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The impact of precipitation, temperature, and soil moisture on wheat yield gap quantification: evidence from Morocco

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Abstract

Background Climate change has devastating impacts on agriculture, increasing the yield gap for most crops, especially in developing nations. This is likely to worsen food insecurity in some countries, calling for efforts to close the yield gap as much as possible. Estimating the yield gap and its drivers is essential for devising strategies to increase yields. This study quantifies the wheat yield gap in Morocco's five major wheat production regions. It analyzes the historical sensitivity of wheat yield to temperature, precipitation, and soil moisture, which are important factors affecting agricultural productivity. Furthermore, it evaluates how these yield gaps impact the revenue of producers in these regions. This analysis was conducted using datasets, including the Global Dataset of Historical Yield (GDHY) for yield gap assessment, soil moisture data, ERA5 reanalysis data, and CHIRPS datasets for climate assessment from 1982 to 2016. Pearson correlation and multiple linear regression analyses were employed to reflect the variation characteristics of wheat yield and to identify the impacts of precipitation, temperature, and soil moisture on wheat yield.

Results High regional differences in wheat yield gaps were observed, with values ranging from 1.64 t/ha in Casablanca Settat to 4.12 t/ha in Marrakech Safi, and temporal variability ranging from 9 to 18%. Wheat yields were found to be strongly correlated with rainfall, particularly from December to March. Temperature fluctuations had a significant negative impact on wheat yield across the regions. Soil moisture was positively correlated with wheat yields throughout all growing periods, showing the strongest impacts during the early vegetative development phase. Additionally, losses due to wheat yield gaps were considerable, ranging between $ 194 and 891 per hectare. The revenue loss due to Yield Gap I ranged from 49 to 71%, while the loss due to Yield Gap II ranged from 240 to 444%, depending on the method used to calculate the wheat yield gap.

Conclusions Results reveal gaps in wheat yield, forming a basis for process-based modeling to understand crop yield gap drivers. Understanding yield gap drivers will play a pivotal role in evidence-based intervention strategies to enhance yields. By applying such strategies, it is possible to not only manage and reduce the variability in wheat production, but also ensure sustainable agricultural practices and achieve food security in Morocco and beyond.

Keywords Wheat, Yield gap, Climate, Food security, Sustainable development goals, Morocco

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Introduction

The United Nations Food and Agriculture Organization (FAO) estimated that 750 million people, about a tenth of the world's population, were facing severe food insecurity globally in 2019 [29]. Food security is an essential element for the sustainable development of the world's economy and human society [78]. In this context, Zero Hunger has been identified as one of the Sustainable Development Goals (SDGs) set by the United Nations, and its realization contributes to the achievement of other goals, such as SDG1 (No Poverty). This highlights the need for increased sustainable food production to meet the needs of a growing global population against the backdrop of climate change [30].

Agriculture plays an important role in Moroccan society and the economy, employing about 40% of the country's population [61]. Cereal crops such as wheat, maize, oats, barley, and rice, are grown in rotation alongside other annual crops like legumes, industrial crops, and fodder crops. These crops are cultivated in various agro-climatic zones across the country [51]. A significant portion of cereal farms in Morocco is located in rainfed regions of the lowlands and plateaus in the regions of Casablanca Settat, Rabat Sale Kenitra, Fes Meknes, Beni Mellal Khenifra, and Marrakech Safi. These rainfed regions are particularly vulnerable to climate variability and change, with recent studies indicating increasing challenges due to erratic rainfall patterns and rising temperatures [19]. Rapid population growth, urbanization, and changing diets, among other stressors, affect agriculture and, consequently, food security, especially for cereals. Thus, in a country like Morocco, where cereals, especially wheat, are among the most important crops and occupy over 3 million hectares of agricultural land, they are likely to be adversely affected.

Wheat is one of the three most important food crops; it is the primary food source for more than 40% of the world's population [1]. Thus, changes in wheat production greatly impact the global grain production pattern and food security. For instance, the COVID-19 pandemic disrupted food systems, exacerbating vulnerabilities, particularly in low- and middle-income countries [11, 75]. Similarly, the Russia–Ukraine conflict, involving two of the world's leading wheat producers, further disrupted wheat farming operations, worsening the global food crisis, especially in nations that depend heavily on food imports [8]. Besides such social factors, wheat yield has been declining globally, driven by several factors, including global change, water depletion, soil fertility decline, and the threat of emerging diseases [40]. According to Shiferaw et al. [85], heat stress and water scarcity are projected to pose more challenges to wheat farming systems, particularly those in South and West Asia and North Africa. The FAO estimates that global food demand will double by 2050 and that productivity will decline because of global warming and a rise in CO_2 concentration [28]. Thus, meeting global food demand will require a 60–70% increase in production by 2050 [4, 28]. This calls for an effective food security strategy at the center of which is reducing agriculture's environmental footprints and the limited availability of land suitable for crop production.

In Morocco, wheat is the second most important crop after olives, with a production value of USD 850 million [10]. Its consumption has recorded a significant rise, growing from 138 kg per person in the 1960s to an average of 255 kg per person by 2016. However, the country's food self-sufficiency has decreased. In the 1960s, domestic wheat production met over 80% of the country's consumption needs, but by the late 1990s, this figure had fallen to 62%, while imports grew from 20 to 38% over the same period. In the early 2000s, domestic wheat output met around 60% of domestic demand on average [10]. Before the 1970s, wheat yield in Morocco was relatively as low as 0.9 t/ha. The situation changed following the introduction of improved wheat cultivars in the 1980s, a strategy that significantly increased yield. In recent years, the average yield for durum wheat has been around 1.5 t/ha, while bread wheat has an average yield of 1.6 t/ha [10]. Despite these improvements, Morocco's wheat yield still faces multiple challenges leading to substantial yield gaps persist, particularly under rainfed conditions. This wide range underscores the ongoing challenge of yield instability and calls for the urgent strategies to narrow the gap.

Morocco's wheat yield continues to lag behind the global and regional benchmarks. The country's average yield remains well below the global average of nearly 3 t/ha, it even falls short of the African average of 2.3 t/ha [10]. This disparity not only highlights the potential for improvement but also points to the complex interplay of factors, mainly climate, that contribute to the persistent yield gaps. Addressing these challenges requires a comprehensive understanding of how these environmental factors impact wheat productivity across Morocco's diverse agricultural landscapes.

Meeting the rising demand for wheat in Morocco is challenging, particularly as the agricultural sector remains largely rainfed. Wheat cultivation, which relies heavily on rainfall, covers over 80% of Morocco's arable land, with yields varying significantly in space and time [56]. Compounding these challenges, Morocco is recognized as a climate change 'hotspot', with projections indicating a 2 °C temperature increase and a 20% reduction in rainfall by 2050 [46]. Such changes are likely to exacerbate stress on agricultural production, making effective water management strategies critical to mitigating yield gaps. In response to these challenges, the Green Morocco Plan (PMV) was introduced to boost agricultural productivity and to ensure the sustainable development of rural areas. The PMV successfully increased cereal production, with studies suggesting yield improvements of 10% to 21% through enhanced farming practices [24].

Farm practices, climate, and other biological factors limit crop yield, creating a gap. This yield gap concept has often been adopted as a framing instrument for agricultural policy globally, as it significantly impacts policy actions to either reduce such gaps or implement revenue security mechanisms to support farmers in years of poor harvest [9, 27, 91]. Potential yield (PY) is time- and location-specific, considering regional differences in growth-defining variables and the advent of improved cultivars over time [32, 33, 57, 58, 69]. In Morocco, the impact of environmental factors on wheat yield is particularly significant. Precipitation, temperature, and soil moisture play critical roles in determining wheat yield, especially in rainfed systems. However, the precise quantification of the contribution of climate variables to the yield gap in Morocco's diverse agroecological zones remains a challenge. Furthermore, the spatial and temporal variations in the yield gap have not been adequately quantified. This limited analysis hinders the development of targeted strategies to improve the much needed wheat productivity in the face of climate variability and change.

Several studies have investigated yield potentials and quantified yield gaps for a wide range of crops. These studies encompass major grain crops such as rice, wheat, and corn [72, 83, 88] as well as various other crops in diverse agroecological environments [36, 63, 99],van Vugt et al., 2018; [3, 64, 87, 98, 102]. Furthermore, researchers have conducted analyses at different spatial scales, ranging from local to global [12, 53, 55, 69, 100].

In the field of yield gap quantification and analysis, researchers integrate various approaches, including field surveys, crop simulation models, remote sensing technology, and statistical methods, to leverage the strengths of each technique. Field surveys offer better precision compared to broader provincial, regional, national, or global studies. However, conducting field surveys over large areas can be resource-intensive and challenging. Recent studies (e.g., [18, 22, 86]) demonstrated that remote sensing and statistical data can effectively analyze yield gaps at provincial, regional, and national levels. These methods enable rapid trend analysis and support strategic decision-making.

Research shows that crop production is substantially affected by regional factors, including socioeconomic, agricultural, and ecological conditions. Additionally, the important role of scientific and technological innovations in enhancing the resilience and productivity of food systems in Africa has been documented [31, 60, 73]. Evidently, quantifying yield gaps and understanding the factors that influence them are essential for making informed decisions to enhance future crop production [23, 57]. In Morocco, studies by Pala et al. [76], Devkota & Yigezu [20], and Epule et al. [26], identified significant yield gaps between rainfed and irrigated environments in the central wheat-growing region. Despite the importance of wheat in Morocco, regional-scale yield studies are limited due to the scarcity of data. This knowledge gap limits the understanding of how climatic factors affect wheat yields, especially in the country's arid and semi-arid regions, highlighting the need for more comprehensive research.

This study aims to address these research gaps by providing a comprehensive analysis of the impact of precipitation, temperature, and soil moisture on wheat yield in Morocco at the regional level. Through the integration of regional-level data, remote sensing, and climate information, this work quantifies the relative contributions of environmental factors to wheat yield across different Moroccan regions. In addition, the study estimates the economic impact of the quantified yield gaps, providing an important perspective on their effects on wheat producers' revenue.

Data and methods

Study area

Morocco is located in the northwest part of North Africa, covering approximately 710,850 km^2 with a population of about 37 million. The country is divided into 12 administrative regions. Its climate exhibits high spatiotemporal variability. The North has a Mediterranean climate, primarily influenced by the Mediterranean Sea. The west experiences a temperate climate, shaped by the Atlantic Ocean, leading to mild winters, moderate temperatures, and relatively cool summers. Inland areas are characterized by a Continental climate, while the southern part of Morocco, bordering Mauritania, is impacted by the Saharan desert, which exerts a significant Sahelian effect on southern Morocco. Rainfall variability is pronounced across the country, with approximately 50% of Morocco's precipitation occurring over just 15% of the total area [81]. Rainfall is mainly recorded in winter, from October to May, increasing from south to north, ranging from less than 150 mm to more than 1000 mm [6]. Throughout the year, the average air temperature ranges from 12 °C to 14 °C in winter and from 22 °C to 24 °C in summer [5, 13]. This study focuses on Morocco's key wheat-producing regions (Fig. 1), which are crucial for the country's agriculture and overall food security.

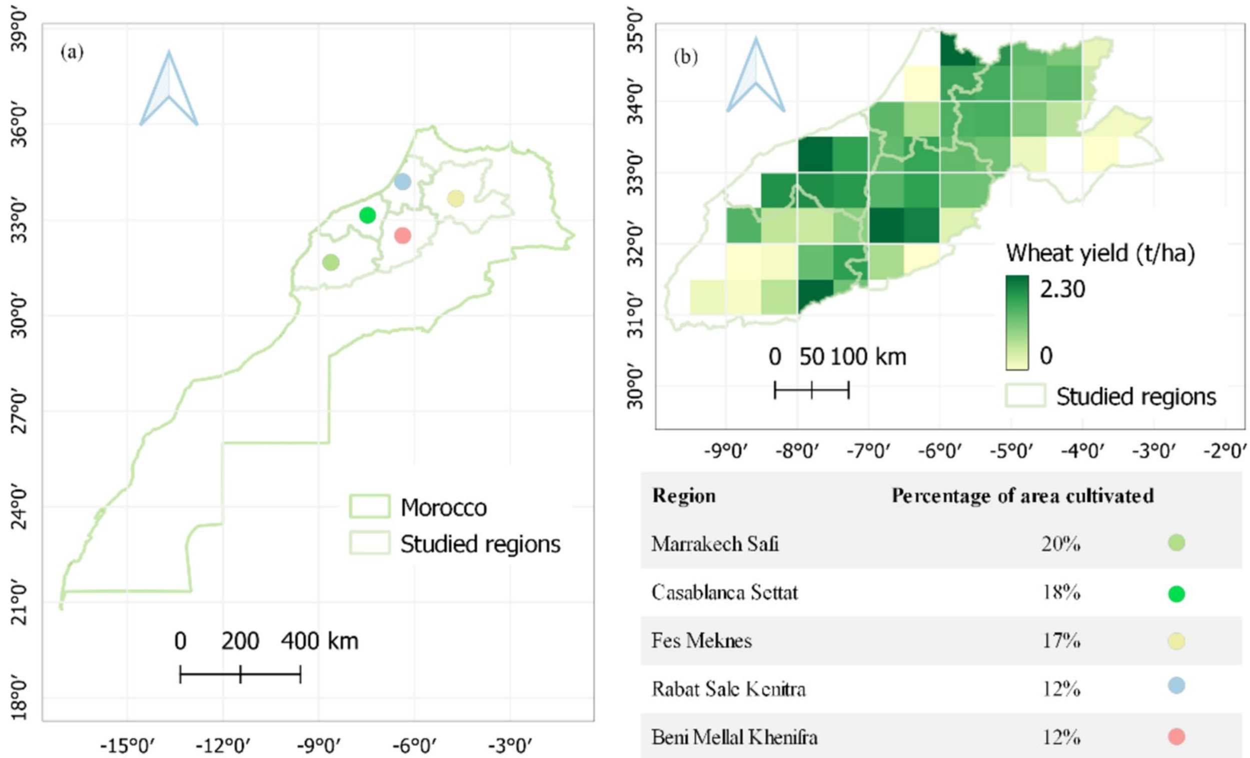

Fig. 1 Morocco a the five major cereal-producing regions in Morocco, and b the spatial distribution of the average 1982–2016 wheat yield across these regions

Datasets

The study utilized various datasets (Table 1) and crop calendars to understand the timing of agricultural activities. Figure 2 illustrates the wheat growth cycle in Morocco, based on Balaghi et al. [6] and Achli et al. [2].

Global data on actual and potential wheat yields

Wheat yield data were sourced from the Global Dataset of Historical Yields (GDHY) [43]. The data are a combination of agricultural census statistics from FAOSTAT and satellite data to produce historical yield data for four major crops around the world and have a spatial resolution of 0.5° for maize, rice, wheat, and soybeans, spanning from 1981 to 2016 [44]. Utilized several other datasets, including satellite products such as GIMMS3g 0.083° bi-monthly leaf area index (LAI) and fraction of photosynthetically active radiation (FPAR) [101] and MOD15A2 1-km 8-day LAI and FPAR [71] to develop this dataset. They also incorporated JRA-55 reanalysis (0.563° and daily) [52], solar radiation data from JRA-25 reanalysis (1.125° and daily) [74], crop calendar information from SAGE [80], harvested area data from M3 Crops [67], and production share data by cropping season from USDA. Iizumi et al. [45] and Iizumi and Sakai [43] provide details on the methodology used to develop the data. The data used in this analysis are based on a calibrated

Table 1 Summary of datasets used in study

Dataset	Data description	Resolution	Type	References
Yield	Actual yield data (GDHY)	0.5°×0.5°	Spatial and temporal	[43]
	Potential yield [69]	0.083°×0.083°	Spatial	[69]
Wheat area	Wheat harvested area	0.083°×0.083°	Spatial	[77]
Climate	Wheat-growing season precipitation	0.05°×0.05°	Spatial and temporal	[34]
	Wheat-growing season temperature	0.1°×0.1°	Spatial and temporal	[41]
Other	Wheat-growing season soil moisture	0.25°×0.25°	Spatial and temporal	[21], [38])

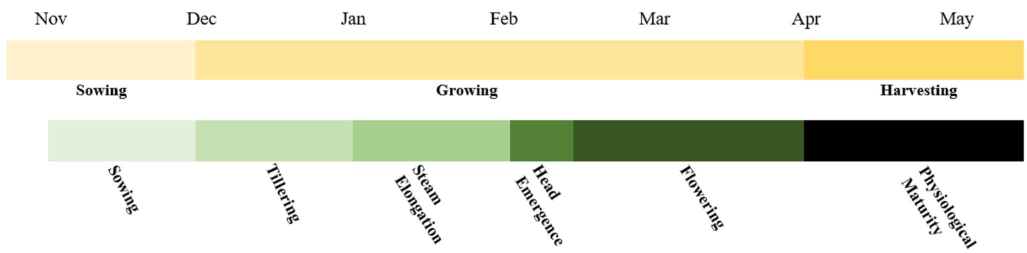

Fig. 2 Wheat calendar in Morocco

version of the yield system (v1.2 and v1.3) compared to other yield products published earlier. Consequently, these historical yield data are of better quality and cover a more extended period to meet scientific research needs. This study considers the wheat yield derived from GDHY as the actual yield (Ya), focusing on Morocco's primary wheat-producing regions. Using climate analog techniques, Mueller et al. [69] derived data on potential yields. Their study analyzed current yields and average climate and mapped them to a climate space using geographic coordinates. The climate space was divided into 100 growing-degree-day precipitation bins with the harvest area evenly distributed among the 100 growing-degree-day precipitation bins. The 95th percentile yield was considered the attainable yield level for each bin, and this value was applied to all geographical areas within the same bin. Mueller et al. [69] provide more information on the methodology used. The PY used in this study is the average census data between 1997 and 2003, derived from Mueller et al. [69] with 0.083° resolution (Fig. 3). The data were preprocessed and extracted for wheat-growing areas in Morocco, and the accuracy of the wheat yield data was evaluated using a reliable crop yield dataset from the Fes-Meknes region and its provinces. This dataset served as a reference to assess the accuracy of GDHY v.1.3 at various levels and on an annual basis.

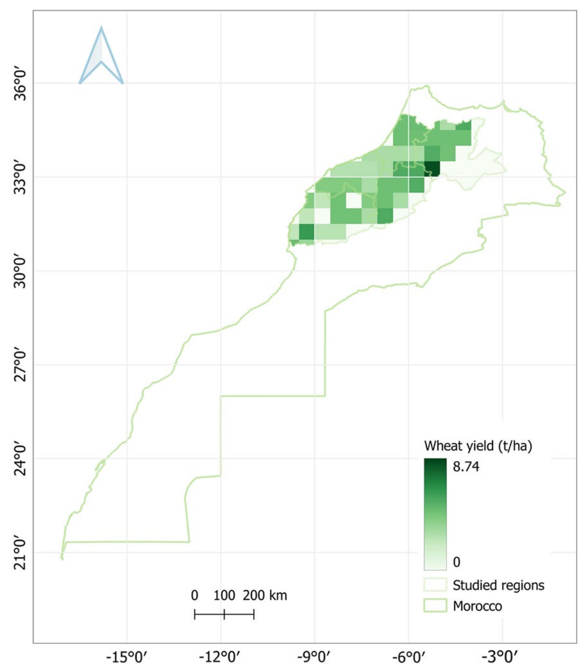

Fig. 3 Potential yield data for Morocco from Mueller et al. [69]

Climate data

Maximum (T_{max}), average (T_{aver}), and minimum (T_{min}) temperature (°C) were obtained from the European 5th generation reanalysis data (ERA5-land) developed by the European Centre for Medium-Range Weather Forecasts (ECMWF) [70]. The data have a spatial resolution of 0.1° and temporal coverage from 1959 to the present (2020). This study used monthly resolution data as our investigation required monthly frequency data. Figure 4 and Fig. 5 represent the maximum, average, and minimum temperatures and the average precipitation recorded between 1982 and 2016.

Monthly precipitation was computed for each wheat-growing season from October to May to represent in-crop rainfall using the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) dataset that provides daily precipitation data at a 0.05° resolution since 1981, combining satellite data on cloud temperatures and rain gauge information [34]. Verner et al. [93] compared four different datasets and found that CHIRPS was statistically accurate in identifying drought events and seasonal precipitation in Morocco. CHIRPS is selected for use in this study based on the findings of Verner et al. [93]. These data were interpolated using the nearest neighbor method into a regular cell of 0.5° × 0.5° to be consistent with yield data. Studies have shown that droughts during crucial growing stages can severely reduce crop yield and even lead to crop failure, while early-season droughts have little impact [37, 54]. By dividing the growing season into calendar months, it is possible to pinpoint the most sensitive phases for wheat crops concerning climate variability.

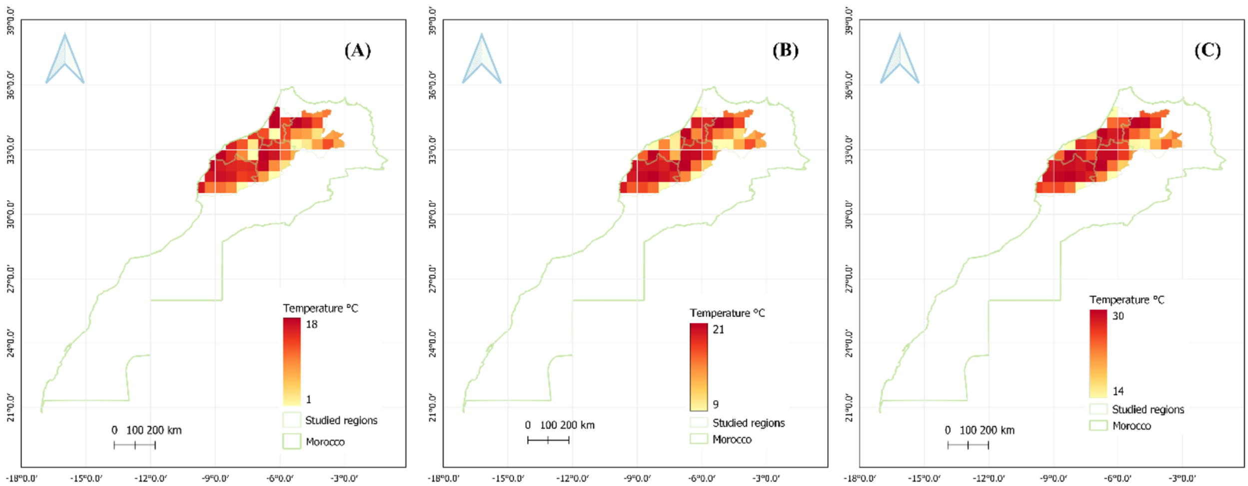

Fig. 4 Average wheat-growing season a T_{min}, b T_{aver}, and c T_{max}, for the period 1982 to 2016

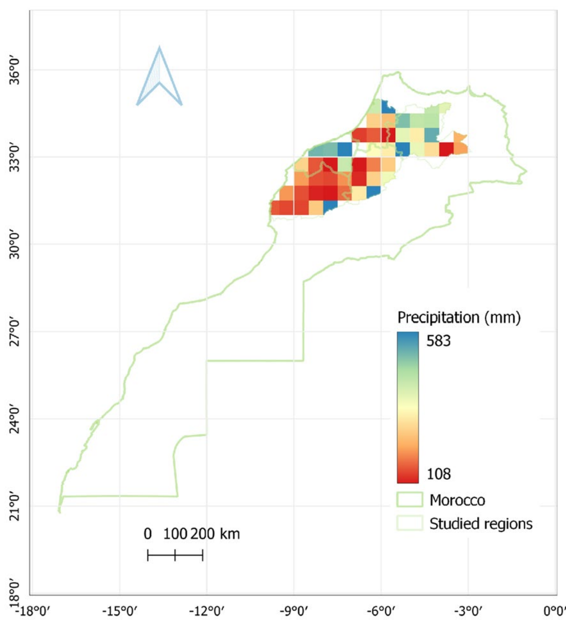

Fig. 5 Cumulative wheat-growing season (November to May) precipitation averaged from 1982 to 2016

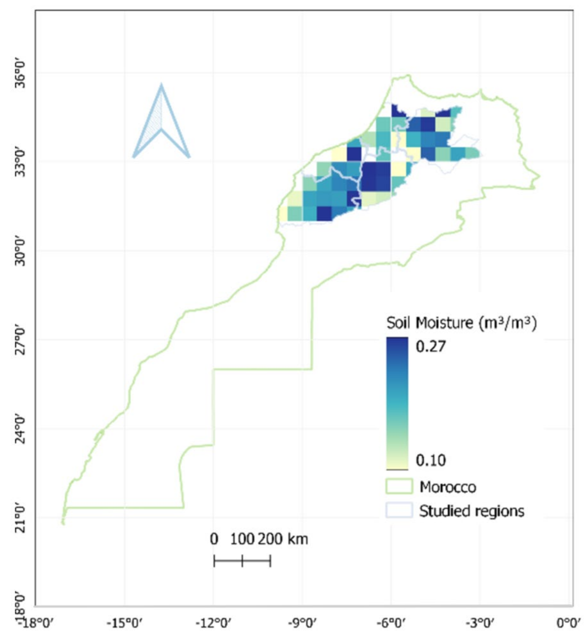

Fig. 6 Soil moisture average during wheat-growing season for the period 1982 to 2016

Soil moisture data

The soil moisture (SM) data used in this study were obtained from the Climate Change Initiative Soil Moisture (CCI-SM) datasets released by the European Space Agency (ESA) for the period from 1981 to 2016 (version v07.1) [21, 38]. Specifically, the combined active–passive product (CCI-C) was utilized, which was aggregated over the wheat-growing season (November–May) and monthly time steps. The CCI-SM v07.1 products provide global daily surface soil moisture content at a spatial resolution of 0.25°. Previous studies [65, 66] have shown the CCI-C product has a higher correlation and lower errors compared to CCI-A or CCI-P when validated against ground measurements. The SM data were used by Zhang and Jia (2013) to calculate the Soil Moisture Condition Index. Figure 6 shows the average wheat-growing season soil moisture for the period 1982 to 2016 in the studied regions.

Harvested area

Monthly Irrigated and Rainfed Crop Areas data from MIRCA2000 for the year 2000 were utilized to determine the wheat harvested area in Morocco. Crop-specific average planting and harvesting dates in 2000 were compiled from national and subnational crop progress reports [77]. Irrigated and rainfed agricultural systems were combined in this study since the GDHY dataset does not differentiate between the two.

Data analyses

This study utilized the locally weighted regression model (LOWESS) detrending method [17] to eliminate the effects of technological advancements, errors in reporting during the study period, as well as non-climatic factors, such as genetics and agronomic improvements, before analyzing the impact of climate on wheat yield. The same approach was employed by related studies (e.g., [62, 84, 89, 96]). The LOWESS is suitable for short time series and accounts for trend non-linearity compared to other methods (e.g., linear regression model, smoothing spline models, and moving average models). The method is one of the most used methods for crop yield detrending [59]. After the trend was fitted, the yield time series were detrended using the additive method that involves subtracting the trend line from the original data. In contrast, the multiplicative method involves computing the detrended time series as the ratio of the original data to the trend line values [59]. Moreover, this work deployed the Akaike Information Criterion (AIC), which is a statistical method used to choose between different models. It measures the balance between a model's goodness-of-fit and complexity, providing a way to compare competing models quantitatively. The AIC value is based on the model's likelihood function and penalizes models with more parameters, favoring simpler models that can explain the data well. The goal is to find the model that strikes the best balance between explaining the data and avoiding overfitting. The LOWESS detrending is used to detrend the data and the AIC is used to compare different detrending methods using different smoothing parameter values ("f" or "span" that determines the degree of smoothing applied to the data). The detrending methods with different "f" values are fitted to the data, and the AIC values are calculated for each fitted model. A lower AIC value indicates a better fit to the data with a reasonable balance of complexity. In this study, the AIC values are calculated for the two detrending methods: additive and multiplicative detrending.

Framework for wheat yield gap quantification and analysis

Yield gaps were quantified in two ways as presented in Fig. 7. The first yield gap (YG I) is the difference between the Ya and the highest achievable yield of the Ya in the time series (PY_{max}) (Eq. 1). The second type of yield gap (YG II) refers to the difference between PY estimated by Mueller et al. [69] ($PY_{mueller}$) and Ya (Eq. 2)

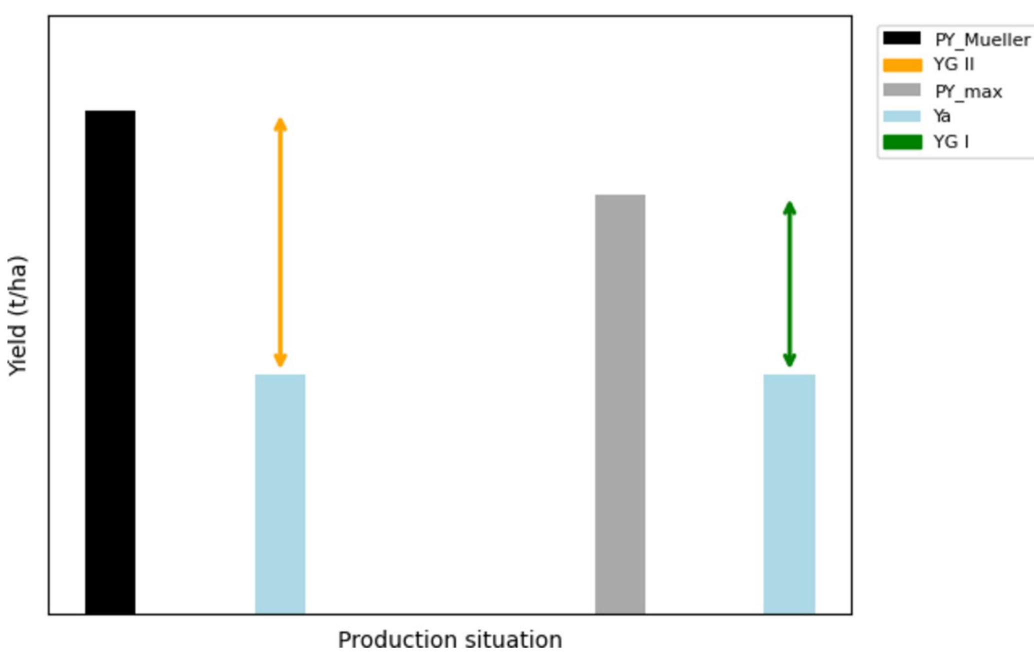

Fig. 7 The framework used to estimate the wheat yield gap

$$YG\,I = PY_{\max} - Y_a \quad (1)$$

$$YG\,II = PY_{mueller} - Y_a \quad (2)$$

Correlation analyses were performed to evaluate the relationships between monthly and growing season cumulative precipitation, monthly and growing season soil moisture condition index (SMCI) calculated using Eq. 3, and detrended wheat yield:

$$SMCI = \frac{SM_i - SM_{min}}{SM_{max} - SM_{min}} * 100 \quad (3)$$

The SMCI formula normalizes the current soil moisture value (SM_i) relative to historical extremes to provide an indicator of dryness. SM_i is scaled as a percentage between the minimum (SM_{min}) and maximum (SM_{max}) soil moisture values from long-term records. SMCI ranges from 0% at the extreme dry end to 100% at the saturated upper limit. This standardized metric quantifies moisture status compared to past wet and dry extremes, supporting agricultural drought monitoring without specifically referring to soil moisture.

Pearson's correlation analysis [95] was used to evaluate the relationship between climate variables and detrended wheat yield. The correlation coefficient's sign and magnitude help reveal the relationship's nature and strength. Additionally, linear regression analysis was utilized to assess the effects of temperature variables (T_{min}, T_{aver}, and T_{max}) and precipitation on wheat yield. This study provides a comprehensive spatiotemporal assessment of the historical yield gap in the studied regions by calculating these two types of yield gap. Furthermore, it highlights the impacts of climatic factors (precipitation and temperature) on wheat crop yield. Figure 8 illustrates the conceptual framework used in our analysis.

Multiple linear regression model

A comprehensive regression model (Eq. 4) was employed to investigate the influence of climatic variables on crop yield, considering both the entire growing season and monthly timescales. This approach allows us to assess intra-annual variability and identify critical periods within the growing season that significantly affect wheat yield:

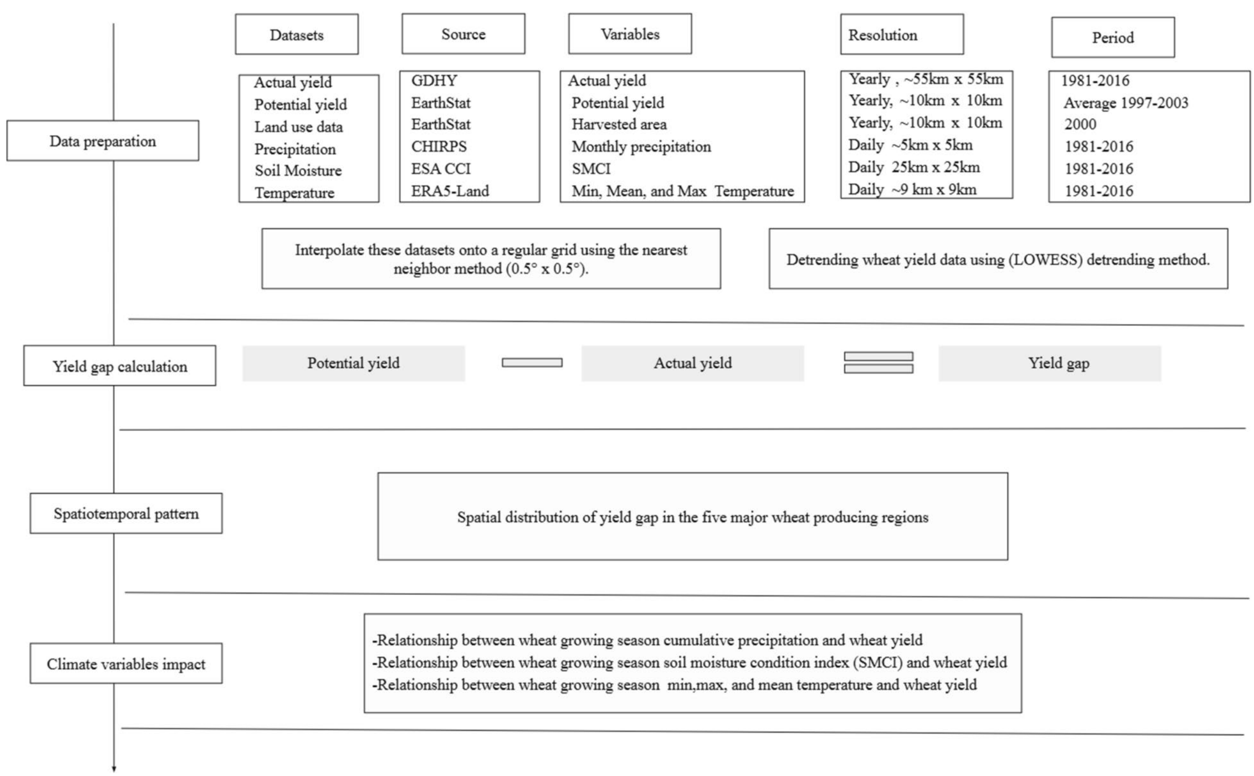

Fig. 8 The overall methodological framework for yield gap analysis

$$\begin{aligned} \mathrm{Y} = \ & \beta_0 + \sum (\beta_i \times X_i, \mathrm{Tmin}) + \sum \left(\beta_j \times X_j, \mathrm{Taver}\right) \\ & + \sum (\beta_k \times X_k, \mathrm{Tmax}) \\ & + \sum (\beta_l \times X_l, \mathrm{precipitation}) \\ & + \sum (\beta_m \times X_m, \mathrm{soil\ moisture}) + \varepsilon. \end{aligned} \tag{4}$$

In the yearly model configuration, Y is wheat yield, β_0 is the model's intercept indicating the expected yield when all predictors are zero, and the coefficients β_1, β_2, β_3 relate to the annual minimum, mean, and maximum temperatures, respectively. The coefficient β_4 is linked to the total annual precipitation, and β_5 corresponds to the average annual soil moisture, with ε representing the error term capturing unexplained variability. For the monthly analysis, Y continues to represent the wheat yield. The coefficients β_1, β_2, β_3, β_4, β_5 are retained but applied to specific monthly data, making it possible to assess how each month's climatic conditions individually affect wheat yield. This allows the model to dissect intra-annual variability and pinpoint critical periods within the growing season that significantly impact wheat yield, such as a specific β coefficient for each month in the wheat-growing season, offering month-specific insights into the climatic drivers of crop yield.

Addressing multicollinearity among predictors is crucial to ensure the reliability of our regression analysis. We assess this using the variance inflation factor (VIF), which quantifies the increase in variance of an estimated regression coefficient caused by multicollinearity. A VIF of 1 indicates no multicollinearity, while values above 5 suggest significant issues, potentially distorting the coefficients and reducing the model's statistical power. In our case, we proactively remove predictors with a VIF greater than 5 to eliminate significant multicollinearity. This strategy enhances the robustness and accuracy of our model, ensuring it effectively captures the impact of climatic variables on crop yield. The VIF for each predictor X_i is calculated using **Eq. 5:**

$$VIF_p = 1/(1 - R_p^2), \tag{5}$$

where R_p^2 is the coefficient of determination from a regression of predictor p on all other predictors. We first identify the statistically insignificant predictors to obtain significant predictors. We then proceed to remove one insignificant predictor at a time and rerun the model. This iterative procedure is repeated until all predictors in the model achieve statistical significance.

Statistical indices

Several statistics were applied at yearly time steps to assess the accuracy of GDHY v.1.3 and the detrended data: coefficient of determination (R^2) (**Eq.** 6), RMSE (root mean square error, t/ha) (**Eq.** 7), MAE (mean absolute error, t/ha) (**Eq.** 8), IA (index of agreement) (**Eq.** 9**),** and NSE (Nash–Sutcliffe efficiency) (**Eq.** 10):

$$R^2 = \frac{1 - \sum (Yi - \hat{Y})^2}{\sum (Yi - \hat{Y})^2}, \tag{6}$$

$$RMSE = \sqrt{\frac{(\sum \left(yi - \hat{Y}\right)^2}{n}}, \tag{7}$$

$$MAE = \frac{\sum |yi - \hat{Y}|}{n}, \tag{8}$$

$$IA = 1 - \frac{\sum |yi - \hat{y}|}{\sum (|yi - \overline{Y}| + |\hat{\overline{Y}} - \overline{Y}|)}, \tag{9}$$

$$NSE = 1 - \frac{\sum (yi - \hat{\overline{Y}})^2}{\sum (yi - \bar{y})^2}, \tag{10}$$

where n refers to the number of samples; yi is the observed data for the year i;$\hat{\overline{Y}}$ is the estimated data for the year i; $\overline{Y}$ is the average.

Wheat yield gap impact on the revenue of the producers

There is a need for detailed farm-level expenditure data, including costs associated with family and hired labor, nitrogen fertilization, phytosanitary use, mechanization (including machine rental and fuel costs), and seeds, as well as regional production costs to measure the impact of wheat yield gap on farmers. However, obtaining this data is a significant challenge. In response to this challenge, this work presents a refined approach to quantify yield gap losses in wheat production. The confounding effects of price trends was addressed by applying the LOWESS method to the FAOSTAT wheat price data to ensure accurate revenue estimation. This effectively isolates yield-driven revenue variations from market fluctuations. Utilizing detrended yield data, actual revenue was calculated by multiplying the detrended yield by the detrended price of wheat. Potential revenue was determined using two benchmarks: the maximum potential yield and Mueller's potential yield, both multiplied by the detrended price of wheat. Yield gap losses were quantified as the difference between potential and actual revenues, based on YG I and YG II. The yield gap losses were further expressed as percentages of the potential revenues to enhance the clarity and interpretability of the results. Specifically, percentage revenue losses were calculated by dividing the absolute revenue losses by their respective potential revenues (maximum potential yield or Mueller's potential yield) and multiplying by 100.

Results

GDHY accuracy assessment and detrending

Visual inspection of trend fitting for wheat yield demonstrates that the fitted trend closely follows the underlying time-series data pattern (Fig. 9). Locally weighted regression models provide accurate trend fitting for both regional and national wheat yield time series. The national level and Fes Meknes region exhibit the best model performance among the evaluated regions, with relatively low RMSE (0.21 t/ha and 0.24 t/ha) and MAE values (0.18 t/ha and 0.15 t/ha), indicating smaller average differences between GDHY-derived actual yield and detrended yield. The high NSE values (68% and 66%) suggest good capture of actual yield variability and strong agreement between detrended and actual yield (90% and 89%). In contrast, Marrakech Safi, Casablanca Settat, and Beni Mellal Khenifra show somewhat higher RMSE (0.33 t/ha, 0.47 t/ha, 0.27 t/ha) and MAE values (0.27 t/ha, 0.38 t/ha, 0.17 t/ha), indicating larger average differences between detrended and actual yield. Their NSE values (20%, 42%, 60%) suggest moderate model performance in capturing actual yield variability, though they maintain reasonably good agreement between detrended and actual yield (86%, 82%, 87%). Rabat Sale Kenitra demonstrates the highest discrepancies, with RMSE of 0.68 t/ha and MAE of 0.62 t/ha, and a negative NSE (-44%), indicating poor model performance compared to the mean of observed values. However, it still shows moderate agreement (68%) between detrended and actual yield. In summary, while the national level and Fes Meknes region demonstrate superior performance, other regions exhibit varying degrees of model accuracy and agreement with actual wheat yield data. Table 2 provides a summary of these results.

The GDHY performance across different scales reveals varying levels of accuracy in predicting wheat yield (Table 3). Taounate demonstrates relatively small average differences between GDHY-derived and observed yield, with an RMSE of 0.38 t/ha and an MAE of 0.29 t/ha. Taza follows with reasonable accuracy (RMSE: 0.42 t/ha, MAE: 0.35 t/ha), while Meknes exhibits higher discrepancies (RMSE: 0.65 t/ha, MAE: 0.51 t/ha). Ifrane showcases better accuracy with lower RMSE (0.36 t/ha) and MAE (0.27 t/ha) values. The Fes Meknes region

Table 2 Quantitative measures of trend-fitting results

Region	RMSE (t/ha)	MAE (t/ha)	NSE (%)	IA (%)
National	0.21	0.18	68	90
Fes Meknes	0.24	0.15	66	89
Marrakech Safi	0.33	0.27	20	86
Casablanca Settat	0.47	0.38	42	82
Beni Mellal Khenifra	0.27	0.17	60	87
Rabat Sale Kenitra	0.68	0.62	−44	68

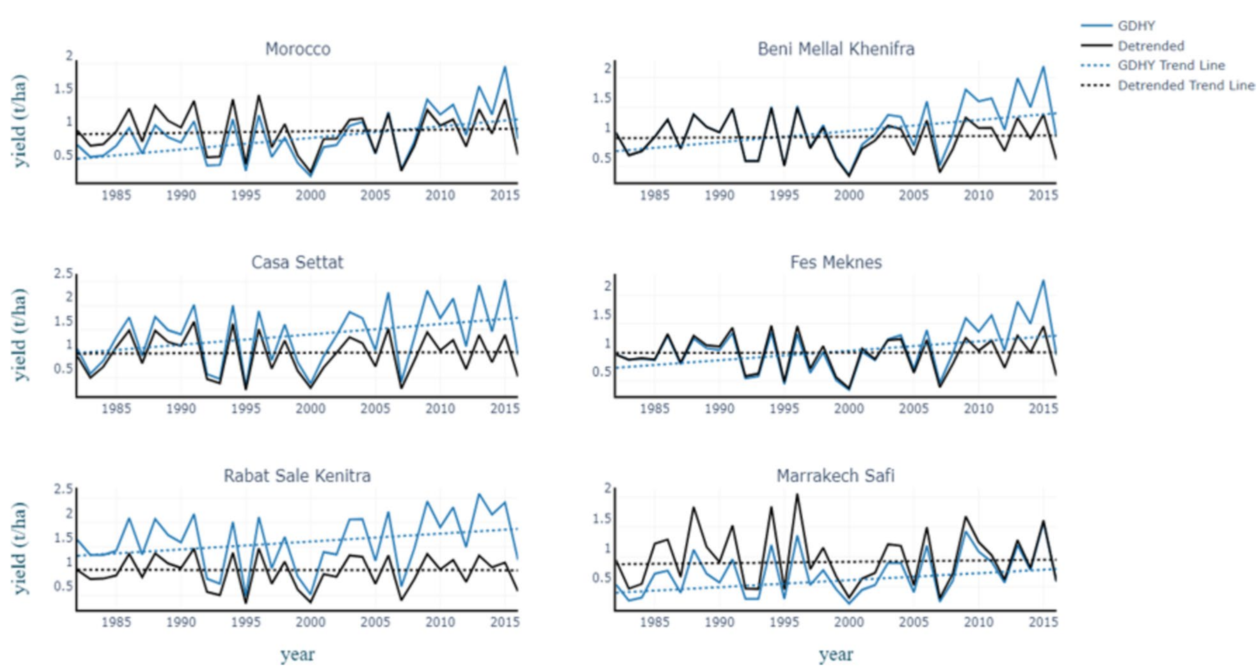

Fig. 9 GDHY wheat yield (for Morocco) against the detrended wheat yield

Table 3 Quantitative measures of GDHY accuracy

	RMSE (t/ha)	MAE (t/ha)	R^2	IA (%)
Taounate	0.38	0.29	0.58	0.82
Taza	0.42	0.35	0.71	0.79
Mekness	0.65	0.51	0.68	0.83
Ifrane	0.36	0.27	0.5	0.83
Fes Meknes	0.45	0.37	0.78	0.82
National	0.5	0.47	0.94	0.76

overall shows intermediate performance (RMSE: 0.45 t/ha, MAE: 0.37 t/ha). At the national level, the model achieves acceptable performance with an RMSE of 0.5 t/ha and an MAE of 0.47 t/ha. The R^2 values demonstrate the model's ability to explain yield data variability, with higher values observed at regional and national levels. Overall, the model shows promising results, capturing localized trends and patterns with varying levels of accuracy across different scales. Based on these findings, we can incorporate this dataset into our analysis at the regional level, as it offers significant insights into regional patterns and trends in wheat yield.

Historical wheat yield gap quantification in Morocco

The wheat yield gap at the national scale is presented in Fig. 10. YG I ranged from a minimum value of 0 to a maximum value of 1.17 t/ha. Notably, the coefficient of variation (CV) for YG I was found to be relatively high at 57%, indicating significant variability. As for YG II, the values range from a minimum of 2.56 t/ha to a maximum of 3.73 t/ha. In contrast to YG I, YG II exhibited a lower CV at 10%, suggesting a comparatively smaller dispersion and greater consistency among the data points.

The temporal evolution of the wheat yield gap across the five studied regions and the national average can be seen in Fig. 11. For YG II, the Casablanca Settat region stands out with the lowest yield gap, indicating higher agricultural productivity compared to the other regions, while Rabat Sale Kenitra closely follows with the second-lowest yield gap. The remaining three regions exhibit consistent yield gap patterns, suggesting similar productivity levels among them. It can be concluded that the trends and patterns are remarkably similar and closely aligned. Figure 12 complements the analysis by displaying the spatial distribution of yield gaps across each region, and it showed marked spatial variations, enhancing our understanding of localized productivity variations. The notable difference between Casablanca Settat and the others highlights the potential for targeted interventions to enhance yields in less productive areas.

Figure 13 provides key insights into the minimum and maximum for YG I and YG II for 35 years (1982–2016) at the national and regional levels. It is observed that the minimum yield for YG I is 0 t/ha in all regions as we consider the maximum in the time series as PY, and ranges from 1.64 t/ha in Casablanca Settat to 3.02 t/ha in Fes Meknes for YG II. On the other hand, the maximum yield gap varies from 1.10 t/ha in Fes Meknes to 1.75 t/ha in Marrakech Safi for YG I, and from 3.07 t/ha in Casablanca Settat to 4.12 t/ha in Marrakech Safi for YG II, representing the highest yield gaps in these regions. Furthermore, the variability of wheat yield over time (represented by coefficients of variation) is presented for both variables, with values ranging from 44 to 68% for YG I and 9% to 18% for YG II.

Impact of precipitation, soil moisture, and temperature on historical wheat yield

The relationship between wheat yield, monthly wheat-growing season, and cumulative inter-season precipitation from 1982 to 2016 is presented in Fig. 14. The correlation between wheat yield and monthly cumulative precipitation across different regions shows certain patterns and variations. The correlation is consistently positive in November across all regions (ranging from

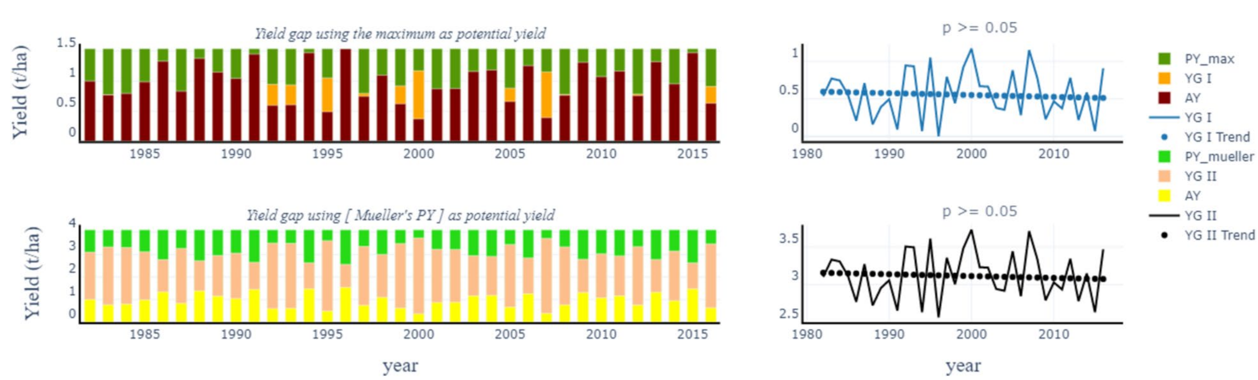

Fig. 10 Wheat yield gap at the national level

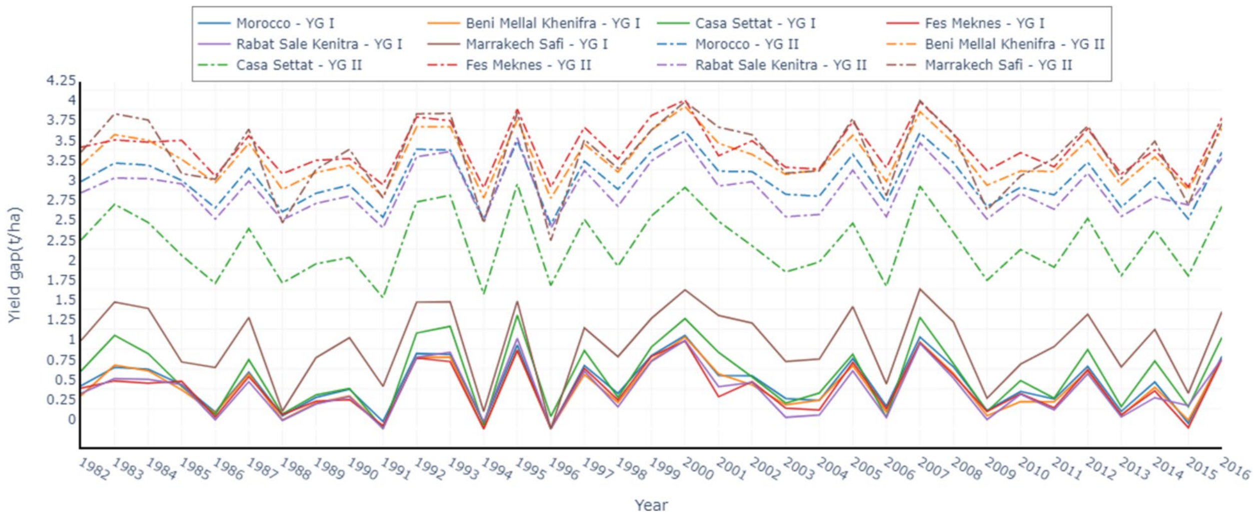

Fig. 11 Wheat yield gap (YG I and YG II) time series in the studied regions

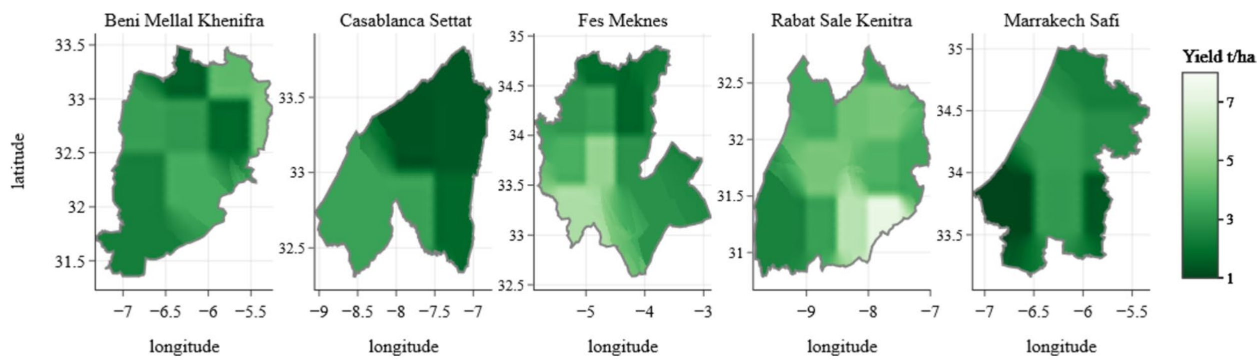

Fig. 12 Average wheat YG II in the five analyzed regions for the period 1982–2016

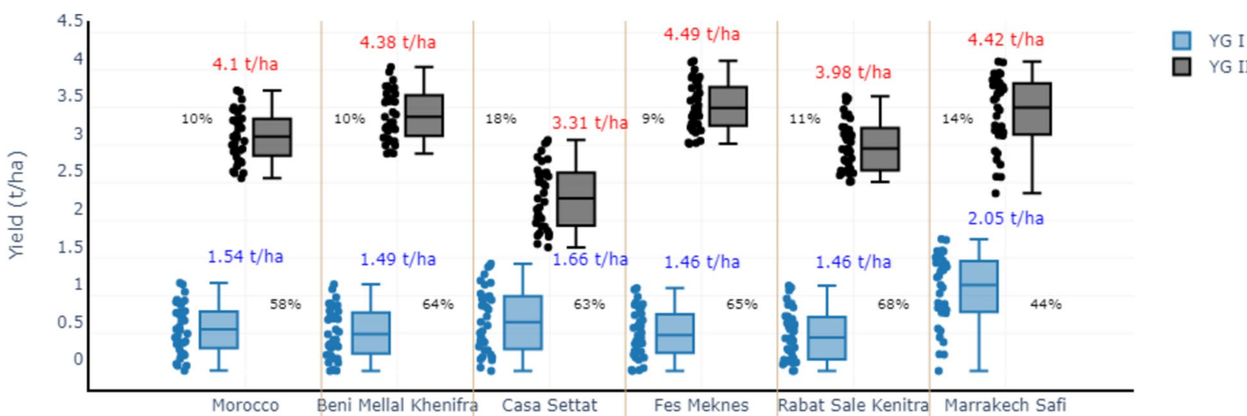

Fig. 13 Wheat yield gap at the regional scale (average $PY_{mueller}$ in red and PY_{max} in blue)

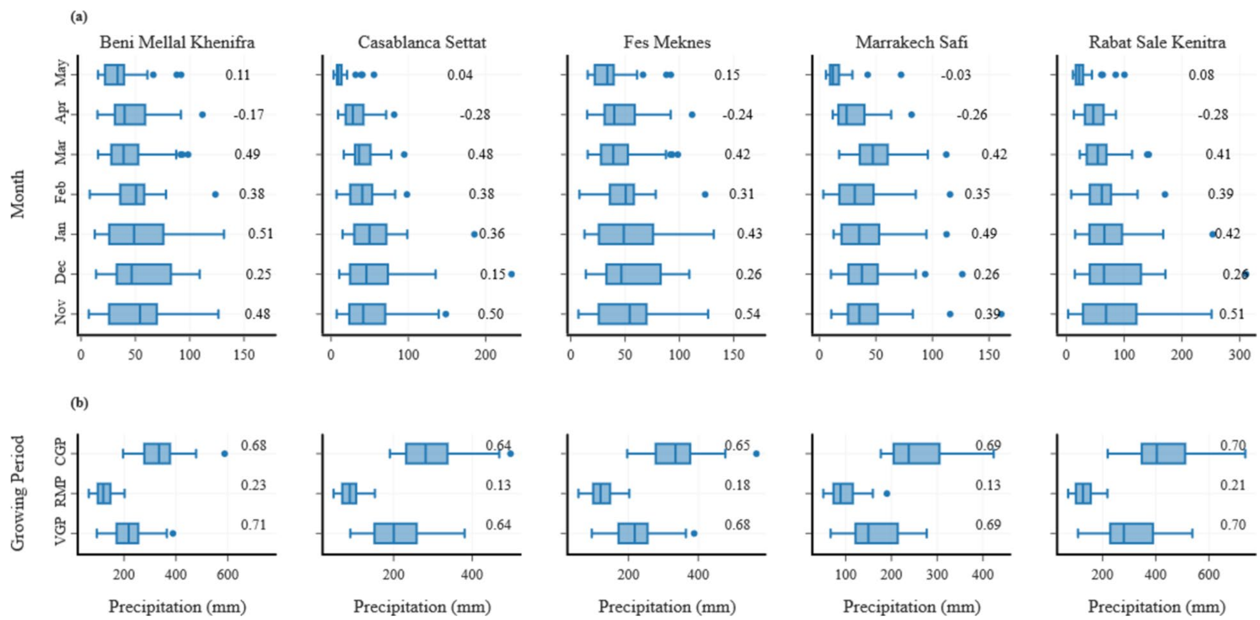

Fig. 14 Box plot and coefficient of correlation of monthly (a) and growing periods (b) cumulative precipitation and wheat yield from 1982 to 2016

0.48 in Beni Mellal Khenifra to 0.54 in Fes Meknes)**,** suggesting that November precipitation is crucial for wheat agricultural productivity. However, in December, the correlations show some variation among regions, although most areas still show a positive relationship. All regions show consistently positive correlations in January (ranging from 0.36 in Casablanca Settat to 0.51 in Beni Mellal Khenifra). While February's correlations vary slightly, the general trend is positive (ranging from 0.31 in Fes Meknes to 0.39 in Rabat Sale Kenitra). Despite small differences among regions, the correlation in March remains positive (from 0.41 in Rabat Sale Kenitra to 0.49 in Beni Mellal Khenifra). In most regions, however, negative correlations (ranging between -0.17 in Beni Mellal Khenifra and -0.28 in Rabat Sale Kenitra and Casablanca Settat)**,** are observed in April. This indicates that precipitation may harm wheat yield during this month. The results from May reveal mixed results, with correlations varying somewhat among the regions (from −0.03 in Marrakech Safi to 0.15 in Fes Meknes). Moreover, studying the relationship between wheat yield and monthly cumulative precipitation is crucial in rainfed regions, where rainfall is essential for crop development.

Positive correlations between these factors are significant since most wheat cultivation relies on rainfall. During the vegetation growing period (VGP) from November to February, which is critical for crop development, there is a correlation ranging from 0.64 in Casablanca Settat to 0.71 in Beni Mellal Khenifra. Similarly, the positive correlation between cumulative precipitation in the reproduction and maturity period (RMP) from March to May ranges from 0.13 in Marrakech Safi and Casablanca Settat to 0.23 in Beni Mellal Khenifra. Throughout the entire growing season (CGP), there are strong positive correlations ranging from 0.64 to 0.70, demonstrating that precipitation plays a major role in determining wheat yield in rainfed regions in Morocco.

A regression analysis between the wheat yield and the mean precipitation received during the wheat-growing season is assessed in Fig. 15.

The analysis of the relationship between average growing season precipitation and wheat yield from 1982 to 2016 (Fig. 15) through linear regression provides valuable insights. The coefficient of determination across different regions indicates that 40% to 49% of the variation in wheat yield can be explained by average growing season precipitation. For instance, the Beni Mellal Khenifra region has an R^2 value of 0.45, suggesting that 45% of the variability in wheat yield can be attributed to variations in average growing season precipitation. Similarly, the Casablanca Settat region has an R^2 value of 0.43, indicating that 43% of the variation in wheat yield can be explained by average growing season precipitation. Additionally, positive slopes for all regions signify a positive relationship between precipitation and wheat yield, with different magnitudes providing estimates of the strength of this relationship, suggesting that for every increase in average growing season precipitation, there is a corresponding increase in wheat yield. The study's low P-values offer robust evidence to support the assertion that fluctuations

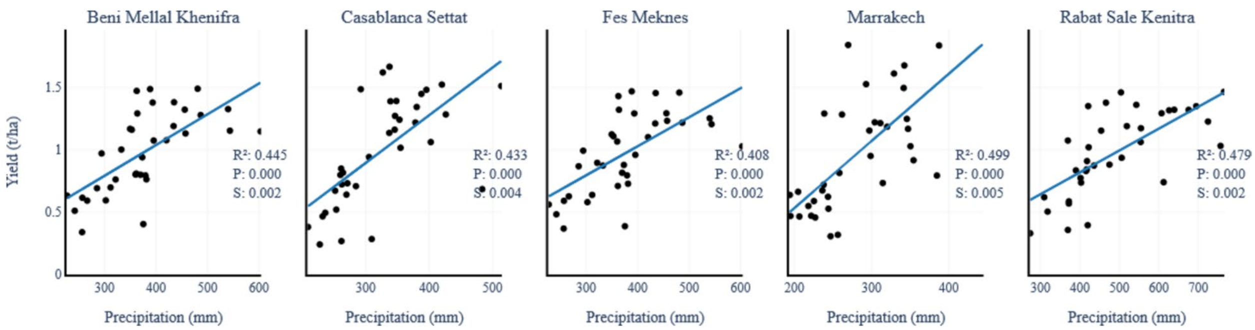

Fig. 15 Regression analysis between wheat yield and average wheat-growing season precipitation

in the amount of precipitation during the growing season have a considerable effect on the productivity of wheat. The results show that changes in precipitation levels have a direct impact on the yield of wheat crops in the studied regions, with statistical significance.

The analysis showed positive correlations between SMCI and wheat yield across all growing periods (Fig. 16). For the vegetative growing period (VGP) lasting from November to February, correlation values ranged from 0.50 in Rabat Sale Kenitra to 0.64 in Marrakech Safi. This reveals that soil moisture during early development impacts wheat yields. In the reproduction and maturity period (RMP) from March to May, correlation values extend from low (0.23 in Marrakech Safi) to moderate (0.62 in Casablanca Settat), showcasing varying levels of correlation strength across regions, the weaker RMP correlations suggest moisture during heading and grain filling is less critical in some regions. For the full cumulative growing period (CGP) lasting from November to June, correlations were strongest, varying from 0.58 in Marrakech Safi to 0.75 in Casablanca Settat. The high CGP correlations underline the importance of sufficient moisture throughout the entire wheat cycle. Overall, while moisture deficits can negatively affect yields, ongoing water sufficiency is most critical early in the growing season.

The analysis of monthly correlations provides additional insights into how soil moisture relates to wheat yield over the growing season. In the early vegetative months of November–December, correlation coefficients were moderately positive, ranging from 0.17 in Fes Meknes to 0.47 in Casablanca Settat. This points to the importance of adequate moisture during germination and emergence for crop establishment. In January and

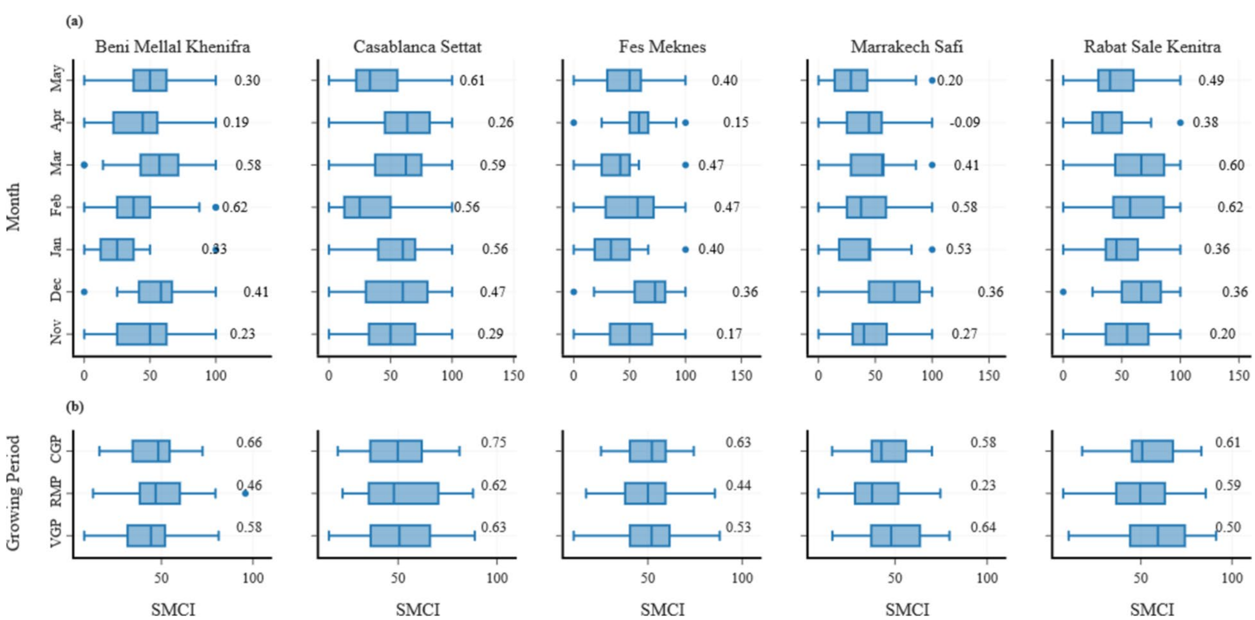

Fig. 16 Box plot and coefficient of correlation of monthly (a) and growing periods (b) SMCI and wheat yield from 1982 to 2016

February, correlations increased, varying from 0.33 in Beni Mellal Khenifra to 0.62 in the same region and Rabat Sale Kenitra as the wheat entered active tillering and stem elongation growth phases, which are sensitive to moisture deficits. During the March–April reproductive period, correlations were more variable, ranging from −0.09 in Marrakech Safi to 0.60 in Rabat Sale Kenitra, indicating moisture stress impacts heading and grain filling differently across regions. Finally, in the May ripening stage, correlations ranged from 0.20 in Marrakech Safi to 0.61 in Casablanca Settat, demonstrating soil water status continues modulating yield as harvest approaches. Overall, the monthly correlations highlight that sufficient moisture is most critical in the December–February span when the wheat is developing vegetative structures, and ongoing adequate moisture remains important through final maturation in May.

The linear regression analysis of the relationship between temperature and wheat yield has revealed that the effect of T_{min}, T_{aver}, and T_{max} during the wheat-growing season on wheat yield differs between regions (Fig. 17). The Beni Mellal Khenifra region shows a significant negative impact with an R^2 value of 0.17 and a slope of −0.15 (p-value = 0.01). Marrakech Safi also has a notable negative effect with an R^2 value of 0.15 and a slope of −0.27 (p-value = 0.02). Casablanca Settat has a moderate impact with a slope of −0.26 (p-value = 0.04) and an R^2 value of 0.12. Regions like Fes Meknes and Rabat Sale Kenitra show weaker relationships with negative slopes of −0.09 (p-value = 0.27) and −0.11 (p-value = 0.28), respectively, and lower R^2 values of 0.04. These findings suggest that the impact of changes in T_{min} on different regions of Morocco varies greatly. Specifically, the regions of Beni Mellal Khenifra and Marrakech Safi seem to be more sensitive to such changes. In contrast, Fes Meknes, and Rabat Sale Kenitra are less affected. Similarly, the impact of T_{aver} on wheat yield also varies across regions. Marrakech Safi and Casablanca Settat show the strongest impact among the regions with a slope of −0.27 (p-value of 0.01 and R^2 of 0.19 and 0.17, respectively). Beni Mellal Khenifra, Fes Meknes, and Rabat Sale Kenitra also exhibit a moderate impact with negative slopes of −0.17 (p-value = 0.01), −0.14 (p-value = 0.06) and −0.16 (p-value = 0.05), respectively, and R^2 values of 0.20, 0.10 and 0.11, respectively. Linear regression did not demonstrate a measurable predictive relationship at accepted significance levels ($p < 0.01$) within any of the studied regions between T_{max} and wheat yield during the growing season. The R^2 values range from 0 to 0.3, indicating that temperature explains about 0% to 3% of wheat yield variation. The P-values range from 0.31 to 0.87.

The performance of the MLR model (Table 4) across the five regions demonstrated its ability to explain a significant portion of the variability in wheat yield over the entire growing season. The R^2 values ranged from 53.16% to 66.13%, with adjusted R^2 values slightly lower, indicating substantial model fit and explanatory power. In Beni Mellal Khenifra, soil moisture (SM) and cumulative precipitation (Precip_cum) positively influenced yield, with coefficients of 0.013 and 0.001, respectively.

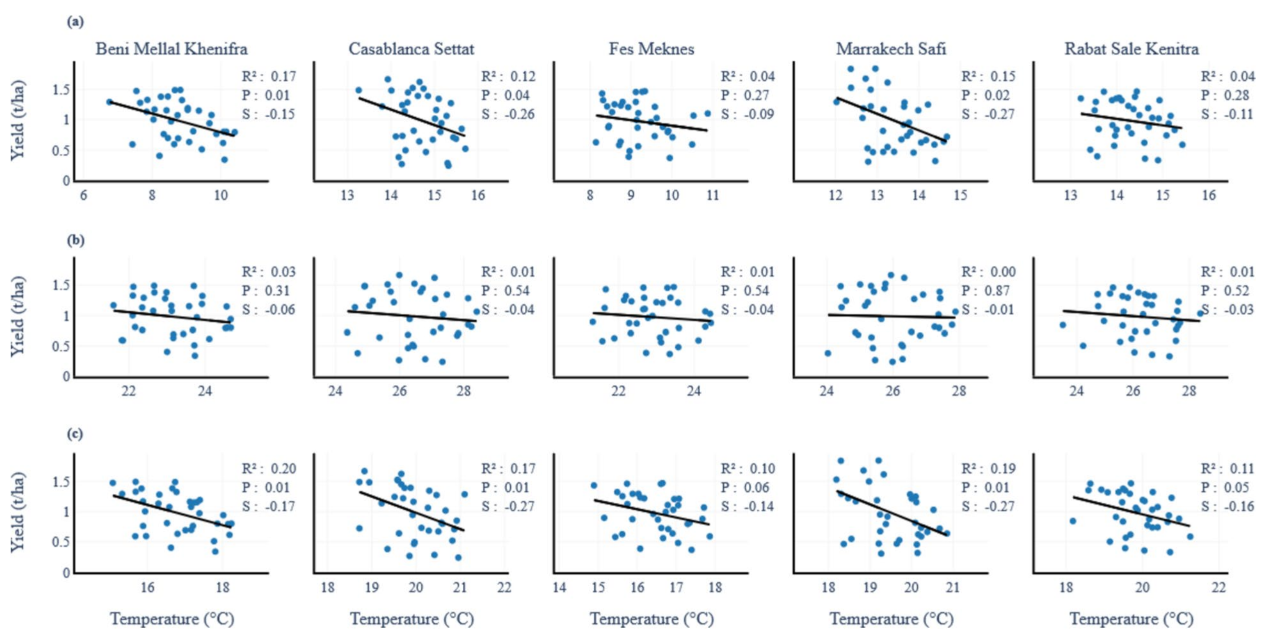

Fig. 17 Regression analysis between wheat yield and average wheat growing T_{min} (**a**), T_{max} (**b**), and T_{aver} (**c**)

Table 4 Summary of multiple linear regression (MLR) statistics for the studied regions (average growing season data)

Region	S	R-sq(%)	R-sq(adj)(%)	R-sq(pred)(%)
Beni Mellal Khenifra	0.211	60.71	58.25	51.46
Marrakech Safi	0.330	53.16	50.23	44.33
Fes Meknes	0.225	55.31	50.98	42.58
Casablanca Settat	0.260	66.13	62.85	55.06
Rabat Sale Kenitra	0.214	62.38	58.74	51.73

Table 5 Summary of multiple linear regression (MLR) statistics for the studied regions (monthly data)

Region	S	R-sq(%)	R-sq(adj)(%)	R-sq(pred)(%)
Beni Mellal Khenifra	0.182	75.26	68.84	57.57
Marrakech Safi	0.272	71.14	67.29	63.32
Fes Meknes	0.179	75.37	68.99	58.08
Casablanca Settat	0.269	63.77	60.26	48.79
Rabat Sale Kenitra	0.216	63.92	57.69	47.92

Marrakech Safi exhibited significant positive effects from soil moisture (coefficient = 0.033) and a negative effect from mean temperature (T_{aver}, coefficient = -0.152). In Fes Meknes, both cumulative precipitation (coefficient = 0.001) and soil moisture (coefficient = 0.010) positively impacted yield, while mean temperature had a negative effect (coefficient = −0.091). Casablanca Settat showed a strong positive influence from cumulative precipitation (coefficient = 0.002) and soil moisture (coefficient = 0.010), with mean temperature negatively affecting yield (coefficient = −0.176). In Rabat Sale Kenitra, soil moisture (coefficient = 0.010) and mean temperature (coefficient = −0.124) were significant predictors, emphasizing the importance of soil moisture across all regions and the detrimental effect of high mean temperatures during the growing season.

The intra-annual analysis provided further insights into the critical monthly impacts of temperature and precipitation on wheat yield (Table 5). In Beni Mellal Khenifra, the model showed a high R^2 of 75.26%, driven by significant predictors such as T_{max} in January (negative effect, coefficient = −0.045), T_{max} in February (negative effect, coefficient = −0.034), and precipitation in November, December, and January (positive effects, coefficients = 0.004, 0.003, and 0.005, respectively). For Marrakech Safi, precipitation in November, January, February, and March had substantial positive impacts on yield, with March precipitation being particularly influential (coefficient = 0.011). The Fes Meknes region's results highlighted the importance of T_{min} in December (positive effect, coefficient = 0.040) and T_{max} in March (negative effect, coefficient = -0.047), alongside precipitation in multiple months. Casablanca Settat region demonstrated the significance of November, January, and March precipitation (positive effects, coefficients = 0.006, 0.005, and 0.013, respectively), while Rabat Sale Kenitra showed notable impacts from T_{max} in December and February (negative effects, coefficients = −0.042 and −0.029) and precipitation in November, January, and March.

Impact of yield gaps on revenue

The impact of the yield gap on revenue varies significantly across the studied regions (Figs. 18 and 19). In the Beni Mellal Khenifra region, the average actual revenue is $ 265 per hectare. The revenue loss attributable to YG I is 57%, while the loss due to YG II is 363%. In the Casablanca Settat region, the average actual revenue is $ 272 per hectare, with revenue losses of 71% due to YG I and 240% due to YG II. For the Fes Meknes region, the average actual revenue is $ 275 per hectare, where the revenue loss from YG I is 49% and from YG II is 356%. In the Marrakech Safi region, the average actual revenue is $ 227 per hectare, with losses of 153% due to YG I and 444% due to YG II. Finally, in the Rabat Sale Kenitra region, the average actual revenue is $ 271 per hectare, with revenue losses of 51% from YG I and 311% from YG II.

Discussion

This study aimed to quantify the wheat yield gap in Morocco, including its spatial and temporal variability. Additionally, it analyzed the effect of climate variables on wheat yield. The yield gap was quantified using two approaches (YG I and YG II) over 35 years (1982 to 2016) at national and regional levels. The results revealed variations in yield metrics, indicating the presence of yield gaps across the studied regions. For example, the yield gap ranged from 0 t/ha to 1.75 t/ha for YG I and from 1.64 t/ha to 4.12 t/ha for YG II.

We explored the variability of wheat yields over time, indicated by the CV, which ranged from 44 to 68% for YG I and 9% to 18% for YG II. The CV values reflected the degree of yield fluctuations relative to the mean, with higher values indicating significant variations. The highest YG I and YG II values were in the south and southwest regions, which record low annual precipitation, while the lowest yield gap was in the north.

Compared to global-scale analyses, our calculated yield gaps aligned well with estimates from the GYGA, especially using YG II. We compared our yield gap analysis using GDHY as Ya to previous studies, particularly examining global EarthStat data for Morocco [67, 69]. This revealed strong similarities between our findings

Fig. 18 Annual achieved revenue and revenue loss per hectare due to the YG I

Fig. 19 Annual achieved revenue and revenue loss per hectare due to the YG II

and those from alternate approaches, with minor differences likely due to variations in data sources, methods, and spatial resolution. Furthermore, studies conducted in Morocco have reported potential yields ranging from as low as 1.53 t/ha during drought years to as high as 5.99 t/ha in favorable years [19]. These findings further illustrate the significant variability in wheat yield driven by climatic factors.

The extensive benchmarking against global and local analyses supports the validity of our yield gap assessment for Moroccan wheat. Mueller's PY appears preferable to using the maximum attainable yield as a proxy for potential yield. Spatial and temporal fluctuations remained consistent despite variations. These insights show that YG II is the best approach since Mueller's technique determines potential yield, whereas YG I considers only the current maximum attainable yield. Overall, Mueller's approach estimates agricultural productivity more robustly, improving yield gap assessment and recommendations by avoiding the limitations of using attainable yields alone.

The wheat productivity in Morocco is below its potential, with rainfed areas producing only about 25% of the achievable yield and irrigated areas producing around 60% [76]. Benaouda and Balaghi [7] reported that by 2050, 71% of Morocco's land will be unsuitable for wheat cultivation. We can measure the extent of underperformance and prioritize areas for improvement by quantifying the yield gap. Analyzing the impact of climate variables helps us recognize the specific climatic constraints affecting wheat growth and yield formation. This information can inform the implementation of tailored strategies to address these limitations, such as introducing heat-tolerant varieties or optimizing water management techniques, and encourage stakeholders to collaborate on increasing wheat yield, particularly in rainfed systems across various regions. This effort requires immediate attention due to the difficulties of a growing population, soil degradation, and climate change. Hence, although Ya in Morocco has stagnated over the years, there appears to be room for further yield improvement.

Furthermore, we discussed the impact of climatic variables (precipitation, maximum, minimum, and average temperature) on wheat yield using linear regression and Pearson correlation to detect relationships and trends. Positive (negative) correlations indicate that increases (decreases) in climate variables tend to raise (lower) yields. Significant correlations were noted between wheat yield and climate variables during the growing season.

Although a warming trend was observed for the wheat growth season in the studied regions, only an increase in T_{min} was statistically significant at $p < 0.01$. The increase in T_{min} was greater than in T_{max}, while no significant change was noted in precipitation. Wheat crops thrive in temperate climates, and high temperatures can negatively impact them during various stages of growth. Temperatures exceeding 30 °C can damage leaves and photosynthesis, accelerating aging (Wilcox et al., 2014; [47]). Kajla et al. [48] indicated that rising temperatures might significantly impact global wheat production, especially during flowering [82].

Changes in precipitation can have mixed effects; increased rainfall benefits water-scarce areas but can harm regions with heavy precipitation by causing soil saturation and nutrient loss. In semi-arid and arid regions like Morocco, rainfall is crucial. This aligns with Yacoubi et al. [103], who found significant correlations between cereal yields and rainfall. Consistent with Tafoughalti et al. [90] in the Fes Meknes region, results show an overall positive and significant correlation between precipitation and wheat yield. However, April rainfall showed weaker correlations (coefficients -0.17 to -0.28) due to potential waterlogging and increased disease risk during wheat maturation.

This study underscores the critical role of precipitation and temperature in influencing wheat yield, particularly during key growth stages such as germination, tillering, and grain filling. Adequate rainfall in months like November, January, and March is vital for maintaining optimal soil moisture levels, which support healthy wheat growth. This positive impact is evident in the Beni Mellal Khenifra, Marrakech Safi, Fes Meknes, and Casablanca Settat regions, where precipitation during these months significantly boosts yield. However, as highlighted by Mamassi et al. [60] the Mediterranean climate's frequent droughts and variable rainfall patterns complicate these dynamics, exacerbated by suboptimal crop management practices. This underscores the need for both climate-adaptive measures and improvements in farming practices to effectively close yield gaps. Conversely, high temperatures in January, February, and March can lead to heat stress, reducing tillering and grain filling, and ultimately decreasing yield. This negative effect of high temperatures is reflected in the results for several regions, highlighting the importance of local climate conditions, soil types, and farming practices. Understanding these dynamics is essential for developing tailored agricultural practices that suit local conditions, especially in regions dependent on rainfed agriculture. In areas where high temperatures negatively impact yield, strategies such as adjusting planting dates or adopting heat-tolerant wheat varieties could mitigate adverse effects. In addition, optimizing irrigation practices to ensure adequate water supply during critical growth periods can enhance yields in regions where precipitation has a substantial positive effect. This study emphasizes the need for region-specific strategies to increase wheat resilience to climate variability.

Multi-scale studies have shown that soil moisture availability notably influences wheat yields under water-limited conditions. A study in the predominantly rainfed wheat-growing regions of Morocco demonstrated wheat production relies heavily on adequate soil moisture, as well as other factors [14]. More localized analysis in two key Moroccan wheat provinces highlighted soil moisture as a primary statistical driver of observed yield variability [39]. Additional work in nearby Mediterranean districts showed soil moisture, along with other climatic factors, plays a major role in determining yields when rainfall is low (Gaona et al. 2022. Collectively, these findings indicate soil moisture is a key constraint on rainfed wheat when water is scarce. These studies follow our findings,we have shown a good correlation between wheat yield data and soil moisture. In irrigated areas, water supply is controlled, and increased soil moisture improves wheat yield. Proper irrigation helps maintain good soil moisture, which is important for plant growth, nutrient utilization, and overall crop health. During critical stages of development such as seedling and flowering, adequate soil moisture is essential for wheat crops. Inadequate rainfall and low soil moisture can lead to reduced yields and yield stress, especially during the dry season. Precipitation timing and amount impact moisture availability, but soil water content in the crop root zone emerges as a proximal factor critical for limiting wheat growth and yields under water limitation. The consistent moisture–yield relationship implies practices like conservation tillage [68] and supplemental irrigation may be needed where rainfall alone is insufficient, as exemplified by using irrigation to supplement rainfall in Moroccan agriculture to maintain crop yields. This irrigation method is used to offset any delay or lack of precipitation during the growing season to meet agricultural water demands. This is a key component of the regulation and management of production, both quantitatively and qualitatively. Consequently, the increase in wheat yield is based on the orientation of irrigation towards the most critical phases, since the crop expresses special water needs at various stages of development. Productivity is negatively affected by water shortage during these crucial periods, as it can lead to a decrease in productivity. Furthermore, to manage wheat irrigation, it is important to identify the development phases that are susceptible to water scarcity.

Morocco's efforts to increase wheat productivity and reduce reliance on imports are driven by the need to become self-sufficient. Currently, almost 40% of the country's wheat supply is imported (FAO, 2020). By closing yield gaps in both rainfed and irrigated environments, Morocco can achieve its goal of relying on its wheat production. To this end, irrigated areas must be expanded to cover 21% of the total wheat area [76], which can be achieved by providing supplemental irrigation in rainfed areas. The Green Morocco Plan (PMV) and National Program for Saving Water in Irrigation (PNEEI) initiatives aimed at promoting sustainable agriculture, integrating smallholder farming into a growth-oriented strategy, reducing rural poverty, and promoting efficient water use. However, the economic benefits of the PMV are unevenly distributed, often favoring external investors over local farmers, raising concerns about long-term sustainability and equity [25]. Furthermore, the PMV's focus on intensification risks exacerbating resource depletion, particularly water, as increased irrigation demands could lead to significant groundwater extraction [24].

Conclusion

This study analyzed wheat yield gaps across Morocco's primary production regions and examined the impact of climate variability on yields. Our findings revealed significant yield variations, with yield gaps averaging 1.75 t/ha for YG I and 4.12 t/ha for YG II, while actual wheat yields remain low. Precipitation, soil moisture, and temperature emerged as crucial factors influencing yield dynamics, with increased temperatures in arid and semi-arid areas causing water stress and impairing wheat grain development during critical growth stages.

There is need for a multifaceted approach to address these challenges. Investing in climate-resilient agriculture through the development of heat-tolerant and drought-resistant wheat varieties is essential. Implementing comprehensive water management policies and promoting efficient irrigation practices can help mitigate water scarcity issues. Enhancing climate information services, including improved weather forecasting and early warning systems, can aid farmers in making informed decisions about planting dates and crop management. Furthermore, promoting the adoption of precision agriculture techniques, such as soil moisture sensors and variable-rate irrigation systems, can optimize resource allocation. Strengthening agricultural research and extension services is crucial to addressing study limitations and disseminating climate-smart farming practices. Developing region-specific adaptation strategies tailored to the unique challenges of different agroecological zones within Morocco is also recommended.

These findings and recommendations provide a foundation for future process-based modeling studies to assess the impacts of various drivers on yield gaps in Morocco. Ultimately, implementing these strategies can contribute to sustainable and economical increases in wheat production, helping to close yield gaps and enhance food security in the face of climate variability.

Notably, the results of this research are not without uncertainties. Firstly, the findings would benefit greatly from having access to cropland masks detailing annual changes in planting areas. As a result of the lack of yearly data in this study, we were limited to analyzing planting masks for the year 2000, which imposes limitations on the robustness of our findings. Secondly, utilizing data with a spatial resolution of 0.5° could introduce some limitations in capturing subtle variations. Lastly, when quantifying YG II, utilizing average census data spanning from 1997 to 2003, we note that over time there may have been variations and developments, and this should be considered in interpretation.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s40066-024-00509-w.

Additional file 1

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Author contributions
LO: conceptualization, methodology, data curation, formal analysis, investigation, visualization. LO, TE, VO, SB, AA, AC: conceptualization, writing—review and editing. All authors read and approved the final manuscript.

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Availability of data and materials
The datasets generated during and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for Publication
The authors agree to publication in the Journal.

Competing interests
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