adaptation. On the contrary, cv. Wolf climbed the ranks while moving towards drier climates in case of early sowings (from 8th and 9th position for SAM classes A and B to top- or second-rank for SAM class C). The same cultivar exceled under mildly dry conditions in late sowing (SAM class D) and fell to mid-rank positions in the driest climate class (SAM class F; Fig. 4). This led to a clear re-ranking among cultivars, especially when

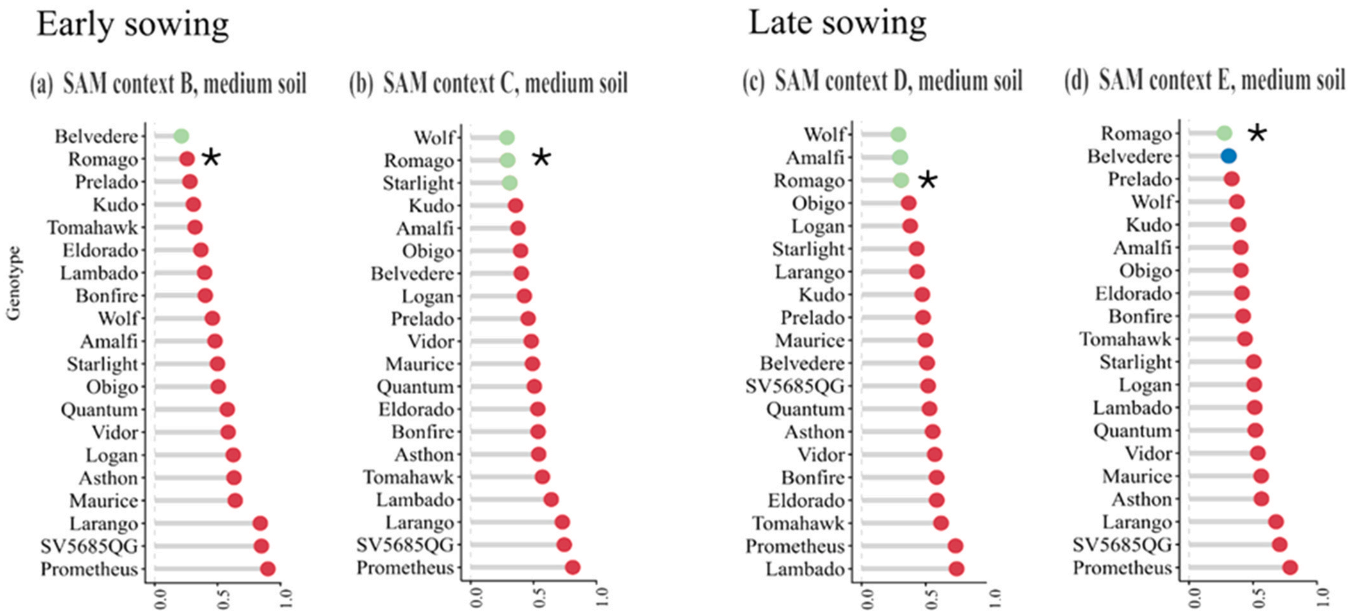

Fig. 3. Example of the cultivar ranking based on the similarity index (IDI) to the ideotypes defined for four agro-climatic contexts. A lower IDI value indicates a higher similarity to the ideotype and, in turn, a higher suitability of the cultivar to the agro-climatic conditions defining the context. Green: varieties recommendable; blue: second-choice varieties; red: varieties less suitable (i.e., their IDI is, respectively, less than 10%, from 10% to 20% and more than 20% larger than the IDI of the cultivar most similar to the ideotype). The star indicates cultivars often ranked at the top under different agro-climatic contexts, thus revealing broader adaptation to growth conditions.

the balance between ET and rainfall was close to zero in case of early sowings (from SAM class B to C), and clearly negative under late sowings (from SAM class D to E). Concerning the sowing time, it did not show a clear effect on rankings, although some cultivars emerged as particularly suitable only for one sowing window. For instance, cv. Starlight was among the top-five only in case of early sowings, whereas cv. Logan only in case of late sowings. Differences across soil types were also negligible, with some variability only under the driest conditions (e.g., SAM class C in early sowings, and SAM classes E and F for late sowings) likely due to the different soil water retention capability. Among the worst-performing cultivars, the least similar to the ideotypes was cv. Prometheus, which ranked poorly regardless of the conditions explored.

The cultivar rankings obtained for the different agro-climatic contexts were supported by the results of the independent cultivar evaluation trials conducted in 2021 within the study area (see Section 2.4). The environmental conditions experienced during that growing season were representative of SAM context C under early-sowing conditions. Yield results showed that the two top-ranked cultivars identified by the model-based framework for this agro-climatic context (Romago and Wolf; Fig. S4, panel i) were among the five highest-yielding cultivars observed in the trial.

4. Discussion

4.1. Variation in cultivar rankings across agro-climatic contexts

Despite the relatively limited size of the study area, a large heterogeneity in the agro-climatic conditions experienced by the crop was found, particularly between the two main sowing windows. Such variability was reflected in the ideotype profiles, and thus in cultivar rankings. Indeed, a clear re-ranking of cultivars was found while changing the agro-climatic conditions, but cultivar performance was not directly related to climate drivers. This clearly highlights the influence of G×E × M interactions on cultivar performance, and thus the importance of analyzing the effects of climate variability in the target area as a preliminary step in cultivar selection, especially for rainfed crops. These results are consistent with the findings of Casadebaig et al. (2016), who observed a clear re-ranking of sunflower cultivars across different water deficit scenarios. Compared to previous studies on cultivar selection carried out in the same area on bean (Paleari et al., 2020) and pea (Paleari et al., 2022), the cultivar re-ranking across different agro-climatic contexts is more pronounced in the present study. This can be due to the fact that the crop in this case is rainfed, whereas it was irrigated in Paleari et al. (2020), and Paleari et al. (2022) focused only on traits involved with phenological development.

4.2. Functional traits improving yield and its stability

Our results indicate that the thermal time from emergence to first pod is the trait most strongly associated with the variability in Y_{index}, followed by radiation use efficiency and thermal time to physiological maturity. This finding aligns with previous results involving the parameter growing degree days for flowering in the WOFOST model (Paleari et al., 2022), further supporting the role of phenology in determining yield performance and stability. Similar results were found by Jeuffroy et al. (2012) in France, where virtual pea genotypes characterized by early first flower appearance led to the highest yield. In our study, ideotypes were characterized by reduced thermal time requirements to first pod which shift the flowering and grain filling phases earlier. This positively affects yield, as confirmed by the negative correlation found between yield and its stability (Y_{index}) and days from sowing to first flower across all environments, and between Y_{index} and thermal time to first pod. Moreover, ideotypes were characterized by lower thermal time requirements to reach germination, which enabled rapid crop establishment and early canopy development (Sadras et al., 2012). These trait variations would likely improve productivity by reducing exposure to thermal stress and water deficit, especially under late sowing. These findings are consistent with recent studies in other legumes, such as lentil, which have highlighted clear links between early vigor, phenology, and yield across environments, including the role of shifting critical reproductive periods to potentially more favorable window within the season (Tefera et al., 2022; 2024). While the importance of phenology for pea adaptation across environments is well established in crop physiology and breeding (e.g., Huang et al., 2017;

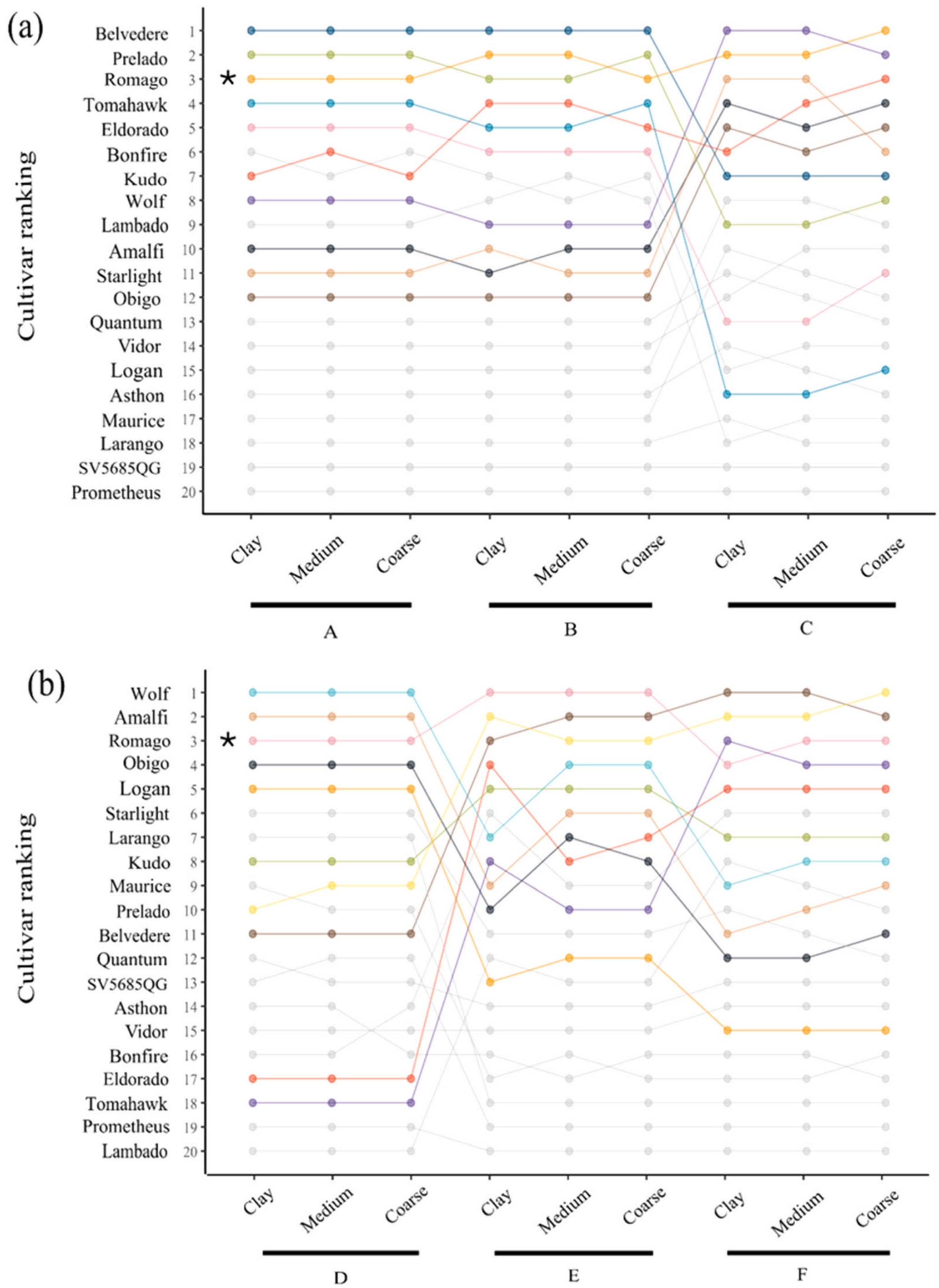

Fig. 4. Bump charts showing the variation of cultivar ranking across agro-climatic contexts for early (a) and late (b) sowing periods. Only cultivars ranked at least once among the top-five are coloured. The letters on the x-axis refer to the SAM classes described in Fig. 1. The star indicates cultivars often ranked at the top under different agro-climatic contexts, thus revealing broader adaptation to growth conditions.

Jiménez-Vaquero et al., 2026), and recent studies have provided empirical evidence of the physiological mechanisms underlying crop adaptation in legumes (Tefera et al., 2022, 2024), this study contributes to existing knowledge by quantifying the relative importance of phenological functional traits within a process-based modelling framework and using that information to design context-specific ideotypes for cultivar recommendation.

The second most influential trait was radiation use efficiency, which even ranked first in one context (the most humid in the case of late sowings). This is likely because, under those weather conditions, improving radiation use efficiency would provide benefits for both canopy development and seed growth (Lecoeur and Nei, 2003), as confirmed by the positive correlation between radiation use efficiency and biomass accumulation observed in all agro-climatic contexts. Within a source-sink framework, yield is constrained either by the number of sinks established at pod set or by the availability of assimilates to fill them (Sandaña and Calderini, 2018). High radiation use efficiency during grain filling allows high photosynthetic activity that, together with remobilization of assimilates from vegetative organs and roots, improves assimilate supply to developing seeds. This is particularly relevant under post-anthesis stress conditions, where maintaining canopy function and carbon assimilation becomes a critical determinant of final yield (Sadras et al., 2012). These results are consistent with findings from Tefera et al. (2022), who identified radiation use efficiency as the trait with the strongest effect on lentil yield, and Sadras et al. (2012), who highlighted that high photosynthetic rates during grain filling are crucial for improving pea yield under rainfed conditions.

4.3. Key advantages of the framework proposed

The methodology proposed in this study is based on the use of functional trait distributions, thus requiring limited phenotyping efforts as subsequent analyses can rely on the established distribution of phenotypic traits. Such efficiency is particularly relevant considering that new cultivars are typically released every few years (Potts et al., 2023). Different crop model-based approaches for cultivar recommendation have been developed in the last decade, mostly leveraging the model capability to reproduce the cultivar response to different agro-climatic conditions as long as a cultivar-specific model parameterization is available. The latter can be developed via data collected in extensive multi-environment trials (Casadebaig et al., 2016; 2022), which clearly limits the applicability of modelling tools for cultivar recommendation in case of smaller but more affordable datasets. The number of observations needed to achieve a reliable model parameterization can be reduced when focusing on a single process such as phenology (Paleari et al., 2022; Grewer et al., 2025), but still the ratio between the number of model parameters under calibration and the number of observations for each genotype must be minimized to reduce the risk of equifinality (Yang et al., 2022; Paleari et al., 2025).

Another advantage of the methodology proposed in this study is that it provides, for each agroclimatic context, a complete ranking of all cultivars together with a quantification of their suitability according to their similarity with the context-specific ideotype. This allows identification of alternative top-ranked cultivars among which the choice can be made by including other criteria. In this study, only functional traits more directly related with growth dynamics and yield were considered. However, other aspects can be relevant for cultivar choice. In particular, traits affecting seed quality, such as seed size and sugar content, play a crucial role in determining the retail value of pea (Ntatsi et al., 2018) and are therefore highly valued by farmers in the study area. Despite the key role of management and environmental factors in defining pea quality (e.g., harvest time, Fallon et al., 2006), the extremely rapid dynamics involved with pea quality around maturity, together with potential constraints on timely harvest because of unfavourable weather conditions, are difficult to simulate using currently available cropping system models. Therefore, the comprehensive model-based cultivar ranking can be complemented by classic field trials, for traits that are not explicitly simulated (e.g., quality-related traits).

4.4. Limitations and future perspectives

This study has limitations to be addressed in future research. In particular, we focused on traits affecting yield under pest-free conditions, although the variability among cultivars in terms of resistance to diseases and competitiveness against weeds can be clearly leveraged to improve the economic and environmental sustainability of pea productions. Modelling approaches for ideotype design targeting resistance traits are available, for both fungal pathogens (e.g., Paleari et al., 2017) and weeds (e.g., Colbach et al., 2022). Such approaches, together with data characterizing cultivar resistance level, can be used to extend the analysis to the impact of biotic stressors on crop productivity and sustainability. Given the clear role of environmental and management factors for pest occurrence and severity, biophysical modelling explicitly accounting for G×E × M interactions are unique tools to quantify the advantages of plant traits related with resistance to biotic stressors (Casadebaig et al., 2012) and support the transition towards cropping systems with reduced chemical inputs (Colbach et al., 2022).

Another limitation of the present study concerns the validation of the cultivar recommendations. While the model has been fully validated for the study area (Ravasi et al., 2020), the cultivar rankings obtained in the different agro-climatic contexts were supported by the results of independent cultivar evaluation trials carried out in 2021 within the same area. However, further data collection through multi-environment trials is needed to strengthen this preliminary validation and to better assess the relationship between similarity to model-derived ideotypes and cultivar performance across environments. While the proposed framework is promising as a flexible tool for cultivar recommendation, this further multi-environment validation is required to confirm its predictive ability and support transfer to operational farming conditions.

Regarding future developments, the full transfer of the present framework to operational contexts would also require the active involvement of end-users, including farmers, agronomic advisors, and agri-food chain stakeholders. Studies have shown that participatory approaches are a key factor to ensure usability and actual uptake of innovation in real-world farming contexts (Cerf et al., 2012; Rose et al., 2016; Queyrel et al., 2023). Moreover, co-development efforts can help better account for the heterogeneity of stakeholders' priorities when defining the relevance of yield and its stability for ideotype design (Y_{index}; Eq. 2), as the relative importance of each of the two performance features may depend on the specific user context (Bockstaller et al., 2008). Future work will involve co-design processes also to identify potential barriers to adoption and tailor the recommendation outputs to formats maximizing the transfer potential to operational farming conditions.

5. Conclusions

This study highlighted the relevance of decision support tools for cultivar recommendation that explicitly account for G×E × M interactions, even in relatively small areas as the one investigated in this study. A clear re-ranking of cultivars was observed while changing agro-climatic conditions, with a more marked effect of climate than of soil properties. The simple methodology used to derive cultivar phenotypic profiles allows easy extension of the framework to other pea cultivars, making the system extendable in case new cultivars are released. The proposed framework represents a useful alternative to data-intensive approaches, for operational contexts with limited resources for cultivar characterization. Building on a crop model validated across multiple environments and statistical distributions of functional traits, the ideotype characterisation and associated cultivar recommendations presented here represent a robust simulation-based framework. While the preliminary evaluation of the recommendations provided by the system confirms its potential reliability, further validation through multi-environment trials is required before the decision support framework can be applied under operational farming conditions. Future studies will also focus on improving the system's transferability and addressing end-users needs via participatory approaches.

CRediT authorship contribution statement

Chiara Marchetti: Writing – original draft, Investigation, Formal analysis, Data curation. **Livia Paleari:** Writing – review & editing, Supervision, Methodology, Investigation, Conceptualization. **Roberto Confalonieri:** Writing – review & editing, Methodology, Investigation, Funding acquisition, Conceptualization.

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.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ijagro.2026.100110.

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