








Research article

Optimizing cereal yields in Morocco's Favorable agro-ecological zone: Integrating dynamic vegetation modeling, machine learning, and climate projections for adaptive agricultural strategies

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ABSTRACT

Climate change poses significant challenges to cereal crop productivity, highlighting the urgent need for effective adaptation strategies to ensure agricultural sustainability. This study investigates the impact of sowing dates on the yields of soft wheat, durum wheat, and barley in Morocco's Favorable agro-ecological zone, a region of critical national food security importance, under changing climate conditions from 2024 to 2099. Utilizing the CARAIB dynamic vegetation model, Random Forest machine learning, and high-resolution regional climate projections from the Euro-CORDEX initiative, this study provides a robust framework for evidence-based adaptation planning. December sowing dates were identified as the most favorable, producing consistent yield increases of up to 15% compared to the 30 October baseline, while late January and early September sowing dates resulted in significant yield reductions of up to 32%. The study also highlights a shift in optimum sowing dates from November to late December over the century, reflecting the need to align planting schedules with changing climatic conditions. Additionally, average growth cycles for wheat and barley are projected to shorten by 2099, suggesting accelerated phenological development driven by rising temperatures, thereby emphasizing the need for the development of heat- and drought-tolerant varieties with adapted growth durations. Despite this shortening, yield increases under optimal sowing dates result from improved synchronization of critical growth stages with periods of higher precipitation and lower thermal and water stress, particularly during grain filling. These findings provide a scientifically grounded basis for informing adaptation strategies and strengthening the resilience of cereal production systems under accelerating climate change.

1. Introduction

Climate change represents a significant threat to agricultural systems and food security worldwide [1]. In fact, rising temperatures, shifting precipitation patterns, and increasing frequency of extreme weather events are already disrupting agricultural productivity across many regions [2]. These impacts are particularly pronounced in regions like Morocco [3,4], especially in the country's Favorable agro-ecological zone, which represents one of the main cereal-producing regions, where the variability of rainfall and heightened sensitivity to drought increase the vulnerability of cereal crops [5,6]. Cereal crops, which are a staple food source globally and play a critical role in food security [7,8], are among the most affected because their growth and productivity

depend heavily on climatic conditions [9,10]. Indeed, cereal crops are central to Morocco's agricultural and economic landscape, occupying 59% of the country's cultivated area and contributing to the agriculture sector, which represents nearly 14% of the national economy, highlighting its critical role in economic growth [11]. Despite its economic significance, cereal crops in Morocco remain highly sensitive to environmental and climatic variations [6,12,13], necessitating effective strategies to maintain productivity [14].

To address the adverse effects of climate change on cereal productivity, various globally recognized adaptation strategies have been identified, as highlighted by the IPCC Sixth Assessment Report (AR6) [2]. These include developing drought- and heat-tolerant crop varieties [15], improved water management practices [16], and conservation

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agriculture practices [17], such as no-till farming [18,19], crop rotation [20], and organic matter management [21]. Adjusting planting dates is a crucial strategy to align cereal crop growth with favorable environmental conditions [22–24], and finally, enhancing on-farm diversity by integrating multiple cereal cultivars increases resilience against climatic uncertainties [25]. These adaptation strategies collectively offer a robust framework for sustaining cereal crop productivity in the face of climate change, and they provide a roadmap for enhancing cereal production resilience in Morocco. Among these, adjusting sowing dates has emerged as a particularly effective strategy to evaluate in our study in order to mitigate climate impacts on cereal yields, as it allows crops to better align with favorable growing conditions [23]. In fact, optimizing sowing dates has the potential to reduce exposure to heat stress during critical growth stages and improve water-use efficiency [26–28]. However, in practice, selecting an optimal sowing date remains challenging due to the current limitations in seasonal climate forecasting, and given the inherent uncertainties in predicting weather patterns, our recommendations are not intended for direct operational implementation but rather to highlight the need for drought-resistant and short-cycle cereal crop varieties that can better cope with climate variability.

This study focuses on evaluating sowing dates' impact on cereal crops, using a dynamic vegetation model (DVM). The CARAIB (CARbon Assimilation In the Biosphere) DVM [29,30] offers a robust framework for this analysis, as it simulates complex interactions between climatic variables, agronomic factors, and crop physiology. The CARAIB model has been validated for major cereal crops in Morocco, further establishing its reliability for assessing cereal productivity under varying climatic conditions [31]. When coupled with high-resolution regional climate models (RCMs), CARAIB provides a process-based framework to evaluate the combined effects of climate change and sowing date adjustments on cereal yields. This study applies the CARAIB DVM to evaluate the impacts of sowing dates on cereal yields in Morocco's Favorable agro-ecological zone within a long-term climate change context. In addition, this study uniquely combines CARAIB's simulation results with a machine learning approach [32] to analyze the simulated dataset in order to quantify the relative contribution of climatic variables and sowing dates to yield variability and identify key drivers of crop responses that remain robust across multiple climate projections. In this context, multiple regional climate models are used to assess how consistent the study's results are under different climate projections, rather than to identify a single best scenario [33]. This approach helps identify sowing dates, key climatic drivers, and crop growth responses that remain stable across models and are therefore more relevant for adaptation planning. In fact, climate projections generated by the RCMs are used as inputs to the CARAIB DVM, which simulates crop growth, yield responses, and water stress under different sowing dates and climatic conditions. The resulting simulation outputs provide a comprehensive dataset that is subsequently analyzed using the machine learning approach to identify the key drivers of yield variability and assess the robustness of sowing strategies across multiple climate projections.

Sowing dates have been extensively studied as a key factor in crop performance. As highlighted by Dadrasi et al. [34], this aspect has been analyzed globally providing valuable insights into its wide-ranging impacts. In fact, adjusting planting dates has been shown to mitigate the effects of extreme climate conditions, such as heatwaves and drought, and by shifting planting dates, farmers can avoid critical stress periods and synchronize crop development with favorable climatic conditions [35]. However, most existing studies of sowing dates' impact on cereals in Morocco focus on short-term projections or specific localized contexts. In Morocco, where cereals form the backbone of agricultural production [11], there is a notable gap in studies linking sowing date adjustments with climate projections and long-term yield outcomes, and by addressing these gaps, this study provides a comprehensive and forward-looking framework for enhancing cereal productivity in Morocco's Favorable zones under changing climatic conditions.

The primary objectives of this study are to evaluate the impacts of sowing dates on cereal yields and growth cycle duration under projected climate scenarios. Specifically, the study analyzes how different sowing dates influence the yields of major cereal crops using four regional climate models, identifies temporal trends from 2024 to 2099, and examines the combined effects of climatic variables (precipitation and temperature), water stress, and sowing dates on yield outcomes. In addition, the study aims to identify optimum sowing dates for maximizing cereal yields, and to assess how shifts in these dates affect crop growth cycle duration, the viability of existing cereal varieties, and the evolution of optimal sowing windows by the end of the century. While highlighting the importance of sowing date optimization for enhancing cereal productivity under future climate conditions, this study aims to support adaptive agricultural strategies, including the development of short-cycle and drought-resistant cereal varieties and the need for improved seasonal climate forecasting. Collectively, these objectives contribute to strengthening the resilience of cereal production systems under future climate conditions.

2. Materials and methods

2.1. Study area: Morocco's Favorable zone

The Favorable agro-ecological zone in Morocco [36], depicted in Fig. 1, has been selected as the focus area for this study due to its substantial contribution to the country's cereal production. This zone contributes significantly to Morocco's agricultural production, accounting for 53% of the country's soft wheat (*Triticum aestivum*), 41% of its durum wheat (*Triticum durum*), and 22% of its barley (*Hordeum vulgare*). Additionally, it encompasses extensive cultivation areas, covering 46% of Morocco's soft wheat area, 39% for durum wheat, and 17% for barley [6]. These significant shares highlight the zone's critical role in ensuring cereal production in Morocco, reinforcing its importance in sustaining Morocco's food security and agricultural economy.

2.2. CARAIB model and input data

The CARAIB (CARbon Assimilation In the Biosphere) model is a dynamic vegetation model designed to simulate the interaction between the vegetation and the global carbon cycle [29,30,37–39]. Its modular structure integrates key components such as soil hydrology [37,40], photosynthesis [41], carbon allocation for plant growth [42], and vegetation dynamics. To expand its applicability to agricultural systems, the model incorporates a crop module [43,44] that calculates crop yield based on net primary productivity and the harvest index [45]. This module employs a two-stage phenology model that simulates crop growth as a function of photosynthesis, constrained by heat accumulation through growing degree days, which are derived from daily temperature and a crop-specific base temperature threshold.

In this study, we used the same input datasets as our previous research [31], including comprehensive soil data [46], climatic inputs [47], crop specific parameters [6,44,48–51], and land use data [52]. Climatic inputs were extracted from four regional climate models (RCMs): KNMI-RACMO22E (KNMI), CLMcom-CLM-CCLM4–8–17 (CCLM4), CLMcomETH-COSMO-crCLIM (COSMO), and DMI-HIRHAM5 (HIRHAM). These models were selected from the Euro-CORDEX initiative because they provide a spatial resolution of $0.11^\circ \times 0.11^\circ$ (approximately 12.5 km), which is essential for capturing the spatial variability in climatic variables of Morocco's Favorable zone. Their selection also ensures the inclusion of different driving global climate models, thereby expanding the representation of climate uncertainty. In addition, these RCMs supply all variables required by the CARAIB DVM, including daily mean temperature, precipitation, solar radiation, relative humidity, wind speed, and daily temperature amplitude (Tmax-Tmin), for the full simulation period (2024–2099) under the RCP 8.5 scenario [53]. RCP 8.5 was selected as it represents a high-emission

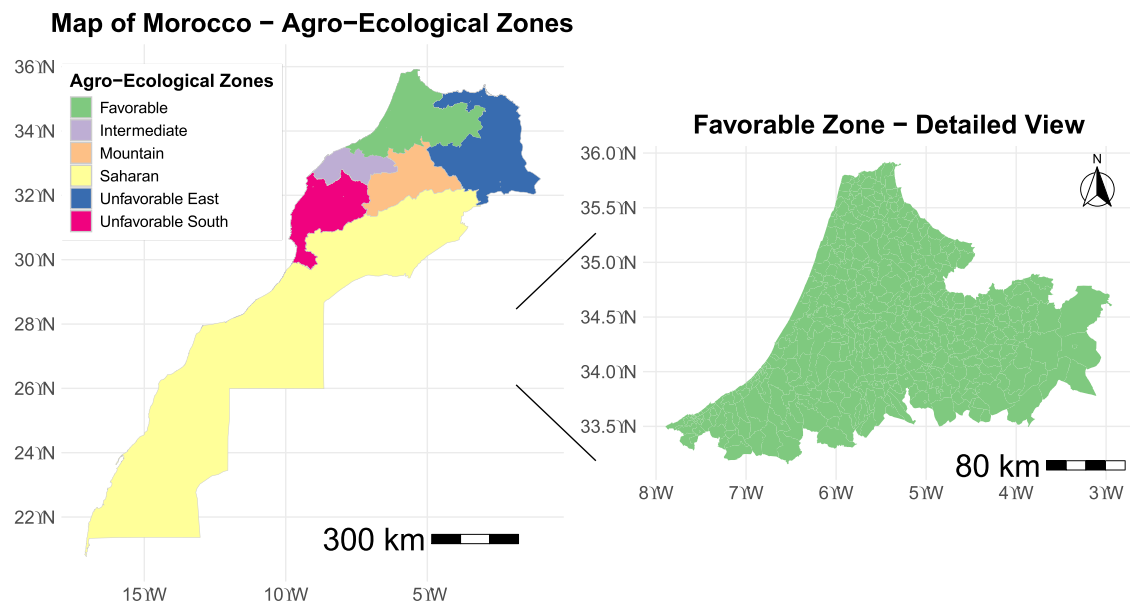


Fig. 1. Distribution of agro-ecological zones in Morocco, highlighting the Favorable Zone alongside other major zones: Intermediate, Mountain, Unfavorable East, Unfavorable South, and Saharan.

pathway, providing a conservative upper-bound assessment of potential climate impacts on cereal yields and allowing for a comprehensive evaluation of adaptation strategies under challenging future conditions.

A new methodological change in this study is the use of interpolated daily climate data, instead of the monthly inputs used in Loudiyi et al. [31]. Using daily input data provides a finer temporal representation of climatic variables, which allows the model to simulate phenological development and sowing date effects in accordance with its daily time-step structure.

The CARAIB model has been validated for soft wheat, durum wheat, and barley in Morocco's Favorable agro-ecological zone using observed yield data [54,55] for the period 2000–2016, excluding 2004 and 2006 due to missing data. In fact, validation results reported in Loudiyi et al. [31] demonstrate robust performance of the CARAIB model in this zone, with coefficient of determination (R^2) values of 0.74, 0.66, and 0.59 for barley, durum wheat, and soft wheat, respectively, and the corresponding root mean square error (RMSE) values are 0.20, 0.52, and 0.29 tonnes ha^{-1} , while normalized root mean square error (NRMSE) values range from 18.49% to 38.76% for all the crops. These validation metrics confirm the model's suitability for simulating cereal yield dynamics in Morocco's Favorable zone and provide a robust foundation for assessing the effects of sowing date variations under future climate scenarios.

For this study, simulations were conducted across a comprehensive range of sowing dates: 7 September, 17 September, 7 October, 17 October, 30 October, 6 November, 16 November, 6 December, 16 December, 26 December, 10 January, 20 January, and 30 January, that span from 2024 to 2099. These simulations were performed for each combination of crop and regional climate model to thoroughly evaluate the impact of sowing dates under varying climatic scenarios. The selected dates encompass a broad spectrum of potential sowing dates, enabling an in-depth assessment of crop responses to diverse environmental conditions and agronomic practices.

The growing degree days (GDD) method was employed to define the crops' growth period, aligning seamlessly with CARAIB's crop module, which simulates phenological stages based on heat accumulation. For each combination of sowing date, crop, and RCM, daily GDD values were calculated using a base temperature of $0^\circ C$ for cereals [56]. Cumulated GDD was tracked until crop-specific thresholds were reached: $2517^\circ C \cdot d$ for barley, $2485^\circ C \cdot d$ for soft wheat, and $2550^\circ C \cdot d$ for durum wheat. Once these thresholds were met, the corresponding

harvest date was determined, ensuring consistency with CARAIB's methodology for simulating crop phenology and yield under varying climatic conditions.

In addition, for each simulation, total precipitation and average temperature during the growth period (from sowing to harvest) were calculated using daily climatic inputs from the RCMs. These environmental metrics provided critical insights into the conditions experienced by the crops during their development, enabling a more nuanced understanding of the interactions between climatic variables and crop performance.

To analyze the impact of water availability on crop growth, we used potential evapotranspiration (PET) and actual evapotranspiration (AET) outputs from CARAIB's hydrological module [37,40] to calculate the Water Stress Ratio (WS) for each combination of crop, RCM, sowing date, and growth period.

Considering that Morocco's Favorable agro-ecological zone is a major cereal production region but remains exposed to periodic drought conditions, the inclusion of the water stress index allows for a more precise quantification of crop water deficits across different sowing dates and projected climatic conditions.

The WS was calculated using the formula: [57]

$$WS = (PET - AET) / PET \quad (1)$$

This Eq. (1) quantifies the water stress experienced by crops during their growing period. The WS index ranges from 0 to 1:

- A value of 0 indicates no water stress, meaning AET equals PET, reflecting optimal water conditions for crop growth.
- As the WS value increases towards 1, it indicates a progressively greater water deficit, with 1 representing maximum water stress, where no water is available for evapotranspiration.

This robust measure allows for the identification of periods of water scarcity, and by analyzing WS values across different sowing dates and scenarios, we can better assess how water availability impacts crop yield and resilience. This measure was specifically included to evaluate the severity of water stress under various sowing dates and climatic scenarios.

The use of WS is particularly relevant in countries like Morocco, where water scarcity is a critical factor affecting crop productivity [58].

Integrating WS with other variables such as temperature, precipitation, sowing date, and yield outcomes enables a comprehensive understanding of the factors driving crop performance. Ultimately, this analysis aims to identify strategies to mitigate water stress, optimize crop yields, and enhance resilience to future climatic challenges.

2.3. Statistical tests and trend analysis

2.3.1. Shapiro-Wilk test for normality

The Shapiro-Wilk test [59,60] examines whether data follow a normal distribution, a key assumption for many parametric analyses. In a normally distributed dataset, data points are symmetrically arranged around the mean, and this test assesses how well the data align with a normal distribution: a p-value below 0.05 suggests that the data are significantly different from a normal distribution, indicating non-normality. In the context of our study, this test is crucial for determining if yield data for each sowing date meet the normality assumption, thereby guiding the choice of appropriate analytical method and statistical test.

2.3.2. Levene's test for homogeneity of variances

Levene's test [61] assesses whether the variance across different groups of different sowing dates remains consistent. In fact, homogeneity of variances implies that the spread of data around the mean is similar across groups, an assumption required for parametric tests to maintain accuracy. A significant Levene's test result (p-value < 0.05) indicates that variances are heterogeneous, meaning they differ across groups, and suggests that parametric methods assuming equal variances may not provide accurate results.

2.3.3. Kruskal-Wallis test

The Kruskal-Wallis test [62,63] is a non-parametric alternative to ANOVA (analysis of variance) that compares the distributions of multiple groups without requiring normality or homogeneity of variances. Rather than comparing means, as ANOVA does, the Kruskal-Wallis test assesses the ranks of data, making it robust against outliers and unequal variances. In fact, this test is particularly valuable in our study, where we are comparing the impacts of different sowing dates on yield across various crop types and climate models, and where parametric assumptions may not hold due to climatic variability and environmental influences. The test outputs a Chi-squared statistic and a p-value; a p-value below 0.05 indicates significant differences among groups, suggesting that at least one sowing date yields a significantly different outcome compared to others.

2.3.4. Mann-Kendall test for trend analysis

The Mann-Kendall test [64,65] is a non-parametric test used to detect trends over time in a data series, independent of its distribution. It is especially useful in time series analysis, where trends may develop gradually due to external factors, and the test identifies if there is a statistically significant monotonic trend (either increasing or decreasing) within the data. The Mann-Kendall test calculates a Kendall's tau coefficient and a corresponding p-value, where a significant p-value (below 0.05) indicates a significant trend in the data over time.

Together, the Shapiro-Wilk, Levene's, Kruskal-Wallis, and Mann-Kendall tests provided a statistical characterization of the simulated yield data by assessing distributional properties, variance homogeneity, differences among sowing date groups, and temporal trends under the different climate projections. These analyses were used to compare yield responses across sowing dates and projected climatic conditions and to support the identification of sowing periods associated with more favorable yield outcomes.

2.4. Random Forest model

The Random Forest analysis [32] was applied to the dataset

generated from the CARAIB simulations driven by the RCM projections. These simulations produced yield responses, water stress indicator, and associated climatic variables under different sowing dates and climate scenarios, which together formed the input dataset used for the machine learning analysis to explore the relationships between these variables and crop yields. In this framework, the CARAIB simulations act as a data-generating process describing crop responses under different climatic and management conditions, while the Random Forest analysis is used to extract patterns and quantify the influence of predictors on yield variability. This Random Forest algorithm was chosen for its ability to handle nonlinear interactions and complex datasets, making it particularly well-suited for analyzing the interdependent environmental and agronomic variables in this study. Compared to other machine learning approaches, Random Forest offers greater interpretability through built-in variable importance metrics and partial dependence plots, which are central to the analytical objectives of this study. Furthermore, its ensemble structure, aggregating results from multiple decision trees, reduces the risk of overfitting while maintaining strong predictive performance across diverse climate and crop combinations.

To incorporate the temporal aspect of sowing dates, these were converted from categorical to numerical values (Julian day values), allowing the model to treat them as continuous variables and detect yield trends and patterns. A temporal data split was implemented to evaluate predictive performance, with 80% of the data (2024–2083) used for training and 20% (2084–2099) reserved for testing.

The Random Forest model was trained using precipitation, temperature, water stress, and sowing dates as predictors, with yield as the response variable. By aggregating results from 100 to 500 decision trees, the model mitigates overfitting and enhances robustness by leveraging an ensemble approach. Each tree was constructed from a bootstrap sample of the training data, and random subsets of predictors were considered at each split, reducing reliance on any single variable or pattern.

Model accuracy was assessed using RMSE, mean absolute error (MAE) [66], and the squared Pearson correlation coefficient (r^2). RMSE quantified the average prediction error, with lower values indicating more precise predictions. MAE provided additional insight by measuring the average absolute prediction error, while r^2 was used to quantify the strength of linear agreement between Random Forest predictions and DVM-simulated yields. Values closer to 1 indicate stronger agreement and higher predictive consistency between simulated and emulated outputs.

2.4.1. Hyperparameter optimization

To optimize model performance, a systematic grid search combined with 5-fold cross-validation [67] was employed to tune key hyperparameters:

- Mtry (number of predictors sampled at each split), tested at 1 and 2.
- Nodesize (minimum size of terminal nodes), varied at 1, 5, and 10 to control tree depth.
- Ntree (number of trees), evaluated at 100, 300, and 500 to ensure model stability.
- Maxnodes (maximum number of terminal nodes per tree), set at 10, 20, and 30.

The combination that minimized RMSE across validation folds was selected for the final model, ensuring both predictive accuracy and generalizability across different temporal splits.

2.4.2. Variable importance and partial dependence analysis

Variable importance was assessed using the increase in mean squared error (IncMSE%) when a predictor was randomly permuted. High IncMSE% values indicated significant predictive roles for variables, while lower values suggested minor contributions.

To gain further insights into predictor-response relationships, Partial

Dependence Plots (PDPs) were generated. PDPs illustrate the marginal effects of individual predictors on yield predictions, holding all other variables constant. Trends in the PDPs provided detailed insights:

- Increasing trends indicated positive associations with yield.
- Decreasing trends suggested negative impacts.
- Plateaus or non-linear patterns highlighted diminishing returns or complex interactions.

PDPs complemented variable importance scores by revealing nuanced relationships, enabling a deeper understanding of how each predictor influenced yield variability. This approach enhanced the interpretability of the Random Forest model, providing actionable insights into optimizing sowing practices and managing environmental challenges.

2.5. Evaluating changes in optimum sowing dates and growth cycles

This analysis aims to identify yield-maximizing sowing dates and assess changes in crop growth cycle length (the period from sowing to harvest) over time. To capture both localized trends and broader shifts across the century, a rolling five-year window approach was employed. This method accommodates year-to-year variability while revealing

longer-term trends in optimum planting schedules.

For each five-year window, average yields were calculated for all sowing dates using the simulated yield outputs generated by the CARAIB DVM across all crop and RCM combinations. The sowing date with the highest average yield was designated as the optimum sowing date, enabling the tracking of changes in these dates under evolving climate conditions. This approach provides valuable insights into adaptive planting strategies necessary for maintaining productivity in response to changing environmental factors. Furthermore, the average crop growth cycle length was calculated for each optimum sowing date. This metric offers a complementary perspective, highlighting how shifts in planting dates influence the overall duration of the crop's growth period. By examining both the timing of optimum planting and the associated growth cycles, this analysis provides a comprehensive understanding of how climate change may necessitate adjustments in sowing practices to sustain agricultural productivity.

3. Results

3.1. Effects of sowing dates on cereal yields with analysis of long-term trends (2024–2099)

The percentage yield differences for soft wheat, durum wheat, and

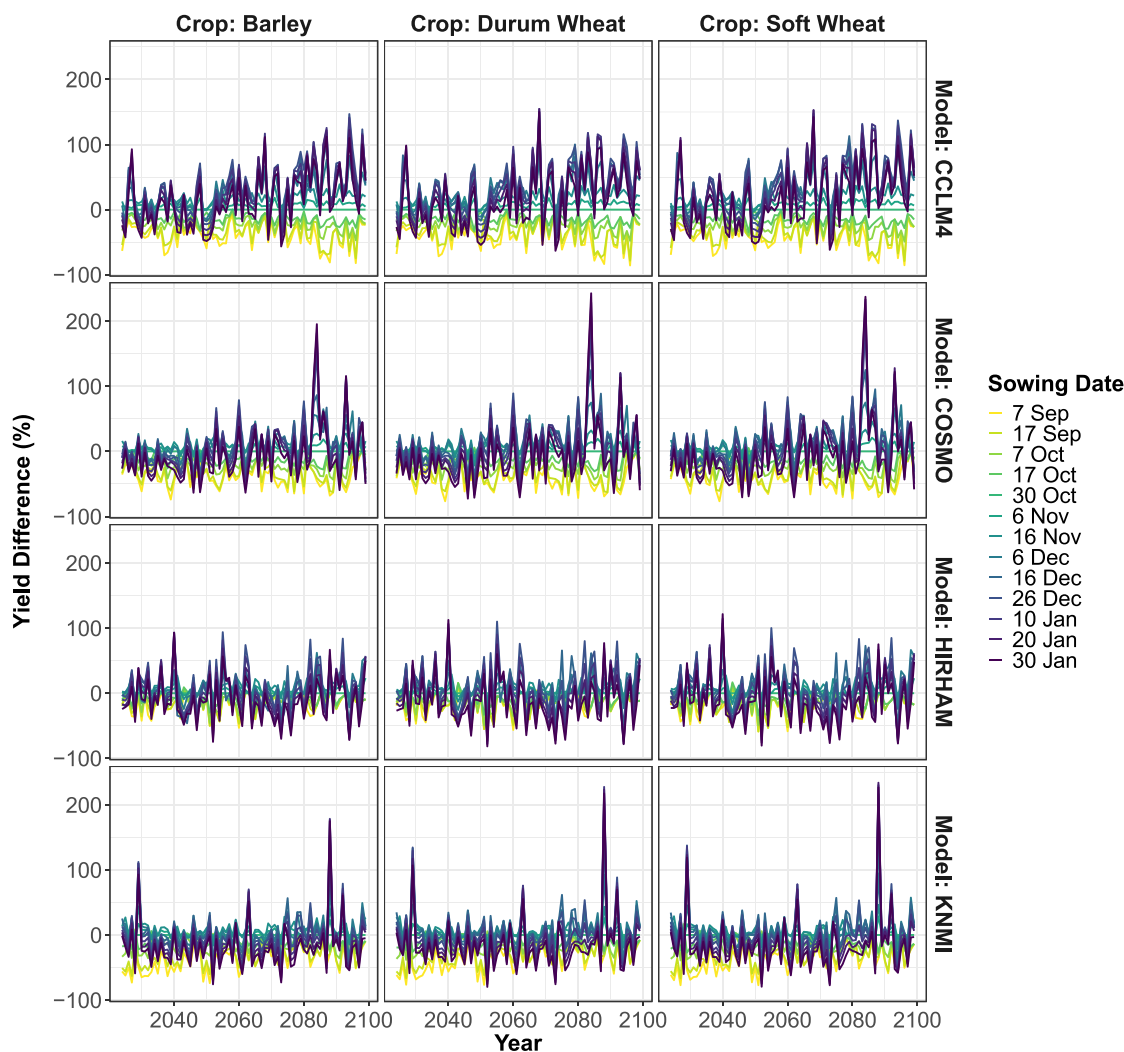


Fig. 2. Percentage yield differences for barley, durum wheat, and soft wheat across thirteen sowing dates (early September to late January) relative to the baseline sowing date (30 October), depicting yield deviations over time across climate models (CCLM4, COSMO, HIRHAM, KNMI) in Morocco’s Favorable zone under projected climate conditions.

barley across thirteen sowing dates, ranging from early September to late January, relative to the baseline date of 30 October are depicted in Fig. 2. The choice of 30 October as the baseline sowing date was due to its use in the CARAIB model's calibration and validation [31], providing a standardized reference against which all other sowing dates are compared. This analysis uses data from four RCMs (CCLM4, COSMO, HIRHAM, KNMI) spanning the years 2024–2099. Percentage yield differences were calculated annually, enabling the visualization of temporal trends and crop performance variations under diverse sowing dates and climatic scenarios.

Fig. 2 reveals marked variations in yield percentages relative to the baseline. Early sowing dates, particularly in September, consistently lead to negative yield differences, across all crops and RCMs. Later sowing dates generally yield higher percentages, with the COSMO and KNMI models exhibiting maximum differences, reaching up to 200% in the late 2080 s.

During the 2024–2040 period, September sowing dates result in significant yield reduction for all crops and models. Soft wheat experiences the most pronounced declines, with -39.86% for 7 September and -33.04% for 17 September. Durum wheat shows a similar trend, with reductions of -38.71% and -31.86% for the same dates, respectively. Barley shows average reductions of -37.65% and -31.25% for the 7 September and 17 September sowing dates, respectively. In contrast, sowing dates in November and December yield more stable or positive results. The 6 December sowing date produces positive average differences across all three crops and models, with soft wheat at 10.80% , durum wheat at 10.82% , and barley at 6.64% . January sowing dates yield mixed outcomes: the 10 January sowing date shows slight increases across crops and models, ranging from 1.84% to 2.67% for wheat, while the 30 January sowing date shifts to negative values, ranging from -11.46% to -9.87% .

In the later period, between 2080 and 2099, early September sowing dates continue to show negative deviations across all crops and models, though to a lesser extent than in the earlier period. For 7 September and 17 September, average yield differences range from -32.90% to -30.22% and -29.35% to -26.69% , respectively. Conversely, sowing dates in November and December yield notable positive differences. The 6 December sowing date yields increases between 23.02% and 28.43% , while the 16 December date produces gains ranging from 19.54% to 32.18% . Sowing dates in January maintain these positive trends, with the 10 January yielding averages between 25.87% and 29.89% and the 30 January date achieves gains between 11.51% and 13.82% across all crops and models.

Across the entire study period from 2024 to 2099, early September sowing dates continue to result in negative yield deviations. The 7 September shows average differences ranging from -33.85% to -31.33% , while the 17 September date ranges from -29.47% to -27.08% . In contrast, November and December sowing dates consistently yield positive results, with the 6 December date showing increases ranging from 12.18% to 16.45% and the 16 December date producing gains from 7.66% to 17.69% . January dates produce mixed outcomes, with the 10 January date resulting in positive differences across crops and models, ranging from 7.14% to 9.30% , while the 30 January date generally shows slight reductions, with averages ranging from -7.74% to -6.43% .

In summary, Fig. 2 underscores that early September sowing dates generally result in the most significant yield reductions, particularly on 7 September. Conversely, November and December sowing dates, especially mid-to-late December, consistently provide the highest yield benefits across crops and models. While early January dates offer some positive outcomes, the latest January dates (30 January) trend toward neutral or negative results. Across all climate models, a consistent response emerges despite differences in yield magnitude, with early September sowing remaining unfavorable, January sowing showing higher variability, and mid-to-late December sowing providing the most stable gains. This analysis highlights the importance of selecting mid-to-

late December sowing dates to optimize yields under future climate scenarios. The remaining differences between RCMs primarily reflect variations in their projected temperature and precipitation patterns, which influence the timing of crop development and water availability during the growing season.

Fig. 3 provides a boxplot visualization of yield distributions for soft wheat, durum wheat and barley across all thirteen sowing dates, spanning from early September to late January. The yields, projected from 2024 to 2099, are displayed for each combination of crop and model, to highlight both the variability and central tendencies in crop performance over the study period.

The sowing dates are arranged chronologically, allowing a straightforward comparison of yield outcomes as planting shifts progressively from September through January. Each boxplot represents the interquartile range (IQR) of yield values for a given sowing date, with the median yield clearly marked within the box. This approach effectively captures the spectrum of potential yield outcomes, with lower quartiles reflecting less favorable conditions and upper quartiles indicating higher yields under diverse climatic scenarios. Outliers are also represented, providing additional insight into extreme conditions or exceptional performances associated with specific sowing dates.

Fig. 3 also illustrates how yield distributions vary across sowing dates, providing insights into periods that consistently result in higher or lower yields across crop and model combinations. This detailed overview provides a clear perspective on yield resilience and variability associated with different sowing schedules, enhancing our understanding of the implications of sowing date choices on cereal crop productivity under projected future climate conditions.

The yield distributions in Fig. 3 reveal distinct patterns for soft wheat, durum wheat and barley. The KNMI model stands out for its higher variability and generally higher median yields across sowing dates. Early sowing dates in September (7 and 17 September) display narrower distributions with lower median yields for all crops and models, indicating limited variability but a consistent trend toward suboptimal yield outcomes. By October (7 and 17 October), yields exhibit a modest increase in both variability and median values, particularly for soft and durum wheat, while barley maintains relatively stable median values.

Mid-season sowing dates in November and December (6 November, 16 November, 6 December, and 16 December), are characterized by wider yield distributions and higher median yields across all crops. Soft wheat and durum wheat exhibit a broader range in yield distributions, while barley shows a noticeable spread with elevated median values, reflecting more diverse and favorable yield outcomes. Conversely, sowing dates in January (10 and 30 January) reveal a decline in variability and median yields. The 30 January date, in particular, exhibits the widest range of values coupled with the lowest medians, indicating less favorable conditions for crop productivity.

Fig. 3 indicates that sowing dates in September and January are associated with the lowest median yields and less stable outcomes. In contrast, November and December sowing dates result in higher median yields and broader variability across crops and models, with the KNMI model consistently highlighting these favorable outcomes.

To evaluate the statistical significance of yield differences across various sowing dates, we conducted a series of tests (normality and homogeneity of variance) to assess whether the assumptions for parametric analysis are met. Based on the results, a non-parametric approach was applied. Table 1 summarizes the outcomes of these tests, including normality, homogeneity of variance, and Kruskal-Wallis tests for soft wheat, durum wheat, and barley under four RCMs. This approach allowed us to determine whether sowing dates produced statistically significant variations in crop yields across different climatic scenarios.

The normality test (Shapiro-Wilk) p-values for all crop and climate model combinations were significantly below 0.05, providing strong evidence that yield residuals do not follow a normal distribution. Similarly, Levene's test for homogeneity of variance revealed significant

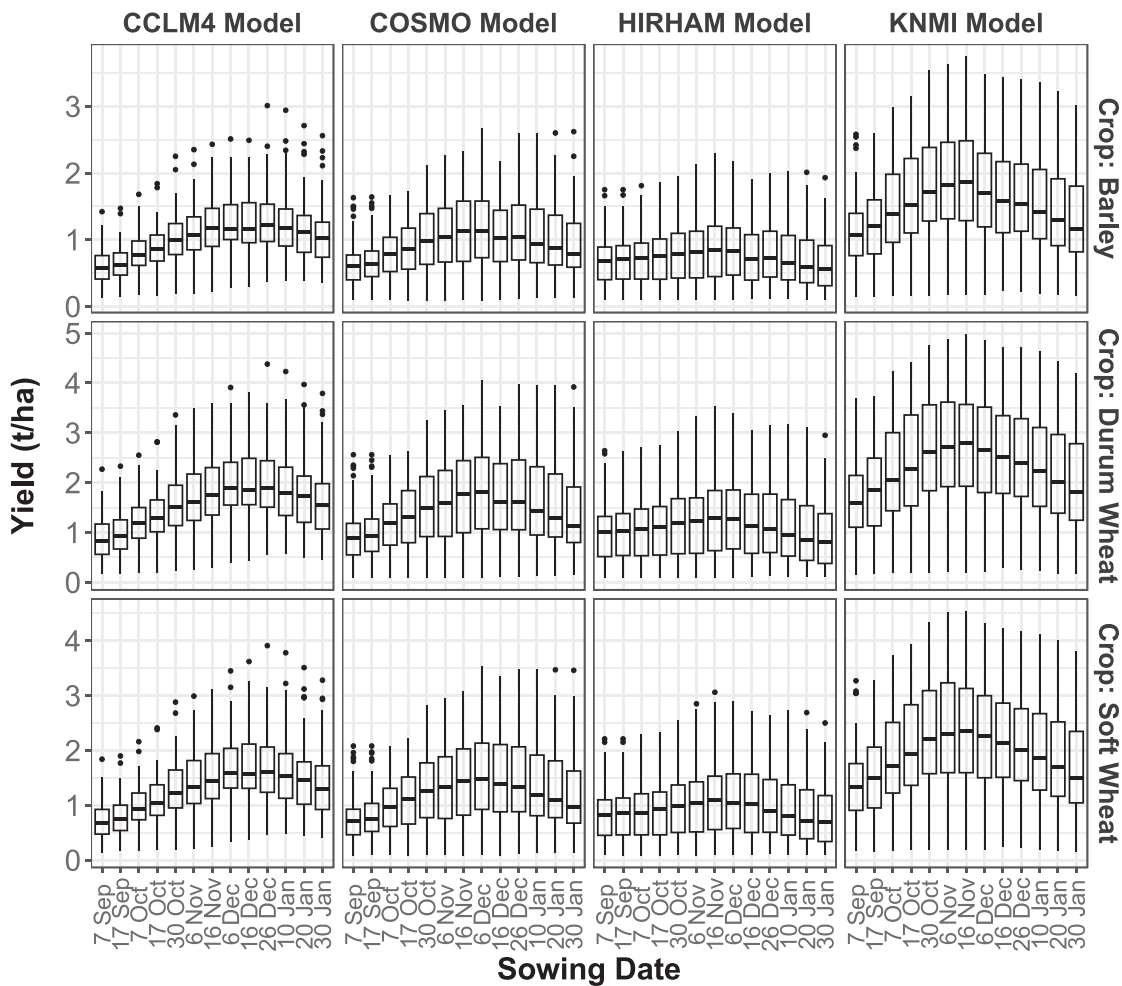


Fig. 3. Yield distributions (tonnes/hectare) for barley, durum wheat, and soft wheat under climate models CCLM4, COSMO, HIRHAM, and KNMI across thirteen sowing dates (from 7 September to 30 January), projected for 2024–2099 in Morocco's Favorable zone, showing variability and central tendencies in crop performance over time.

variance heterogeneity in most cases, with the exception of durum wheat under the KNMI model ($p\text{-value} = 0.0846$), for which the homogeneity of variance assumption was not violated. Overall, these results confirm widespread violations of the assumptions for parametric testing.

As a result, the Kruskal-Wallis test was employed to assess the significance of yield differences across sowing dates. The Chi-squared and p -values from this test indicated highly significant differences in median yields for nearly all crop and model combinations. For example, soft wheat under the CCLM4 model showed a substantial Chi-squared value of $2.63E+02$ and a p -value of $3.23E-49$, indicating that the differences in median yields across sowing dates are statistically significant.

Table 1 clearly illustrates that both normality and homogeneity of variance assumptions are not met in most scenarios, justifying the use of the Kruskal-Wallis test. The consistently significant results across all crop and model combinations underscore the critical impact of sowing dates on cereal crop yields, highlighting the importance of optimizing sowing timing to adapt to projected future climatic conditions and sustain productivity.

Fig. 4 presents the long-term yield trends for soft wheat, durum wheat, and barley across different sowing dates, showcasing how planting timings may influence productivity under projected climate scenarios. Yield trends are expressed as the rate of change in yield over time ($\text{tonnes}\cdot\text{ha}^{-1}\cdot\text{year}^{-1}$) for each crop and climate model combination from 2024 to 2099. Statistically significant trends, as determined by the

Mann-Kendall test ($p\text{-value} < 0.05$), are marked with black dots, enabling straightforward identification of sowing dates that consistently impact yield trends. This analysis provides critical insights into how shifts in sowing dates could affect yield outcomes over time, highlighting opportunities to enhance crop resilience and stabilize yields in a changing climate.

For early sowing dates (7–17 September), yield trends vary significantly across models. The CCLM4 model consistently shows negative slopes for all crops, indicating potential yield declines over time with early planting, ranging from -0.0059 to $-0.0032 \text{ tonnes}\cdot\text{ha}^{-1}\cdot\text{year}^{-1}$. Conversely, the KNMI model displays positive trends for early sowing, particularly for soft and durum wheat, showing upward slopes of 0.0129 and $0.0108 \text{ tonnes}\cdot\text{ha}^{-1}\cdot\text{year}^{-1}$, suggesting yield improvements. The COSMO and HIRHAM models exhibit minimal slopes near zero, indicating stable yields over time without marked increases or decreases for early planting.

Mid-season sowing dates (7 October to 16 November) produce more varied results. The CCLM4 model generally indicates slight declines, with slopes ranging from -0.0057 to $-0.0010 \text{ tonnes}\cdot\text{ha}^{-1}\cdot\text{year}^{-1}$. In contrast, the KNMI model maintains moderate positive slopes across all crops, with trends between 0.0002 and $0.0037 \text{ tonnes}\cdot\text{ha}^{-1}\cdot\text{year}^{-1}$, indicating gradual yield improvements. The COSMO and HIRHAM models remain largely stable, with negligible slopes across crops, suggesting limited yield variation over time for mid-season planting.

Late sowing dates (6 December to 30 January) demonstrate

Table 1

Statistical tests results for barley, durum wheat, and soft wheat across thirteen sowing dates (from 7 September to 30 January), under the climate models (CCLM4, COSMO, HIRHAM, and KNMI) in Morocco's Favorable zone, covering the period from 2024 to 2099, including Shapiro-Wilk test for normality, Levene's test for homogeneity of variances, and the Kruskal-Wallis test, highlighting variability and statistical significance of yield outcomes under projected climate scenarios.

Crop	Climate model	Normality test (p-value)	Homogeneity of variance test (p-value)	Kruskal Wallis chi squared	Kruskal Wallis p-value
Barley	CCLM4	1.90E-11	2.14E-08	2.48E+ 02	3.75E-46
	COSMO	9.85E-12	7.99E-08	1.02E+ 02	2.43E-16
	HIRHAM	1.35E-13	3.92E-02	2.24E+ 01	3.31E-02
	KNMI	1.60E-08	5.94E-03	9.18E+ 01	2.21E-14
Durum Wheat	CCLM4	5.28E-08	4.78E-08	2.44E+ 02	2.30E-45
	COSMO	3.54E-11	3.48E-08	1.02E+ 02	1.88E-16
	HIRHAM	1.47E-14	1.95E-02	2.34E+ 01	2.46E-02
	KNMI	5.39E-08	8.46E-02	9.15E+ 01	2.50E-14
Soft Wheat	CCLM4	1.36E-10	1.15E-09	2.63E+ 02	3.23E-49
	COSMO	1.44E-11	2.67E-09	1.13E+ 02	1.25E-18
	HIRHAM	7.44E-15	4.81E-03	2.71E+ 01	7.59E-03
	KNMI	3.86E-08	7.50E-03	9.58E+ 01	3.66E-15

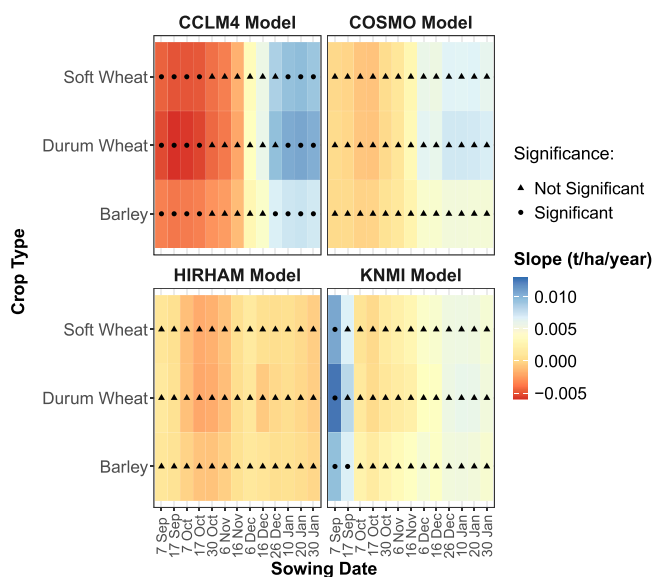


Fig. 4. Long-term yield trends (tonnes.ha⁻¹.year⁻¹) for barley, durum wheat, and soft wheat across various sowing dates under different climate models (CCLM4, COSMO, HIRHAM, and KNMI) in Morocco's Favorable zone, highlighting rates of yield change over time and statistically significant trends (Mann-Kendall test, p < 0.05).

predominantly positive yield trends, especially under the CCLM4 model, where all three crops display substantial upward slopes, ranging from 0.0027 to 0.0109 tonnes.ha⁻¹.year⁻¹, reflecting strong yield improvement over time. The KNMI model shows consistent positive trends for late sowing, with slopes between 0.0036 and 0.0059 tonnes.ha⁻¹.

year⁻¹. The COSMO model reflects yield increases for all crops, with slopes ranging from 0.0043 to 0.0073 tonnes.ha⁻¹.year⁻¹. In contrast, the HIRHAM model shows minimal yield change across late sowing dates, with slopes near zero, indicating stable trends over time.

The Mann-Kendall test results reinforce these findings, confirming the statistical significance of yield trends across different sowing dates and models. Under the CCLM4 model, early sowing dates in September show statistically significant negative trends for soft wheat, durum wheat, and barley (p-values from 0.001 to 0.04), indicating yield declines with early planting. Conversely, late December and January sowing dates exhibit significant positive trends, with p-values between 0.02 and 0.05, supporting strong yield improvements with later planting.

The KNMI model shows occasional significance in early September for positive trends for barley and soft wheat, with p-values below 0.004, suggesting potential benefits of early planting. Meanwhile, COSMO and HIRHAM models display predominantly non-significant p-values across all dates, indicating stable yield trends without pronounced directional changes over time.

Overall, these findings underscore model-dependent yield responses to sowing dates. In fact, the CCLM4 model shows pronounced trends, with negative slopes for early sowing dates and positive slopes for late dates across all crops, suggesting that late sowing dates in December and January maximize yield potential. The KNMI model favors both early and late sowing dates, particularly benefiting durum and soft wheat. In contrast, the HIRHAM model projects stable yields irrespective of sowing timing, while the COSMO model shows positive trends for December and January sowing dates for soft and durum wheat, though these trends are not statistically significant. These findings underscore the potential benefits of adjusting sowing dates towards late December and early January to optimize yields and enhance crop resilience under future climate conditions.

While Section 3.1 identified the sowing dates associated with favorable or unfavorable yield responses, the mechanisms driving these patterns require further exploration. Section 3.2 therefore analyzes the relationships between cereal yields and key environmental drivers across the different sowing dates.

3.2. Influence of climatic variables and water stress on cereal yields across sowing dates

Building on the initial analysis of sowing dates' direct impacts on yields, this section explores how key climatic variables, precipitation (Prc), temperature (Tem), and water stress (WS), interact with sowing dates to influence cereal yields, providing deeper insights into the environmental conditions that shape yield outcomes based on planting timing. Fig. 5 illustrates the correlation coefficients between cereal yields and these key climatic variables for various sowing dates and RCMs. The correlation coefficients, which range from -1 to 1, capture the strength and direction of these relationships, with positive values indicating that higher levels of these variables are associated with increased yields and negative values indicating adverse impact. By depicting these relationships for each crop and model combination, Fig. 5 offers an integrated view of how temperature, precipitation, and drought conditions align with yield responses across different planting schedules, enhancing our understanding of optimal sowing strategies under future climate scenarios.

3.2.1. Temperature

Yield-temperature correlations show a predominantly negative relationship across early (7–17 September), mid-season (7 October to 16 November), and late (6 December to 30 January) sowing periods. Exceptions include weak positive correlations for early September sowing date in the KNMI model and for all January sowing dates in the CCLM4 model. The correlation coefficients generally range from -0.47 to -0.06, indicating a weak to moderate inverse association. The mid-

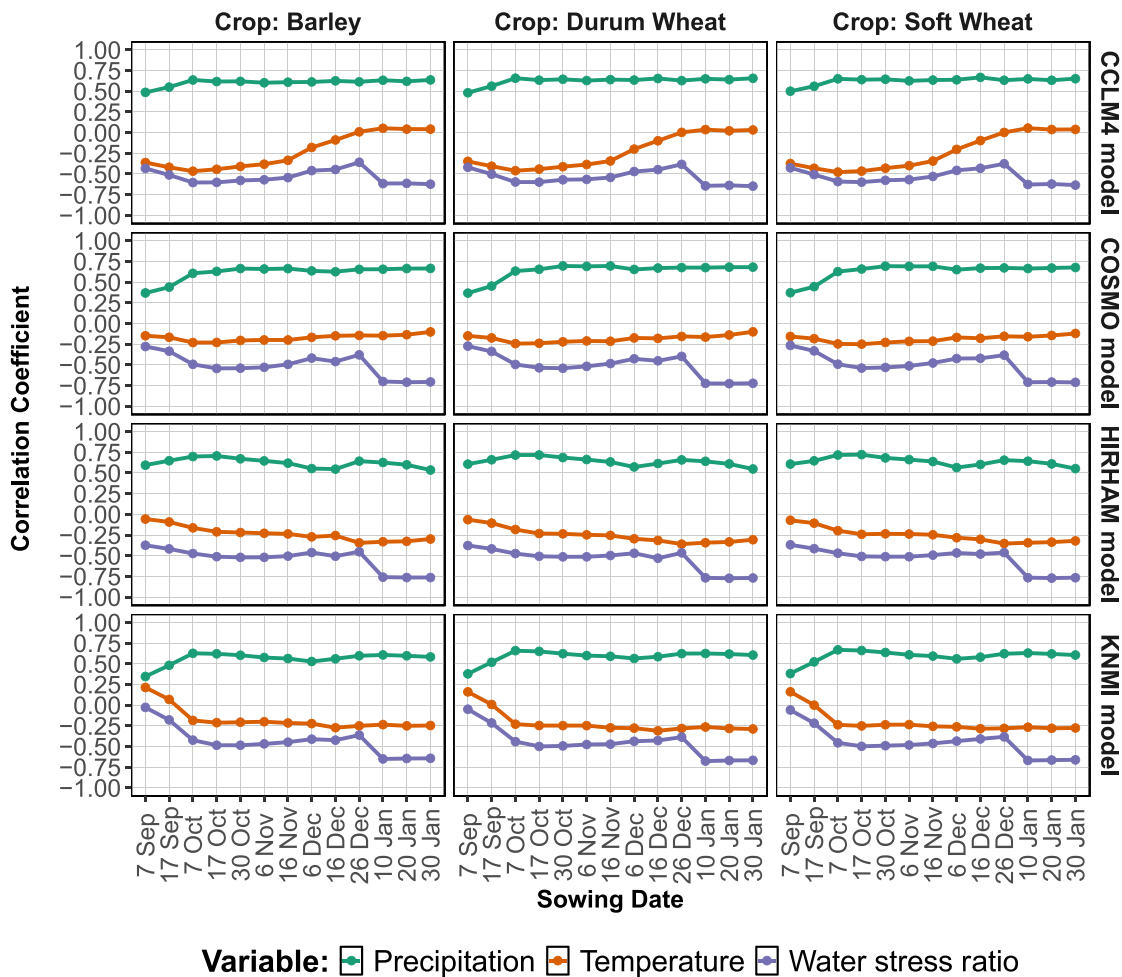


Fig. 5. Correlation coefficients between cereal yields (barley, durum wheat, and soft wheat) and key climatic variables (precipitation, temperature, Water Stress Ratio) across sowing dates (7 September to 30 January) under climate models (CCLM4, COSMO, HIRHAM, and KNMI) in Morocco’s Favorable zone.

season period exhibits the strongest negative correlations, with values reaching -0.47 , highlighting the heightened sensitivity of crops to thermal stress during this time. In the late sowing period, the negative relationship is less pronounced, with coefficients ranging from -0.35 – 0.05 . These findings underscore the adverse effects of increased temperatures on crop productivity, particularly during critical growth phases.

3.2.2. Precipitation

Precipitation consistently demonstrates a strong positive correlation with yields across all evaluated sowing dates, crops and RCMs. Correlation coefficients range from 0.37 to 0.71 , reflecting moderate to strong associations. The mid-season sowing date shows the highest correlations, peaking at 0.71 , emphasizing the critical role of adequate rainfall in enhancing yields. Early and late sowing dates also show positive correlations, although slightly weaker than those observed in mid-season dates. The uniformity of this positive association across all crops and models reinforces the necessity of sufficient precipitation to support optimal crop performance and maximize agricultural productivity.

3.2.3. Water stress

Water stress exhibits a consistently negative impact on yield across all sowing dates, crops and climate models. In fact, this variable is not independent of temperature (T) and precipitation (P), as it increases when precipitation decreases, and temperature rises. Correlation

coefficients vary from -0.77 to -0.05 , with the strongest negative values observed during late sowing dates, particularly in January, where negative correlations as low as -0.77 are reached. This trend highlights the severe adverse effects of drought conditions during critical stages of crop development. Negative correlations are also significant in the early and mid-season periods, underscoring the pervasive threat of water scarcity throughout the growing season. The consistently inverse relationship between water stress and yields across different models and crops underscores the importance of mitigating drought impacts to sustain agricultural productivity.

3.2.4. Summary

The analysis reveals that precipitation consistently enhances crop yields across all sowing dates, crops, and climate models, with the most pronounced benefits occurring during mid-season sowing dates. In contrast, water stress negatively impacts yields across all time periods, crops, and climate models, with the most severe effects observed in the late sowing period (January dates). Temperature generally exhibits a negative relationship with yields, particularly during mid-season sowing dates, reflecting the detrimental effects of thermal stress on cereal productivity. These findings highlight the critical role of adequate rainfall and effective drought mitigation strategies in optimizing cereal yields under future climate scenarios.

3.3. Evaluation of the Random Forest model

To evaluate the Random Forest model, the dataset was temporally split with observations from 2024 to 2083 designated as the training set and those from 2084 to 2099 reserved for testing. The dataset used in this analysis was derived from the CARAIB DVM simulations driven by RCMs, allowing the Random Forest model to further analyze and extract patterns from the simulated yield responses across sowing dates and climatic conditions. This temporal split ensures that the model is trained on earlier data and assessed on its predictive capability for subsequent years, providing a realistic measure of its performance under future conditions.

The hyperparameter configuration was consistent across all crop-climate model combinations, with *mtry* set to 2 and *maxnodes* fixed at 30. The parameters *nodesize* and *ntree*, however, were adjusted to optimize performance for specific crop-climate interactions, emphasizing the necessity of customizing these parameters to enhance model accuracy.

Evaluation metrics, as displayed in Table 2, revealed significant variability in model performance across different crops and climate models. RMSE values ranged from 0.50 to 1.19 tonnes.ha⁻¹, MAE from 0.37 to 0.99 tonnes.ha⁻¹, and r² between 0.52 and 0.73. Among the climate models, COSMO consistently achieved the most accurate predictions, with lower RMSE and MAE values and higher r² scores across all crops, indicating superior predictive accuracy and explanatory power. In contrast, the KNMI model exhibited the highest error metrics, suggesting less reliable yield predictions. The CCLM4 and HIRHAM models exhibited intermediate performance, reflecting moderate predictive accuracy. These results underscore the critical influence of climate model selection on prediction performance and highlight the effectiveness of tailored hyperparameter tuning in optimizing the Random Forest model for agricultural yield forecasting.

Table 3 presents the Increase in Mean Squared Error (IncMSE %) scores for four key predictors (water stress, precipitation, sowing date, and temperature) across crop and climate model combinations. These scores quantify the variable relative importance to model accuracy, with higher percentages indicating greater influence on yield predictions. The table reveals that precipitation ranks as the most influential predictor across the majority of models and crops, particularly under the KNMI model. Here, IncMSE % values reach 99.50% for durum wheat and 84.89% for barley, highlighting its critical role in yield predictions. Water stress also exhibits substantial importance, especially in the CCLM4 and KNMI models, with scores ranging between 17.57% and 47.07% for all crop and climate model combinations.

Interestingly, sowing date shows moderate importance, with IncMSE % values ranging from 10.20% to 47.43%. In some cases, such as barley and under KNMI model, its importance is comparable to that of water

Table 2

Optimized hyperparameters (*mtry*, *nodesize*, *ntree*, and *maxnodes*) and evaluation metrics (RMSE, MAE, and r²) for the Random Forest model applied to barley, durum wheat, and soft wheat under climate models CCLM4, COSMO, HIRHAM, and KNMI in Morocco's Favorable zone. The table covers model training (2024–2083) and evaluation (2084–2099), showcasing the impact of hyperparameter settings on model accuracy across crop and climate model combinations.

Crop	Climate model	Hyperparameters				Evaluation metrics		
		<i>mtry</i>	<i>nodesize</i>	<i>ntree</i>	<i>maxnodes</i>	RMSE (t/ha)	MAE (t/ha)	r ²
Barley	CCLM4	2	10	300	30	0.54	0.41	0.52
	COSMO	2	10	100	30	0.51	0.37	0.71
	HIRHAM	2	10	100	30	0.50	0.38	0.58
	KNMI	2	5	500	30	0.91	0.75	0.58
	CCLM4	2	10	300	30	0.82	0.64	0.56
Durum wheat	COSMO	2	1	100	30	0.78	0.58	0.72
	HIRHAM	2	10	100	30	0.81	0.61	0.58
	KNMI	2	10	500	30	1.19	0.99	0.56
	CCLM4	2	10	300	30	0.72	0.54	0.56
Soft wheat	COSMO	2	10	500	30	0.68	0.50	0.73
	HIRHAM	2	5	300	30	0.67	0.50	0.60
	KNMI	2	10	100	30	1.09	0.90	0.58

Table 3

Increase in mean squared error (IncMSE %) scores for water stress, precipitation, sowing date, and temperature from the Random Forest model, indicating the importance of each variable in yield predictions for barley, durum wheat, and soft wheat under four RCMs from 2024 to 2099 in Morocco's Favorable zone.

Crop	Model	IncMSE (%)			
		Water stress	Precipitation	Sowing date	Temperature
Barley	CCLM4	42.38	26.55	23.13	21.55
	COSMO	22.82	38.25	20.18	8.38
	HIRHAM	19.70	37.01	10.29	10.94
	KNMI	36.64	84.89	36.91	29.72
Durum wheat	CCLM4	45.73	27.95	27.37	21.07
	COSMO	22.35	36.56	21.07	10.28
	HIRHAM	19.00	31.48	10.20	10.55
	KNMI	37.52	99.50	43.21	28.12
Soft wheat	CCLM4	45.59	31.01	28.19	24.01
	COSMO	47.07	69.54	47.43	20.50
	HIRHAM	37.33	55.84	17.36	17.76
	KNMI	17.57	40.78	19.70	11.36

stress, underscoring the effect of sowing date on yield and its similar impact to water stress in certain cases.

Temperature, while generally less influential compared to other predictors, still holds significance with IncMSE % values between 8.38% and 29.72%. Its contribution varies across different climate models and crops, reflecting a context-dependent influence on yield predictions.

These findings emphasize the importance of precipitation and water stress in cereal yield forecasting. However, the essential contributions of sowing date and the role of temperature underscore their critical roles in optimizing crop yields under varying climate scenarios.

3.4. Insights from partial dependence plots (PDPs)

The Partial Dependence Plots (PDPs) presented in Fig. 6 reveal that distinct patterns emerge across the predictor variables, illustrating their individual contributions to crop yield predictions. These plots demonstrate the marginal effects of each feature on yield, holding all other variables constant, and provide insights into whether these relationships are linear, monotonic, or exhibit more complex trends.

3.4.1. Precipitation

PDPs consistently indicate a positive relationship between precipitation and yield across all crops. As precipitation rises, yield steadily increases, highlighting how crucial adequate precipitation is for optimal crop growth. This trend continues up to around 400 mm, where yields stabilize, indicating that additional precipitation beyond this point provides limited productivity gains in our Random Forest model. This stabilization may be due to the limited productivity potential of current

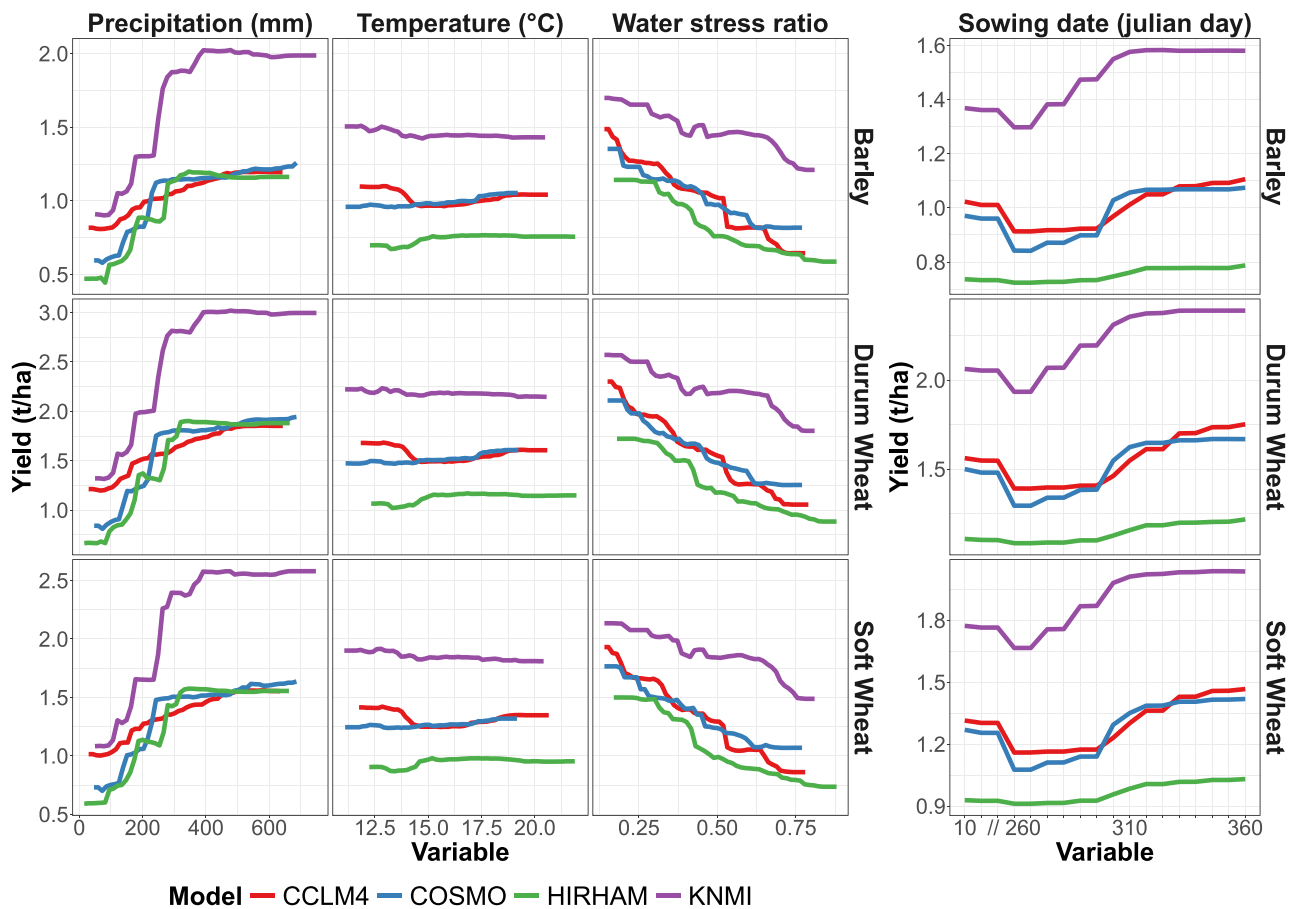


Fig. 6. Partial Dependence Plots (PDPs) showing the marginal effects of water stress, precipitation, sowing date, and temperature on predicted crop yields for barley, durum wheat, and soft wheat using the Random Forest model under climate models CCLM4, COSMO, HIRHAM, and KNMI from 2024 to 2099 in Morocco's Favorable zone. These plots illustrate how variations in a single predictor influence yield predictions while holding other variables constant, revealing key relationships between environmental factors and yield outcomes across different climate scenarios.

varieties or suboptimal agronomic practices. The KNMI climate model consistently shows higher yield values than other models, suggesting that its specific precipitation projections align with more favorable conditions for yield outcomes, particularly reaching yields between 2.5 and 3 tonnes.ha⁻¹ for some crops.

3.4.2. Water stress

PDPs for water stress depict a sharp and negative impact on yield across all crop and climate model combinations. As drought severity intensifies, yields decline significantly, highlighting the sensitivity of crop productivity to water. This robust trend is observed across all scenarios, emphasizing drought as a major limiting factor in agricultural performance. The findings reinforce the critical need for effective drought management strategies to maintain yield stability, regardless of crop type or climatic conditions.

3.4.3. Temperature

Temperature PDPs reveal a stable yield response across the projected temperature range. This stability does not imply a lack of effect but rather reflects that temperature projections in this study may fall within the optimal range for crop resilience. Small variations across some PDPs point to potential interactions between temperature and other variables, suggesting that while temperature plays a role, it is moderated by other environmental factors in influencing yields.

3.4.4. Sowing date

The PDPs for sowing date reveal more complex interactions. Yields

remain relatively steady across earlier sowing dates (e.g., from September to late November and January), suggesting limited yield advantages from early planting. However, yields increase notably with sowing dates moving toward late December (between Julian days 340 and 360). This upward trend suggests that the moderate late sowing in December may optimize yield outcomes by aligning with optimal growth conditions, such as improved water availability or climate factors in Morocco's Favorable zone.

3.4.5. Interpretation of findings

The PDPs clearly illustrate the dominant influence of precipitation and water stress on yield outcomes. Precipitation emerges as a key driver of productivity, while water stress serves as a significant constraint, emphasizing the critical importance of managing water availability. Temperature exhibits a moderated effect, with its impact likely shaped by interactions with other variables. Sowing date adjustments, particularly toward late December, provide potential productivity gains, by aligning planting schedules with favorable environmental conditions.

The visualizations from PDPs enable a nuanced view of each predictor's marginal effect, supporting strategic agricultural planning under projected climate scenarios. By visualizing each predictor's marginal effect, PDPs enable a clearer understanding of complex feature interactions within the Random Forest model, supporting strategic decision-making for yield optimization under projected climate conditions.

Building on the previous analyses of yield responses across sowing

dates and their relationships with climatic conditions, the following section focuses on identifying the sowing periods associated with the most favorable yield outcomes and examining their implications for crop growth cycle length.

3.5. Identifying optimum sowing dates that maximize cereal yields and their effects on crop cycle length

This section presents findings on the projected shifts in optimum sowing dates and associated crop growth cycle lengths over the 21st century, based on simulations for soft wheat, durum wheat, and barley across four climate models (CCLM4, COSMO, HIRHAM, and KNMI). The results reveal dynamic changes in optimum sowing date and crop

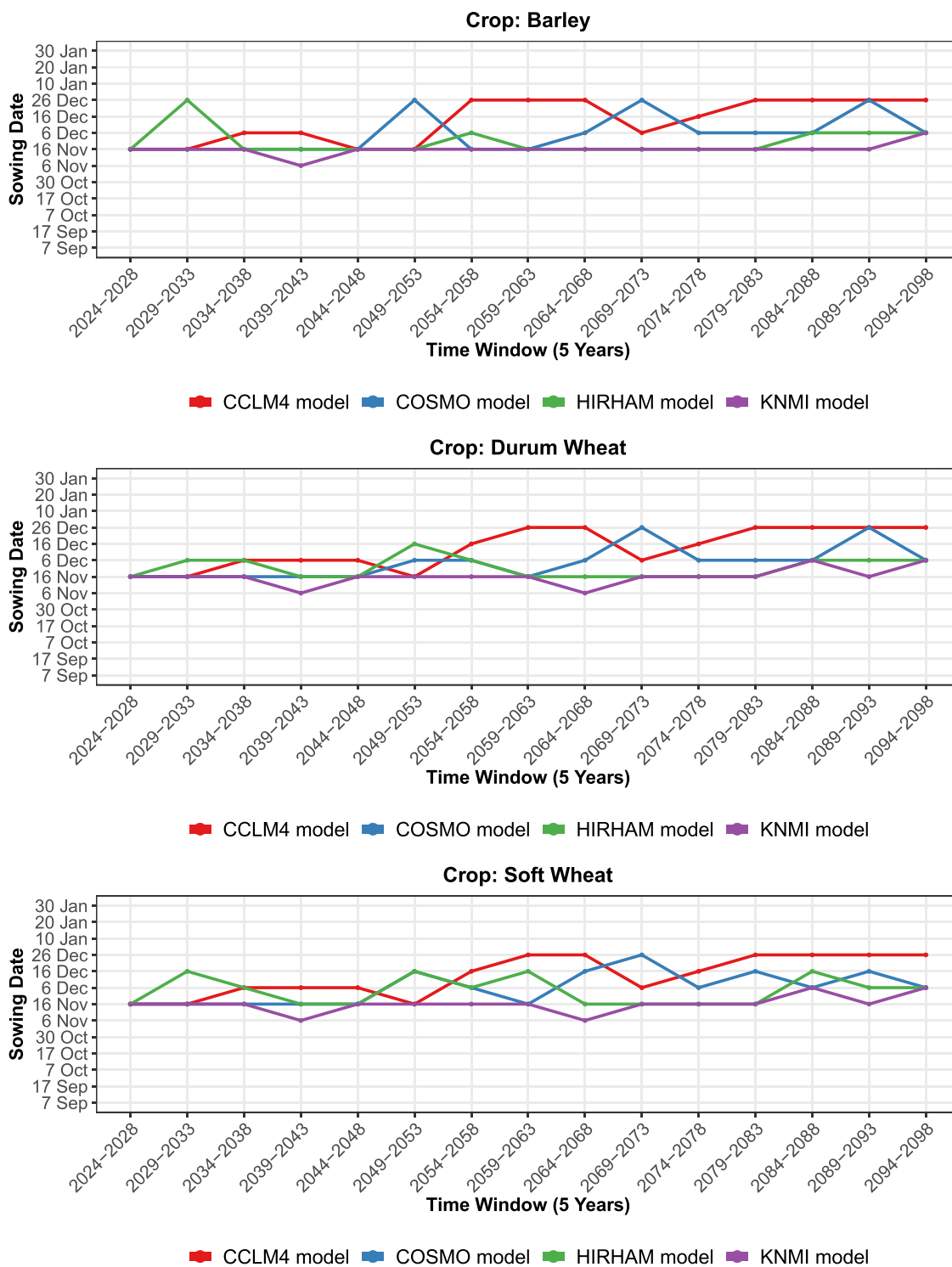


Fig. 7. Projected shifts in optimum sowing dates for barley, soft wheat, and durum wheat in Morocco’s Favorable zone from 2024 to 2099, under climate models CCLM4, COSMO, HIRHAM, and KNMI.

development timelines as climate conditions evolve.

3.5.1. Optimum sowing dates

Fig. 7 illustrates the variation of optimum sowing dates across consecutive five-year windows, providing a dynamic view of how these dates are expected to evolve. The results indicate a clear shift from mid-November toward late-December over the century. This trend reflects a gradual shift in the optimal planting window to cooler periods later in

the season, as changing climate conditions make December increasingly favorable for maximizing yields.

Interestingly, while the optimum dates move toward December, this trend stabilizes around late December and does not extend into January. This stabilization implies a threshold, where planting in late December becomes the most suitable option without further delay into the new year, likely due to climate factors that restrict further postponement of sowing.

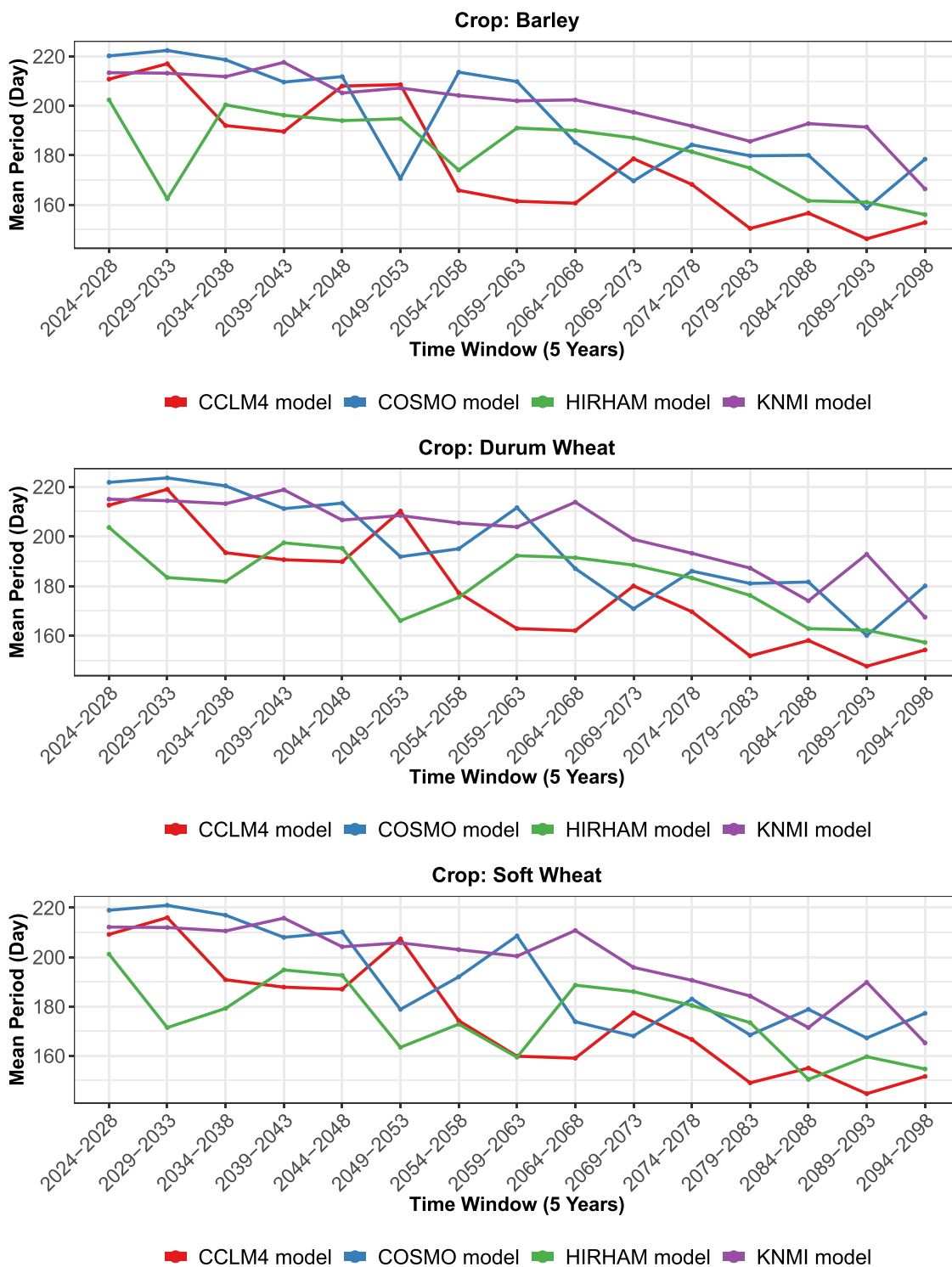


Fig. 8. Variations in crop growth cycle lengths associated with optimum sowing dates of barley, soft wheat, and durum wheat in Morocco’s Favorable zone from 2024 to 2099, across climate models CCLM4, COSMO, HIRHAM, and KNMI.

The four climate models (CCLM4, COSMO, HIRHAM, and KNMI) display some variation in this transition, with CCLM4 and COSMO showing a smoother and more gradual progression compared to KNMI and HIRHAM, which display more pronounced shifts at specific periods. These differences underline the model-specific sensitivities to climate variables that affect crop yield potential, illustrating varied responses to projected changes in temperature and precipitation.

3.5.2. Crop growth cycle lengths

Fig. 8 displays the crop growth cycle length associated with each identified optimum sowing date across the time windows. As sowing dates shift, the growth cycle length decreases significantly, with a clear trend toward shorter durations by the end of the century across all four RCMs (CCLM4, COSMO, HIRHAM, and KNMI). Initially, the average growth cycle ranges around 212 days, but this gradually reduces to stabilize between 152 and 180 days in the later decades of the study period.

This decline suggests that under projected climate conditions, factors such as warmer temperatures are accelerating crop development, leading to faster maturation. Each climate model follows this general downward trend, though the rate of decline varies slightly, reflecting model-specific responses to changing environmental conditions. In fact, in the CARAIB model, crop phenology is governed only by cumulative GDD, and the projected increase in temperature leads to faster GDD accumulation, causing crops to reach their phenological thresholds earlier and resulting in shorter growth cycles.

For barley, the average growth period begins at 212 days during 2024–2028 and decreases to 163 days by 2094–2098. Both durum and soft wheat exhibit similar reductions in their growth periods, with durum wheat decreasing from 213 to 165 days and soft wheat from 210 to 162 days over the century. However, there are differences between climate models, with some projecting a more noticeable reduction in the growth period.

These trends underscore the profound impact of climate shifts on cereal crop development, as the consistent shortening of crop growth cycles suggests that higher temperatures and changing environmental factors are reshaping their physiological development. Although variations in the rate of decline across crops suggest some differences in sensitivity to climatic conditions, the differences between climate models are more pronounced than those among crops. For a given climate model, the three crops exhibit very similar results in both the optimal sowing dates and the decline in the growth period. This similarity is expected, as the GDD values used in plant parameters [31] are closely aligned across all cereal crops. Nonetheless, the overall trend highlights the need for adaptive planting strategies and management practices to sustain agricultural productivity in the face of evolving climate change.

4. Discussion

This study explores how sowing dates influence cereal yields (soft wheat, durum wheat, and barley) in Morocco's Favorable agro-ecological zone using the CARAIB dynamic vegetation model between 2024 and 2099 driven by four RCMs from the Euro-CORDEX initiative. The findings highlight their critical role in determining crop productivity under varying climatic conditions.

4.1. Optimum sowing dates and yield outcomes

Across all RCMs, sowing dates show a consistent progression in their effects on cereal productivity, despite differences in the magnitude of projected yield responses. Early September sowing remains unfavorable, while January sowing is associated with greater variability and increased risk. In contrast, mid-to-late December sowing systematically provides the most stable and highest yield outcomes across crops and models. This convergence among climate projections indicates that

December sowing represents a robust adaptation option that performs consistently under a wide range of future climatic conditions.

These findings align closely with previous research conducted in the Mediterranean region. For instance, Plaza-Bonilla et al. [68] observed a significant yield increase for barley and wheat when sowing was delayed from October to December in northeastern Spain. Similarly, Allende-Montalban et al. [69] reported a 30% yield improvement for November-sown wheat compared to October sowing, with yield reductions noted for later sowing dates in February. These studies underscore the critical role of sowing timing in mitigating water stress and optimizing water-use efficiency in Mediterranean climates, findings that are consistent with the December sowing advantages observed in our study.

In addition, Bassu et al. [70] highlighted that the interaction of sowing dates with rainfall distribution is a key determinant of yields in Sardinia, Italy, where waterlogging in winter often limits the benefits of earlier sowing. Their simulations suggested that December sowing is generally optimal under current conditions due to reduced waterlogging risk, consistent with the findings of our study, which show the advantages of mid-to-late December sowing in mitigating both water stress and temperature impacts. Collectively, these studies validate the potential of mid-to-late December sowing to enhance cereal productivity in Mediterranean regions under projected climate stressors, emphasizing the importance of tailoring sowing schedules to local climatic and agronomic conditions.

However, several studies conducted in Morocco have highlighted early sowing as an optimal strategy for wheat production under certain contexts. For instance, Belaqziz et al. [26] demonstrated that early sowing in the semi-arid Haouz region resulted in higher yields and reduced irrigation water requirements by more than 40%. Similarly, Brouziyne et al. [71] investigated early sowing in the R'dom region, showing that advancing sowing dates by 10–20 days earlier than the first of November improved water use efficiency and reduced the risk of adverse effects linked to climate change.

The differences between these findings and our study arise from spatial and temporal contexts and the analytical approaches used. The cited studies [26,71] focus on different regions with localized agro-climatic characteristics and rely on short-term field experiments, past climate data, or mid-term future projections, that reflect current or near-future conditions. In contrast, our study employs a DVM and high-resolution RCMs to provide long-term projections (2024–2099) over a broader spatial scale. This enables a more comprehensive evaluation of sowing dates under future climate scenarios, highlighting that while early sowing may perform well under current or mid-term conditions, mid-to-late December sowing may ensure greater yield stability for cereals in Morocco's Favorable agro-ecological zone under projected long-term climate scenarios.

These findings have practical implications for cereal production in Morocco's Favorable agro-ecological zone. For farmers, the identified shift in optimum sowing windows toward mid-to-late December highlights how adjusting planting calendars may help better align crop development with favorable climatic conditions under future projections. However, given the uncertainties associated with seasonal climate forecasting, these results should be interpreted as strategic insights rather than direct operational recommendations. For policymakers and agricultural institutions, the findings underscore the importance of supporting adaptation efforts such as the development of short-cycle and drought-tolerant cereal varieties, improving access to climate information services, and integrating climate projections into long-term agricultural planning.

4.2. Climatic drivers of yield variability

The interaction of climatic variables, such as precipitation, temperature, and water stress ratio, with sowing dates highlights their combined impact on yield outcomes. Consistent with findings from Morocco,

precipitation emerged as the most influential factor, exerting positive effects across all sowing dates, particularly during mid-season sowing dates, which supports critical crop development stages [3,6,72]. In contrast, water stress negatively impacted yields, with late or early sowing dates showing heightened vulnerability and lower yields. This aligns with studies showing that recurrent droughts and reduced rainfall significantly constrain cereal production in Morocco [73]. In fact, a study by Achli et al. [13] identifies precipitation as a primary driver of crop yields, interacting with factors such as irrigation, fertilization, water stress, temperature, technical efficiency, soil properties, conservation agriculture, insects and pests, sowing date, drought, crop varieties and genetics, diseases, herbicides, and extreme climatic events, highlighting the critical role of water availability in sustaining crop productivity.

Temperature showed a more variable role, with extreme heat leading to yield losses, which supports findings that a 1% increase in annual average temperature can reduce cereal yields by as much as 32% [74]. Finally, shifting sowing dates in Mediterranean-type environments can serve as a reliable strategy to adapt to future climate changes, as it reduces the exposure of the grain-filling period to high temperatures and drought stress in late spring, potentially leading to higher wheat yields [75,76].

Although the relative influence of climatic drivers varies among climate models, precipitation and water stress consistently emerge as the main determinants of yield across crops and projections. The remaining differences between RCM projections primarily reflect variations in their simulated temperature and precipitation patterns, which arise from differences in model structure and physical parameterizations [77]. Despite these inter-model differences, the consistent importance of precipitation and water stress indicates that strategies aimed at limiting water stress, including appropriate sowing date adjustment, remain relevant under different climate projections [23,75].

Beyond the interpretation of individual climatic drivers, the integrated methodological framework adopted in this study provides additional insights that would be difficult to obtain using a single modeling approach. The CARAIB DVM simulates crop responses to environmental conditions through process-based representations of plant growth, water balance, and phenology, generating detailed outputs under multiple RCMs. These simulated datasets were then analyzed using a Random Forest model, which acts as a data-driven pattern recognition tool capable of identifying complex, non-linear relationships between climatic variables, sowing dates, and yield outcomes. By combining process-based crop modeling, machine learning analysis, and an ensemble of regional climate projections, the framework enables a systematic evaluation of crop-climate-management interactions across a large number of scenarios. This integration not only improves the understanding of how temperature, precipitation, sowing strategies, and water stress jointly influence cereal productivity, but also facilitates the identification of dominant drivers and robust adaptation strategies under multiple future climate conditions. Consequently, the approach links mechanistic crop responses with data-driven knowledge extraction, allowing complex simulation outputs to be synthesized into actionable insights for climate adaptation planning.

4.3. Implications for growth cycles and crop varieties

The determination of optimum sowing dates also reveals important implications for crop growth cycles and the viability of existing cereal varieties under changing climatic conditions. Across the regional climate models considered, crop growth cycles are projected to shorten over time, although the magnitude and timing of these changes vary among projections. This overall tendency reflects the accelerating impact of climate change on phenological development and suggests increasing constraints on the productivity of traditional cereal varieties. Under progressively shorter growth cycles, existing varieties may struggle to complete key developmental stages, highlighting the need to

better align sowing strategies with crop phenology and to promote short-cycle and drought-tolerant cereal varieties as part of future adaptation efforts [78]. In this context, breeding efforts may benefit from targeting traits such as earlier flowering and improved tolerance to heat and water stress.

Under climate change, the projected shortening of growth cycles aligns with global trends observed in other studies. In fact, Yang et al. [79] demonstrated that wheat yield reductions are primarily driven by shorter growth durations, with flowering and maturity stages advanced due to rising temperatures and rainfall changes. This accelerated phenology reduces the time crops have to assimilate nutrients, impacting both yield quantity and quality. Similarly, Fatima et al. [10] highlighted how climate warming has globally shifted phenological events earlier, compressing the growth period and reducing the time available for plants to assimilate CO₂, thereby exacerbating yield reductions.

The role of temperature is critical in this phenomenon, where Asseng et al. [80] demonstrate that higher temperatures reduce plant production by accelerating phenological phases, while Minoli et al. [81] emphasized that without adaptation, temperature increases dominate by shortening the growing period and significantly reducing grain yields. These studies support our findings that shortened growth cycles due to projected warming pose challenges for maintaining productivity with traditional cereal varieties.

Furthermore, extreme heat exacerbates these issues by accelerating crop senescence. In fact, Lobell et al. [82] observed that exposure to temperatures exceeding 34°C significantly advanced the senescence of wheat crops, reducing their productive lifespan. This trend is particularly concerning for Morocco's Favorable zone, where increasing temperatures may intensify the impacts of shorter growth cycles, further limiting yields.

4.4. Limitations and future directions

While this study provides valuable insights, it is subject to several limitations and uncertainties that must be acknowledged. As noted by Loudiyi et al. [31], reliance on a single DVM and projections from only four RCMs under a single high-emission scenario (RCP 8.5) narrows the scope of potential outcomes. Like most DVMs, CARAIB operates under simplifying assumptions, including the representation of crop phenology through heat accumulation alone and the exclusion of management practices such as fertilization and irrigation, which may limit the model's ability to fully capture real-world yield dynamics. These inherent uncertainties underscore the importance of interpreting the results within the context of the modeling framework used. The use of RCP 8.5, a worst-case scenario, assumes significant increases in greenhouse gas emissions throughout the 21st century. While this pathway is critical for understanding the upper bounds of climate impacts, it may overestimate the severity of climatic stressors, such as rising temperatures and water scarcity. Conversely, if global mitigation efforts succeed, and emissions follow lower trajectories (e.g., RCP 4.5 or Shared Socio-economic Pathway (SSP) SSP1-2.6), the impacts on cereal yields may be less pronounced. These uncertainties highlight the need for future research to explore a broader range of emission scenarios to enhance the robustness and applicability of the findings.

Additionally, the study's focus on natural environmental variables excludes management practices such as fertilization, irrigation, and acclimation, which can significantly influence yield outcomes in real-world agricultural systems. While this approach allows for a more controlled assessment of climate-driven impacts, it does not account for the potential mitigating effects of these practices, such as improved water-use efficiency and irrigation, which are commonly employed by farmers to adapt to environmental stressors. Future research should therefore examine how the integration of these agronomic practices with optimized sowing strategies may further enhance crop resilience under changing climatic conditions.

The use of the Random Forest model introduces additional

uncertainties. Although effective in capturing complex, non-linear interactions, Random Forest models are sensitive to overfitting and scenario diversity. Limited representation of extreme or novel future conditions in the training data may reduce the generalizability of the results. Future research should incorporate cross-validation techniques, ensemble modeling, and expanded datasets to mitigate these uncertainties and improve predictive accuracy.

In addition, the exclusion of socioeconomic factors, such as resource availability, farmer decision-making, and institutional constraints, further limits the real-world applicability of the findings. These factors play a critical role in determining the feasibility of implementing adaptive strategies at scale. For example, while December sowing dates emerge as the optimal planting window under projected climate conditions, their adoption may be constrained by labor availability, market dynamics, or policy frameworks. Integrating socioeconomic variables into future studies will provide a more holistic understanding of the challenges and opportunities associated with climate adaptation in agriculture.

The projected shortening of crop growth cycles underscores the urgency of developing adaptive strategies to sustain cereal production under climate change. Soft wheat, durum wheat, and barley are expected to experience significant reductions in growth periods by the end of the century. These compressed cycles are driven by rising temperatures, which accelerate phenological development and limit the time available for nutrient assimilation, reducing yield.

To address these challenges, the development of crop varieties with shorter and more efficient growth cycles and enhanced tolerance to heat and drought stress is critical [83]. Integrating these genetic improvements with optimized sowing schedules could mitigate the adverse effects of climate change on cereal productivity [10,23,84]. Mid-to-late December sowing dates offer a practical approach to align crop cycles with favorable environmental conditions, leveraging existing precipitation patterns and avoiding periods of peak heat stress. However, this adjustment alone is insufficient to fully counteract the impacts of climate change, emphasizing the need for a multifaceted approach.

Future research should adopt multi-model approaches, encompassing additional dynamic vegetation models and RCMs across a range of emission scenarios, to capture the full spectrum of possible outcomes [85]. Broader scenario analyses will enhance the reliability of projections and provide more nuanced insights into potential adaptive measures. In parallel, integrating advanced agronomic strategies, such as precision water management, crop diversification, and breeding programs targeting climate resilience, will be essential for building sustainable agricultural systems [86].

Ecosystem-based adaptation practices, improved access to climate services, and policies supporting sustainable transitions must complement these technical measures [2]. Such policies should prioritize investments in climate-smart agriculture, enhanced infrastructure, and farmer training to ensure the successful implementation of adaptation strategies, while also considering trade-offs like economic costs and social impacts. This comprehensive approach will enable Morocco's cereal production systems to adapt to the accelerating impacts of climate change, ensuring long-term food security and sustainability.

5. Conclusion

This study demonstrates the value of integrating dynamic vegetation modeling, machine learning, and regional climate projections to evaluate cereal productivity under future climate conditions. By jointly analyzing crop responses across multiple climate models and sowing strategies, the framework enables a comprehensive assessment of crop-climate-management interactions and their influence on yield outcomes. The results identify mid-to-late December sowing as a robust adaptation option for cereals in Morocco's Favorable agro-ecological zone. At the same time, the projections indicate a progressive shortening of crop growth cycles and highlight the key roles of precipitation, temperature,

and water stress in shaping yield variability. These findings emphasize the importance of aligning sowing strategies and crop phenology with projected climatic conditions while supporting the development of short-cycle and stress-tolerant cereal varieties. Overall, the study provides a methodological and scientific basis for evaluating climate adaptation strategies aimed at sustaining cereal production in Morocco under future climate change.

CRedit authorship contribution statement

Iliass Loudiyi: Writing – review & editing, Writing – original draft, Visualization, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ingrid Jacquemin:** Writing – review & editing, Software. **Riad Balaghi:** Writing – review & editing, Validation, Methodology, Funding acquisition, Conceptualization. **Louis François:** Writing – review & editing, Validation, Supervision, Software, Methodology, Funding acquisition, Conceptualization. **Mouanis Lahlou:** Writing – review & editing, Validation, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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