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A modeling System for Identification of Maize Ideotypes, optimal sowing dates and nitrogen fertilization under climate change – PREPCLIM-v1

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Abstract

The impact of climate change on crops and agricultural yield is an actual threat while being a challenging issue due to the high complexity of factors that intervene at the local scale of the crop. Assessing it, requires the use of coupled models climate-phenology, meanwhile methods to identify management and genotypes suitable for local future conditions, in order to sustain adaptation strategies. We present the implementation and use of a new integrated climate-phenology adaptation support modeling system based on regional CORDEX climate models and the CERES Maize model from DSSAT platform, with new modules for optimal management and genotype identification using a hybrid method: deterministic modeling and -ML/ genetic algorithms. It was run as a regional pilot over Romania, operating in real-time in interaction with users, performing agro-climate projections (combination of fertilization, sowing date, soil) and providing best crop management simulated under climate change projections. Multi-model ensemble simulations for two climate scenarios RCP4.5 and RCP8.5 and twelve management scenarios show new results for the region.
For the actual genotype we find a projected mean decrease in yield in both climate scenarios for all sowing dates and fertilization levels tested, response shown to be sensitive to initial soil parameters. This response was linked to two factors: a shorter growing season by up to 10% and a loss of fertilization efficiency in a warmer climate. A warning points to results showing a narrowing of agro-management opportunities for crop yield but in opposite it is shown a significant role of optimal genotype-range identification that may provide crop solutions under climate change even in extreme years. Identifying best genotype under warmer climate along sets of six cross-parameter simulations show systematic lower values of the maximal yields, but emphasizes genotype windows of increases in the intermediate yield values in scenarios compared to actual climate. The highest harvest sensitivity to genotype is shown to be to changes in the thermal time to juvenil respectively to maturity stage under warmer climate. The results sustain using a deterministic coupled modeling system combined with data-driven modeling for identifying optimal adaptation including fertilization paths that contribute to climate change mitigation.

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1. Introduction

According to the IPCC reports (IPCC, 2022) climate change is evident and the prospects appear more worrying today than a few decades ago. Although progress is being made in studying the impacts of climate change on crops and agricultural yield (Arnell and Freeman, 2021; Hatfield at al, 2021, these are rarely directly applicable to provide solutions due to the extremely high complexity of factors that intervene at the local scale of the crop (Malhi et al., 2021, Eyring et al., 2021). These factors include culture-scale sensitivities to the interacting climate sub-components atmosphere/ soil/ phenological processes/ ecosystems, to climate change, to natural causes or human activities (Wheeler and Braun, 2013, Xie et al, 2023).

Taking into account scientific research estimating that the world population will continue to grow' and it is expected to arrive to 9,1 milliards until the year 2050 (Godfray and Charles, 2010), the total food yield will have to grow by 70-100% (Smil, 2005; World Development Report, 2008; Selvarju et al, 2011). Meanwhile the agro-climatic conditions are expected to become vulnerable and gradually, more deficient in the context of climate change and its impact on water availability (Villalobos et al., 2012; van Ittersum et al., 2013; Roccuzzo et al., 2014; Stehr and von Storch, 2009).
Another face of the problem comes from the need that approaches and solutions should both: merge user needs, and be in line with neutral climate adaptation stringency (Semenov et Stratonovitch, 2015; Dainelli et al., 2022; Mitchell et al., 2022).

Early studies on climate change impact on crops have pointed to the need of very high resolution modeling, capable of representing management practices and local scale impact of climate on plant as temperature and precipitation (Trnka et al, 2015; Adams et al., 1998; Mkee et al, 1993) affecting water stress (e.g. the stomatal opening, stem water potential, leaf transpiration efficiency (Espadafor et al, 2017)). Further at regional scale, water availability relation to yield indicated a strong dependence on crop, region, time-scale and plant physiological stage (Webber et al, 2020; Webber et al. 2018; Ceglar et al,, 2020; Wu et al, 2021; Berti et al. 2019; Marcinkowski and Piniewski 2018). In this regard, under future climate changes, perspectives for corn yield rises (15%) under irrigated conditions were identified by simulations for areas currently more arid than the geographical region of interest considered in this paper (Kothari et al., 2022). This points out the need for continuation of the simulations taking in consideration soil humidity accuracy and various irrigation strategies.
Apart from atmospheric conditions, soil changes significantly affect plant growth through interactions with climate and through changes in chemical compositions. Increasing air temperature was shown to affect the soil carbon budget, its decrease affecting plant and root level processes, biochemical cycles, and species (Abhik Patra et al, 2021).

Modeling at local, regional and also global scale reported significant advances in understanding, simulating and projecting future crop (Tao *et al*., 2009; Ganguly et al., 2010; Cock et al., 2021; Chen and Tao, 2022; Schauberger et al., 2020). These emphasize global projected yield mean reductions (Asseng et al., 2015) with differences in the regional pattern of climate change impact on crop and yield (Li et al. 2022). Not only projected regional but also time variability of the impact appears larger and accelerated, motivating intensified efforts on seasonal predictions of plant development and yield (Baez-Gonzalez et al., 2005; Jin et al., 2022) using crop models. These simulations' results significance

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was analyzed suggesting the need to include crop uncertainty in climate scenarios assessments (Meehl *et al*., 2007, Rosenzweig *et al*., 2013, Basso Bruno et al., 2019; Chapagain et al., 2022). In addition, model simulations proved to be a highly useful tool in plant breeding analysis (Bernardo, 2002; Hoogenboom *et al*., 2004; Cooper and Messina *et al*., 2023) considered a support in developing superior genotypes and plant-breeding methods for maximizing crop effectiveness. Demonstrations of model simulations' potential as a valuable tool for breeders were reported in finding paths for optimal cultivar using techniques such as parental selection, breeding by design, etc. (Peleman and van der Voort, 2003, Qiao et al., 2022).

In most recent years developments climate-crop modeling extended from deterministic crop models (Boogaard et al. 2013; Morell et al., 2016) to data-driven techniques or hybrid approaches for assessing crop response to weather and climate change (Zhuang, 2024; Morales and Villalobos, 2023, Meroni et al., 2021; Schwalbert et al., 2020; Zhang et al., 2021). Statistical methods as well as ML used for crop forecast and modeling were however shown to bring for now, limited benefits (Paudel et al. 2021), pointing to possibly hybrid techniques that include physical process in the modeling as a key approach for this challenging issue.

On the other hand, deterministic breeding techniques using model simulations require a huge number of simulations, analysis and inter-comparisons of predicted cross performance (Wang and Pfeiffer, 2007).

Here we present a novel approach developed in the frame of the PREPCLIM ("preparing for Climate Change") project in which we solve plant phenology development using deterministic modeling and merge this technique with ML-genetic algorithms along simulations in order to iteratively select a cross-range of optimal genotype parameters according to a pre-set user-criteria of the optimum. Genetic algorithms (GA) simulate the evolution of a population by iteratively applying genetic operators, such as selection, crossover, and mutation, to a set of candidate solutions (chromosomes). The chromosomes represent potential solutions to the problem and are encoded as strings of binary or symbolic values, with their fitness assessed by a problem-specific evaluation function here, user-request based. GA was successfully used with DSSAT for optimizing irrigation and fertilizer applications (Bai et al, 2021, Wang et al, 2023).

The hybrid approach implemented here presents the advantage of physically treating the crop complex process involved each time along optimizing iterations, so allowing analysis of causes of the responses to various climate or /and management scenarios, meanwhile enhancing the ability of choosing optimum conditions from a continuous interval, not a discrete one, of gene parameter values. The continuum values approach is an important feature mainly for isolated extremes, or broad parameters' range, both of increasing interest, as we show in this work the a tendency toward narrower adaptation opportunity windows under warmer climate.

We present the system developed and data flow in section 2. The motivation of its development, linked to projected climate change in the target region are shown in section 3a. We show results of the system used to estimate changes in plant phenology and crop parameters under climate change scenarios and for different management scenarios, for the actual control genotype in section 3b. Then we discuss in section 3c, results using the genotype optimization package of the system. Perspectives and conclusions are discussed in section 4.

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2. Data and methods

Projected changes in agro-climate indicators over Romania are computed for two climate scenarios: RCP45 and RCP85 as anomalies reported to historical simulations, using an ensemble of three CORDEX models (Benestad et al., 2021). Then, projected changes in phenological and yield parameters are simulated using the DSSAT crop model (Hoogenboom et al., 2019; Jones et al., 2003) forced with the atmospheric conditions from the CORDEX models (from GFDL, HadGEM, MiIROC, IPSL, NorESM), for each model of the ensemble for the historical period and for each of the two climate scenarios.
A software package was developed for the DSSAT model that performs identification of optimal model parameters set-up according to user-criteria, user chosen climate-management scenario, region, time-horizon. The user-criteria for optimisation includes maximum yield, stable yield, across years, minimizing the amount of leached nitrogen below the maximum level of the root front (reducing the risk of water pollution), etc. Management scenarios include cross-options for sowing date, fertilization amount, genotype (six parameters defining the genotype). By default, twelve agro-management simulations are performed, for four planting dates (separated by 5 days interval) and three fertilization amounts with Nitrogen (zero, a mean value of the region and the double of the mean value). For each agro-management scenario, genotype optimization by selection of the values for the cultivar related coefficients (named further G-parameters) was performed through two methods: a fixed-discretisation runs and post-processing ordering and a continuum space-search with iterative selection along simulations, by genetic algorithms methods (GA). The proposed GA-based method commences with an initial population of randomly generated chromosomes and undergoes iterative cycles (generations). In each generation, a selection process is performed to choose the fittest chromosomes to reproduce, based on their fitness scores. Subsequently, crossover (recombination) and mutation operators are applied to the selected chromosomes, generating offspring that inherit traits from their parents. The new offspring replace some of the least fit individuals in the population, ensuring that the average fitness of the population improves over time. The convergence of the GA toward an optimal or near-optimal solution is achieved by balancing exploration (searching the problem space for diverse solutions) and exploitation (refining the best solutions found so far). Here GA have even been applied to develop an innovative crop selection algorithm to optimize genotype along agro-management scenarios. Steps along the algorithms are shown in Schema from Annex1.

The overall output information from the system (climate, agro-climate and optimal paths) is directed on two platform-components (Fig.1). One is a platform (Info-Platform, Fig. 1a) providing static agro-climate information at local scale (NUTS3) over the region, delivering climate indicators, agro-climate, and agro-climate extremes indices computed from observations and re-analysis for the actual climate and from climate scenarios (anomalies relative to historical runs) for future.
The second platform is an operational online, user-interactive in real-time component, where requests are placed, treated, and results sent back to the user (User-Platform, Fig. 1b).

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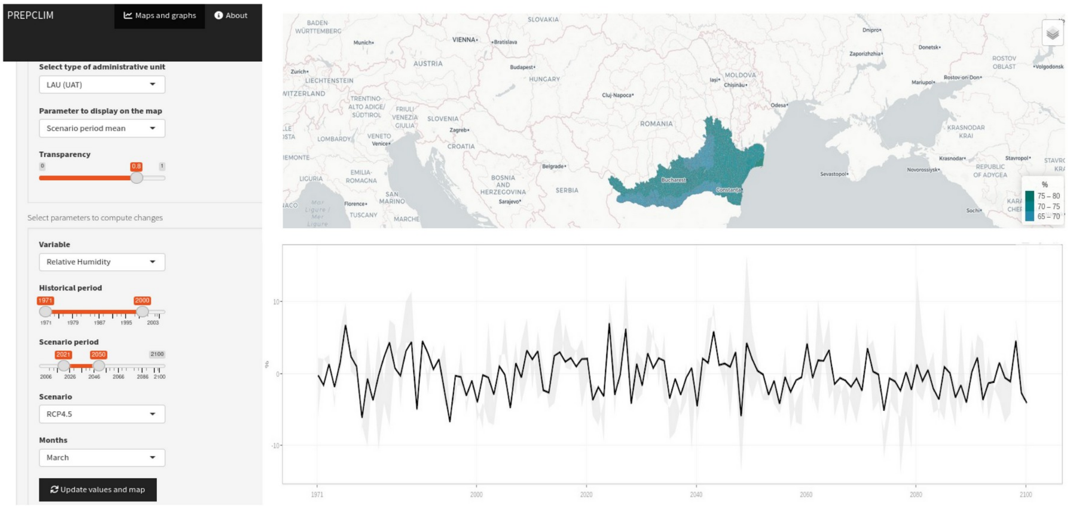

Fig. 1a: Info-Platform for information at local scale, derived from regional climate high resolution models CORDEX, presenting climate, agro-climate, agro-climate extremes indices at NUTS3 level.

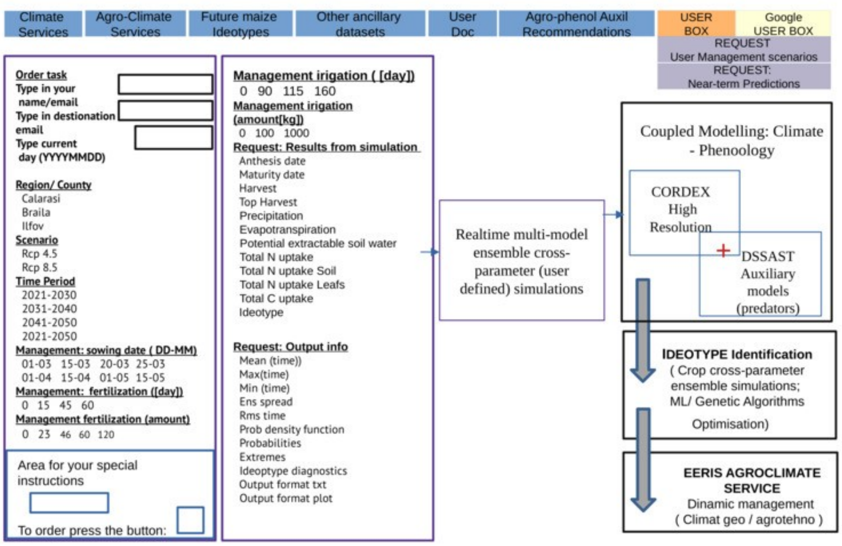

Fig. 1b: User-Platform: the user-interactive component to specify requests on adaptation management simulations. User request (left) on: the region, time slice present or climate scenarios, choices for: sowing date, fertilization/ irrigation (time, amount), genotype and output requests (right) on results: yields, phenology dates, evapo-transpiration, N and C balance, optimal management path (dates, management), optimal genotype.

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The pilot area where the system was implemented and validated is Southern Romania, for maize. The potential beneficiaries of this system are users, researchers, farmers, and policy makers. Maize breeders also can adapt using the system to the climate conditions by accommodating or testing genotypes that are more resistant to challenging climate. Accelerated climate change makes such a system a useful support in many respects.

The core of the modeling system relies on coupled modeling by DSSAT crop model (Linux OS) interfaced with regional climate models (Fig.2), with new feature allowing multiple cross-parameter simulations under iterative loops (parameter perturbations) and new features for optimal agro-management x genotype identification (parameter' value selection).

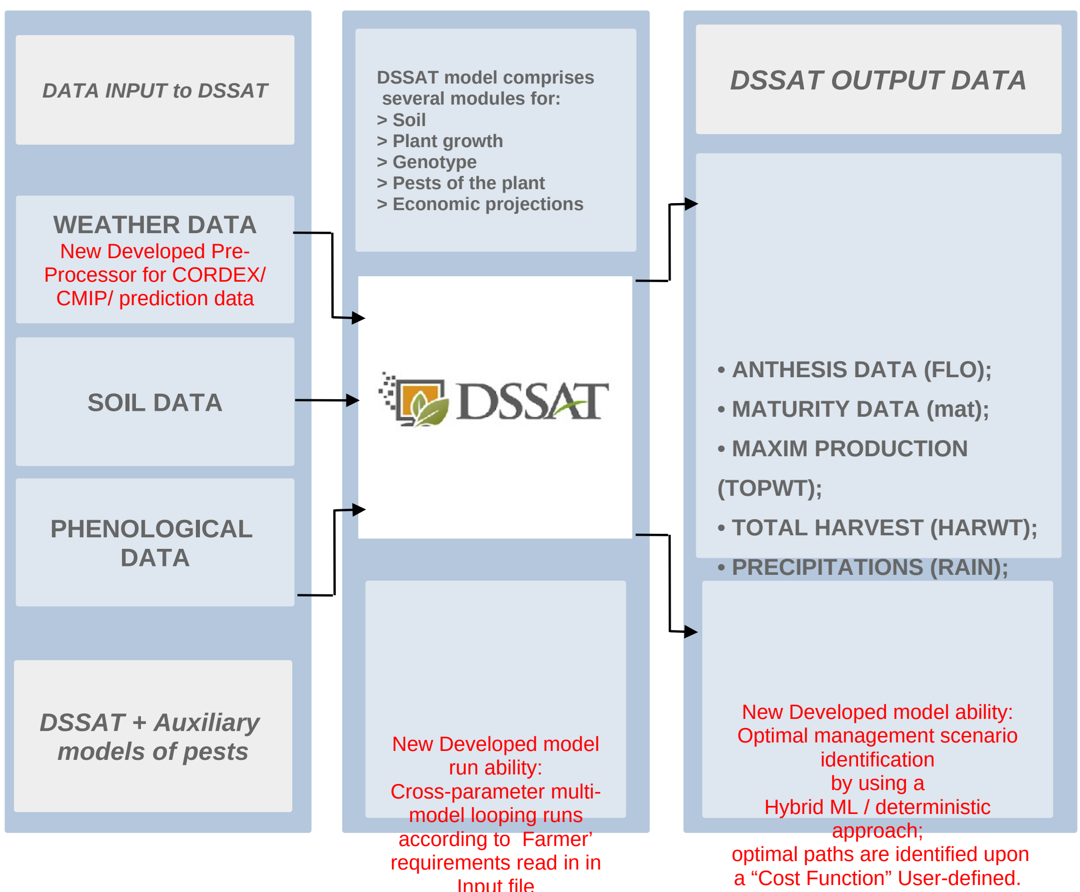

Fig. 2: DSSAT-core and the Optimal-Crop modeling system. Data flow: Input data (left), output information (right); model components and set-up (middle). Red modules were developed within the project.

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Table 1: Treatment description in terms of the sowing date and fertilization amount, N [kg/ha].

Treatment	TR1	TR2	TR3	TR4	TR5	TR6	TR7	TR8	TR9	TR10	TR11	TR12
Sowing date	1.04	15.05	1.05	15.05	1.04	15.05	1.05	15.05	1.04	15.05	1.05	15.05
Fertilization (3N)	Fx0=0	Fx1=60	Fx2=120	Fx0	Fx1	Fx1	Fx1	Fx1	Fx2	Fx2	Fx2	Fx2
Fertilization (1N)	Fx0=0	Fx1=23	Fx2=46	Fx0	Fx1	Fx1	Fx1	Fx1	Fx2	Fx2	Fx2	Fx2

3. Results

a) Agro-climate changes in the region

a.1) Changes in agro-climate indicators

Agro-climate Indicators (provided on Info-Platform) are computed from CORDEX models, and provide derived parameters information as time slices for ensemble or model metrics from country to NUT3 level over South Romania. At the country region Fig.3 shows projected changes in main agro-climatological characteristics. Region's climate is expected to shift as shown (Fig. 3a) by the Johansson continentality index (Baltas, E. 2007; Flocas, 1994) defined as:

$$JCI=1.7\, dT/ \sin (phi) -20.4$$

where dT is the annual maximal thermal range of monthly mean temperatures and *phi* is the latitude. Changes in JCI show an increase in the entire Southern part up to 5.5% of the interval required to switch to "extreme continental" from "continental" class already in the first 10 years (2021-2030) in the ensemble mean (and up to 10% change per model). Changes are towards "maritime" in the Northern half, this zonal differentiation creating strong thermal wind gradients and being stronger in RCP85. For agriculture, an often-used regional-indicator is the scorching days number (SC), computed over the region as the number of degrees in summer days (JJA) over the temperature of 34ºC. SC is constantly increasing (Fig. 3a) in the overall country, with a stronger increase in RCP85 both, in the first decade and until 2050 than in RCP45, emphasizing as well, the enhancement of the north- south gradient. Relevant for composed temperature and precipitation, the deMartonne aridity index (IM) computed as the ratio between annual total precipitation ([mm]) and annual mean temperature ([C] +10) shows in Fig. 3b significant changes in its classes as well, decreasing (towards aridity) mainly in the South, SE and SW, the main agricultural areas discussed here. Identification of projected changes in aridity was shown to be a key issue for adaptation in semiarid environments (Ignacio Lorite, et al, 2018).

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We summarize that changes are accelerating in the South in RCP85 (differences 2071-2100 versus Hist are higher than those over 2021-2050).

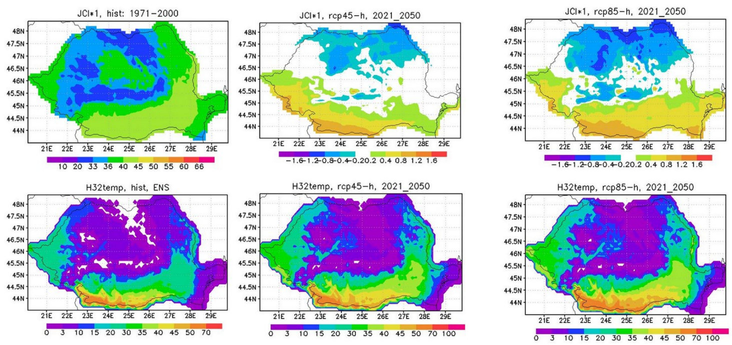

Fig. 3a: Historical (left) and changes relative to it under RCP45 (middle) and RCP85 (right) along 2021-2050, for: the Johansson conventionality index JCI (top): the JCI climate is marine for 0<k<33, continental for 33<k<66 and exceptionally continental for 67<k<100; the Scorching index SC (bottom).

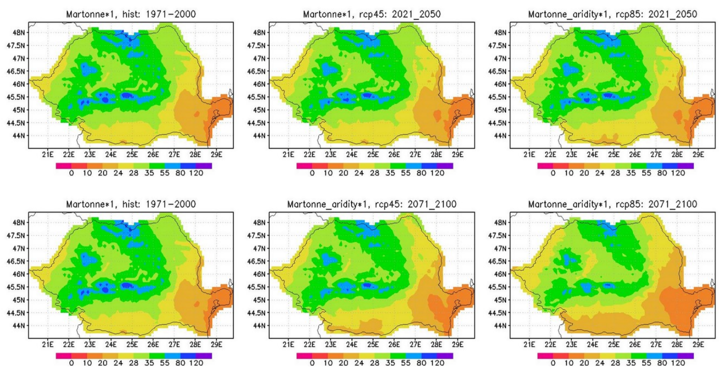

Fig. 3b: Historical (left) and changes relative to it under RCP45 (middle) and RCP85 (right) along 2021-2050 (top) and 2071-2100 (bottom) for the Martonne aridity index. (0<IM<10 arid; 10<IM<20 semi-arid; 20<IM<24 Mediterranean; 24<IM<28 semi-humid; 28<IM<36 wet; 36<IM<55 very wet; ID>55 extreme wet).

a.2) Changes in agro-climate extremes

Projected changes in extremes are analyzed for the ensemble models in Fig. 4 that shows for Călăraşi target subregion changes in RCP85 versus Hist, in the number of freezing days (FD), total precipitation (RR), severe precipitation (RR10 the number of days with daily accumulated > 10 mm) and total

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precipitation (RR), for each of the three decades (10 days) of April (the main sowing month for maize). We note a decreasing tendency in FD for both decades, but interestingly intervals with even higher numbers of FD may occur in RCP85 scenario compared to Hist in the third decade. This late spring blizzard feature over the region, important for plant evolution, was shown in a previous work, to be related to the combined context of Polar Jet instability meanwhile with warmer sea surface temperature in the Eastern Mediterranean (Caian and Andrei, 2019). Both these features are projected to enhance in a warmer climate (Lelieveld et al., 2012; Shaw and Miyawaki, 2024;), which for the region indicates a higher potential for severe spring blizzard, affecting crops and the year's yield under warmer climate.

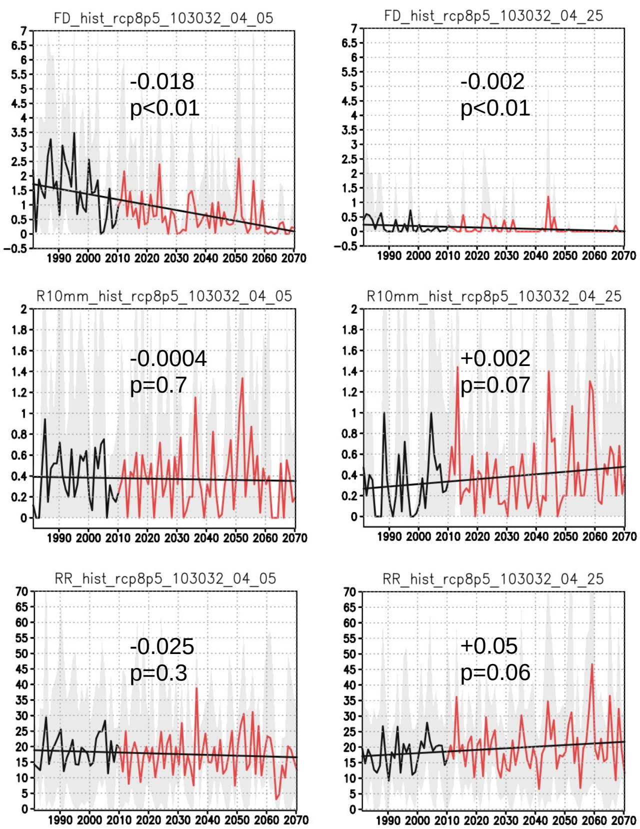

Fig. 4: Time evolution ([years], Ox axis) in Hist and RCP85 (1981-2070) of extreme climate parameters: number of frost days (minimum temperature <0ºC, per 10 days slice, top), number of days total per 10days slice with heavy precipitation (>10mm) (middle); precipitation sum (10 days, [mm] bottom); 10 days slices are centered: 5 April (left), 25 April (right). Boxes indicate the slope of the linear trend (black line) and the p-value of significance (p-value <0.05 -> significant at 5% level of falsely rejecting the null hypothesis of linear regression coefficient =0).

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Extreme (RR10) and total precipitation RR show the following: a negative trend in the first decade of the month turns in opposite to positive trends in the third (and second) month's decade, that indicate a time-shift towards end-April -May of accumulated precipitation peack along April month. We note that this feature of precipitation shift is present systematically in each model of the five-member CMIP5 ensemble (Karl et al. 2011). RR10 (and RR20, not shown) extremes enhance even more towards 2070. Also, RR10 and RR show higher variability with significantly higher isolated extremes in the third decade of the month in scenario compared to Hist. Extreme daily precipitation is, in most cases detrimental for the crop, causing soil erosion and surface runoff after drought periods.

b) Phenology and Yield projected changes for the control genotype

Projected changes in phenology were simulated with the DSSAT forced by multi-model Hist and climate scenarios RCP45 and RCP85, using first the control genotype G0 (Pioneer 375*) of the region. The implemented system validation was done in Control simulations that used reanalysis climate data from ERA5 (Simmons, 2021) over 1976-2005. These show a good time variability of the simulated Yield against available measured values for the region, and that the modeling system is able to capture years of high and low yield (Fig.5). The model set-up involved soil parameters calibration, that was performed along sensitivity experiments for soil water and Nitrogen and Carbon organic content.

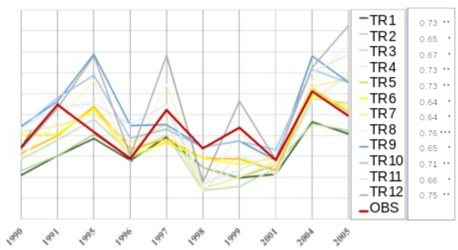

Fig. 5: Harvest simulated under twelve default management scenarios (Table 1, 3N) and measured (red thick line), for the S-Romania. Blue box shows the Pearson correlation between treatments and measured Harvest with statistical significance (*** p=0.01; ** p=0.02; * p=0.05).

b.1) Phenology dates - projected changes

Ensemble model simulations over 30 year scenarios up to 2050, compared against historical runs (for RCP 4.5 and RCP 8.5) indicate projected changes in the anthesis and maturity days in Fig. 6, for the control genotype G0, fertilization 3N (Table 1, experiment E_3N_G0). These show that the anthesis date is projected to occur earlier by up to ~6 days while maturity days come also earlier by up to about 10 days (ensemble mean, time mean), regardless of the planting date and the fertilization level. The two shifts together lead to a shortening of the growing season by up to 10%. The average maturity date

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may show small variations with the fertilization level, due to occurrence of slowed grain feeling (Fig. 6).

a) b)

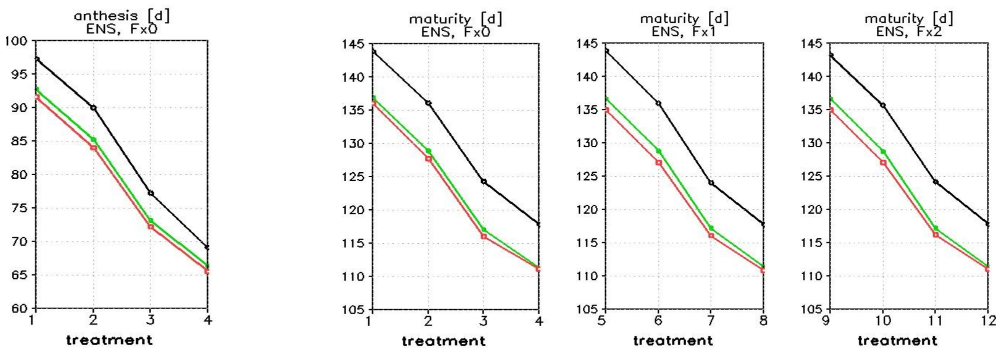

Fig.6: a) Anthesis dates ([dap], day after planting) simulated for the historical period (black), RCP45 scenario (green) and RCP85 scenario (red) for treatments 1 to 4; b) the same for the maturity date, for treatments 1 to 12. On the Ox axis there are the treatments (1-12, Table 1, 3N, experiment E_3N_G0).

b.2) Yield - projected changes

Same multi-model simulations experiment E_3N_G0 show an overall decrease, in the ensemble mean, of the yield in both climate scenarios, for all tested (Table 1) management scenarios with perturbed sowing dates and fertilization levels (Fig. 7a,b,c).

This decrease was related to several factors: - a decrease in the accumulated rainfall in the growing period (Fig. 8a,b,c) in scenarios compared to Hist in both climate scenarios and for all managements scenarios; - a systematic earlier flowering date and date of reaching physiological maturity, the two leading a shortening of the crop season (Fig. 6); - a decrease of fertilization efficiency with increasing warming: the decrease in Harvest in scenario compared to Hist is higher for later sowing dates and for higher emission in RCP8.5 than in RCP4.5 (Fig. 7c).

In the non-fertilized (Fig. 7a) case, we note is a Harvest increase with delaying sowing, for Hist and for scenarios, indicating in the lack of nutrients, a stronger relation with precipitation: more accumulated precipitation (Fig. 8a) for later dates (season's length increases for later sowing, for all treatments). Also, RCP85 shows higher H values than RCP45 due to precipitation time shift (Fig. 4), more appropriate for the plant development phase. This is no more valid when fertilization occurs (Harvest decreases are obtained for later sowing dates in this case) pointing to nonlinear relation climate-fertilization and to a decay of fertilization efficiency with warming.
The robustness of these is further analyzed in sensitivity simulations with enriched soil nutrients.

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b.3) Sensitivity of changes to nutrients

In a second experiment we use the same fertilization levels but change in addition the initial soil content in Carbon and Nitrogen (increased). The aim is to understand if less fertilization (less pollution) could be compensated by better soil characteristics choice. Achieving best Harvest in warmer climate versus actual climate enhancing the support towards a neutral climate, is a crucial point.
The sensitivity ensemble simulations increase soil Carbon and Nitrogen at the initial time by 20%, for the same control genotype (Experiment E_1N_G0_soil+CN).

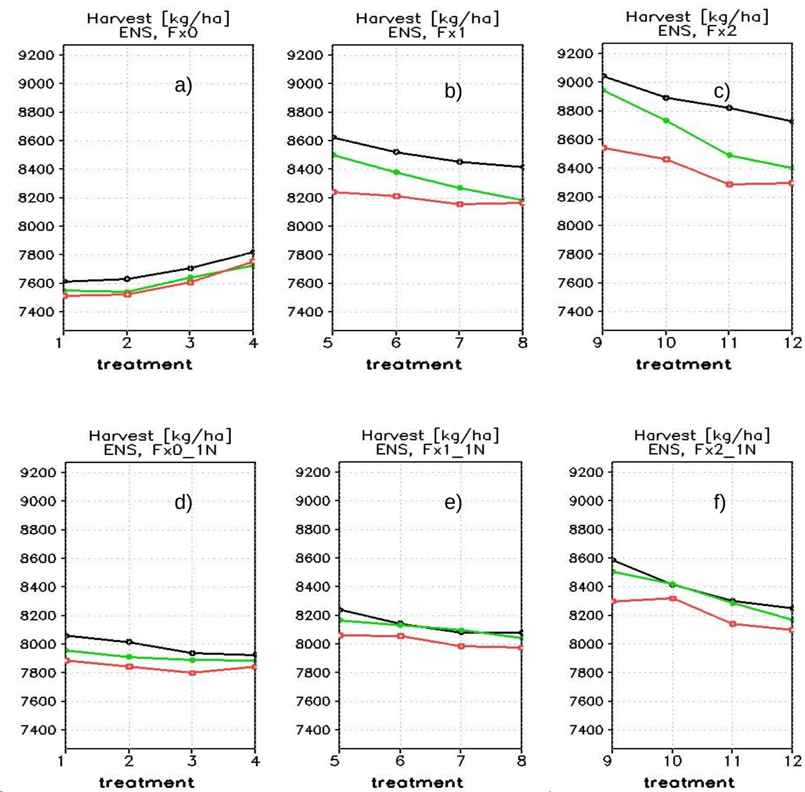

Fig. 7: Same as Fig.6b, for Harvest ([kg/ha]) for experiment E_3N_G0 (top) and for experiment E_1N_G0_soil+CN (bottom).

Experiment E_1N_G0_soil+CN compared to E_3N_G0 (Fig.7) shows that the Harvest is reduced by only up to 7% for about 60% reduction in fertilization when the soil nutrients content is increased by 20%. In addition, we note two interesting features also for adaptation decisional support. One is that there are still options even under warmer climate to overestimate the historical Harvest under appropriate initial soil composition (e.g. in RCP45 TR6 and TR7, Fig. 7e) and even under RCP85 (TR10 and TR11, Fig.7f). The mechanism behind appears to be linked to richer soil (N, C) leading to a slower maturity (Fig. 8b) with consequent more precipitation accumulated along the growing season

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(Fig. 8c). This slower maturity is stronger for early sowing (Fig. 8b) hence better date option (Fig. 7d, differences diminishing at later sowing due to precipitation shift).

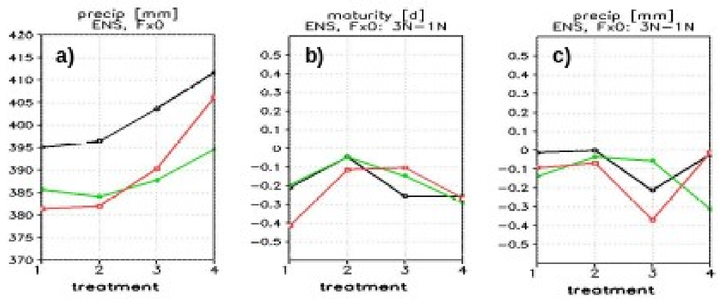

Fig.8: a): Accumulated precipitation from the initial time of the simulation until the maturity date ([mm]), for scenarios as in Fig.7, for E_3N_G0; in b) are shown differences [dap] in the maturity date and in precipitation for (E_3N_G0) minus (E_1N_G0_soil+CN); c) same differences as in b for the precipitation accumulated along growing season ([mm]).

In summary for the control genotype, in both climate scenarios, and for all the management scenarios tested for sowing-date and fertilization level but keeping the same genotype, it is projected a shortening of the growing season (and earlier development phases) with mean decrease of the projected yield. Meanwhile, it is shown that one can get comparable outcomes if astuciously using soil richness, elongating the growing season, instead of enhancing fertilization levels and pollution.

c) Optimal genotype identification

The system was further developed to extend the management scenarios for multi-genotype simulations and algorithms for optimal identification under each agro-climate scenario. Best options are searched that lead to optimal (user-defined) yield: highest harvest, stable yield, less pollutant.
Two optimization methods are implemented: a discrete-value pure deterministic technique and a hybrid optimization technique combining deterministic modeling with ML Genetic Algorithms for iterative selection.
Deterministic method performs multiple simulations (and optimisation is part of the the post-processing), for pre-established limits and discretisation intervals for each of the genotype parameters considered (here six). Multi-model simulations in which each parameter is varied while the others have fixed values are performed, resulting in a number of simulations depending on the discretisation. An example for the criteria of “maximum yield” is illustrated in Fig.9a, for six genotype parameters: P1 the thermal time from seedling emergence to the end of the juvenile phase; P2 a photoperiod-development delay parameter; P3: the thermal time from silking to physiological maturity; P4 linked to maximum kernels per plant, P5 linked to kernel filling rate and P6 the phyllochron interval), for Hist, RCP45 and RCP85, each for the twelve default sowing date- fertilization treatments and each model of the

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ensemble. We discuss here the results of genotype optimization (experiments E_1N_Gn+w) that are based on the setup of E_1N_G0 but in which we increased the initial soil water content by 5% as indicated by the projected maximum change over the pilot area (Fig. 1S, Suppl). Parameter P4 was kept constant as having known impact.

i) Optimal Harvest under climate change

Fig. 9 shows, for the ordered genotype upon Harvest (H), a projected average decrease of the Harvest (H) in maximum values' genotype-range range (top 2.5% cases), for RCP45 and emphasized also in RCP85 for earlier sowing. This response is not systematic among models (Fig. 2S, Suppl). Among models, we note a strong link between H differences and models' projected precipitation (a parameter with high intra-model variability and regional-scale uncertainty) mainly for unfertilized case. In opposite, the warming trend is a parameter in models' consensus for this region, leading to systematic responses as earlier anthesis and maturity dates with a season shortening in RCP45 and even more in RCP85 affecting mainly in the range of highest H (Fig. 3S, Suppl).
We further analyze robust features of the projected yield that are systematically seen among model-simulations. Important climate-adaptation information appears from these diagrams.

One is the different response obtained for maximum H (GX) and for intermediate H (GI). Any ("n") ordered simulations has a harvest, and a genotype associated, that we call "H-range" and respectively "G-range" (of the top "n"-th value of H). We call GX the ranges of highest H values, GI of intermediate H values and GN of lowest H values.
The large ensemble of genotype-treatment simulations indicate a decrease that is projected for the highest yield (GX, Fig.9b) that is projected in RCP45 and RCP85 (except late sowing, low fertilization, potentially linked to precipitation shift towards later in April mainly in RCP85). In opposite, a H increase is projected for the intermediate yield genotype ranges (GI) for almost all treatments (Fig. 9c). The explanation comes from the fact that we test a broad range of parameter P3 (the thermal interval to maturity) and H increases significantly with P3 increase, in scenarios relative to Hist, a cause being the fact that at highest values of P3 the plant maturity comes earlier in scenario compared to Hist with an overall shortening of the season (with increasing P3, allowing stage accomplishment). These two tendencies become systematic for all models in RCP85. Tendency towards H overestimations in scenarios is not excluded neither for the Control genotype under conditions of higher soil water as it was already noticed in Fig.7 e,f for the control Genotype. Here its G-parameters are located in the intermediate range (400-1400) and have a central P3 value, but a lower initial soil moisture.
P3 value appears a key parameter on managing H. However care should be taken as extreme P3 increase leads to a too slow grain filling, and crop failure, more often in scenarios than in Hist (Fig. 3S), when P3 is above a threshold (that is P1 and P2 dependent, not shown).

The second feature is the fact that while for the highest H (GX) range it is systematic that earlier sowing conditions are better options in E_1N_Gn+w (as P1 is small in maximal H), this is no more valid for intermediate H genotype ranges (GI, Fig. 9a zooms, more days with precipitation improving mainly the unfertilised cases). We note ranges with e.g. TR2 worse than TR3 (at GI ranges) and better than TR1 (at GX ranges) mainly in RCP85. At mid-low H (ranges 1400-1890, GI, GN), there are

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intervals of cross-parameter (sowing-fertilization) critical cases under unfertilized early sowing, rather than fertilized (top zoom in Fig. 9a, e.g. for RCP85).

How one can use the PREPCLIM-v1 system output to assess a best management under climate scenarios? For a given genotype one can identify in these diagrams, either the optimal sowing-fertilization for a given scenario (on the vertical Ox=constant on Fig. 9a), or, for a given H one can identify the genotype ranges (per each sowing-fertilization) allowing this solution (line Oy=constant on Fig. 9a). These may propose variate options to improve yield, using the modeling system.

Third, we note a systematic narrowing of the spread among treatments (all models, all scenarios, as shown in Fig. 9a) all along genotype spectra (G-range belts), indicating a reduction of response options in future.

a)

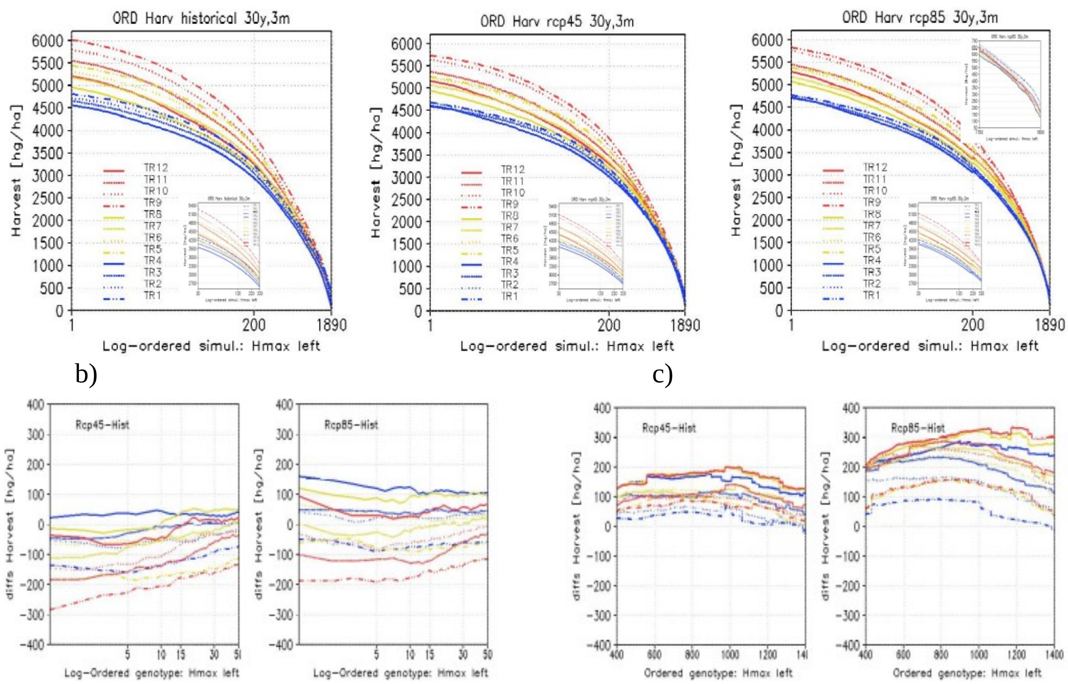

Fig.9 a): Ordered simulation results for Harvest (Oy, model ensemble mean, time mean over 30 years). The simulations are for: Hist (left), Rcp45 (middle) and Rcp85 (right); a logarithmic scale was used for the simulations index in order to emphasize high H values. On Ox is the simulation rank (logarithmic scale) increasing for decreasing H (set-up E_1N_Gn+w with cross-genotype changes in six Pi parameters resulting 1890 experiments); each panel has a small zoom over intermediate H genotype ranges [20-320] at bottom and over [1700-1890] for RCP85, top corner; b) differences of H over two genotype range windows indicating a mean change for: the window of highest H in (b) ; c) same aș b) for the window of intermediate H values. Colors în b) and c) have the same meaning as in a).

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The third feature to be noticed is the role of the initial soil moisture. We note that the control genotype in E_1N_G0+soil (Fig. 7d,e,f) falls in the intermediate H values of E_1N_Gn+w here (Fig. 9) with higher yield in scenarios than Hist, feature already but marginally reached in Fig 7e,f, mainly due to enhanced initial soil moisture in E_1N_G0_soil+w. In this regard, Fig.1Sa indicates a projected overall decrease in soil moisture over the main agricultural area in the target region, with stronger decrease în the Eastern and SE parts.

ii) Optimal Genotype under climate change

We saw a response of optimal H to the genotype choice in climate scenarios, and a different one for the highest H (highest 0-2.5% H), intermediate (interval 21%-75% of genotype range) and then lowest H values. For practical applications the crop projected response should be discriminated per genotype parameter (P1-P6) to provide efficient support in adaptation decisions.
We analyze the role of each P1-P6 genotype sub-parameter related to crop performance under climate scenarios versus Hist.

Management-genotype scenarios show that main drivers of increasing H in Hist runs are: decreasing P1 the thermal interval seedling-juvenile phase and decreasing the photoperiod delay parameter P2 (their increases are associated with lower H). Contributions come then from a longer thermal time to maturity (increasing P3), increasing the kernel-filling rate P5, and decreasing the phyllochron interval P6. The slopes of Pi variation as a function of G-ranged index (the index increasing from maximal H to minimal H) are positive for P1 and P2, negative for P3 and for P5 and P6 positive only in the GX range of highest Harvest.
At lowest H we mention a particular sensitivity behavior of mainly P3 and P5 under increased fertilization and sowing date. In this case, both small and high P values may lead to H decreases (Fig.10a). This is related to critical situations of too slow grain filling that occur at high P3. We raise warning for careful consideration when perturbing parameters as P3, P5 to perform genotype adaptation, requiring additional modelling: finer discretisation of genotype parameters intervals, highly accurate soil conditions set-up, close analysis of warming thresholds and phenology interactions implied).

How one can use the PREPCLIM-v1 system output to assess a best genotype range under climate scenarios? We compare scenarios against Hist first for the different Pi in Fig. 10. Simulations show for all Pi a slope increase (Pi are functions of the G-ranged index) in the GX interval. Compensating the slopes decrease in GI and GN (the variation limits for Pi being kept the same) in scenarios relative to Hist. Relating these to H, we obtain estimates of projected impact of G-parameter perturbations, under climate change.

For GX, the slope decrease found for positive slopes (P1,P2,P5,P6, Fig.10a) means that a G-range in GX will be obtained up to higher Pi values than in Hist (Fig. 10b) hence an enlargement of actually possible values (lower Pi values correspond to higher H in positive slopes). For GX, the slope increase found for the negative slope of P3 means that higher H values than a given H-range here will require higher P3 values (seen Fig 10b, as high values are giving best H in negative slopes), so constraining its variation interval in GX to a narrower interval. This can be understood as a constraint

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on using P3 for enhancing H and an enhanced efficiency on using P1,P2,P5,P6 options for enhancing H under warmer climate, for maximal H (GX range).

For GI, a same analysis, links the slope increase for positive slopes (P1, P2, P5, P6, Fig. 10a) to constraints on these parameters as options for increasing H, while the slope decrease of negative slope for P3 represents an enhanced efficiency on using this parameter for improving H in the intermediate range values.

For GN as discussed above, the response present bifurcations in the relation (Pi,H) and careful simulations are required. These are however very important in the critical years, when yield is estimated to be very low and we are searching for solutions. Note that over GN P6 has a third slope change (otherwise main, non-bifurcated slopes and changes are as in GI), becoming positive (Fig.10a), with enhanced efficiency.

We finally note the interesting aspect of differences between the two scenarios, in which important changes of response (reversal) occur in P5 and P6 in RCP85 compared to RCP45, with consequent impact on measure efficiency / constraint, that should be accounted for in adaptation.

In summary of the tis analysis, it is revealed that the main impact on H of genotype parameters' changes are from P1, P2 and P3. It is shown that using shorter thermal time to flowering P1 values or species with a shorter photoperiod-development delay P2 (for ensuring intermediate H-range values) and higher P3 values (longer thermal time to maturity) for getting maximal H-range values are constraints for Pi under warmer climate compared to Hist, emphasized for the pilot region.

Equally important, we note that changes in sign of responses (scenarios minus Hist) occur in Fig. 10b in the GI range [400-1500], that is about the actual Control genotype range (Fig. 4S). This points definitely to necessity for model simulations in order to identify which slight changes in Pi would lead better or worse H in a warmer climate.

Regarding now the hybrid method deterministic-ML, this involves the same cross-simulations but this time the selection of values for parameters is no more following a pre-defined discretisation and instead it is a random picking up over a continuous interval of values and successively retrieving the best generation, applying for optimization classic Genetic Algorithms methods in which selection of pairs is based on the user-criteria (e.g. maximum yield, stable yield, etc.). Our results show that for the same physical intervals of genotype parameters the ML hybrid technique only after 20 generations shows at least 50% chances to get a better result than the deterministic model, while after 100 generations, it already increases at 80% chances to get better results. A better result means here, identifying an optimal configuration that has not been able to be emphasized by deterministic simulations.

In each of the two techniques used for optimal genotype identification, we note that in climate scenarios versus historical climate, it is projected a significant narrowing of the management options range leading, for a given genotype, to high yields (Fig. 8b), that is a severe warning for future decision planning. Also there is a lower maxima potentially reachable under scenarios managements under warmer climate (including genotype, sowing, fertilization).

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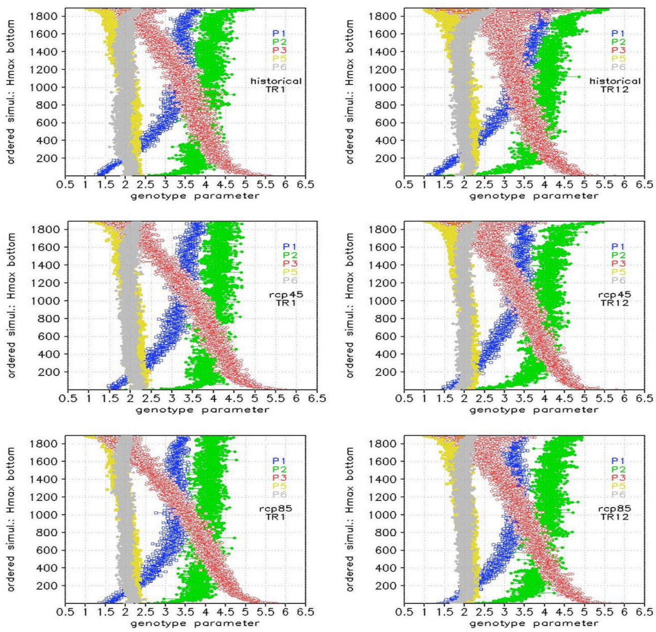

Fig.10a : Indices of the Genotype' six parameters (Ox) that correspond to Harvest ordered from max Harvest (Oy bottom) to min Harvest (Oy top). Here are 1890 genotypes (5x7x6x1x3x3 simulations with parameters, per model in [1,7]), shown as ensemble mean for two treatments (TR1 left column and TR12 right column). Indices are time-averaged (30 years) for simulations along Hist (top row), Rcp45 (middle row) and Rcp85 (bottom row) scenarios.

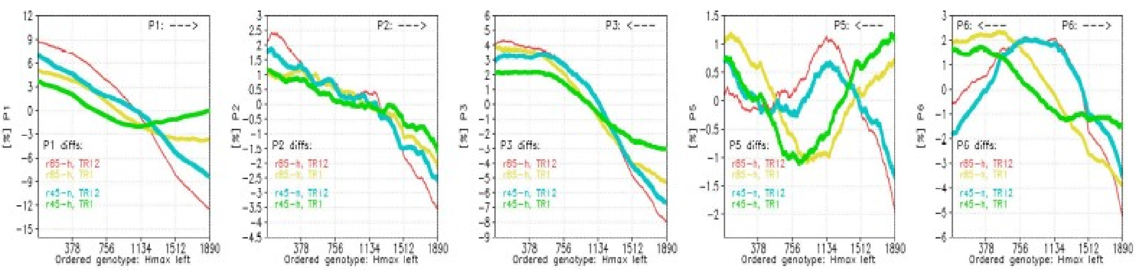

Fig. 10b: Percent changes in Genotype parameters Pi as a function of the ordered Harvest from highest (left, Ox) to lowest (right, Ox). Differences (running means over 378=P2*P3*P4*P5*P6 values) are shown for TR1 (yellow for RCP45 minus Hist) and green (RCP45 minus Hist) and for TR12 (red (yellow for RCP85 minus Hist) and blue (for RCP45 minus Hist). Differences in indices are expressed in percent relative to the parameter's range. Arrows indicate the (Pi,G-ranged index) overall linear trend from Fig.10a. (on Ox: the G-ranged index; on Oy the values of Pi).

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The complex interactions for cross-parameters choice regarding sowing-fertilization-soil composition, shown before, would make it difficult for assessing an optimal path, in the absence of a modeling system. Even more, when it comes to choosing an optimal genotype with fixed or cross-optimal sowing-fertilization-soil configuration the added value of such a modeling for optimum identification becomes obvious and necessary, under warmer climate when traditional genotypes might no longer be suitable.

Discussions and Conclusions

The main conclusion of this study is that an agroclimate real-time Interactive Service was developed that goes beyond interrogation platforms for agro-climate information, stepping forwards and performing in real-time, under user request, agro-management scenarios for the region. These allow crop simulations for time-slice of interest, specified climate scenario, and user-specified management scenarios.
A main novel feature of the system is the ability for identifying optimal management paths along cross-cultivar management parameters and climate scenarios, as e.g. sowing date, genotype parameters, amount and date of fertilization. The system provides solutions and uncertainty associated by using multi-model ensemble for each agro-climate and management scenario. The optimisation criteria are user-defined and can relate to high yield, stable yield, low pollution. The optimization module implemented a hybrid deterministic and ML methodology. It performs multi-model simulations using physical models of climate and plant penology and optimisation is done either through simulating discrete cross-parameters intervals pre-definied and optimisation post-processing, either using the advantage of continuous parameter space investigation by using ML Genetic algorithms along multiple model simulations. ML is spanning continuous parameter's space and interactively selecting along the simulations the best fit parameters, allowing to identify unprecedented optimal configurations, not-reachable under the discrete deterministic method.

The overall system output information is layered and accessed from two interfaces. One static, contains high resolution agro-climate information (phenology, yield, extremes) at NUTS3 level that is useful for user-analysis, management and adaptation and research. The second interface is interactive online through which the system receives user requests and performs required simulations providing the results. The user request refers to regional management scenarios or on optimal management identification under climate change. These platforms are operational and were tested for two climate scenarios RCP45 and RCP85 and twelve management scenarios (sowing dates and fertilization), for the time-horizon up to 2050, with open-source code (EERIS platform). The results of these tests are discussed here for the pilot region South Romania.

For the control genotype, in both climate scenarios it is projected a shortening of the growing season (and an earlier shift of anthesis and maturity phases) and a mean decrease of the projected yield, for all the management scenarios, sowing-date and fertilization level tested. We show that the decrease is also linked to a lower efficiency of fertilization under warmer climate. Compared with the previous

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observed unirrigated yields, here the shown reduction is significant (around 50%) in simulated yields of rainfed corn cultivated in South-eastern Romania under the new climatic conditions.

However, we show that this response is highly sensitive to initial soil parameters as soil water content, Nitrogen, Carbon. One could get an improved outcome if using richer soil (by 15%) but lower fertilization (by 60%), elongating the growing season. This solution prevents a detrimental increase of pollution that would otherwise enhance climate warming. It is shown the importance of precipitation projections in relation with the sowing date: a time-shift towards end-April was identified in climate scenarios for the region with an important link to planting date's Harvest.

The results for optimal genotype identification show, for the pilot area, under warmer climate two main features. One is a mean decrease of maximal reachable H (in the genotype G-range of highest harvest values) linked to a reduction of the agro-season length in the same genotype range (and earlier anthesis and maturity dates). This response becomes systematic for all models in RCP85. Another is for the genotypes range of intermediate H values, under climate scenarios, where rising tendencies are found. These are linked on one hand to the broader range allowed for the P3 parameter (thermal time to maturity), higher P3 values leading higher H-range even against season' length decrease as shown further in the G-parameter analysis. To note here that caution is required and additional modeling of P3 extreme increases that give uncontrolled (bifurcation) of the H response as it leads, above a threshold (P1 and P2 dependent) to crop failure due to a too slow grain filling, at a higher rate in scenarios than in Hist. On the other hand, another contribution to higher intermediate-range harvest comes from the mean precipitation decade-shift, mainly in RCP85 projections.
When discriminating the results upon genotype parameters we obtain that the main H changes are linked to changes in P1 and P3 the thermal times to juvenil/ maturity phases. We show that there is a stronger constraint to their decrease respectively increase.
Using shorter thermal time to flowering P1 values or species with a shorter photoperiod-development delay P2 (for a same intermediate Harvest range) and longer thermal time to maturity P3 for maximal H-range values are constraints emphasized for Pi under warmer climate compared to Hist.
These could be exploited in adaptation strategies for enhancing yield optimization in scenarios. We showed that the actual Control genotype falls in the broader range of most sensitive H response to these changes for the region.

It was shown that the optimisation search is improved by using a hybrid ML genetic algorithm method coupled to the deterministic model-output, leading to detecting better optimal solutions. Of equal perspective interest would be using the system for managing critical levels under periods of prolonged or extreme drought, as emphasized in climate projections. As shown here, extreme events changes under warmer climate (frost, precipitation shift, heat stress and soil moisture deficit, etc) are projected to occur at different crop stages. In addition we showed that sink–source relationships (fertilization efficiency - harvest, initial soil humidity) are projected to change, all leading to changes in yield parameters. Hence, targeted understanding, validation and identification of optimal configurations (genotype-management) for extreme cases or dynamics of their physical links, appropriate to alleviate the impact, are a perspective of near-future exploitation of the system.

The main outcome of this work is the implementation and demonstration of the ability of deterministic coupled modeling system combined with data-driven modeling for identifying optimal crop solutions.

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This can be extended for other regions, scenarios, crops as a performant tool for adaptation support and agro-climate research. Futures perspectives are opened to use the system for more complex issues as rainfed yield level and stability in the new climatic conditions, where combination of cultivar dependent coefficients that control the phenology of maize could help identify in the same way, phenological evolutions that are more performant in certain patterns of water and heat stress distribution along the year. Also, the improvement of the forecasts for the 6-12 months range may increase chances to use this methods with weather prediction data in order to early select the most suitable combination of hybrids for the current agro-season. Automatisation of these processes already done, further supports extending the system towards a pilot regional agro-climate digital twin fed with actualized data.

Code and data availability: The code is available in the Github repository at: https://github.com/pneague/Genetic-Algorithm-for-Corn-Genotype-Planting-Date-Optimization under a BSD 2-Clause Simplified License.

Author contribution: MC: model implementation, code for optimal adaptation tool, pre and post-processing, model simulations, results analysis, development of the User-Platform, paper writing; LC: DSSAT model set-up, simulations, results analysis, paper review; PN: ML method implementation and runs, results analysis, paper writing; AD: model validation; VA: development of the Info-Platform; ZC and AI: platforms upload and update; AP: agro-meteorological station data providing; GC: DSSAT model input for the target region.

Competing interests: The contact author has declared that none of the authors has any competing interests

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Annex 1: Data and Methods

Schema of steps in work-flow of ML algorithms for optimal genotype identification:

- Start with 10 randomly chosen solutions within the bounds of P1-P6;
- Calculate the mean and std of harvest of each solution for the 30 years 1976-2005;
- Calculate fitness = (Mean of harvest) – (Standard-deviation of Harvest/4);
- Randomly choose 4 pairs of 'parents', with the probability being chosen weighted by the fitness;
- For each pair of parents A and B, create identical children 'a' and 'b' to the parents, then choose a random number of P's to be subjected to crossover, called x;
- For each child, modify Px as follows:
    - Pxa = round (B * Pxa + (1 - B) * Pxb)
    - Pxb = round (1 - B) * Pxa + B * Pxb)

  Where Pxa is the value of the x parameter of child a (initially identical to that of parent A), and B is the blending factor, set in this paper to 0.75. This technique is called blending and it generates offspring chromosomes that inherit real-valued traits from both parents while exploring the search space between the parents' positions. The blending crossover promotes a smoother and more gradual search for optimal solutions in continuous domains;

- Then take each child, and with a probability of 0.5 perform a mutation on one of its chromosomes. This means setting one of the P's to a random value between its allowed minimum and maximum;
- At this point the children have been fully constructed. Discard the 8 parents with the lowest fitness and substitute them with the children;
- Repeat.