

## Article

# Harnessing Radiation-Use Efficiency to Enhance Crop Yields and Soil Carbon Sequestration in the North China Plain

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## Abstract

Sustainable agriculture requires simultaneously increasing food production and mitigating climate change, yet the extent to which crop improvement strategies deliver co-benefits at regional scales remains poorly understood. Improving radiation-use efficiency (RUE) has been widely proposed as a pathway to increase crop productivity, but its potential benefits such as soil organic carbon (SOC) sequestration are not well understood. Here, we developed a hybrid modeling framework that integrates a process-based agricultural system model (APSIM) with machine learning to capture genetic  $\times$  environment  $\times$  management ( $G \times E \times M$ ) interactions and their effects on crop yield and SOC dynamics across the North China Plain. The results show that improving RUE increases both crop yields and SOC, but the magnitude of these benefits is strongly modulated by nitrogen inputs and varies widely across the region. In the future period (2021–2060) under a moderate-emissions scenario SSP2-4.5, increasing RUE of current cultivars by 10% and 20% led to additional wheat yield gains of 1.1 (+16%) and 1.8 t ha<sup>−1</sup> (+26%) and maize gains of 0.8 (+11%) and 1.1 t ha<sup>−1</sup> (+14%), respectively. These productivity gains also translated into an increase in SOC sequestration (+10% and +26%, respectively), as a consequence of enhanced carbon inputs. Notably, the coupling between yield gains and SOC sequestration varied substantially across the region, indicating spatially differentiated benefits. Our results highlight that improving RUE can contribute to both productivity and soil carbon gains, but these co-benefits are not universal and depend on local environmental and management contexts. This study provides a scalable and feasible approach for evaluating crop improvement strategies and their environmental consequences represented by SOC dynamics, as well as demonstrate that RUE improvement offers great opportunities for sustainable agriculture.

**Keywords:** APSIM; machine learning; radiation-use efficiency; cultivar; yield; soil organic carbon



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## 1. Introduction

Agricultural production faces the dual challenge of sustaining crop yield while safeguarding environmental quality. Although global crop production has increased in recent decades, it remains insufficient to meet the demands of a growing population by 2050, particularly for major staple crops such as wheat and maize [1]. Meanwhile, agricultural inputs, especially nitrogen, have exceeded safe environmental limits in many regions, inducing widespread ecological degradation [2]. Expanding cropland area may increase

production, but it often comes at the expense of ecosystem integrity and environmental sustainability [3]. These constraints highlight the urgent need to enhance crop productivity through genetic improvement rather than intensification of inputs or land expansion [4].

Crop yield potential can be expressed as the product of light interception (LI), radiation-use efficiency (RUE), and harvest index (HI) [5]. Over the past 50 years, HI in major grain crops of modern cultivars has nearly doubled and now approaches its theoretical limit (0.6) [6]. Similarly, LI has reached 0.8–0.9 in current crop genotypes and is close to its biological maximum [7,8]. In contrast, RUE—representing the efficiency with which absorbed radiation is converted into biomass—remains far below its theoretical potential, with estimates suggesting that RUE in crops such as wheat could be increased by 50% [4,9]. Improving RUE through breeding and biotechnological approaches therefore represents a promising pathway to further enhance yield potential [9]. Advances in crop physiology and molecular biology have demonstrated multiple avenues for improving RUE [7,10,11]. For example, over-expressing of Rubisco subunits and associated chaperones has improved photosynthesis in maize [12], while increased expression of sedoheptulose-1,7-bisphosphatase has enhanced RUE and biomass production of wheat [13]. However, despite these advances, most studies remain at the proof-of-concept stage due to substantial economic and practical costs.

Soil organic carbon (SOC), a key indicator of soil health and sustainability [14], is also closely associated with RUE albeit indirectly to a large extent. Practically, photosynthesis is the first source of carbon inputs to soil, representing the most fundamental constraint to SOC sequestration [15]. Previous studies have concluded that SOC accumulation rates increased linearly with carbon inputs in croplands [16,17]. By enhancing crop productivity via improved RUE, positive feedback loops that contribute to overall carbon sequestration could be achieved in croplands [18]. However, increases in crop productivity do not necessarily translate into SOC gains, as carbon inputs and their stabilization are mediated by various environmental constraints, soil processes, and microbial activities (e.g., priming effects) that vary widely across large spatial extents [19]. For instance, under climate warming, the contribution of increased crop productivity to SOC would decline and exhibit substantial spatial variation depending on local temperature and moisture conditions [20]. In general, the benefits of improved RUE on both crop yield and SOC—particularly under field conditions characterized by heterogeneous environments and management practices—vary across regions and remain highly uncertain.

Process-based crop models provide a powerful tool to bridge this gap by explicitly representing biophysical processes and enabling the evaluation of genotype  $\times$  environment  $\times$  management ( $G \times E \times M$ ) interactions [21–23]. These models have been widely used to design crop ideotypes and assess their performance under varying climatic and management conditions. For example, virtual maize cultivars differing in phenology and grain development have been evaluated under different sowing dates to identify high-yielding ideotypes [24], while alternative wheat genotypes with modified dwarfing traits have been assessed across multiple sites under historical and future climates [25]. However, such simulations are typically constrained to site-specific analyses due to high computational demands, limiting their ability to capture spatial heterogeneity in climate, soil properties, and management practices across large regions. Recent advances in hybrid modeling—combining process-based models with machine learning (ML)—offers a promising pathway to overcome these limitations by enabling efficient, high-resolution simulations while preserving biophysical consistency [26,27]. While these studies have incorporated environmental and management variability into ML frameworks, genetic variation—and particularly its interactions with environmental and management—has received far less attention. This omission limits our ability to assess how  $G \times E \times M$  interactions shape not only crop productivity but also SOC.

To address these gaps, this study developed a hybrid modeling approach that integrates machine learning with a process-based agricultural system model, the Agricultural Production Systems sIMulator (APSIM) [28,29]. We explicitly incorporated variation in RUE and other key genotype parameters controlling crop growth and grain development. APSIM simulations were conducted for the period 1980–2060 across 6000 representative grid cells in the North China Plain (NCP), spanning a wide range of environmental conditions and management scenarios. These simulations were then used to train machine-learning emulators to capture the processes in APSIM, enabling computationally efficient predictions of crop yield and SOC dynamics at 1 km resolution for both historical (1981–2020) and future (2021–2060) periods. Our objectives were to (i) quantify the effects of improving RUE on crop yields and SOC at regional scale, (ii) assess how these effects are modulated by  $G \times E \times M$  interactions, and (iii) evaluate the potential of RUE-improved cultivars to deliver co-benefits for productivity and soil carbon sequestration.

## 2. Materials and Methods

### 2.1. Study Region and Data Sources

The North China Plain (NCP, Supplementary Figure S1) is the largest agricultural production region in China, contributing approximately 33% and 60% of national maize and wheat production, respectively [30]. The region is characterized by a temperate monsoon climate, with mean annual temperature (MAT) ranging from 11 °C to 17 °C and mean annual precipitation (MAP) from 461 mm to 1033 mm during 1981–2020. The dominant cropping system is an irrigated winter wheat–summer maize double rotation, with wheat grown from October to June and maize from June to September.

Daily historical meteorological data, including maximum and minimum temperature, precipitation, sunshine duration, relative humidity, and wind speed, were obtained from 318 stations across the NCP for 1981–2014 from the China Meteorological Administration (<http://data.cma.cn>, accessed on 5 March 2024). Daily solar radiation required by the model was estimated from sunshine duration [31]. Future climate data (2015–2060) were derived from six global climate models (BCC\_CSM2\_MR, HadGEM3\_GC31\_LL, FGOALS-g3, IPSL\_CM6A\_LR, GFDL\_ESM4, and MIROC6) participating in the CMIP6 under the shared socio-economic pathway (SSP2-4.5) scenario [32,33]. SSP2-4.5 assumes intermediate anthropogenic radiation forces increases that closely aligns with current global policy trajectories [32,33]. The selected GCMs have demonstrated strong performance and are considered representative for projecting future climate conditions across China [32].

Soil data were obtained from the China Soil Scientific Database at ~1 km resolution, which was derived from over 7000 soil profiles. Variables included SOC content, total nitrogen content, bulk density, clay fraction, pH, and hydraulic properties (saturated water content, drained upper limit, and lower limit of plant-available water) for soil layers down to 2.5 m, which were required as key inputs to drive the APSIM model.

### 2.2. The APSIM Model

The Agricultural Production Systems sIMulator (APSIM) is a process-based model designed to simulate crop growth and soil biogeochemical processes under varying climate, soil, and management conditions [29]. Crop growth is simulated at a daily time step, with biomass accumulation determined by RUE and constrained by temperature, water, and nutrient availability. Soil organic carbon (SOC) decomposition is represented using first-order kinetics, regulated by soil temperature, moisture, and nutrient status. Carbon fluxes are coupled with nitrogen cycling through carbon-to-nitrogen ratios across soil pools. APSIM also allows explicit representation of management practices such as fertilization, irrigation, tillage, and residue management.

The performance of APSIM in simulating wheat and maize yields, as well as soil carbon and nitrogen dynamics, has been extensively validated across diverse environmental conditions [34,35]. Key cultivar parameters for wheat and maize, as well as key parameters related to SOC turnover and nitrogen transformations, have been previously calibrated and validated in the study region [27,36,37]. In this study, we adopted these calibrated parameters (Supplementary Tables S2 and S3) and further validated the APSIM model (version: 2023.3.7170.0) against observations from seven long-term field experiments in the NCP, including crop yields and SOC dynamics (Supplementary Figure S1; Supplementary Table S1). Although these long-term field experiments could not fully capture the vast spatial heterogeneity of the NCP, they were representative for model validation.

### 2.3. Hybrid Simulations Coupling APSIM and Machine Learning

To explore  $G \times E \times M$  interactions across the region, a hybrid modeling framework that combines APSIM simulations with machine-learning (ML) emulators was developed. We first constructed a comprehensive scenario space incorporating genotype traits, management practices, and soil and climate conditions across NCP croplands. Cultivar parameters were represented using three key parameters closely related to crop yields for both wheat and maize: RUE, grain size (GS), and grain number (GN) [34]. For wheat, RUE was set to range from 1.2 to 1.8 g MJ<sup>-1</sup>, GS from 0.04 to 0.06 g, and GN from 20 to 32 grains g<sup>-1</sup>; for maize, RUE from 1.6 to 2.4 g MJ<sup>-1</sup>, GS from 0.2 to 0.4 g, and GN from 500 to 900 grains g<sup>-1</sup>.

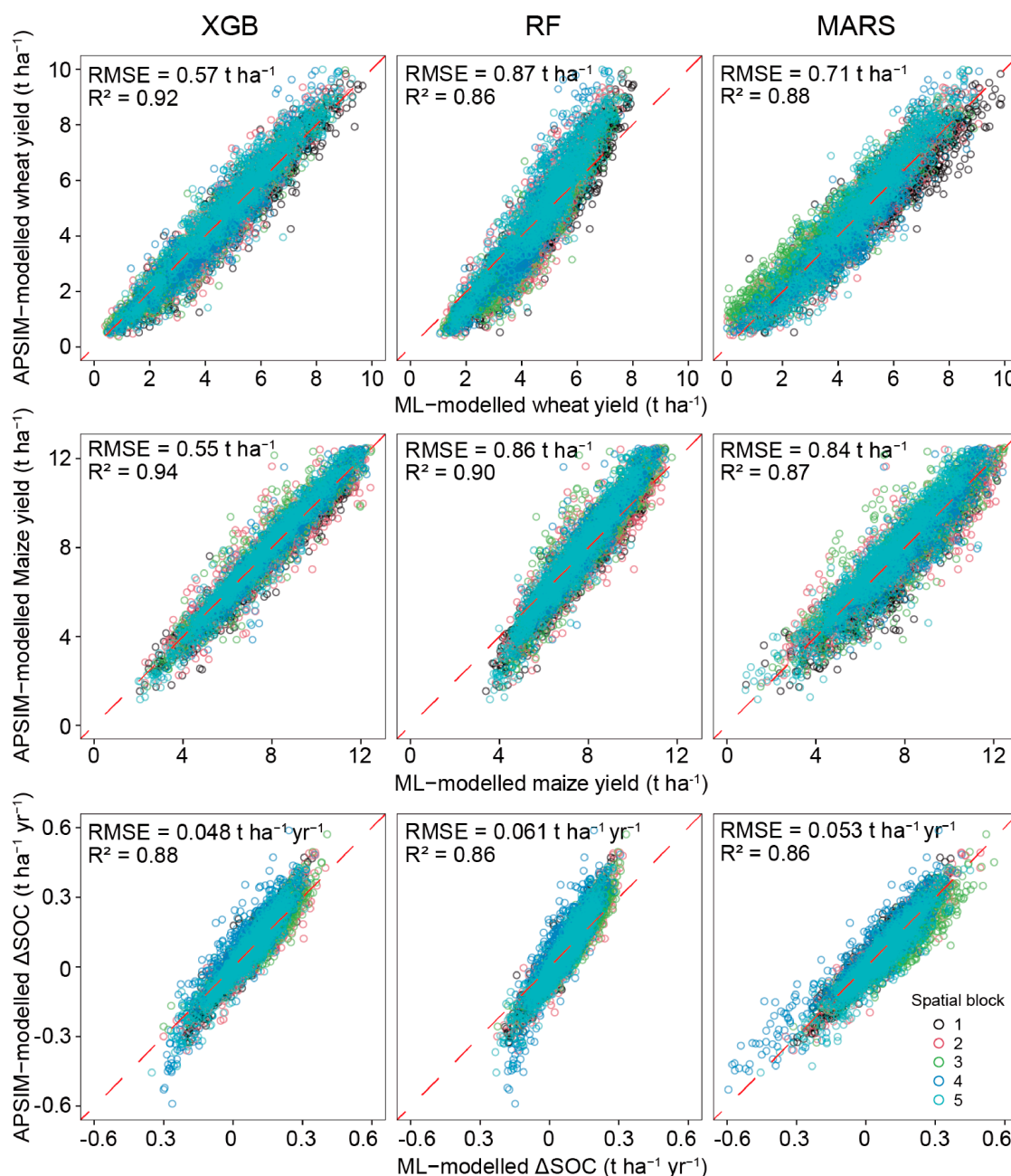
Management scenarios included nitrogen application rates from 0 to 300 kg N ha<sup>-1</sup> per season. For nitrogen inputs  $\leq 30$  kg ha<sup>-1</sup>, all fertilizers were applied at sowing; for higher inputs, 40% was applied basally and the remainder was applied during key growth stages (i.e., stem elongation for wheat and leaf development for maize). Irrigation scenarios ranged from rainfed conditions to multiple irrigation and automatic irrigation triggered by soil water deficits. Crop residue management varied from 0% to 100% removal or incorporation (0–0.3 m soil layer). Other nutrients (e.g., phosphorus and potassium) were assumed to be non-limiting throughout the simulation.

Due to the high computational cost of APSIM, 6000 sites (i.e., cropland grids across the NCP) were randomly sampled across the NCP together with randomly selected management practices, and thus generating 6000 APSIM simulation covering diverse soil, climate, management, and crop cultivars. The APSIM model was run at daily time step during the period 1981–2060, and crop yields and SOC (0–0.3 m) were output. These simulations were used to train ML emulators, including extreme gradient boosting (XGB), random forest (RF), and multivariate adaptive regression splines (MARS). Predictor variables included genotype traits represented by cultivar parameters, management practices, and environmental conditions (Supplementary Table S4). To confirm the ML emulators were not over-fitted, a 5-fold spatial cross-validation strategy using the R package *caret* 3.45 was performed for hyperparameter tuning of all three models [38]. Briefly, for the XGB model, the trees = 1000 and tree\_depth = 6; for the RF model, ntree = 1000, mtry = 5, nodesize = 3; for the MARS model, num\_terms = 25, prod\_degree = 2. The model performances were evaluated using root mean square error (RMSE) and coefficient of determination (R<sup>2</sup>).

### 2.4. Relative Importance and Interconnection of Variables

Using SHapley Additive exPlanations (SHAP) analysis based on the XGB model (the best among the three ML models (Figure 1)), the relative importance and potential non-linear relationships of the explanatory variables were explored. This approach quantified the marginal contributions of each variable and the additional contributions arising from pairwise variable interactions to the model predictions. Two key metrics were computed: (1) main effects: the mean absolute SHAP values representing the overall importance of

individual variables; (2) interactive effects: SHAP interaction values (top 20%) that quantify pairwise variable interactions.



**Figure 1.** Performance of three machine learning emulators. Comparison of APSIM-simulated versus ML-modeled values for wheat yield, maize yield, and  $\Delta$ SOC using XGB, RF, and MARS models. The five colored circles represent five spatial blocks for 5-fold spatial cross-validation, respectively (Supplementary Figure S2). Annotations show validation performance metrics. Red dashed lines represent the 1:1 line.

### 2.5. Simulation of RUE-Nitrogen Combined Scenarios

The selected ML emulator was used to quantify the effects of RUE under varying nitrogen inputs for both historical (1981–2020) and future (2021–2060) periods. RUE values were varied within  $\pm 20\%$  of baseline cultivar values ( $V_0$ ,  $1.5 \text{ g MJ}^{-1}$  for wheat and  $2.0 \text{ g MJ}^{-1}$  for maize), with increments of  $0.05 \text{ g MJ}^{-1}$ . Nitrogen inputs ranged from 60 to  $240 \text{ kg N ha}^{-1}$  per season at  $10 \text{ kg}$  increments. Residue was assumed to be 100% retained and fully incorporated into 0–0.3 m depth, a conventional residue practice widely adopted

in the NCP to promote organic carbon inputs into the soil and therefore benefitting SOC [39]. Irrigation was non-limiting to minimize its impact on yield. Regional mean yields and  $\Delta$ SOC were calculated across all grid cells to assess the gross effects of RUE and nitrogen under different scenarios. In addition, non-linear relationships between the responses of crop yields and SOC to nitrogen inputs were quantified based on differences between baseline and modified RUE scenarios. Uncertainty in these responses of six GCMs was estimated using their standard deviation.

### 2.6. Estimation of Yield and SOC Benefits of RUE-Improved Cultivars

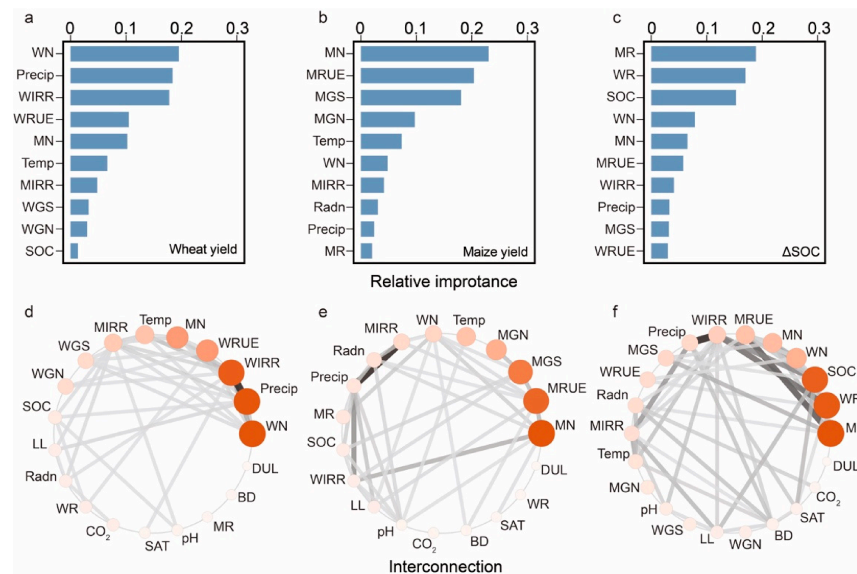
Two improved cultivars were defined relative to the baseline (V0): V1 (+10% RUE) and V2 (+20% RUE). Using the selected ML emulators, the 90% yield potential and corresponding  $\Delta$ SOC under minimum nitrogen inputs were estimated for each cultivar at each grid cell for both historical and future periods through a differential evolution algorithm [40] based on previous studies [27,41]. Residue was assumed to be fully incorporated into 0–0.3 m depth according to a conventional residue practice and nitrogen application and irrigation were non-limiting to achieve the yield target. The 90% yield threshold was adopted to reflect realistic field conditions, acknowledging constraints such as pests, diseases, and suboptimal management. Model outputs were compared with literature-derived yield and SOC data (Supplementary Table S5). Spatial differences in yield and SOC between improved and baseline cultivars were then quantified across the NCP.

## 3. Results

### 3.1. Model Performance and Variable Importance

The calibrated APSIM model accurately reproduced crop yields, explaining 73% of the variance in wheat and 74% in maize across seven long-term field experiments in the NCP (Supplementary Figure S1). SOC dynamics were also well simulated ( $R^2 = 0.80$ ; Supplementary Figure S1). Using APSIM outputs from 6000 randomly sampled cultivar–climate–soil management scenarios, three machine learning (ML) models—MARS, RF, and XGB—were trained to emulate APSIM-predicted wheat yield, maize yield, and  $\Delta$ SOC. Model performance differed substantially in the spatial five-fold cross-validation (Figure 1; Supplementary Figure S2). XGB model outperformed the others, explaining >92%, >94%, and >88% of the variance in wheat yield, maize yield, and  $\Delta$ SOC, respectively (Figure 1). In comparison, the RF and MARS models yielded inferior results, with RF accounting for >86%, >90%, and >86%, and MARS accounting for >88%, >87%, and >86% of the variance for the three respective response variables (Figure 1). Given its superior performance, XGB model was used for subsequent analyses.

Analysis of variable importance and interconnection (Figure 2) revealed the contributions of distinct drivers and their interactions to the explained variance of yields and SOC changes. For wheat yield, although RUE was the most important genotype variable, management (e.g., nitrogen inputs) and climatic variables (e.g., precipitation) dominated predictions (Figure 2a). For maize, RUE ranked second following nitrogen inputs, contributing about 20% to the explained variance (Figure 2b). Except their individual contributions, the RUE–nitrogen interaction also significantly contributed to variance in wheat and maize yields (Figure 2d,e). For  $\Delta$ SOC, initial SOC, residue retention, and nitrogen inputs were the main drivers, with genotype variables contributed 11% to the explained variance (Figure 2c). Moreover, strong interactions were observed for RUE–nitrogen and RUE–residue (Figure 2f). These results highlighted the critical effects of RUE and its interactions with management practices on crop yields and  $\Delta$ SOC.



**Figure 2.** Relative importance and interconnections of variables for predicting wheat yield, maize yield, and  $\Delta$ SOC based on the XGB model. Relative importance for (a) wheat yield, (b) maize yield, and (c)  $\Delta$ SOC; interconnections of variables for (d) wheat yield, (e) maize yield, and (f)  $\Delta$ SOC. Abbreviations: WRUE and MRUE, radiation-use efficiency for wheat and maize; WGS and MGS, grain size for wheat and maize; WGN and MGN, grain number for wheat and maize; Precip, precipitation; Temp, temperature; Radn, radiation; SOC, initial soil organic carbon; WN and MN, nitrogen input for wheat and maize; WIRR and MIRR, irrigation for wheat and maize; WR and MR, residue retention for wheat and maize.

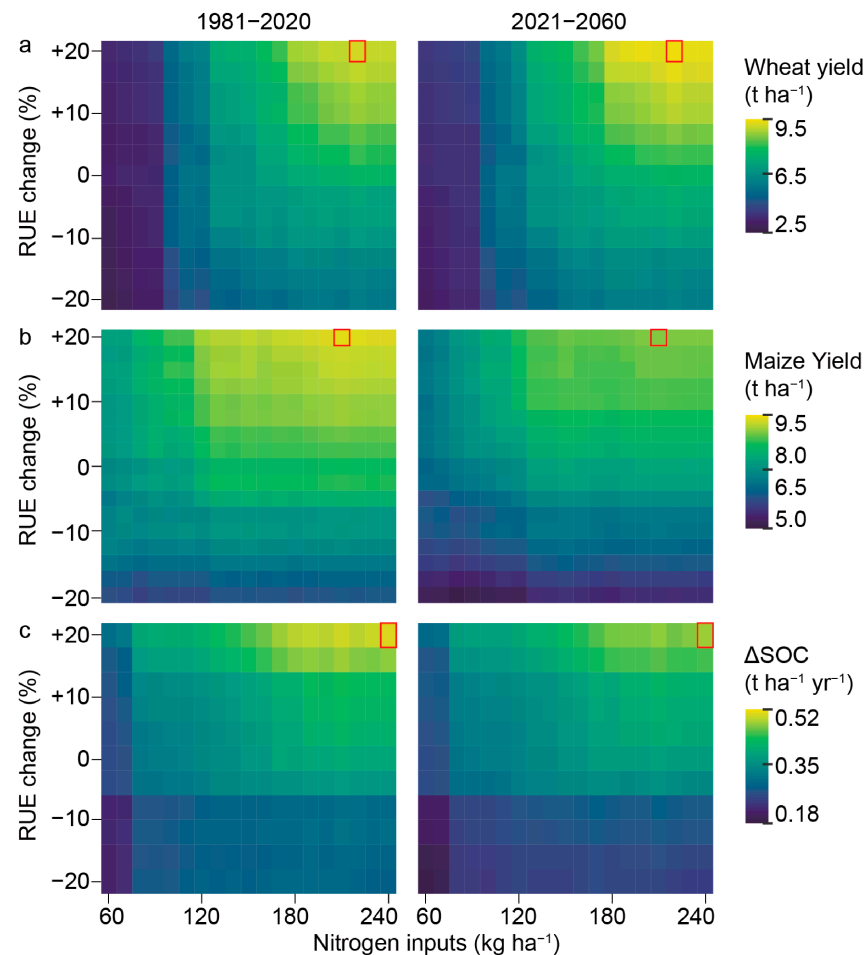
### 3.2. Effects of RUE on Crop Yields and SOC Across the NCP

Simulated yields and  $\Delta$ SOC varied with RUE and nitrogen input (Figure 3). Maximum yields for wheat and maize were achieved at the highest RUE ( $1.8 \text{ g MJ}^{-1}$  for wheat;  $2.4 \text{ g MJ}^{-1}$  for maize) and nitrogen inputs of  $220$  and  $210 \text{ kg N ha}^{-1}$ , respectively (Figure 3a,b). Maximum wheat yields increased from  $9.1 \text{ t ha}^{-1}$  in the historical period to  $9.4 \text{ t ha}^{-1}$  in the future period (Figure 3a,b). In contrast, maximum maize yields declined from  $9.4 \text{ t ha}^{-1}$  in the historical period to  $8.9 \text{ t ha}^{-1}$  in the future period (Figure 3a,b), driven by intensified heat stress during the maize growing season under future warming. Maximum  $\Delta$ SOC was  $0.51 \text{ t ha}^{-1} \text{ yr}^{-1}$  in the historical period and  $0.48 \text{ t ha}^{-1} \text{ yr}^{-1}$  in the future period, achieved at the highest RUE and nitrogen inputs (Figure 3c). Although improved RUE consistently increased yields, its benefits were nitrogen-dependent (Figure 4a,b). Additional yield gains peaked near  $220 \text{ kg N ha}^{-1}$  for wheat and  $210 \text{ kg N ha}^{-1}$  for maize, ranging at  $0.6$ – $3.7 \text{ t ha}^{-1}$  for wheat and  $1.5$ – $3.2 \text{ t ha}^{-1}$  for maize (Figure 4a,b). Notably, maize benefited more than wheat at low nitrogen but less at high nitrogen (Figure 4a,b). Additional SOC gains ( $0.1$ – $0.23 \text{ t ha}^{-1}$ ) increased steadily with nitrogen, with higher benefits projected under future climate conditions (Figure 4c).

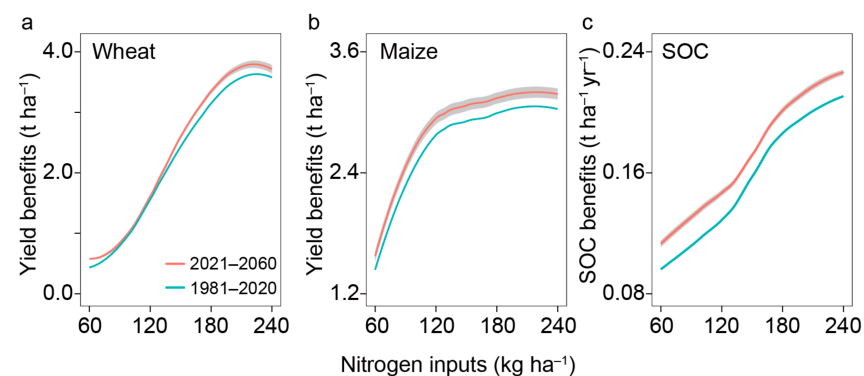
### 3.3. Yield and SOC Benefits of RUE-Improved Cultivars Across the NCP

The 90% maximum yield potential was estimated for the current cultivar (V0) and RUE-improved cultivars (V1: +10% RUE; V2: +20% RUE). During 1981–2020, V0 wheat and maize yields averaged  $6.5 \text{ t ha}^{-1}$  ( $5.8$ – $7.2 \text{ t ha}^{-1}$ ) and  $8.0 \text{ t ha}^{-1}$  ( $7.5$ – $8.4 \text{ t ha}^{-1}$ ), respectively, generally in line with field observations under no limitations of water and nutrients (Supplementary Table S5; Figure 5a,b). During 2021–2060, wheat V0 yield increased to  $7.0 \text{ t ha}^{-1}$ , whereas maize V0 declined to  $7.6 \text{ t ha}^{-1}$  (Figure 5a,b). Spatially, wheat yield benefits were significantly greater at lower latitudes, especially in the historical period (Figure 6a). Relative to V0, V1 and V2 wheat yields increased by  $1.0 \text{ t ha}^{-1}$  (15.7%) and

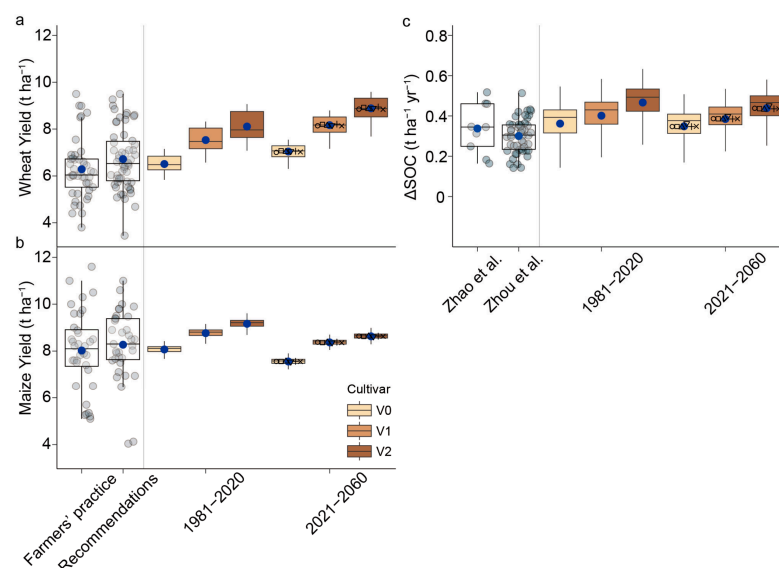
1.6 t ha<sup>-1</sup> (24.6%) in the historical period, respectively, and increased by 1.1 t ha<sup>-1</sup> (16.0%) and 1.8 t ha<sup>-1</sup> (26.2%) in the future period, respectively (Figure 7a). In contrast, maize yield benefits were universal across the NCP (Figure 6b). Besides, maize yield benefits were smaller: +0.7 t ha<sup>-1</sup> (8.6%) for V1 and +1.1 t ha<sup>-1</sup> (13.6%) for V2 in the historical period, and +0.8 t ha<sup>-1</sup> (10.8%) for V1 and +1.1 t ha<sup>-1</sup> (14.2%) for V2 in the future period, with V2 benefits remaining consistent across periods (Figure 7b).



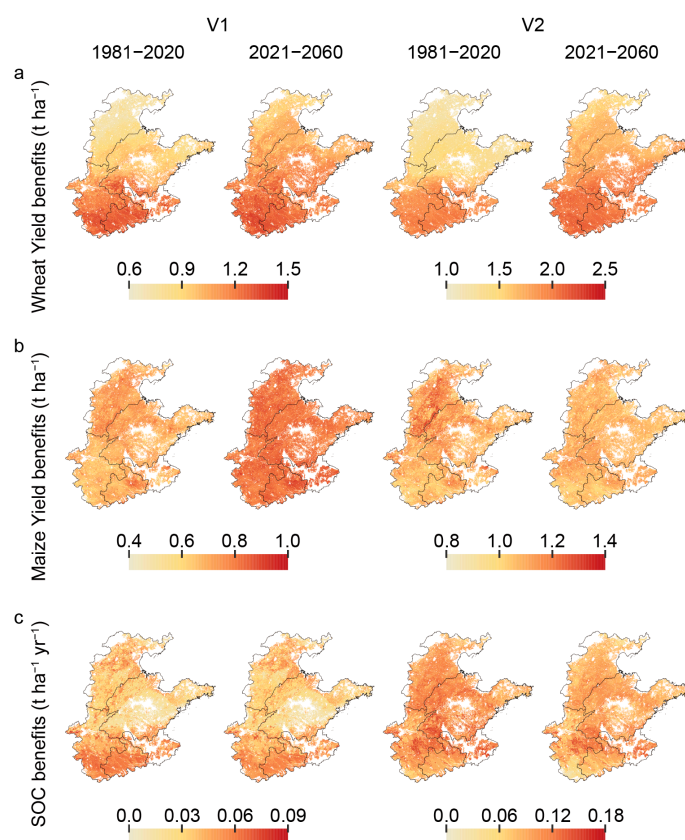
**Figure 3.** Simulated average crop yields and  $\Delta$ SOC across the North China Plain under combined RUE and nitrogen input scenarios. (a) Wheat yield, (b) maize yield, and (c)  $\Delta$ SOC. Red squares indicate maximum yields and  $\Delta$ SOC.



**Figure 4.** Yield and SOC benefits induced by RUE improvement at each nitrogen input level during the historical and future period. (a) Wheat yield, (b) maize yield, and (c) SOC. The benefits are calculated as the difference between  $\pm 20\%$  RUE relative to the current cultivar. The gray shaded area in the future period indicates the standard deviation of six GCMs.

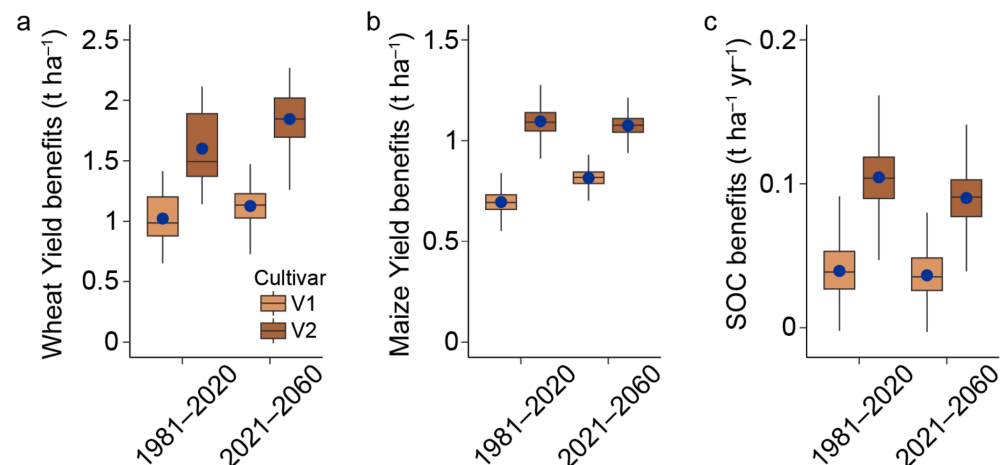


**Figure 5.** Distribution of 90% maximum yields and  $\Delta$ SOC for three wheat and maize cultivars across the North China Plain. (a) Wheat yield, (b) maize yield, and (c)  $\Delta$ SOC. Yield projections are compared with local farmers' reported yields and field trial recommendations by Xiao et al. [41], while  $\Delta$ SOC projections are compared with empirical  $\Delta$ SOC from Zhao et al. [17] and Zhou et al. [42] (Supplementary Table S5). V0, V1, and V2 represent the current cultivar, cultivar with 10% improved RUE, and cultivar with 20% improved RUE, respectively. Boxplots show the median and interquartile range, with whiskers extending to  $1.5\times$  the interquartile range. Solid blue circles indicate mean values; other symbols show the projected average under each GCM.



**Figure 6.** Spatial pattern of yield and SOC benefits of RUE-improved cultivars relative to the current cultivar across the North China Plain. (a) Wheat yield, (b) maize yield, and (c) SOC. V1 and V2 represent cultivars with 10% and 20% improved RUE, respectively. The value of each grid cell in the future period shows the ensemble mean of six GCMs.

RUE-improved cultivars also enhanced SOC sequestration. For V0, historical  $\Delta$ SOC (0–0.3 m) averaged  $0.36 \text{ t ha}^{-1} \text{ yr}^{-1}$  (max  $0.55 \text{ t ha}^{-1} \text{ yr}^{-1}$ ), aligning with field observations (Supplementary Table S5; Figure 5c). Future  $\Delta$ SOC for V0 slightly decreased to  $0.35 \text{ t ha}^{-1} \text{ yr}^{-1}$  (max  $0.51 \text{ t ha}^{-1} \text{ yr}^{-1}$ ) (Figure 5c). Relative to V0, V1 and V2 enhanced  $\Delta$ SOC to  $0.40 \text{ t ha}^{-1} \text{ yr}^{-1}$  (10.8% max  $0.58 \text{ t ha}^{-1} \text{ yr}^{-1}$ ) and  $0.47 \text{ t ha}^{-1} \text{ yr}^{-1}$  (28.9% max  $0.63 \text{ t ha}^{-1} \text{ yr}^{-1}$ ) historically, and  $0.39 \text{ t ha}^{-1} \text{ yr}^{-1}$  (10.3% max  $0.53 \text{ t ha}^{-1} \text{ yr}^{-1}$ ) and  $0.44 \text{ t ha}^{-1} \text{ yr}^{-1}$  (25.9% max  $0.58 \text{ t ha}^{-1} \text{ yr}^{-1}$ ) in the future, respectively (Figures 5c and 7c). Spatially, the SOC benefits of V1 were smaller at mid-to-high latitudes, whereas those of V2 were more evenly distributed (Figure 6c).



**Figure 7.** Distribution of yield and SOC benefits of RUE-improved cultivars relative to the current cultivar across the North China Plain. (a) Wheat yield, (b) maize yield, and (c) SOC. V1 and V2 represent cultivars with 10% and 20% improved RUE, respectively. Boxplots show the median and interquartile range, with whiskers extending to  $1.5\times$  the interquartile range. Solid blue circles indicate mean values.

#### 4. Discussion

Our study demonstrates that coupling APSIM with machine learning can effectively capture  $G \times E \times M$  interactions of new cultivars at the regional scale (Figures 1 and 2). Advances in gene editing now enable the development of cultivars with enhanced radiation, nitrogen, and water-use efficiency [4,43,44]. However, adoption and scaling of these cultivars involve substantial economic and practical costs. By integrating modeling approaches that account for  $G \times E \times M$  interactions, cultivar performance under diverse climatic, edaphic, and management conditions can be evaluated efficiently, guiding development and deployment decisions. Despite these advances, key genotypes related to tolerance of extreme climate events, such as heat and waterlogging, remain underrepresented in current agricultural system models. For instance, waterlogging can reduce yields by approximately one-third, with effects varying by crop species and environmental context [45]. In the absence of extreme climate effects, the yield benefits of improved RUE in this study might be overestimated (Figures 6 and 7). Therefore, expanding model representation to include such traits, through robust parameterization and integration of diverse genotypes, is essential [46]. Achieving this will require coordinated efforts across agriculture, genetics, biology, robotics, computer science, and engineering disciplines.

Our results show that the projected yields are slightly lower than field observations under recommended management practices, with deviations within  $0.3 \text{ t ha}^{-1}$  for both crops (Figure 5). Such discrepancy is expected, as our projection represents the 90% yield potential rather than maximum yield potential. In contrast, the projected  $\Delta$ SOC is higher than field observations, exceeding Zhao et al. [17] by  $0.02 \text{ t ha}^{-1}$  and Zhou et al. [42] by

0.06 t ha<sup>-1</sup>. This bias could be partly explained by our assumption of 100% residue retention in the projections, whereas actual rates are 60–80% [37]. It should also be noted that our  $\Delta$ SOC analysis is restricted to the topsoil (Figure 5). Compared to topsoil SOC, subsoil SOC could respond differently to management practices and climate changes [20,47]. However, long-term observational data for subsoil SOC remain scarce in the study region, and the representation of subsoil processes—such as deep rooting—remains poorly validated in most biophysical models [48].

Our results indicate that improving RUE enhances both crop yields and SOC sequestration (Figures 3–5). RUE-improved cultivars (Supplementary Table S2) could substantially alleviate food security pressures while contributing to soil carbon sequestration, thereby supporting sustainable agriculture goals, including yield stability and environmental quality [49,50]. The benefits of RUE, however, are strongly nitrogen-dependent (Figures 3 and 4). Photosynthetic capacity relies on a complex protein system that constitutes the majority of leaf nitrogen, explaining the need for adequate nitrogen inputs in high-yield crops [51]. While theoretical calculations suggest that doubling global crop production requires at least a 50% increase in RUE [7], the relative gains of RUE enhancements diminish at higher RUE levels (Figure 6) and are modulated by environmental conditions and management practices [52]. Optimizing management to match cultivar traits remains a key challenge. For example, deeper-rooted cultivars can enhance resource uptake and minimize nutrient losses, but require precise sowing depth and timing [48,53]. Adjusting growing periods and cultivar selection to local climate remains central to adaptive crop management [54].

Our analysis highlights that RUE benefits vary across spatial and temporal scales (Figure 6). Regionally heterogeneous climate change [32] necessitates long-term evaluation to identify suitable areas for cultivar deployment. In low-latitude regions, warming combined with increased precipitation may favor cultivars tolerant to heat and waterlogging [55]. In contrast, high-latitude regions may benefit from conventional cultivars, with limited advantages from heat-tolerant cultivars [56]. In North China, frequent heat stress has already caused significant yield losses, with precipitation amount and distribution being key yield-limiting factors [57,58]. As climate change progresses, region-specific trends must guide breeding programs [59]. Continuous cultivar renewal, shifts in cultivation areas, and optimized management are therefore critical [60,61]. Our modeling framework offers a practical tool to support these decisions, complementing governmental breeding, research, and extension programs.

While our framework advances the modeling of  $G \times E \times M$  interactions, several limitations remain. First, process-based models like APSIM capture key biophysical processes but reflect an incomplete understanding of mechanisms, particularly root architecture and function, which strongly influence SOC inputs, water uptake, and nutrient acquisition [48]. Assumptions in scenario simulations are unavoidable but reduce realism. Long-term monitoring, including three-dimensional root and soil data, is needed to facilitate realistic modeling [53]. Second, rapid advances in gene-editing and functional genomics are generating cultivars with new traits [4]. Agricultural system models must evolve to represent these genotypes accurately, and model-informed cultivar design should remain aligned with feasible breeding strategies. Finally, while this study simulated  $G \times E \times M$  interactions under climate change, extreme events were not explicitly considered. These events—heatwaves, droughts, or waterlogging—can profoundly affect cultivar performance. Incorporating extreme event impacts will be essential for realistic modeling and robust assessment of new cultivars under future climates [62].

## 5. Conclusions

Our study demonstrates that coupling process-based crop models with machine learning provides a feasible framework to evaluate genotype–environment–management interactions across large regions. By simulating RUE-improved wheat and maize cultivars under diverse nitrogen inputs and climate scenarios, we show that enhancing RUE could benefit both crop yields and soil carbon sequestration, supporting food security and sustainable agriculture goals. These benefits are context-dependent, varying with nitrogen availability and spatial–temporal climate heterogeneity. Low-latitude regions across the NCP show the greatest yield and SOC gains, while high-latitude areas experience more moderate improvements. These findings highlight the importance of aligning breeding strategies with local environmental conditions and adaptive management practices, including fertilizer application and cultivar selection. Despite model limitations—particularly regarding extreme climate events, dynamic root architecture and complex realistic conditions—our framework offers a practical tool to guide cultivar development, deployment, and policy support for sustainable agriculture. Overall, RUE-focused breeding, combined with informed management, represents a promising pathway to sustainably intensify crop production while mitigating climate impacts.

**Supplementary Materials:** The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/agriculture16151624/s1>. Figure S1: Study region and model evaluation; Figure S2: Spatial blocks for 5-fold cross-validation; Figure S3: Spatial pattern of crop yields and  $\Delta$ SOC during 1981–2020; Figure S4: Spatial pattern of crop yields and  $\Delta$ SOC during 2021–2060; Figure S5: Distribution of  $\Delta$ SOC for three cultivars under 50% and 75% residue retention across the North China Plain; Table S1: Overview of seven long-term field trials; Table S2: Genotype parameters for V0, V1, and V2 in APSIM; Table S3: Optimized key parameters related to SOC turnover in APSIM; Table S4: Input features used in XGB model; Table S5: Average crop yields and  $\Delta$ SOC based on literature-derived results; Table S6: Spatial 5-fold cross-validation performance of XGB. Refs. [17,41,42,63–69] are cited in the Supplementary Materials.

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