A ~~modeling System~~modelling system for ~~Identification~~identification of ~~Maize Ideotypes~~maize ideotypes, optimal sowing dates and nitrogen

fertilization under climate change – PREPCLIM-v1

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Abstract

~~The impact of climate.~~ Climate change ~~on crops~~significantly threatens crop yields levels and ~~agricultural yield is an actual threat while being a challenging issue due to the high complexity~~stability. The complex interplay of factors ~~that intervene~~ at the local scale ~~of the crop. Assessing it, requires the use of~~makes assessing these impacts difficult, requiring coupled ~~models~~ climate-phenology~~, meanwhile methods to identify management~~ models, which integrate climate data and ~~genotypes~~crop information. Identifying suitable ~~for~~ local management practices and crop varieties under future conditions~~, in order to sustain~~ becomes essential for developing effective adaptation strategies. ~~We present~~This study presents the implementation and ~~use~~application of ~~a new~~an integrated climate-phenology adaptation support ~~modeling~~modelling system. This is based on regional CORDEX climate models and the CERES Maize model from the DSSAT platform~~, with new~~. Novel modules for optimal management and genotype identification ~~using~~under climate change have been developed in the system, employing a hybrid ~~method:~~approach that combines deterministic ~~modeling and –~~modelling with machine learning (ML~~/~~) techniques and genetic algorithms. ~~It~~This system 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~~genotype) and providing best crop management simulated under climate change projections. Multi-model ensemble simulations were conducted for two ~~climate~~radiative forcing scenarios RCP4.5 and RCP8.5 and twelve management scenarios ~~show new~~, yielding novel results for the region. Results indicate a projected decrease in maize

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yields for the current genotype across all tested scenarios, primarily attributed to a shortened grain-filling period and reduced fertilization efficiency under warmer conditions. Soil initial conditions were found to significantly influence yield responses.

~~For the actual genotype we find~~ The analysis warns about 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 the agro-management ~~opportunities~~options for ~~crop~~maintaining a high yield ~~but in opposite it is shown a significant role~~level. However, we find an added value from the impact of ~~optimal~~ genotype ~~range identification that may provide crop solutions under~~ selection in mitigating climate change impacts, even in extreme years. ~~Identifying best genotype under warmer climate along sets of~~Genotype optimisation across six ~~cross-parameter simulations show systematic lower values of the maximal~~crossed cultivar dependent parameters revealed that while maximum yields~~, but emphasizes~~ declines, specific genotype windows ~~of increases in the~~exhibit increased intermediate ~~yield values in scenarios~~yields under future climates compared to ~~actual climate. The highest harvest sensitivity to genotype is shown to be to changes in~~current conditions. Sensitivity analysis identified the thermal time ~~to juvenil respectively to~~ requirements during juvenile and maturity ~~stage~~stages as the most critical factors influencing genotype performance under warmer ~~climate. The results sustain using a~~climates.

This research demonstrates the added value of combining deterministic ~~coupled modeling system combined with~~ and data-driven ~~modeling for identifying optimal~~modelling approaches within a coupled climate-crop system for developing effective adaptation strategies, including optimised fertilization ~~paths~~pathways that contribute to climate change mitigation.

1. Introduction

According to the IPCC ~~reports (IPCC,~~ (2022~~)~~), climate change is ~~evident~~unequivocal, and ~~the prospects~~ its impacts appear more worrying today than ~~a few decades~~dekades ago. ~~Although progress is being made in studying the impacts~~ While research on the effects of climate change on ~~crops~~crop yields and agricultural ~~yield~~harvests has advanced (Arnell and Freeman, 2021; Hatfield ~~at~~et al~~,~~., 2021~~;~~; Rezaei et al., 2024), translating these ~~are rarely directly applicable to provide~~findings into actionable solutions and scales remains a challenge. This is primarily 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~~) including sensitivities ~~to~~of the ~~interacting~~exchanges to variations in climate sub-components as

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atmosphere / soil/ ~~phenological processes/~~biosphere's ecosystems~~, to~~ under climate change, ~~to~~ natural causes ~~or~~and human activities (Wheeler and Braun, 2013~~,~~; Xie et al, 2023).

~~Taking into account scientific research estimating that~~Given the ~~world~~ projected global population ~~will continue~~increase estimated in scientific reports to ~~grow, and it is expected to arrive to~~ over 9~~,1 milliards until the year~~ billions by 2050 (Godfray and Charles, 2010), ~~the total~~global food ~~yield will~~production would have to ~~grow~~increase by 70-100% to meet the growing demand (Smil, 2005; World Development Report, 2008; ~~Selvarju~~Selvaraju et al~~,~~., 2011). ~~Meanwhile~~ This challenge is further compounded by the agro-climatic conditions ~~are~~ expected to become vulnerable and gradually~~, more deficient in the context of~~ decline due to climate change ~~and its impact on~~, particularly impacting water availability (Stehr and von Storch, 2009; Villalobos et al., 2012; van Ittersum et al., 2013~~; Roccuzzo et al., 2014; Stehr and von Storch, 2009).~~).

Another ~~face~~challenge of the problem comes from the need that approaches, and sustainable solutions ~~should both: merge user~~ must not only address the needs~~, and be in line~~ of agricultural producers but also align with ~~neutral climate adaptation stringency~~climate change mitigation goals for 2050, aiming for climate neutrality (Semenov ~~et~~and Stratonovitch, 2015; Dainelli et al., 2022; Mitchell et al., 2022).

Early studies ~~on~~ investigating the impact of climate change ~~impact on crops have pointed to~~on crop yields emphasized the ~~need~~necessity of ~~very~~ high-~~-~~resolution ~~modeling, capable of representing~~modelling approaches. These models should accurately represent management practices and the local ~~scale impact~~effects of climate ~~on plant~~variables, such as temperature and precipitation (McKee et al., 1993; Trnka et al~~, 2015~~., 1995; Adams et al., 1998~~; Mkee et al, 1993) affecting~~). These affect thermal and water stress ~~(e.g. the stomatal opening,~~ and plant physiological processes like stem water potential, stomatal opening, leaf transpiration efficiency (Espadafor et al~~,~~., 2017~~)). Further at~~). At the regional scale, the relationship between crop yield and water and thermal availability ~~relation to yield indicated a~~ may exhibit strong ~~dependence~~dependencies on the crop~~, region, time~~ type, geographical location, temporal scale, and plant ~~physiological~~developmental stage (Webber et al., 2018, 2020; ~~Webber et al. 2018;~~ Marcinkowski and Piniewski, 2018; Berti et al., 2019; Ceglar et al~~,~~., 2020; Wu et al~~, 2021; Berti et al. 2019; Marcinkowski and Piniewski 2018). In this regard, under~~ ., 2021). For instance, simulations conducted by Kothari et al. (2022) in regions with arid climates,

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indicated for future climate ~~changes, perspectives for corn yield rises~~change a significant (~30%) decrease without adaptation, but a potential increase (15%) in corn yields 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~~ or under radiation-based genotype efficient use. These findings underscore the critical need for regional simulations ~~taking in consideration soil humidity accuracy and~~ that incorporate phenological characteristics with accurate soil moisture estimates to evaluate the effectiveness of various irrigation strategies under future climate scenarios.

~~Apart from~~ In addition to atmospheric conditions, soil ~~changes~~properties significantly ~~affect~~influence plant growth. These influences occur through physics-based interactions with climate and through ~~changes~~alterations in soil chemical ~~compositions. Increasing air temperature was~~composition. Rising air temperatures have been shown to ~~affect~~impact the soil carbon budget, ~~its decrease~~ with a decline in soil carbon potentially affecting plant and root ~~level~~ processes, biochemical cycles, and species composition (Abhik Patra et al~~,~~., 2021).

~~Modeling~~Crop modelling at local, regional and ~~also~~ global scale ~~reported significant advances in~~has significantly advanced, enhancing our understanding~~, simulating and projecting future crop (~~ of crop systems and enabling the simulation and projection of future yields. Studies (Tsvetsinskaya et al, 2001; Tao et al., 2009; Ganguly et al., ~~2010; Cock et al., 2021; Chen and Tao, 2022~~2013; Schauberger et al., 2020~~). These emphasize~~; Chen and Tao, 2022) consistently project global ~~projected yield~~ mean harvest reductions ~~(Asseng et al., 2015)~~ with differences in the regional pattern of climate change impact on crop and ~~yield (~~harvest (Asseng et al., 2015; Li et al. 2022). Not only projected ~~regional~~spatial but also ~~time~~temporal variability of the climate change impact appears larger and accelerated, motivating intensified efforts on seasonal and multi-annual predictions of plant development and ~~yield~~harvest (Baez-Gonzalez et al., 2005; Jin et al., 2022~~) using crop models. These simulations' results significance was analyzed suggesting~~). Analysis of these simulations emphasized also 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~~

Meanwhile, model simulations ~~proved to be a highly~~emerged as useful tool in plant breeding analysis (Bernardo, 2002; ~~Hoogenboom~~Banterng et al.~~,~~., 2004; Cooper and Messina et al., 2023~~) considered a support in developing~~; Mamassi et al., 2023), supporting the development of 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~~performance. These simulations have proven effective in guiding cultivar ~~using~~

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selection through techniques such as parental selection~~,~~ and breeding by design~~, etc.~~ (Peleman and van der Voort, 2003~~,~~; Qiao et al., 2022).

In most recent years ~~developments~~ climate-crop ~~modeling~~modelling 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;~~ Schwalbert et al., 2020; Meroni et al., 2021; Morales and Villalobos, 2023~~, Meroni et al., 2021; Schwalbert et al., 2020; Zhang~~; Chang et al., ~~2021).~~2023; Zhuang et al., 2024). Statistical methods as well as machine learning (ML) used for crop forecast and ~~modeling~~modelling 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~~modelling as a key approach for this challenging issue.

On the other hand, ~~deterministic~~ breeding optimization techniques using fully deterministic model simulations require a huge number of simulations, analysis and inter-comparisons of predicted ~~cross~~crop performance (~~Wang and~~ Pfeiffer~~,~~ et al., 2007; Wang et al., 2023).

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Here we present a novel hybrid approach developed in the frame of the PREPCLIM ("~~preparing~~Preparing for ~~Climate Change~~climate change") project in which we solve plant phenology ~~development~~ using deterministic ~~modeling~~modelling and merge this technique with an on-line ML-genetic algorithms (GA) iteratively selecting along simulations ~~in order to iteratively select a~~ the cross-range of optimal ~~genotype~~crop cultivar parameters, according to ~~a pre-set~~ user-defined criteria ~~of the optimum. Genetic algorithms (GA) simulate~~for optimal target. The GA simulates the evolution of a population by ~~iteratively~~ applying in iterations, 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~~required based. ~~GA was successfully used with~~GAs have demonstrated success for optimizing agricultural practices using models like DSSAT for ~~optimizing~~ irrigation and fertilizer applications (Bai ~~-~~et al~~,~~., 2021~~,~~; Wang et al~~,~~., 2023).

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The hybrid approach implemented ~~here~~in this work focused on ideotype identification presents the advantage of physically treating the crop -complex process involved ~~each time~~ along optimizing iterations, ~~so~~thus allowing ~~analysis~~specific inclusion and understanding of physical causes of ~~the~~ responses ~~to~~ and of optimal paths in various climate ~~or /~~and management scenarios~~, meanwhile enhancing~~. Furthermore, it enhances the ability of choosing optimum conditions from ~~a~~ continuous ~~interval, not a~~ multi-dimensional intervals for gene parameters, as opposed to discrete ~~one, of gene~~

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~~parameter values.~~sets. The continuum values approach is an important feature mainly for isolated ~~extremes~~extreme yield detection, or ~~broad~~broader parameters' range and high non-linearity, both aspects of increasing ~~interest, as we show in this work the a tendency toward narrower~~ relevance in the context of climate change. Our findings suggest a narrowing of agro-management adaptation ~~opportunity windows~~opportunities under warmer ~~climate~~climates, further emphasizing the importance of this hybrid genotype-agro-management approach to support finding solutions for the future.

~~We present the system~~ The developed ~~and~~ system aims to provide efficient and operational support for farmers and stakeholders. It leverages the state-of-the art DSSAT model, a widely used and extensively validated platform for agricultural modelling across diverse applications. The DSSAT model, incorporating complex parameterizations for soil processes, surface-atmosphere exchange, plant development stages, and their interactions with climate and management practices, undergoes continuous refinement through ongoing research and regional calibrations. For this study, the model was specifically adapted to the unique soil characteristics of the pilot region, including parameters such as porosity, composition per soil layers, and thermal properties. The developed system exhibits portability to other regions with available soil and management data. Its functionality and user-friendliness are expected to improve through widespread adoption and the incorporation of advanced user requests and management options.

Section 2 presents the developed system and its data flow ~~in section 2. The~~. Section 3a provides the motivation ~~of its~~for system development, ~~linked to~~focusing on projected climate change ~~in~~impacts for the target region ~~are shown in section 3a. We show~~. Section 3b presents results ~~of~~obtained using the system ~~used~~ to ~~estimate~~simulate projected changes in plant phenology and crop parameters for the target region, under various climate ~~change~~and management scenarios ~~and for different management scenarios~~, for the ~~actual~~current control genotype ~~in section 3b. Then we discuss in section~~. Section 3c~~,~~ discusses results obtained using the system's genotype optimization package ~~of the system. Perspectives~~along agro-management scenarios. Finally, Section 4 presents perspectives and conclusions ~~are discussed in section 4~~.

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2. Data and methods

Projected changes in agro-~~climate indicators over~~ climatic parameters for Romania ~~are~~were assessed under two Representative Concentration Pathways (RCPs): RCP4.5 and RCP8.5. These changes were computed ~~for two climate scenarios: RCP45 and RCP85~~ as anomalies ~~reported~~relative to historical simulations~~,~~ (Hist) using an ensemble of three CMIP5-CORDEX ~~models~~ (Benestad et al., 2021~~). Then, projected changes in phenological and yield parameters are simulated using~~ , Karl et al., 2011) high resolution (11 km) climate models, based on the CNRM, EC-EARTH, and MPI global models coupled to the regional climate model RCA4. Subsequently, the DSSAT crop model (Jones et al., 2003; Hoogenboom et al., 2019~~; Jones et al., 2003) forced with the~~) was employed to simulate projected changes in phenological and harvest parameters. The DSSAT model was driven by atmospheric conditions ~~from the CORDEX models (from GFDL, HadGEM, MiIROC, IPSL, NorESM), for~~derived from each model of the ensemble for the historical period and for ~~each of~~ the two ~~climate~~RCP emission scenarios.

A software package was developed for the DSSAT model that ~~-~~performs identification of optimal model parameters ~~set-up according to~~ based on user-defined: criteria~~, user chosen~~ for optimum, climate-management scenario, region, and time~~-~~horizon. ~~The user-criteria for optimisation includes maximum yield,~~Optimization goals include maximizing harvest, ensuring stable ~~yield, across years,~~ yields over time, and minimizing ~~the amount of leached~~ nitrogen ~~below the maximum level of~~leaching beyond the root ~~front~~zone (reducing ~~the risk of~~ water pollution~~), etc.~~ risk). Management scenarios ~~include~~ allow users to explore optimal cross-~~options for~~combinations of sowing ~~date~~dates, 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).~~, and genotypes.

Six main cultivar-specific parameters (P1 to P6) characterizing the maize genotype were analysed across wide ranges of physically realistic values, considering both current and extreme future climate projections for the target area. P1 represents the thermal time from seedling emergence to the end of the juvenile phase (ranging in these simulations from 100 to 500-degree days above 8°C). It significantly influences crop flowering times (Liu et al., 2020), water availability, and ultimately, yield. Studies have shown that utilizing longer-season maize cultivars (dependent also on P1) can lead to increased harvest in humid regions but decreased harvest in semi-humid regions (Mi et al., 2021).

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P2, the photoperiod-development delay parameter (ranging in simulations here from 0.1 to 2.6 days) shows the extent to which development is delayed for each hour of photoperiod increase above the longest photoperiod of maximum development rate (considered 12.5 hours). P2 influences the flowering time (Langworthy et al. 2018) and the rate of plant development, with long-day plants exhibiting faster development under longer day lengths (Angus et al., 1981). Related to these, studies have demonstrated the significant role of P2 in mitigating the negative impacts of waterlogging in warmer climates (Liu et al., 2023). P3, the thermal time from silking to physiological maturity (tested here for values from 500 to 1500-degree days above 8°C), significantly influences maturity dates. It also has a main role in plant stress levels (longer-maturity hybrids increase harvest but under water stress it may provide lower yield (Su et al., 2021; Grewer et al, 2024)) and grain moisture at maturity (Tsimba et al., 2013). P4, representing the maximum number of kernels per plant, exhibits a relatively predictable numerical response and is therefore held constant at the control value of 797.5 estimated for the region, in this analysis. P5, the kernel filling rate parameter (ranging from 6 to 12 mg/day), influences grain filling duration, desiccation, moisture at maturity and harvest (Chazarreta et al., 2021). P6, the phyllochron interval or the thermal time between successive leaves (ranging from 3 to 70 °C) is a critical parameter for estimating the duration of vegetative development (Birch et al., 1998; Xu et al., 2023). P5 and P6 are important parameters of optimal plant adaptation to climate conditions, since they are drivers of the phenological response and yield formation, in conjunction with the temperature, radiation, humidity, water stress. These genotype (or cultivar specific) parameters are the primary ones considered in DSSAT model parameterizations for plant development processes (Hoogenboom et al., 2019).

The parameter ranges were rigorously tested in simulations to ensure their representatives for the target region, including an analysis of extreme values. The control values for these cultivar-specific parameters Pi in the region are: P1=200, P2=0.7, P3=800, P4=797.5, P5=8.60, and P6=38.90. All the simulations for combinations of parameters values (cross-Pi simulations) were performed under Hist, RCP4.5, and RCP8.5 emission scenarios. For each scenario, simulations were conducted for twelve agro-management scenarios consisting of sowing date changes and fertilization treatments, for each model of the ensemble.

By default, the twelve agro-management scenarios encompass four sowing dates (spaced five days apart) and three fertilization levels (zero, then a regional average and its double). For each agro-management scenario, genotype optimization ~~by selection~~(finding the optimal set of ~~the~~Pi values ~~for~~under the ~~cultivar related coefficients (named further G-parameters~~given climate -agro-management and optimum criteria) was performed ~~through~~using two methods: ~~a fixed-discretisation~~1) discretized parameter-space runs ~~and~~ with subsequent post-processing ordering, and ~~a~~2) continuum parameter-space~~-~~ search with iterative selection ~~along~~during simulations, ~~by~~employing genetic algorithms ~~methods~~ (GA). The proposed GA-based method employs an iterative approach. It commences with an initial population of randomly generated solutions (chromosomes) and undergoes iterative cycles (generations). In each generation, a selection process is performed to choose the fittest chromosomes ~~to reproduce~~for reproduction, based on their fitness scores. Subsequently, crossover

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(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~~problem's space for diverse solutions exploiting promising regions) and exploitation (refining the best solutions found so far). Here GA ~~have even~~has been newly applied to develop an innovative crop selection algorithm ~~to optimize genotype along~~, optimizing genotypes across various agro-management scenarios. Steps along the algorithms are ~~shown~~described in ~~Schema from Annex1~~Annex.

The ~~overall~~system generates output ~~information from the system (climate,~~ data (agro-climate and optimal paths) which is ~~directed~~disseminated on two ~~platform components (~~platforms (Fig.1). One is a platform (Info-Platform, Fig. 1a) providing one-way interactive (static) agro-climate information at local scale (NUTS3 level, aligned with the European Union's Nomenclature of Territorial Units for Statistics) over the region~~, delivering~~. It delivers pre-computed climate -agro-climate indicators, ~~agro-climate, and~~ indices of agro-climate extremes ~~indices computed from~~ based on observations ~~and~~, re-analysis ~~for the actual climate~~ and ~~from~~ climate scenarios ~~(anomalies relative to historical runs)~~ for future projections for the region.

The second platform (User-Platform, Fig.1b) is an operational, online, user-interactive (two-way) in real-time component, where user requests are ~~placed, treated,~~submitted, processed as input to the modelling chain and results ~~sent~~delivered back to the user ~~(User-Platform, Fig. 1b).~~for a new, refined request.

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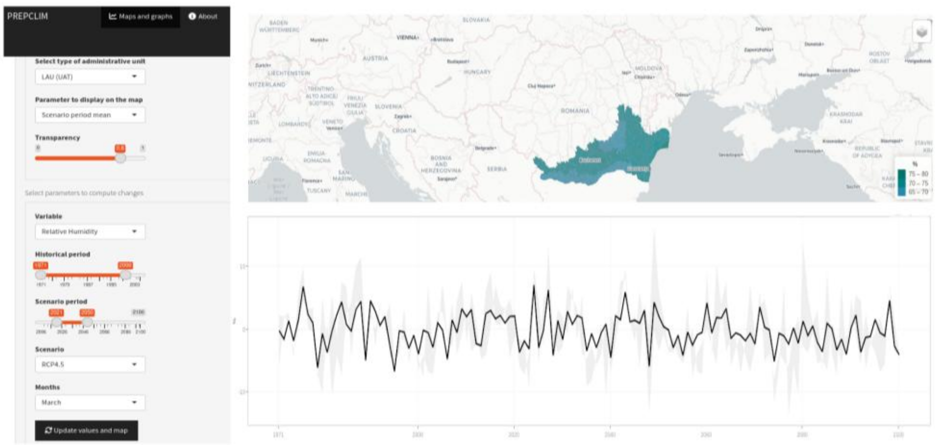

~~Fig. 1a:~~The core of the modelling system integrates the DSSAT crop model (running on Linux OS) with regional climate models (Fig.2), with a pre-processing pack developed for coupling. This coupled system incorporates new features, that include the ability of conducting parameter-varying cross-simulations and advanced algorithms for identifying optimal agro-management practices and genotype selections along simulations.

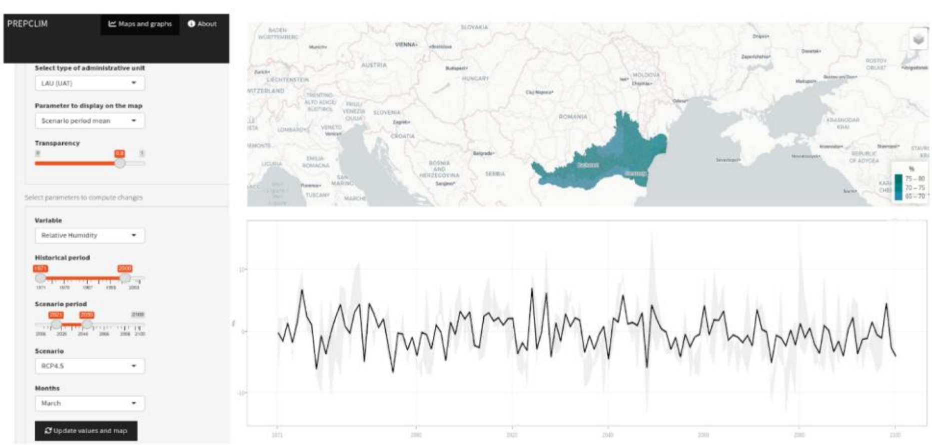

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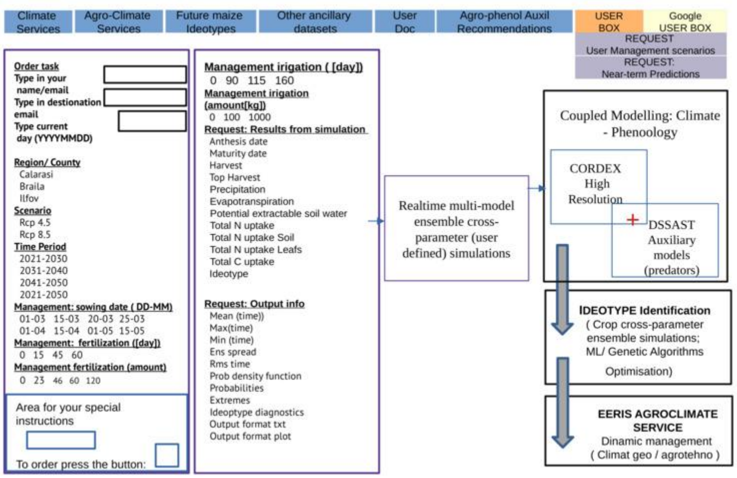
Fig.1 a): Info-Platform ~~for information at~~ : Provides local-regional scale~~,~~ information derived from ~~regional climate~~ high~~-~~-resolution regional climate models (CORDEX~~, presenting climate, agro-~~), e.g. climate, agro-climate data and indicators, indices of agro-climate extremes ~~indices~~ at the NUTS3 level.

b)



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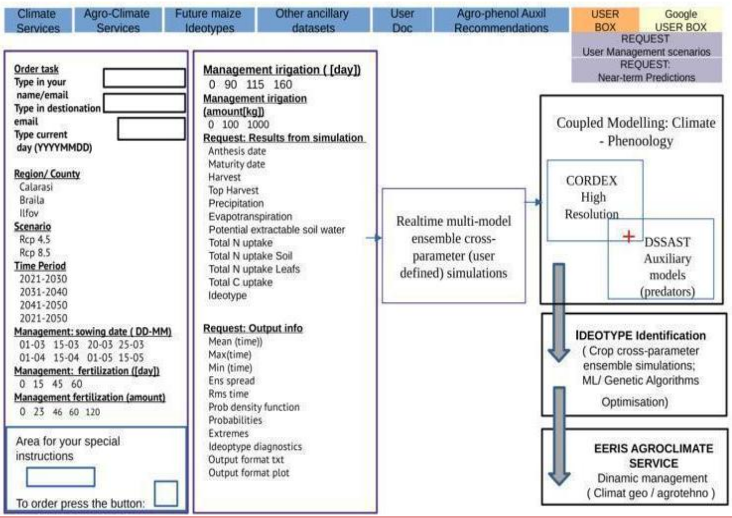

Fig. ~~1b:~~1 b): **User-Platform**~~: the user-interactive component **to specify requests on**~~ for **adaptation** ~~management simulations. User request~~support: Processes in real time specific user requests, and simulates management scenarios, identifying optimal paths: Users input parameters **(left**~~) on: the~~, e.g: **region,** ~~time slice~~ period (**present** ~~or~~/ future **climate scenarios**~~, choices for:~~), management options (e.g. **sowing date, fertilization/**~~-~~**irrigation** ~~(~~**time**~~,~~ and **amount**~~)~~, **genotype** ~~and output requests~~): System Output **(right**~~) on results: yields,~~, e.g: harvest, projected **phenology dates,** ~~evapo-transpiration,~~ ~~N~~precipitation/evapotranspiration, Nitrogen **and** ~~C balance~~carbon balances, **optimal management** ~~path~~paths **(dates**~~,~~ and **management** actions**), optimal genotype**) estimated from ensemble simulations.

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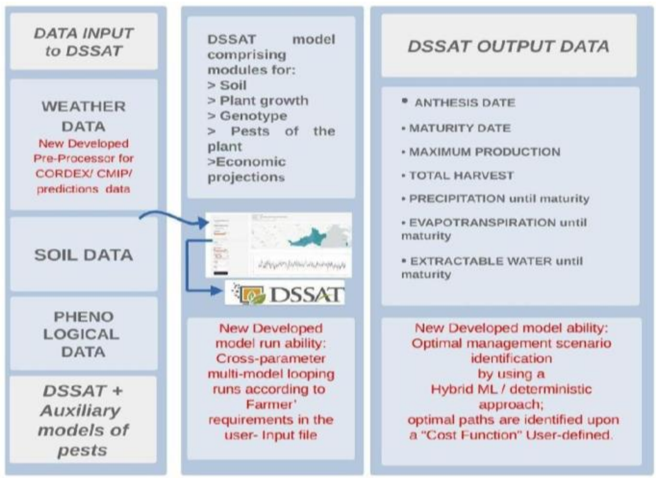
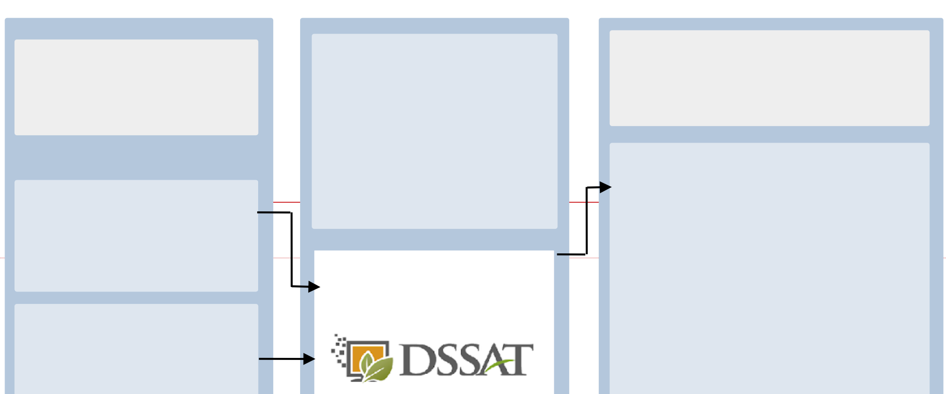


~~The pilot area where the~~

Fig.2: The PREPCLIM-v1 work schema: DSSAT-core and modelling components (middle), and data flow: input data (left), output information (right). Red modules were developed in PREPCLIM-v1.

The system was implemented and validated ~~is~~over Southern Romania, target agricultural area, for maize. ~~The potential~~Potential beneficiaries ~~of this system are users,~~include researchers, farmers, policymakers, and ~~policy makers. Maize~~maize breeders~~-~~. The system can also ~~can adapt using the system~~assist maize breeders in adapting to climate change by enabling them to ~~the climate conditions by accommodating or testing~~evaluate and select genotypes ~~that are~~ more resistant to challenging ~~climate. Accelerated~~climatic conditions. Given the accelerating pace of climate change~~ makes,~~ such a system ~~a useful~~may provide valuable support in ~~many respects~~numerous ways.

~~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).~~



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~~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.~~

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

Table 1: The agro-management treatments (TR): each treatment is described in terms of the sowing date and fertilization amount, Nitrogen [kg/ha]. We denote two experiments: exper “1N” and exper “3N”, and fertilisations Fx0, Fx1, Fx2 have values dependent on the experiment: Fx0 is no fertilisation, Fx1 is the unit fertilisation of the experiment and Fx2 is the double unit fertilisation of the experiment. We define the unit fertilisation of the exper “1N” equal to 23 N/kg and the unit fertilisation of the exper “3N” as 60 kg/ha. Sowing date format is “DD.MM”.

Treatment	TR1	TR2	TR3	TR4	TR5	TR6	TR7	TR8	TR9	TR10	TR11	TR12
Sowing date	1.04	15.~~05~~04	1.05	15.05	1.04	15.~~05~~04	1.05	15.05	1.04	15.~~05~~04	1.05	15.05
Fertilization (exper “3N~~)~~”)	Fx0 =0	~~Fx1=60~~Fx0	~~Fx2~~ Fx0= ~~120~~	Fx0	Fx1=60	Fx1 =60	Fx1=60	Fx1=60	Fx2 =120	Fx2 =120	Fx2 =120	Fx2 =120

Fertilization (exper "1N~~)~~")	Fx0 =0	~~Fx1=23~~Fx0	~~Fx2 =46~~ Fx0	Fx0	Fx1=23	Fx1 =23	Fx1=23	Fx1=23	Fx2 =46	Fx2 =46	Fx2 =46	Fx2 =46

3. Results

~~a)~~3.1 Agro-climate changes in the region

~~a~~ 3.1~~) Changes~~.1 Climate changes in agro-climate indicators

Agro-~~climate~~climatic Indicators ~~(provided on Info-Platform) are computed~~ , derived from CORDEX models~~,~~ and available on the Info-Platform, provide ~~derived parameters information as~~ time ~~slices~~-series data for ensemble or individual model metrics ~~from country to NUT3~~at the NUTS3 level ~~over South~~across Romania. ~~At the country region Fig.3 shows~~ Figure 3 illustrates projected changes in ~~main~~key agro-~~climatological~~climatic characteristics. ~~Region's~~

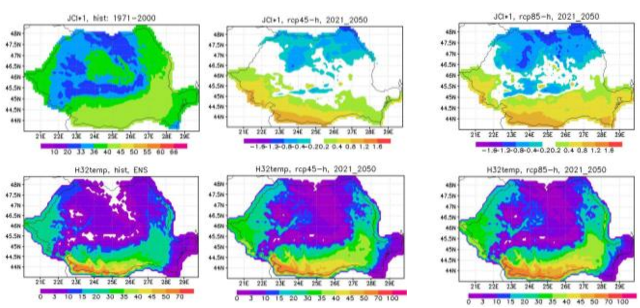
The anticipated climate ~~is expected to~~ shift ~~as shown (Fig. 3a)~~in the region is evidenced by changes in the Johansson ~~continentality index (Baltas, E. 2007; Flocas, 1994) defined as:~~

Continentality Index (JCI~~=~~, Fig.3a), calculated as JCI = 1.7 * dT / sin ~~(*phi*)~~ (φ) - 20.4

(where dT is the annual ~~maximal thermal~~maximum range of monthly mean temperatures and ~~*phi*~~φ is ~~the~~ latitude~~.~~; (Flocas, 1994; Baltas, 2007)). 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~~ JCI generally reveal robust evidence of large-scale changes influences on the 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~~ climate. For this domain it shows a Southwards meridional gradient~~. Relevant for composed temperature and precipitation, the deMartonne aridity index (IM) computed as the ratio between~~ of the intra-annual ~~total precipitation ([mm]) and~~ variability (Arctic amplification remote impacts on Europe). Hence enhanced intra-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,~~ variability (JCI) with much warmer summers than winters over 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).~~

~~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~~in South (and the opposite in the North), information useful for farmers to estimate 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).~~ in the sowing time.

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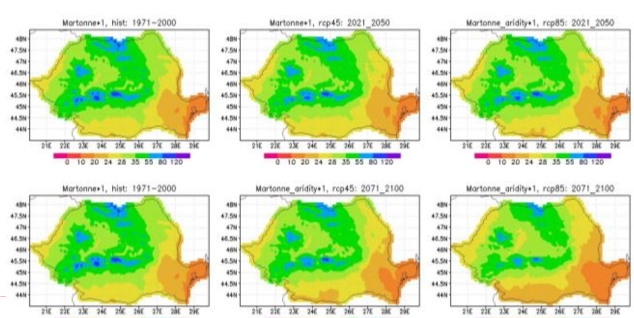

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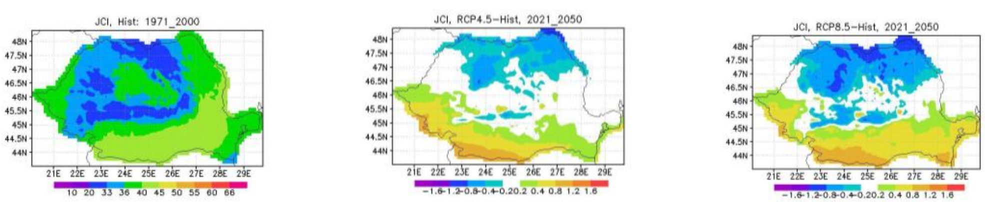
~~Fig. 3b: Historical (left) and changes relative to it under RCP45 (middle) and RCP85 (right) along~~In agreement with this, the Scorching Index (H32temp, Fig.3b, computed as the total degrees in summer days exceeding 32°C), used by farmers and agro-meteorologists to characterize the sub-regional drought conditions, projects severe drought conditions (H32temp ≥ 51), about doubling the Hist values and expanding significantly across the southern regions in RCP8.5 with already high-level drought conditions (31<H32temp<51) occurring in RCP4.5 (Fig.3b).

Accounting also for precipitation changes, the de Martonne Aridity Index (IM, the ratio of annual precipitation to a translation function (+10C) of the annual mean temperature), exhibits also significant projected changes. It shows particularly increased aridity (low IM) in the south, southeast, and southwest regions, the major agricultural areas with an accelerating change up to 2100 (Fig.4, comparing projected differences to Hist for 2071-2100 versus 2021-2050).

a)



b)

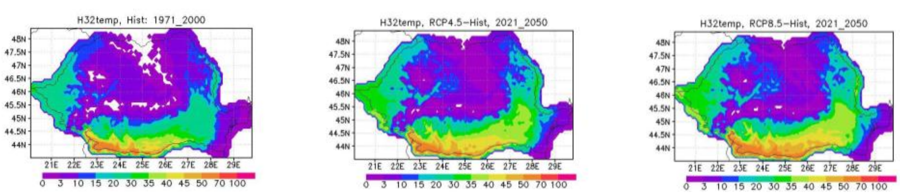


Fig.3: The JCI and the Scorching index H32temp indices. For each: (left): the index over Hist period 1971-2000 and changes (2021-2050) relative to it, under RCP4.5 (middle) and RCP8.5 (right). a) The JCI climate index classes are: marine for 0<k≤33, continental for 33<k≤66 and exceptionally continental for 66<k≤100). b) The Scorching index H32temp classes are: reduced intensity drought for H32temp∈[0,10], moderate intensity for H32temp∈(10,30], high intensity for H32temp∈(30,50] and severe drought conditions for H32temp > 50.

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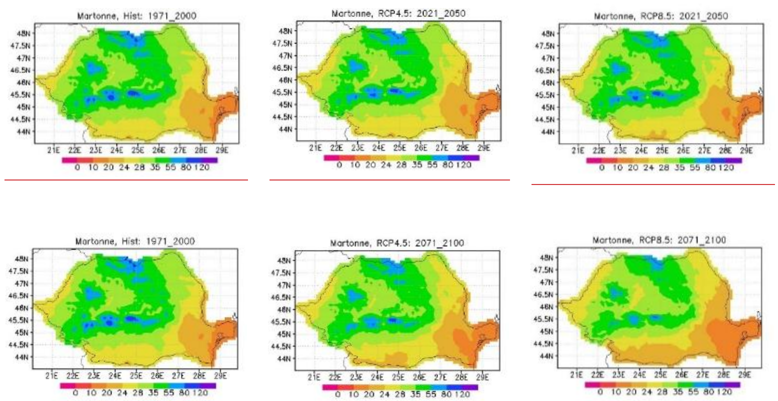
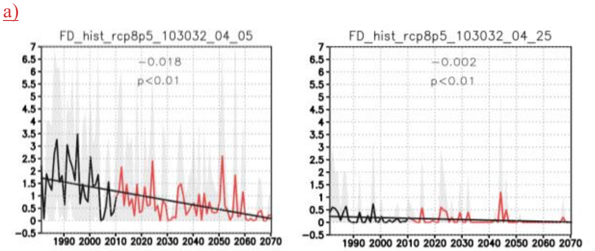


Fig.4: The de Martonne aridity index (IM) for: Hist (left), RCP4.5 (middle) and RCP8.5 (right) for two horizons: 2021-2050 (top) and 2071-2100 (bottom)~~) for the Martonne aridity~~). IM index~~. (0<IM<10~~ classes are: arid~~; 10~~ for 0<IM~~<20~~≤10 arid, semi-arid~~; 20~~ for 10<IM~~<24~~≤20, Mediterranean~~; 24~~ for 20<IM~~<28~~≤24, semi-humid~~;~~ for 24<IM≤28, wet for 28<IM~~<~~≤36, very wet~~;~~ for 36<IM~~<~~≤55 very wet~~; ID~~ and extreme wet for IM>55~~ extreme wet~~; (all indices are time mean 30 years, ensemble mean).

~~a~~3.1.2~~)~~ Changes in agro-climate extremes

Projected changes in extremes ~~are analyzed for the ensemble models in Fig. 4 that~~ for temperature and precipitation, highly useful information for agriculture, show important features in the region. A main aspect of interest is related to late-spring freezing days that may drastically affect the whole crop of the year. Fig.5a shows for South Romania (Călăraşi ~~target~~ subregion~~ changes~~) that in ~~RCP85 versus Hist, in~~ spite of the decreasing trend (5% p-level significance) of the total number of freezing days ~~(FD), total precipitation (RR), severe precipitation (RR10 the number of days with daily accumulated > 10 mm) and total 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~~in spring, we still may have severe events with interestingly~~ intervals with~~ , a number of freezing days in late-spring that is even higher ~~numbers of FD~~in scenarios than in Hist, late-spring being one of the most vulnerable period to freezing for the plant already under development. Also note that successive extreme freezing years in late spring may occur~~ in RCP85 scenario compared to Hist in the third decade. ~~.

a)



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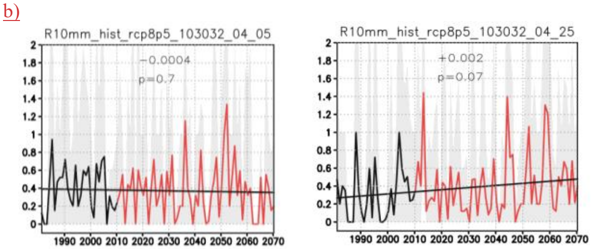

c)

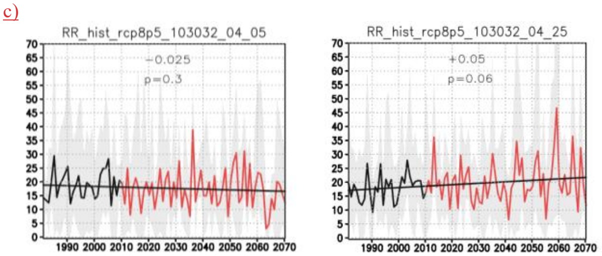

Fig.5: Extreme climate parameters (NUTS region 103032, representative for the target region), along historical (Hist) and RCP8.5 scenarios; a): FD, the number of frost days (minimum temperature < 0°C in a 10-day period); b): RR10, the number of days with heavy precipitation (>10 mm per day) in a 10-day period; c): RR, total precipitation (mm) per 10-day period; (left): the 10-day period is centred on April 5th~~;~~; (right): the 10-day period is centred on April 25th. Values indicate the slope of the linear trend (black line) and the p-value of significance (p-values < 0.05 are statistically significant at the 5% level).

This late spring blizzard feature over the region, ~~important for plant evolution, was shown~~was analysed in a previous work~~,~~ and shown 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

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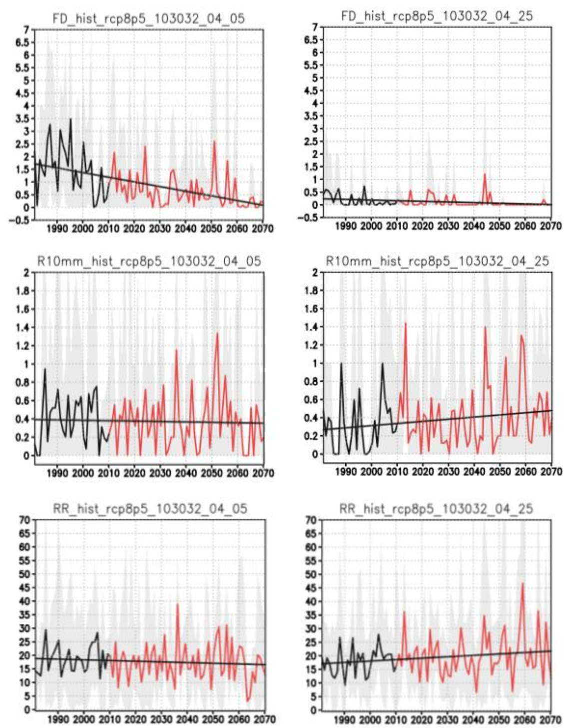
(Lelieveld et al., 2012; Shaw and Miyawaki, 2024~~;), which for the region indicates a~~), indicating higher potential for severe late-spring ~~blizzard, affecting crops and the year's yield under warmer climate~~blizzards in the region.



~~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~~For precipitation ~~(>10mm) (middle); ~~, analysis of extreme 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~~events (RR10mm) and total precipitation (RR~~ show the following:~~) reveals a ~~negative trend~~ notable shift in their temporal distribution within April. While a decreasing trend is observed in the first ~~decade of the month turns in opposite to~~ dekad, a positive ~~trends~~trend emerges 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.~~dekades (Fig.5b). These suggest a time-shift tendency towards the end of April and into early May for the occurrence of intense and accumulated precipitation. Although statistically insignificant at the 5% level, this shift is consistently observed across all models within the CMIP5 ensemble. As for FD we note that higher extreme values of RR and RR10 are projected to occur under emission scenarios than Hist, mainly in RCP8.5 (Fig.5b,c), more often during late spring. Extreme daily precipitation is, in most cases detrimental for the crop, causing soil erosion and surface runoff mainly after drought periods.

~~b)~~3.2 Phenology and ~~Yield projected changes~~Harvest Projections for the ~~control genotype~~Control Genotype

Projected changes in phenology for the control genotype (Pioneer 375) were simulated ~~with~~using the DSSAT ~~forced by~~ model under historical (Hist) and multi-model ~~Hist and~~ climate projections of CRP4.5 and RCP8.5 scenarios ~~RCP45 and RCP85, using first the control genotype G0 (Pioneer 375*) of the region. The implemented system~~. Further, multi-genotype simulations are discussed in Section 3.c.

Model validation was ~~done in~~ conducted using Control simulations ~~that used~~ (Ctrl) driven by ERA5 reanalysis ~~climate~~ data ~~from ERA5~~ (Simmons~~,~~ et al., 2021) ~~over~~ for each treatment outlined in Table 1 (experiment "3N").

These simulations, spanning the period 1976-2005~~. These show a good time~~, demonstrate the model's ability to capture inter-annual variability ~~of the simulated Yield against available measured values for the region, and that the modeling system is able to capture years of~~ in harvest yields, including both high and low yield ~~(Fig.5). The~~ years, when compared to the measured available data for the region (suppl. S1). They also allowed model set-up

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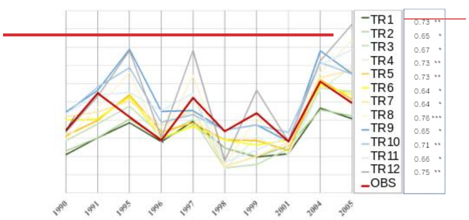
~~involved~~improvements through sensitivity simulations and model calibration including soil parameters ~~calibration, that was performed along sensitivity experiments for~~ (suppl. S2) as soil water, nitrogen, and ~~Nitrogen and Carbon~~ organic carbon content.



~~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~~However, further improvements in model accuracy are to be achieved if incorporating factors such as inter-annual soil variability, the yearly impact of pests and diseases or the year-to-year variations in practices of fertilization and sowing dates. For example, simulations with fertilization specifications closer to the year's management practices (e.g. approximately 80-120 kg N/ha and sowing around April 15th for 1995) resulted in more accurate (reduced bias) predictions (TR6, TR10). These, together with the well simulated inter-annual variability, demonstrate the model's ability to capture the combined influence of climate and management practices on crop performance.

3.2.1~~)~~ 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~~provide projected changes in ~~the anthesis and maturity days in Fig. 6~~phenology, for the control genotype ~~G0, fertilization 3N (Table 1,~~ (G0), under different fertilization levels (0, 60, 120 kg/ha, Table 1, exper "3N") and sowing dates, averaged over 30-years, in scenarios (2021-2050, RCP4.5 and RCP8.5), versus Hist (experiment set-up "E_3N_G0~~). These show that the~~"). Figure 6a,b illustrates the ensemble model changes, demonstrating an earlier anthesis date ~~is projected to occur earlier~~ by up to ~6 days ~~while~~ and an earlier maturity date by up to ~10 days across

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all scenarios. These time-shifts result in a shortening of the grain-filling period by up to 10% across the ensemble, and are a consistent response observed in each individual model. Early sowing dates exhibit a more pronounced earlier shift in anthesis under warming scenarios, a response even more pronounced under RCP8.5.

Under warmer climates we note more frequent occurrences of critical situations with suboptimal grain filling and potential crop failure, under fertilization. These were linked in previous studies to non-linear interactions between fertilization and temperature (Huang et al., 2024) with excessive fertilization during reproductive stages under elevated temperatures potentially inducing higher stress conditions. In our study premature ending of simulated vegetation season occurred more frequently in treatments with higher nitrogen fertilization, leading in average only small changes in maturity days ~~come also~~. This may favour leaves development, enhanced transpiration and earlier ~~by up~~depletion of the soil moisture leading later to ~~about 10~~water stress.

a) b)

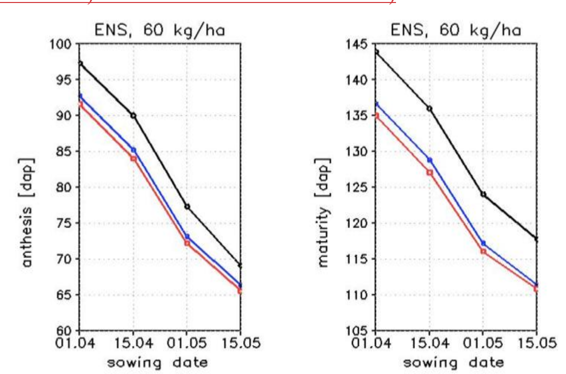
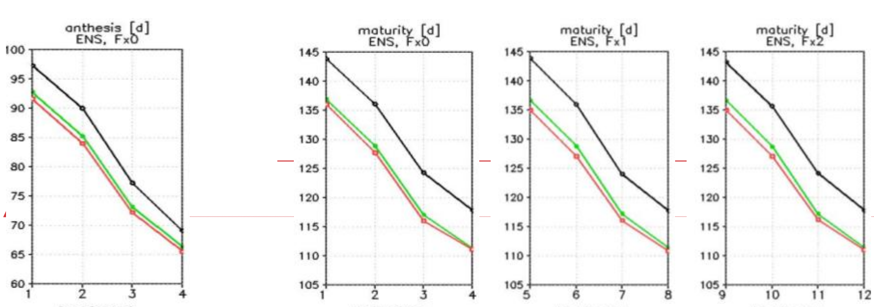


Fig.6: Simulated a): anthesis dates ([dap], days ~~(ensemble mean, time mean), regardless of the planting date and~~ after sowing) and b): maturity dates ([dap]), under historical conditions (black), RCP4.5 (blue), and RCP8.5 (red) scenarios, experiment setup E_3N_G0. Results are shown for the four sowing dates and nitrogen fertilization level~~. The two shifts together lead to a shortening of the growing season by up to 10%. The average maturity date may show small variations with the fertilization level, due to occurrence of slowed grain feeling (Fig. 6).~~ of 60 kg/ha (Table 1, exper "3N").

~~a)~~ ~~b)~~



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~~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~~3.2~~) Yield~~.2 Harvest - projected changes

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~~Same multi-model~~For harvest, the ensemble simulations ~~experiment~~(along E_3N_G0~~ show~~) project an overall decrease~~,~~ ~~in the ensemble mean, of the yield in~~ under both ~~climate~~RCP4.5 and RCP8.5 scenarios~~, for~~ and across all ~~tested (Table 1) management scenarios with perturbed~~ sowing dates and fertilization levels (Fig.~~ 7a,b,c).~~7), compared to the historical period.

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~~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.~~

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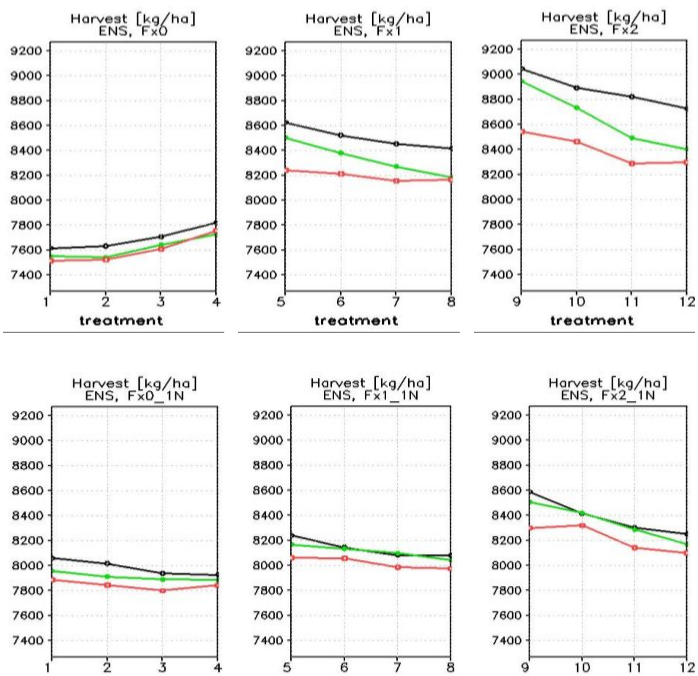
~~The robustness of these is further analyzed in sensitivity simulations with enriched soil nutrients.~~

~~**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~~Harvest decline in climate scenarios is attributed to several factors: 1) reduced rainfall during the growing season (Fig.8), as evidenced by a strong correlation (0.5 in April to 0.8-0.9 in July-

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August, over 30 years) found between harvest (H) and accumulated precipitation in the Ctrl and in model simulations; 2) a shortened grain-filling period due to a projected earlier flowering and an even earlier maturity across all the models (Fig.6), potentially limiting biomass accumulation; and 3) decreased fertilization efficiency under warming conditions, in the sense that H difference Hist minus scenario, increases (non-linearly) with enhanced fertilisation (Fig.7). Hence for a same climate, the same increase in fertilisation brings less benefit in a warmer climate. This benefit for H is of about 10% in Hist versus 7.6% in RCP8.5 for early sowing and about 8% in Hist versus 4.3% in RCP8.5 for later sowing for doubling the N amount of nitrogen (Fig.7b,c). This efficiency decay feature underscores the primacy of reduced accumulated precipitation (Fig.8) and of higher temperature, that lead to a non-linear H response to fertilization (Huang et al, 2024). Their influence is noticed as well in the absence of fertilization (Fig.7a), when H still declines in warmer climates, with a dominant control from precipitation. The correlation along sowing dates between H and accumulated precipitation until maturity (Pmat, Fig.8), is r(H, Pmat) >0.96 in both scenarios.

a) b) c)

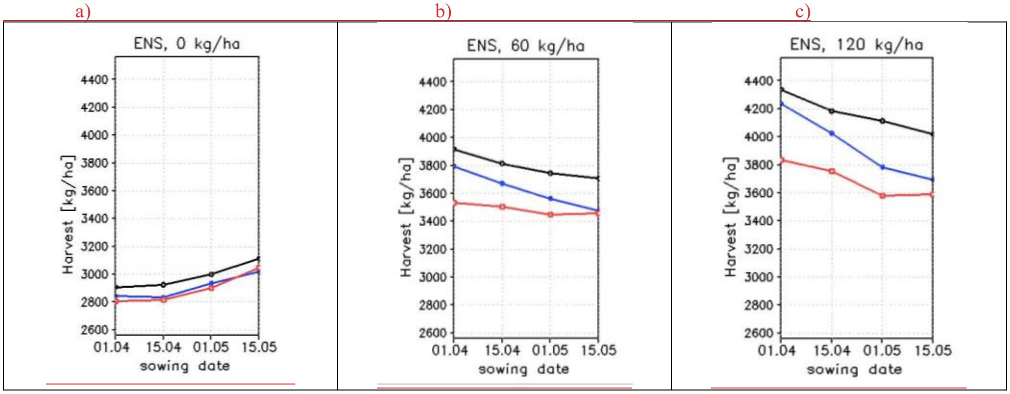

Fig.7: Simulated Harvest (kg/ha) under Hist (black), RCP4.5 (blue) and RCP8.5 (red) scenarios, for four sowing dates across three fertilization levels (Table 1, exper "3N"): 0 (a), 60 (b), and 120 (c) kg N/ha (from left to right), experiment setup E_3N_G0.

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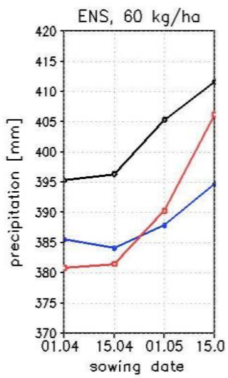

Fig.8: Precipitation accumulated until maturity (mm) in experiment E_3N_G0 (~~top) and for experiment E_1N_G0_soil+CN (bottom).~~ legend as in Fig. 7).

The role of the precipitation timing is emphasised: for late sowing, RCP8.5 shows more accumulated Pmat (and H) despite a shorter accumulation season (Fig.6) but having projected a precipitation increase towards late spring (Fig.5), that may significantly favour critical growth stages.

3.3

~~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 (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).~~

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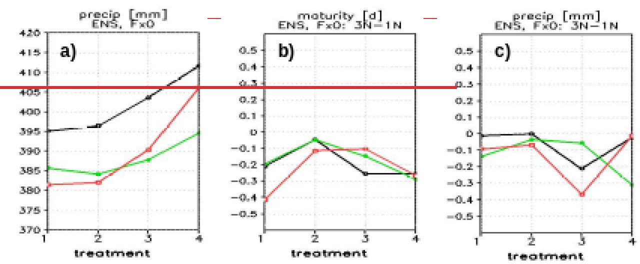

~~Fig.8: a): Accumulated precipitation from the initial time of the simulation until the maturity date ([mm]), for scenarios as in Fig.7, for E_3N_G0; in b) are shown differences [dap] in the maturity date and in precipitation for (E_3N_G0) minus (E_1N_G0_soil+CN); c) same differences as in b for the 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~~ 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.~~ implement methods to identify ideotypes under each agro-climate scenario. The aim is to search for management scenarios that yield optimal outcomes defined by user-criteria such as maximizing harvest yield, stabilizing yield, or minimizing pollutant emissions. Two optimization methods are implemented: a discrete-parameter, purely deterministic technique, and a hybrid approach that combines deterministic modelling with continuous-parameter Machine Learning-based Genetic Algorithms for iterative genotype selection.

~~Two optimization methods are implemented: a discrete-value pure~~ The deterministic ~~technique and a hybrid optimization technique combining deterministic modeling with ML Genetic Algorithms for iterative selection.~~

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~~Deterministic~~ method ~~performs~~involves conducting 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).~~crop model simulations, with optimization performed as a post-processing step. Genotype parameters Pi are defined within pre-established limits and discretization. Multi-model simulations ~~in which ~~are then performed, where each parameter is individually 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~~remaining 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 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~~held 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 ~~. The total number of simulations in this case is determined by the chosen discretization level. In contrast, in the hybrid technique the Pi values are selected from a continuous 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 ~~of 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~~

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~~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~~identifying and iteratively 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 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~~ the 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)~~

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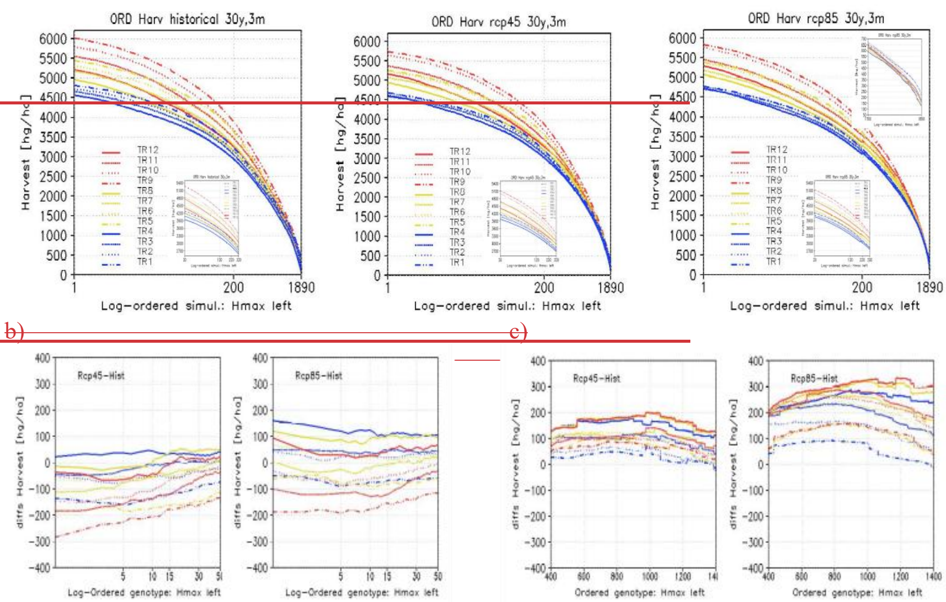

~~b)~~ ~~c)~~

~~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).~~

~~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.~~

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~~**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.~~domains. This section presents the results of genotype optimization experiments (E_1N_Gn+w), built upon the E_1N_G0 and sets up initial (1st of January, yearly) soil moisture as best agreement with projections targeting near-term (2035 as centre of interval 2021-2050).

~~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 on using P3 for enhancing~~

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~~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~~3.3.1 Optimal genotype under climate change

i) harvest as a function of the genotype H(G) in scenarios versus current climate

We analyse the distribution of H obtained along multi-genotype simulations, ordered from maximum to minimum values and denote the genotypes corresponding to this ordering "H-ordered genotypes", chain which is simulation (model, scenario) dependent. Comparing these H distributions for the two climate scenarios against Hist, indicates projected changes in the ensemble-model PDF (probability density function) of H under warmer climate.

A first outcome demonstrates in Fig.9a, b that for the H-ordered genotypes, a projected average decrease in Harvest (H) occurs within the range of maximum H values (genotypes in the upper H-percentile, interval GX (0%, 2.5%) of the H-ordered genotypes), under both scenarios, and mostly affecting the earlier sowing dates (Fig.9b). Across models of the ensemble, we note a strong modulation of this behaviour by precipitation, particularly for unfertilized scenarios. Precipitation exhibits high

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inter-model variability and significant regional-scale uncertainty, pointing to the need of ensemble modelling for reducing it. In contrast, the warming trend is a consistent feature across models in the region, contributing other model-systematic responses such as earlier anthesis and maturity dates and shortening of the grain filling season.

The second note regards a different response projected in the intermediate H values (Fig.9a, c). Genotypes corresponding to the intermediate H values (genotypes of middle H-percentile, the interval GI (25%, 70%) of the H-ordered genotypes) show projected higher H values in GI in climate scenarios than in Hist (Fig.9c), affecting less the earlier sowing (Fig.9c).

These together lead to a narrowing of the H-values range of responses, in GX and GI, to the same managements applied, in scenarios compared to Hist. Same management spread would lead to closer H-responses, with enhancing the expectancy for occurrence of intermediate values and decreasing the expectancy for highest H values (a third feature of projected changes).

Finally, we note that despite this narrowing, earlier sowings appear systematically as better timing options (Fig.9a), improving by up to 2-(4) % in scenarios (respectively Hist) unfertilized case and up to 8-(12) % in fertilised case (Fig.9a), with the lowest percentage for RCP8.5. Earlier sowing was reported in other recent studies as optimal for spring maize harvest (Djaman et al, 2022).

ii) options for adaptation and mitigation using genotype analysis

These three features of cross genotype-agro-management impact: - projected lower maxims of H in scenarios (mainly for early sowing), projected higher intermediate H (mainly mid-late sowing); - a narrowing of the range of H in GX and GI with higher/ lower expectancy of intermediate/ high values occurrence, have practical adaptation outcomes.

The first two points are equivalent to slopes' change of H as a function of the ordered genotype, as shown in (Supl. S3) in climate scenario versus Hist. Slope change information indicates the percentile (and genotype) threshold for improving the result in scenario compared to Hist, for a given agro management. Alternatively, for a given genotype one could find how a change in management practice could optimize the result. In this last case for example, one could choose a small shift in the sowing, but using less fertilisation, less pollutant, meanwhile getting a same or even higher H, as shown for example in TR5 versus TR11 in Fig.9a, RCP4.5 (Fig.9).

a)

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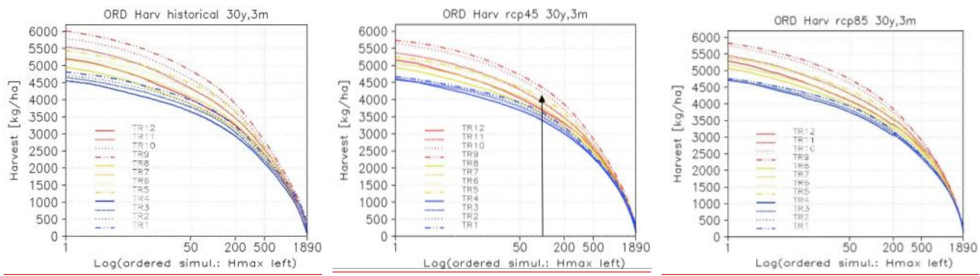

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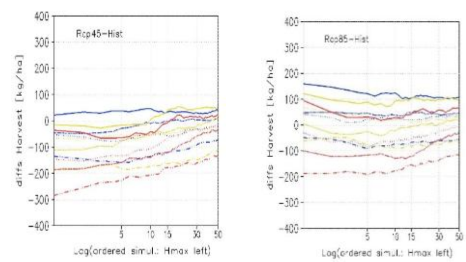

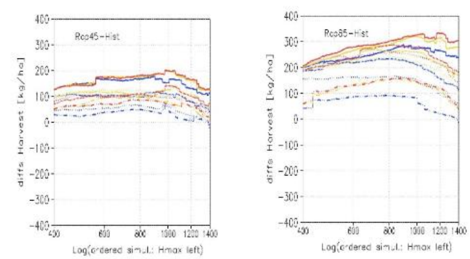

Fig.9 a): Harvest multi-model time mean, ordered from maximum to minimum value (left to right on x-axis, logarithmic scale). The simulations are for: Hist (left), RCP4.5 (middle) and RCP8.5 (right), experiment setup E_1N_Gn+w, for cross-genotype changes in six Pi parameters (resulting 1890 simulations, x-axis); b) differences in projected harvest for a) RCP4.5 minus Hist (left) and RCP8.5 minus Hist (right), for the upper H percentile (the first 50 values, [1-50] on x axis) and intermediate in c), range [400-1400] on x-axis. ("Hmax left" indicates that increasing values of H are on leftward direction of the axis).

Apart from any comparison with Hist, it is important for long term adaptation, that one may find genetic combinations with high yield in specific target percentile under a given climate (e.g. first 50 values, as in Fig.9b).

At yearly level, the interest for some of these genotype parameters combinations may increase, providing that distinct weather favourable patterns will be identified, once with progress achieved in seasonal and annual weather forecasting (Dewitte et al., 2021).

3.3.2 Optimal Genotype parameters Pi under climate change

i) optimal genotype parameters

We further discriminate H response per genotype parameters (P1-P6), to understand the source of the changes in Fig.9 and the possible adaptation paths under climate and management scenarios.

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Parameters' analysis (Fig. 10) shows that in all simulations, higher harvest is obtained under: shorter thermal time from seedling to juvenile phase (P1, Fig. 10 a), shorter photoperiod-delay (P2, Fig.10b), slightly shorter thermal time between successive leaves appearance (phyllochron, P6, Fig. 10 e) in GI and longer in GX, but longer thermal time to maturity (P3, Fig.10c) and higher grain filling rate (P5, Fig. 10d). These results are in coherence with findings along recent works. Shorter P1 or lowering the seedling-juvenile thermal time for increasing H (Fig. 10a) is in agreement with Mi et al., (2021) for semi-humid areas, (the current class of this region, with semi-arid trends projected, Fig. 4), and the same for P2, while slower maturity (P3) and enhanced filling rate (P5) being linked to higher kernel weight and harvest in agreement with recent studies (Grewer et al., 2024).

ii) changes in optimal genotype parameters in climate scenarios

Comparing Pi in climate scenarios against Hist, reveals the new plant strategy put in place in the new climatic conditions, for maximizing the harvest. The ensemble simulations (Fig. 10) shows that highest harvests are reached with genotypes that ensure a longer thermal time from seedling to juvenile phase and longer thermal time to maturity in scenarios compared to Hist. To a smaller extent this is also achieved by a longer photoperiod delay, higher grain filling rate and longer phyllochron interval, in scenarios, than for a same percentile of the Harvest in Hist. These show that under warmer climate it is essentially important to avoid too fast growth on main stages of the development.

Indeed, slower development phases are obtained in scenarios mainly by increasing P1 and P3 (Fig.10a, b) and related to these, under longer photoperiod (P2 increases, Fig.10b). Other contributions come from ensuring a slower rate of appearance of successive leaves (P5 increase), while a higher grain filling rate (P6 increase) appears to partly compensate for the negative effect of higher temperature that decreases the seed-filling duration and seeds number and size and finally the harvest.

In other studies, this compensation was shown to be minor compared to the loss of seed-filling duration in warmer climate (Singh et al., 2013) that points to P1 and P3 as main drivers for Harvest in climate scenarios. Percentages of the Pi changes in scenarios versus Hist for a given percentile of harvest (suppl. S4) confirm this main driving.

a) b) c) d) e)

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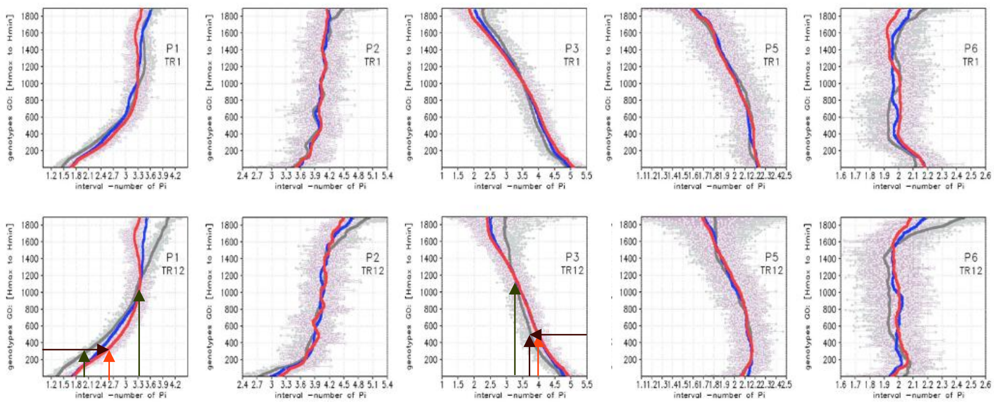

Fig.10: Pi values corresponding to ordered, decreasing harvest (on y axis, the number of the ordered simulation, y=1 is the highest harvest simulation). X-axis shows the Pi interval-number of discretization, increasing with increased values. Discretization here have used 5x7x6x1x3x3 intervals for P1xP2xP3xP4xP5xP6 (total 1890). Simulations are shown for two treatments (TR1 at top and TR12 at bottom), for: Hist (black), RCP4.5 (blue, only shown for the running mean) and RCP8.5 (red), ensemble time-mean; full lines show running means over 100 values window. The short arrows in a) and c) indicate, for a same harvest percentile (y=constant) the corresponding Pi intervals for Hist (black) and RCP8.5 (red); long arrows indicate the P0i values of the intersection of running-mean Pi for Hist with RCP8.5.

iii) optimal genotype parameters in management and climate scenarios

Agro-treatments choice may significantly modulate the H response to genotype parameters. Delaying sowing, requires gradually decreasing Pi in order to maximize H (Fig.11, also in Fig.10), for both Hist and climate scenarios. For P1-P3 this decrease reflects the priority in avoiding a too late end of the juvenile stage (and shift in climate conditions) and a too late (autumn) maturity stage that is slowing the grain filling and leading crop failure.

However, Fig. 11 also shows that these Pi decreases cease or even reverse under extreme delay of sowing. For highest delays the development stage is getting too short under P1's too strong decrease while daily temperatures becoming higher, hampering the development. The same is seen for the maturity, with P3' too strong decrease favouring a too quick grain filling. Hence the plant strategy for adaptation after a threshold of sowing-delay is similar to the one already seen in its adaptation to warmer climate, in scenarios. Higher harvest is then reached by gradually switching to only moderate decrease or even increases of Pi parameters along with gradual increasing delays in the sowing date.

This gradual switch in the mechanism of Pi performing high harvest, with sowing delay appears quite systematic for all Pi. This crop adaptation mechanism, converging to the one projected for climate scenarios, shows that gradually under enhanced

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warming, the crucial priority in adaptation transfers, from the key issue of ensuring climatological conditions for the development to the key issue of avoiding a too fast growth leading crop failure.

This gradual switch in the mechanism of Pi performing high harvest, with sowing delay appears quite systematic for all Pi. This crop adaptation mechanism, converging to the one projected for climate scenarios, shows that gradually under enhanced warming, the crucial priority in adaptation transfers, from the key issue of ensuring climatological conditions for the development to the key issue of avoiding a too fast growth leading crop failure.

a) b) c) d) e)

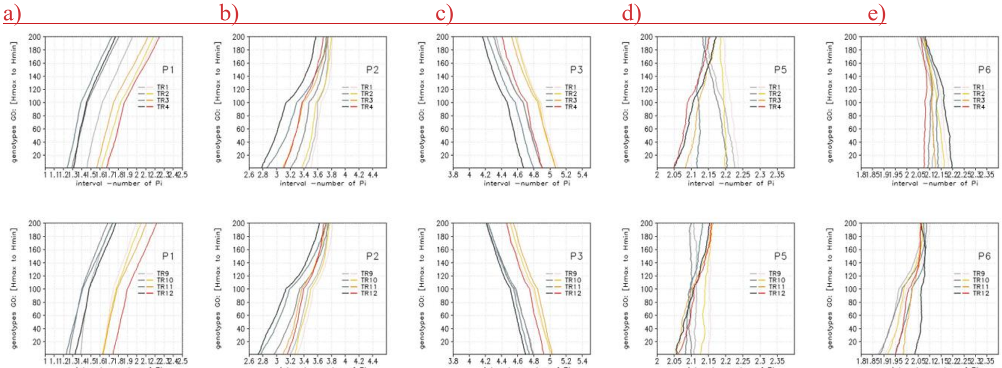

Fig.11 As in Fig.10 but for all sowing dates, no fertilization Fx0 (TR1-4, top) and with fertilization Fx2 (TR9-12, bottom). Parameters Pi are shown for the top 200 highest harvest (y from 1 to 400). Grey colours are for Hist and yellow-red for RCP8.5 (light to dark from earlier to latest sowing).

iv) optimal genotype parameters in adaptation and mitigation strategy

For each agro-management and climate scenario one can identify threshold values of Pi (P0i that depend on the Pi, the sowing date and the fertilization level, shown in Fig.10) of intersection between scenario and Hist. At this value, for the genotype the two have the same H percentile. So P0i shows if we get an enhanced percentile or decreased from genotypes with higher or lower Pi in the scenario compared to Hist (Fig.10, shown by arrows).

Second remark is on the expectancy of an outcome. Since all the slopes of Pi, each as a function of H ordered-values are lower than in Hist (suppl. S3), there is a narrower Pi interval for all those Pi decreasing with H (e.g. P1) and a border one for those Pi increasing with H (P3, Fig.10c), in climate scenarios. P3 increases are broadening the interval for H-highest percentile, potentially presenting, in this sense, more expectancy (than P1, Fig.10a) on highest values outcome.

The genotyping results were found both in simulations involving deterministic and the hybrid ~~method~~ deterministic-ML~~,~~ ~~this involves~~ methods. The hybrid method involved the same cross-simulations, but ~~this time~~ the selection of Pi values

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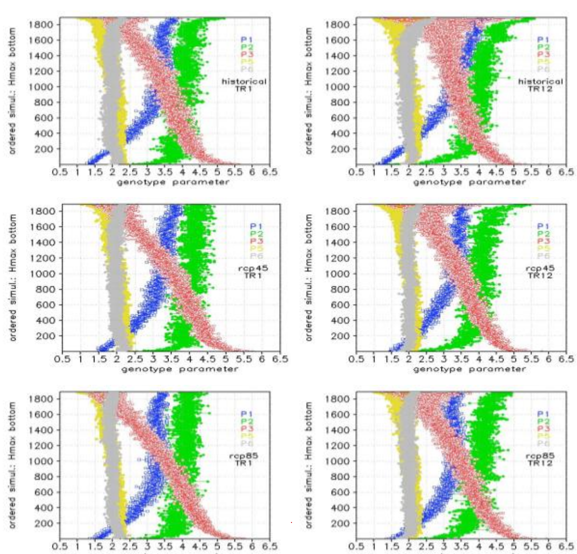
for ~~parameters is~~ H optimization and ordering was no more following a pre-defined discretisation ~~and~~but instead ~~it is~~ a random picking up over a continuous interval of values ~~and~~with successively retrieving the best generation~~, applying~~. It applies for optimization, classic Genetic Algorithms methods in which selection of pairs is based on the user-criteria (e.g. maximum ~~yield~~harvest, stable ~~yield~~harvest, etc.). Our results show that for the same physical intervals of the 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~~ with also computational efficiency. CPU time is reduced in this case by more than 30% using the hybrid technique compared to the fully deterministic model on a VM Linux platform. Hybrid method emerges as a better solution since it can identify improved optimums at lower computational prices.

~~In each of~~ 4. Discussions ~~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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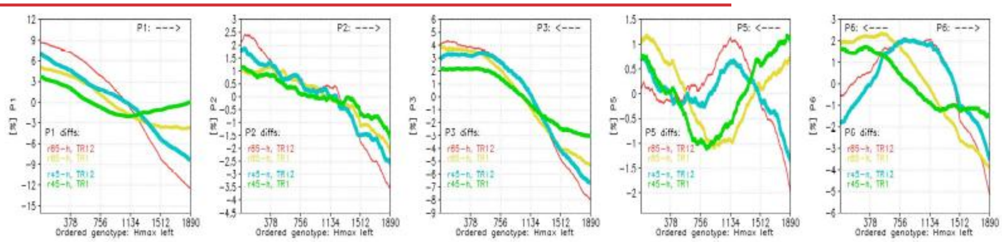
~~Fig.10a : Indices of the Genotype' six parameters (Ox) that correspond to Harvest ordered from max Harvest (Oy bottom) to min Harvest (Oy top). Here are 1890 genotypes (5x7x6x1x3x3 simulations with parameters, per model in [1,7]), shown as ensemble mean for two treatments (TR1 left column and TR12 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).~~

~~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.~~

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The results found are in line with other results in recent studies, using different approaches and observational data, and offer an extended (continuum-parameter) assessment towards a more generalised frame, allowed by the implemented system. For the plant response under management treatment delaying sowing date, limiting elongations of the development phase was also found in other studies (Huang et al., 2020) to reduce the impact of temperature increase and, in some cases, precipitation decrease and water stress. This response was also found stronger under enhanced fertilization and delayed sowing (Fig. 10, 11). Also fertilization lowering P6 and enhancing leaf appearance rate (Fig. 10f), assessed in earlier studies mainly for warmer climates (Hokmalipour et al., 2011; Sardans et al., 2017; dos Santos et al., 2021) was recently put in relation to P2 decrease mainly along sensitive photoperiods (Hu et al., 2023) and to higher harvest, through enhanced evapo-transpiration maximizing the high N uptake (Lu et al., 2024). In warmer climate scenarios (Fig.10f, 11f), limitations in the expansion of new leaves (increase of P6, Fig.10) was shown to be an adaptive tolerance mechanism to drought and heat stress conditions (Fahad et al., 2017).

Further, for moderate sowing delay fertilisation was shown to require slower grain filling (P5, Fig.11d) under reduced P1, P2 and P3, controlling N stimulated growth under hydric stress conditions of current and projected climate for non-irrigated crop (Yang et al., 2024). Under high delay and warmer climate, a higher grain filling is required (Fig.11d). This increase for P5 under increased warming may reflect an adaptive strategy of plants to accelerate development under drought stress, allowing plants to end their life cycle before impact of severe drought stress occurs (McKay et al., 2003; Roeber at al., 2022).

Simulations here emphasize and compare adaptation paths of gradual plant response to warming climate. These emphasise some reduction in the efficiency of adaptation through crop management in warmer climates. Meanwhile, genotyping shows the possibility of identifying parameters still able to enhance efficiency of adaptation under climate and agro-management scenarios, hence suitable methods for an accelerating change. The ability of exploring continuum-parameter space not only offers a general picture of adaptation cross-solutions but identifies critical values of the parameters that for small perturbations may lead the system response into different states (threshold sowing-delays, or P0i for genotypes). Without an integrated modelling approach, estimating or emphasising these points meaningful for adaptation is hard, moreover since these are simulation (climate-management scenario) dependent.

5. ~~Discussions~~ ~~and~~ Conclusions

The main ~~conclusion~~outcome of this study is that an ~~agroclimate~~agroclimatic real-time Interactive Service was ~~developed that goes beyond interrogation platforms for agro-climate information, stepping forwards and~~ implemented towards adaptation support, that allows performing ~~in~~ real-time, ~~under~~ user ~~request-~~

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requested, agro-management modelling scenarios for the region~~. These allow crop simulations for time-slice of interest, specified climate scenario, and user-specified management scenarios.~~
~~A main~~, under current and future climate. A novel feature of the system is the ability for identifying optimal management paths for the user's request, along with multiple cross-cultivar ~~management~~ parameters ~~and climate scenarios,~~, such as ~~e.g.~~ cross-optimal sowing date, genotype parameters, amount and date of fertilization.

The system provides solutions and estimates the associated uncertainty ~~associated~~ by using multi-model ~~ensemble~~ensembles for each agro-climate and management scenario. The ~~optimisation~~crop optimization criteria are user-defined and can relate to high ~~yield,~~ harvest, stable ~~yield~~harvest, low pollution. The optimization module implemented uses a hybrid deterministic ~~and~~- ML methodology. It performs multi-model simulations using physical models of climate and plant penology and ~~optimisation~~optimization is done either through ~~simulating discrete cross-parameters intervals pre-definied~~ discretizing the parameters' space and optimisation post-processing~~, either~~ or using ~~the advantage of continuous parameter space investigation by using~~ hybrid physical-ML Genetic ~~algorithms along multiple model simulations.~~Algorithms methods. ML ~~is~~methods are spanning continuous parameter's space and ~~interactively~~iteratively selecting along the simulations the best fit parameters, allowing to identify unprecedented optimal configurations~~,~~, (H maxims), not~~-~~ reachable under the discrete deterministic method.

The overall system output information is layered and accessed from two interfaces~~. One~~: one static, ~~contains high resolution agro-climate~~ for information purpose (phenology, ~~yield~~harvest, climate, extremes~~)~~ at high resolution NUTS3 level ~~that is useful for user-analysis, management~~) and ~~adaptation and research. The~~a second ~~interface~~ is real-time interactive online, through which the ~~system receives~~ user places requests and ~~performs required~~ receives the system-performed management simulations ~~providing the results. The user request refers to regional management scenarios or on~~required (including uncertainty along multi-models) and identified optimal ~~management identification under climate change.~~paths for adaptation. These platforms are operational for two emission scenarios RCP4.5 and ~~were tested for two climate scenarios RCP45 and RCP85~~RCP8.5 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~~were discussed ~~here~~in this work for the pilot region South Romania.

For the ~~control~~current genotype, in both ~~climate~~emission scenarios it is projected ~~a~~ a mean decrease (14% in ensemble mean, with higher values per model) of the projected harvest, for all the management scenarios (sowing-dates and fertilization) tested. This was linked to a projected shortening of the ~~growing~~grain filling season (~~and~~ 10% quicker with an

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earlier shift of both anthesis (5 day) and maturity (10 day) phases) and ~~a mean decrease of the projected yield, for all the management scenarios, sowing-date and fertilization level tested. We show that the~~ to a mean decrease ~~is also linked to a lower~~ of the fertilisation efficiency ~~of fertilization~~ under ~~warmer~~ climatic scenarios, stronger in RCP 8.5 emissions.

The impact of genotype perturbations on crop parameters is analysed along six cross-genotype parameters, for agro-management-climate scenarios. The main questions: i) Can we identify optimal genotype parameters that lead to maximal harvest? How do these differ under projected climate~~. Compared with the previous observed unirrigated yields, here the shown reduction~~ change and/ or under agro-management options and can these enhance our understanding to guide our options? iii) Can be genotyping a (better) solution for adaptation under climate change in the region?

These simulations showed that the maximal H values are projected to decline for all agro-management and breeding simulations performed, in emission scenarios compared to Hist, with a higher decline for earlier sowing. H-values then increase in the intermediate-percentile harvest in scenarios versus Hist and there is enhanced expectancy in scenarios to reach the historical values in this range through agro-management and breeding. These indicate a narrowing of the responses range to same agro-managements, with less / more expectancy of reaching values in the highest / intermediate H-range of Hist, in climate scenarios. In practice, these express that we can identify the H-percentile (genotype), where agro-management choice will optimize the outcome compared to Hist, including finding solutions with lower fertilisation, less pollutant.

For effective support in adaptation applications, individual genotype parameters Pi were analysed in climate scenarios versus Hist. This showed that the thermal times to juvenile (P1) and maturity (P3) are key genotype parameters driving harvest changes in the region, requiring increased values in climate scenarios compared to Hist for a same highest harvest-percentile range. This range is identified through critical values of the parameters (P01), determined for each treatment and climate scenario. There is significant ~~(around 50%) in simulated yields of rainfed corn cultivated in South-eastern Romania under the new climatic conditions~~variability of P0i under agro-management treatments. Moderate delayed sowing and enhanced fertilisation may diminish the shifts in Pi in scenarios compared to Hist for a same H-percentile, in contrast to extreme managements.

~~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~~ These results show that Genetic approaches offer adaptation strategy support in helping plants to resist drought stress under 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.~~

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~~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~~ climate. Moreover, 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~~ optimization 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~~, under a continuous-parameter space search. The system can be further used for ~~managing critical levels under periods of prolonged or~~searching paths along 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. This can be extended for other regions, scenarios, crops as a performant tool for adaptation~~

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~~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~~ years, along with irrigation options investigation. Coupled 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~~extended predictions (seasonal, year -decadal) this could provide near real-time adaptation support.

Code and data availability: The code is available in the Github repository at: https://github.com/pneague/Genetic-Algorithm-for-Corn-Genotype-~~Planting~~sowing-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: Steps in ML algorithm

Schema of steps in ~~work-flow~~workflow 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.

Supplementary material:

S1: Simulated (ERA5 control runs) versus measured harvest

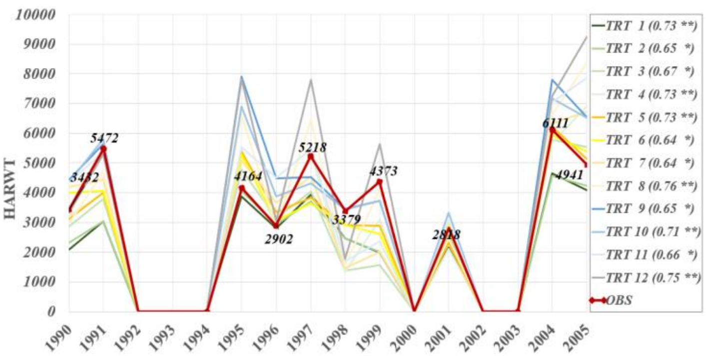

Fig.S1: Simulated (thin lines) vs. measured (red, thick) harvest in southern Romania for 12 management scenarios (Table 1, exper "3N"). Box: Pearson correlation between simulated treatments and measured Harvest (* p<0.01, ** p<0.05, * p<0.10; zero are missing values).**

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S2: Sensitivity to changes in nutrients

Replicability for system portability on other pilot regions requires estimates of sensitivity to new local forcing. Sensitivity ensemble simulations were performed, with increasing soil Carbon and Nitrogen at the initial time by 20%, for a same control genotype (experiment setup E_1N_G0_soil+CN).

a) b) c)

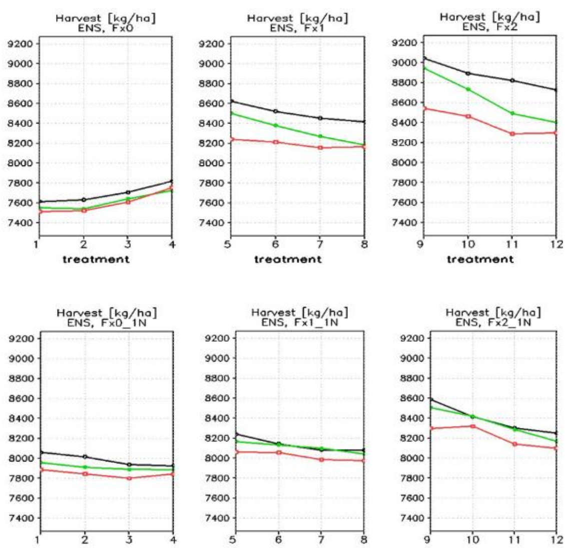

Fig.S2.1: Harvest ([kg/ha]) comparison between the experiment setup E_3N_G0 (top, same as Fig.7) and the experiment setup E_1N_G0_soil+CN (bottom). Panels are as in Fig7, for Fx0(a), Fx1 (b), Fx2 (c), ensemble time mean for Hist (black), RCP4.5 (green) and RCP8.5 (red), on Ox there is the treatment (1 to 12, Table 1).

Experiment E_1N_G0_soil+CN compared to E_3N_G0 (Fig.7) shows that

—Harvest loss is only up to 7% for about 60% reduction in fertilization (exper "1N" versus "3N", Table 1), when the soil nutrients content is increased by 20%. Also, the comparison shows that there are still options even under warmer climate to

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equal or exceed the historical Harvest if there is an appropriate soil composition (e.g. in RCP4.5 TR6 and TR7, Fig.S2.1b-bottom), also under RCP8.5 (TR10 and TR11, Fig.S2.1c-bottom), and even at lower fertilization levels (exp “1N”, Table 1). A possible mechanism in this case involves delayed maturity (Fig.S2.2b), and consequent more precipitation accumulated (Fig.S2.2a, c). In practice this slower maturity could be due to soil C/N composition influencing soil water holding capacity, moisture and temperature, slowing germination or plant growth. Previous research (Kakar et al. 2014; Khan et al., 2014) also reported delayed silking and maturity in the case of enhanced soil nitrogen when compared to control case, showing also a stronger response for early sowing.

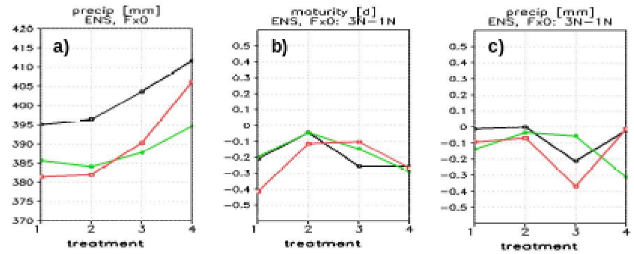

Fig.S2.2: Precipitation (mm) accumulated from the initial time of the simulation for experiment setup E_3N_G0 (a), (same as Fig.7); differences [dap] in the maturity date (b) and in precipitation accumulated until maturity (c) for the experiment setup E_3N_G0 minus the experiment setup E_1N_G0_soil+CN, (mm). Lines are for Hist (black), RCP4.5 (green) and RCP8.5 (red).

S3: Slopes of Pi genotype parameters in Hist and climate scenarios

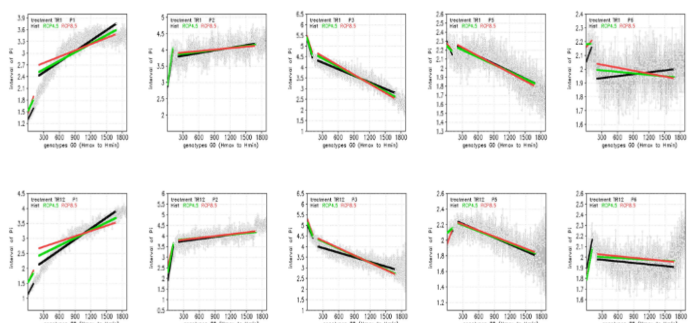

Fig.S3 The slopes (thick lines) of Pi genotype parameters (y-axis) as a function of decreasing ordered harvest (x-axis) for Hist (black), RCP4.5 (green and RCP8.5 (red) computed over 2 sub-intervals of highest 200 values of harvest and over the rest of decreasing ordered values (200-1890). The values (light grey) are plot for Hist, ensemble time mean, TR12 (as in Fig.10 bottom, grey).

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S4: Percent changes in Pi in climate scenarios relative to Hist

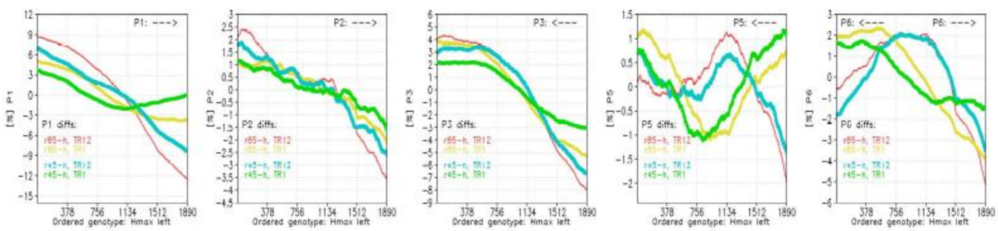

Fig.S4: Percent changes of Pi genotype parameters (y-axis) as a function of the ordered Harvest from highest (left, x-axis) to lowest (right, x-axis). Differences (running means over 378=P2xP3xP4xP5xP6 the product of discretization intervals for P1-P6) are shown for TR1 (yellow for RCP4.5 minus Hist) and green (RCP4.5 minus Hist) and for TR12 (red for RCP8.5 minus Hist) and blue (for RCP4.5 minus Hist). Percent changes are expressed as differences relative to Hist. Arrows indicate the monotony of Pi values that correspond to the ordered decreasing harvest (shown in Fig.10).

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