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Climatic Impacts on Wheat Yields in Iran: A Two-Step Statistical Analysis across Diverse Climate Zones

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Abstract

This study investigates the impact of climatic variables and agricultural practices on wheat yield across different climate zones in Iran. Using a comprehensive dataset, we analyse how temperature, precipitation, soil type, and fertilizer usage influence wheat productivity. Our findings reveal significant yield variability across temperate, arid, and cold zones, with temperate regions showing the highest mean yields due to moderate temperatures and adequate precipitation. In contrast, arid and cold regions face challenges from extreme temperatures and insufficient rainfall. The study employs a two-step estimation process to isolate the effects of climatic variables from other factors, enhancing the accuracy of yield predictions. Our results underscore the critical role of temperature and precipitation in agricultural productivity, corroborating previous research while providing novel insights through methodological innovations. We propose several policy recommendations, including improving irrigation infrastructure, promoting climate-resilient wheat varieties, and developing comprehensive climate adaptation strategies. These policies aim to enhance agricultural resilience and sustainability in the face of climate change. Our research contributes to the growing body of literature on climate change and agriculture, offering a detailed understanding of how climatic factors affect wheat yields and informing more effective agricultural policies and practices.

Keywords: Climate Change, Climate Risk, Statistical Modelling, Wheat Yield, Iran.

Introduction

Climate change, as highlighted by the Intergovernmental Panel on Climate Change (IPCC), is one of the most significant threats to global agriculture, with developing countries being the most vulnerable. In Iran, climate change is expected to exacerbate the already challenging conditions for agriculture, especially wheat production, by increasing temperatures and altering precipitation patterns, which in turn affect water resources, farming systems, and ecosystems (Karimi et al., 2018; Nassiri et al., 2006).

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Agriculture remains the fundamental source of food supply worldwide, across all levels of national development (Praburaj et al., 2018). Around 60% of Iran's cultivated land is dedicated to rainfed crops, contributing 32% of Iran's total agricultural output (https://amar.org.ir/). Wheat, one of the most essential crops, is pivotal for food security and the growing global demand for grains. In Iran, wheat is a strategic crop, forming the backbone of almost all cropping patterns and occupying a special place in the Iranian diet (Araghi et al., 2018; Bannayan et al., 2010; Mojaverian et al., 2021). In 2021, approximately 33% of agricultural land was allocated to irrigated wheat, while 67% was used for rainfed and dryland wheat, with rainfed wheat production reaching about 4.47 million tons, accounting for 74.98% of all rainfed crops (https://maj.ir). The country's per capita bread consumption is 156 kg per year, significantly higher than the 59 kg per year in European countries (Babashahi and Shokri, 2021; Eglite and Kunkulberga, 2017). Achieving self-sufficiency in wheat production has thus become a primary goal in Iran's agricultural policies (Alizadeh-Dehkordi et al., 2024). The climatic shifts have significant implications for Iran's agricultural sector. Various studies have examined the impacts of climate change on crop yields in the country, particularly for wheat. For example, Maddah et al. (2015) used crop models to predict wheat yields in Gorgan, attributing yield variations primarily to temperature changes. Similarly, Zarakani et al. (2014) and Nazari et al. (2021) found that temperature and precipitation are crucial factors influencing rainfed wheat yields across different regions of Iran. These findings underscore the importance of climatic factors in agricultural planning and policy-making.

The growing concern about climate change has prompted researchers to investigate how crop yields might respond to its potential impacts, in order to understand the nature of these effects (Pakrooh and Kamal, 2023; Schierhorn et al., 2020; Wu et al., 2021). Various approaches have been employed in studies examining the impacts of climate factors on agricultural production, including crop models, machine learning techniques, and statistical approaches. Crop modeling is a widely used method for assessing the risks of climate change on crop production (Muller and Martre, 2019). In a review study, Luo et al. (2023) highlighted that crop models, such as WOFOST, DSSAT, AquaCrop, and SAFY, are widely used in data assimilation for yield estimation. These models provide precise simulations of crop growth at the field scale; however, their effectiveness is limited in larger regional contexts due to the variability in spatial input parameters (Luo et al., 2023). Despite accounting for physiological processes of crop growth and development, these models require significant input data, which can be time-consuming and costly (Eyshi Rezaie and Bannayan, 2012). Machine learning is another technique explored in this context (Elbasi et al., 2023; Kuradusenge et al., 2023). While sophisticated machine learning algorithms, such as Random Forest, AdaBoost, decision trees, and support vector machines, have successfully enhanced crop yield predictions by utilizing various variables and advanced techniques like data assimilation and remote sensing, traditional regression models still offer significant advantages. The statistical approach involves estimating the impact of changes in climate factors on crop yields using a statistical regression equation with historical datasets on global, national, and regional scales (Singh et al., 2022). These methods are particularly notable for their flexibility in measuring interaction terms among climate variables and other factors, making them powerful tools for evaluating the impacts of climate change on crop production across different levels (Pakrooh and Kamal, 2023). For example, Heil et al. (2020) assessed the impacts of climate change on wheat yields in Germany using the ARIMA model and Multiple Regression Analysis, finding that climate change had a negligible effect on wheat yield variation during the winter and spring seasons.

In examining the impact of climate change on wheat yields, we saw a range of methodologies employed in existing studies, highlighting the significance of temperature and precipitation as critical climatic factors. Recent studies suggest that future climate change will significantly limit crop yield across most of Iran's cultivated regions (Karimi et al., 2018). In Hamedan Province, rainfed wheat yields are expected to decline by 20.6–41.3% by the 2080s due to decreased precipitation and rising temperatures (Mohammadian Mosammam et al., 2016). In Esfahan Province, irrigated wheat yields may drop by 1.49–2.1% under different climate scenarios (Ababaei et al., 2010). Following the literature, this study aims to apply a novel statistical approach to predict wheat yield under various climate scenarios, given the relative simplicity and interpretability of statistical methods. A distinctive feature of our research is the implementation of a two-step estimation process designed to isolate the effects of climate variables from other influencing factors.

While numerous studies have assessed the impacts of climate change on wheat yields in Iran, most have focused on individual regions or employed either crop simulation models or single-stage statistical regressions. These approaches often confound the effects of climatic variables with those of management practices, such as fertilizer use and soil characteristics. Moreover, there is a lack of comparative analysis that systematically examines how wheat yield responds to climate variability across Iran's major climate zones, temperate, arid, and cold, within a unified analytical framework. This limits the generalizability and relevance of their findings to policy. The present study introduces a two-step statistical estimation procedure to fill this gap.

In the first step, we estimate the effects of fertilizer and soil type on wheat yield; in the second step, we analyse the residual yield variability as a function of climate factors. This methodological innovation enhances the precision of climate impact attribution and enables more reliable, zone-specific yield projections to inform targeted adaptation strategies.

Initially, we assess the impact of a single management factor, specifically fertilizer use, on wheat yield. According to the literature, fertilizer is recognized as one of the effective factors in enhancing crop yield (Krasilnikov et al., 2022; Liu et al., 2021). We also included soil type in our initial model. Soil type is another factor affecting yield and remains constant over time (Reith et al., 1984). We consider four main types of soil according to the FAO soil classification. In this study, we assume that the impact of fertilizer on yield will remain constant in the future, as it has in the past. In the subsequent step, we analyze the residuals from the first model, representing the portion of yield variability unexplained by fertilizer and soil effects. These residuals are then used as the dependent variable in a second regression model where temperature and precipitation are predictors. The idea originated from Heil et al. (2020) and Singh et al. (2022), who have used techniques to evaluate direct and indirect influences on agricultural yield outcomes separately. By utilizing future temperature and precipitation projections, we generate predictions of the residual component. The final yield predictions are obtained by combining these residual predictions with the mean yield-hat estimate from the first model, thereby providing a comprehensive forecast for future wheat yields.

Data Description

Our data comprises wheat yield and fertilizer usage for 183 cities in Iran, spanning up to 23 years, depending on the availability of data. This data has been extracted from the Ministry of Agriculture Jihad (https://maj.ir) in Iran. In this study, we aim to develop a simpleyet powerful method to predict future wheat yield. To ensure the accessibility of data for an extensive case study or even for future projections, we focus on two critical climate factors: precipitation and temperature. Climate factors include precipitation, maximum and minimum temperatures, obtained from the ERA5 reanalysis database. We have also extracted projected data for these factors from the CMIP6 climate projections for future predictions. As the effects of climate factors are the main part of this study, careful consideration is required. The Ministry of Agriculture Jihad highlights the variability in wheat harvesting and cultivation durations across different climatic conditions. Accordingly, we have classified our study area into three climatic types, arid, temperate, and cold, based on the Köppen-Geiger classification system.

Iran, according to this system, has 10 distinct climate types: BWh, BWk, BSh, BSk, Cfa, Cfb, Csa, Csb, Dsa, and Dsb, (Ghiai et al., 2021; Raziei, 2022). Considering only the main groups, we integrated them into three main classes. Tables A.1 to A.3 (in Appendix) present the regions within each class. This classification informs our analysis, enabling a more nuanced understanding of yield predictionsacross diverse climate scenarios. Soil type information for each city was obtained from the SoilGrids database (https://soilgrids.org), which provides globally consistent, high-resolution estimates of soil properties. Using the dominant soil characteristics per location, we assigned each city to one of four aggregated soil types: Loamy-Soil.1, Loamy-Soil.2, Loamy-Soil.3, and Sandy-Soil, following the FAO soil taxonomy classification guidelines.

Fig. 1 shows the selected cities along with their climate classifications. The map highlights the temperate regions in green, the arid regions in orange, and the cold regions in blue. The blank (white) areas in Fig. 1 represent regions of Iran that were not included in the study because they are not wheat cultivation areas.

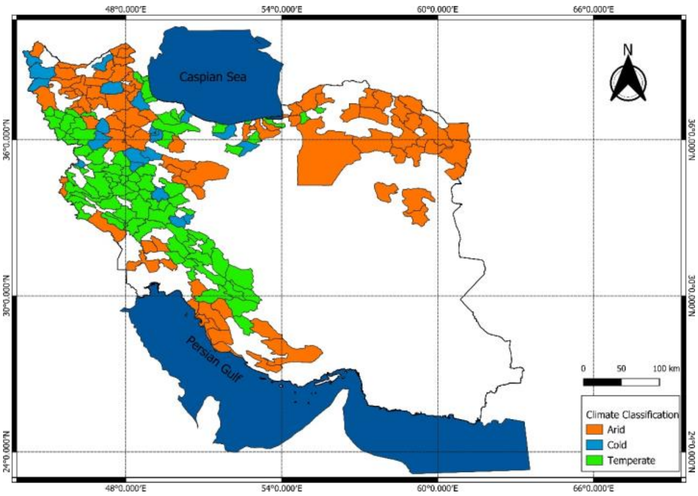


Figure 1. Merging climate types of Iran into three classes according to the Köppen-Geiger climate classification.

Methods

To achieve the study's goal, we look at the data pattern concerning yield, as presented in Figs. 2 and 3. The figures indicate no clear pattern between climate factors and yield within any climate type zone. However, it appears the use of fertilizer influences that yield. Based on this observation, we decided to employa two-step estimation approach.

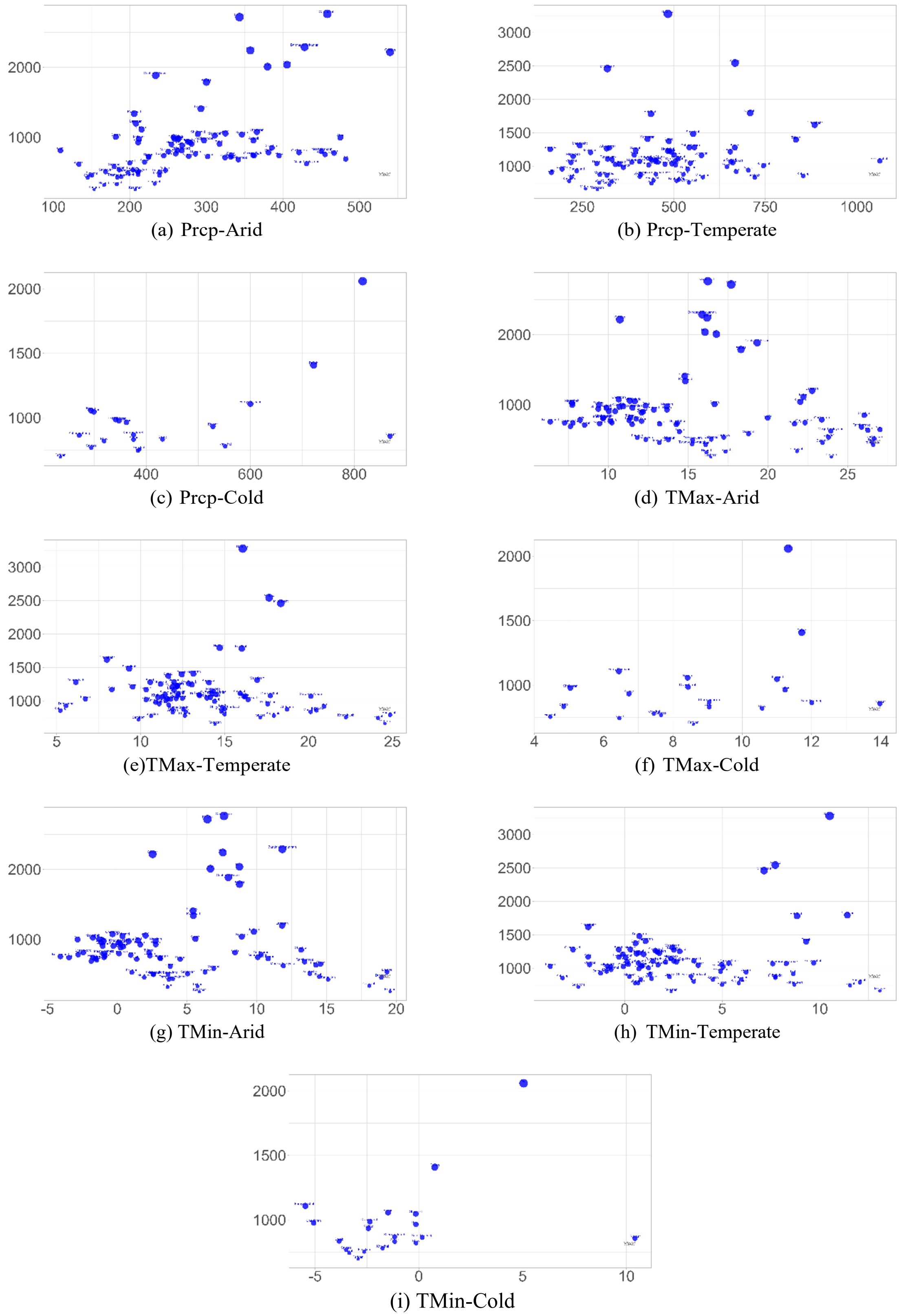


Figure 2. Yield Pattern Considering Climate Factors _ y axis = Yield, x axis = Climate Factors.

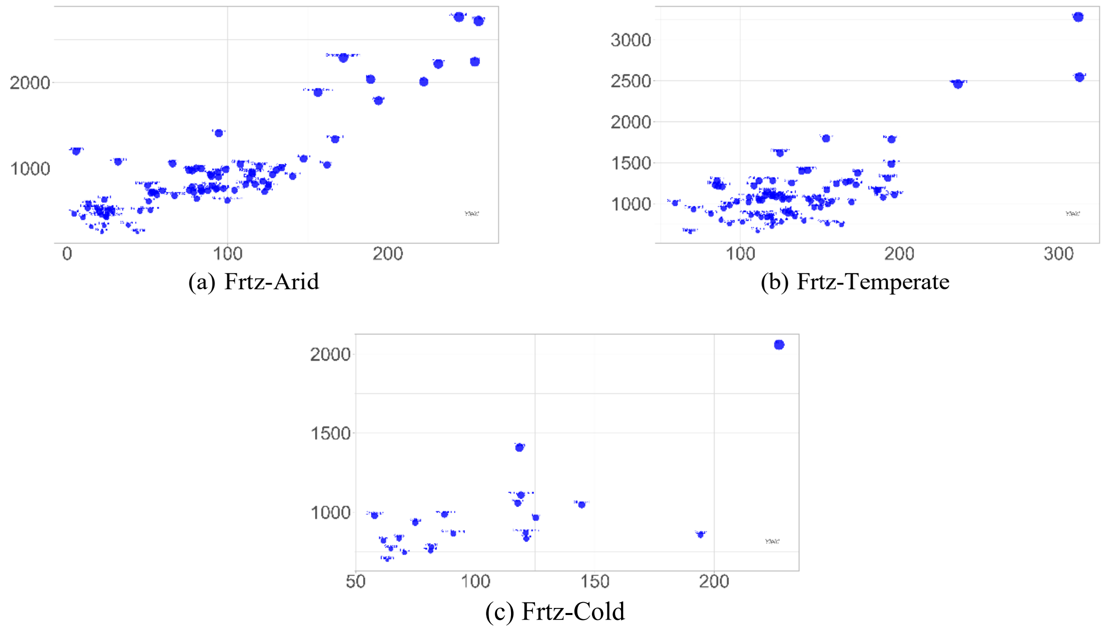


Figure 3. Yield Pattern Considering Fertilizer _ y axis = Yield, x axis = Fertilizer (Frtz).

Estimation of Fertilizer and Soil Type Effects

In the first step, to simplify the model, we focus on fertilizer and soil type as direct influencers on yield using the following model:

$$Y_{i,t,c} = B_0 + B_1 F_{i,t} + B_2 S_{i,t} + Y_{residual_{i,t,c}} \qquad (1)$$

Where Y is the yield, F is the amount of fertilizer applied, and *S* represents soil type. *i*, *t*, and *c* are city, time, and climate type. B_0 to B_3 are the parameters and *Y residual* is the residual which we call $Y_{residual}$.

This procedure was necessary because modeling agricultural yields is complicated by the numerous factors that influence them. Various elements impact crop yields directly and indirectly; however, considering all of them is often not feasible due to inadequate documentation of many data points (Heil et al., 2020).

After estimating this model, we extracted the residuals, representing the portion of yield not explained by fertilizer and soil type. We also identified the explained portion of the model (Y_{hat}), which includes fertilizer effectiveness, soil type, and the intercept. The mean of Y_{hat} was used as the fixed component for future predictions based on each climate type.

$$Y_{hat} = B_0^* + B_1^* F + B_2^* S \qquad (2)$$

Regression of Residuals on Climate Factors

In the second step, we regressed the residuals from the first model on climate variables to isolate the indirect influence of climate.

Since future climate projections are available but fertilizer usage data is not, this approach allows us to estimate future outcomes more reliably. Assuming fertilizer usage remains constant, given that its impact has already been accounted for, we can isolate the effects of climate on yield and project future agricultural productivity accordingly (Heil et al., 2020). Zhu et al. (2022) demonstrated the significant influence of temperature changes on precipitation patterns and intensity, highlighting the importance of this relationship in climate studies. However, many studies overlook this interaction when examining the impact of climate factors on yield. To address this gap, we conducted a simultaneous regression that considers the relationship between temperature and precipitation, providing a more comprehensive analysis of the climate factors affecting yield. We also include their squared terms in our analysis to capture the nonlinear effects of climate factors.

$$\mathrm{P}_{i,t} = \zeta_0 + \zeta_1 \mathrm{T}_{\mathrm{Max}_{i,t}} + \zeta_2 \mathrm{T}_{\mathrm{Min}_{i,t}} + \zeta_3 \mathrm{T}^2_{\mathrm{Max}_{i,t}} + \zeta_4 \mathrm{T}^2_{\mathrm{Min}_{i,t}} + \pi_{i,t,c} \quad (3)$$

$$Y_{residual_{i,t,c}} = \gamma_0 + \gamma_1 T_{Max_{i,t}} + \gamma_2 T_{Min_{i,t}} + \gamma_3 P_{i,t} + \gamma_4 \mathrm{T}^2_{\mathrm{Max}_{i,t}} + \gamma_5 \mathrm{T}^2_{\mathrm{Min}_{i,t}} + \gamma_6 P_{i,t_2} + \nu_{i,t,c} \quad (4)$$

Where TMaxi,t is the maximum temperature, TMini,t is the minimum temperature, and $P_{i,t}$ represents precipitation. γ_0 to γ_6 and ζ_0 to ζ_4 are the parameters that show the amount of effects that come from each factor. For temperature, we used the mean temperature during the cultivation period, and for precipitation, we used the total amount over the same period.

Results

In our estimations, first, the data was split into training and testing sets to compare the performance of multiple regression with the two-step approach. Multiple regression models were developed for all climate zones using all available variables as predictors. The results are in Table 1. MAE quantifies the average magnitude of errors between predicted and observed values, expressed in the same units as the target variable (kg/ha). A lower MAE indicates more accurate predictions on average. Across all zones, the two-step methodology consistently achieved lower MAE values than multiple regression, indicating improved average predictive precision. RMSE provides a measure of prediction error that penalizes larger deviations more severely due to the squaring of residuals. This makes RMSE particularly sensitive to outliers. The two-step approach consistently demonstrated lower RMSE values, indicating better performance in minimizing significant prediction errors. R^2 reflects the proportion of variance in the dependent variable explained by the model. An R^2 value closer to 1 indicates a better model fit. The two-step methodology yielded higher R^2 values in all climate zones, signifying enhanced explanatory power relative to the multiple regression model. MAPE expresses prediction errors as a percentage of the actual values, enabling a scale-independent assessment of model accuracy. For instance, the MAPE decreased from 19.78% under the multiple regression model in the Temperate Zone to 14.43% using the two-step methodology, further confirming the latter's superior performance.

Overall, the two-step methodology demonstrated notable improvements across all performance metrics and climate zones, affirming its robustness and greater predictive capability in estimating wheat yields.

Table 1. Comparison of Multiple Regression and Two-Step Methodology for Predicting Wheat Yields.

Climate Zone	Model	MAE (kg/ha)	RMSE (kg/ha)	MAPE (%)	R^2
Arid Zone	Multiple Regression	240.5	310.2	26.63	0.62
	Two-Step Methodology	180.4	250.1	19.22	0.74
Cold Zone	Multiple Regression	190.3	280.7	20.01	0.65
	Two-Step Methodology	140.6	230.5	14.78	0.78
Temperate Zone	Multiple Regression	220.7	300.4	19.79	0.68
	Two-Step Methodology	160.9	240.2	14.43	0.76

Table 2 provides a comprehensive summary of agricultural yields and climatic variables across three climate types: Arid, Cold, and Temperate. The variables include Yield (kg/ha), Minimum Temperature (°C), Maximum Temperature (°C), Precipitation (mm), and fertilizer usage (kg/ha). The data reveals that the Temperate climate zone offers the highest mean yield compared to the Arid and Cold zones, indicating a more favourable environment for crop production. Temperature notably differs among these zones; the Temperate zone experiences the most moderate minimum and maximum temperatures, potentially contributing to its higher yields. Specifically, the mean minimum and maximum temperatures in the Temperate zone are between those of the Arid and Cold zones, which may mitigate the extremes that could otherwise stress crops. Precipitation patterns also vary significantly, with the Temperate zone receiving the highest mean precipitation, supporting more robust growth than the Arid and Cold zones. This table highlights that while the Temperate climate zone offers the optimal conditions for agricultural yield, the Cold and Arid zones present more challenging environments due to lower temperatures and variable precipitation levels. These findings underscore the importance of climate considerations in agricultural planning and yield optimization.

Table 2. Variable Description and Classification.

Climate	Arid	Cold	Temp
Yield_min	17.21	127.69	34.35
Yield_mean	938.36	950.75	1115.37
Yield_max	4385.00	3285.96	4415.00
T_{Min}_min	-6.13	-8.17	-5.84
T_{Min}_mean	3.84	-1.24	2.83
T_{Min}_max	20.13	11.31	14.73
T_{Max}_min	3.96	1.87	3.17
T_{Max}_mean	14.41	8.65	13.68
T_{Max}_max	28.81	15.03	26.99
Prcp_min	47.84	137.61	74.97
Prcp_mean	293.52	428.59	466.38
Prcp_max	806.03	1093.11	1319.26
Frtz_min	0.06	1.00	3.21
Frtz_mean	94.86	101.99	134.54
Frtz_max	587.50	356.19	519.78

T_Max = Max Temperature, T_Min = Min Temperature, Prcp = Precipitation, Frtz = Fertilizer.

Table 3 presents the correlation coefficients between agricultural yield and various climate factors, precipitation (Prcp), minimum temperature (T_{Min}), maximum temperature (T_{Max}), and fertilizer usage (Frtz), across three different climate zones: Arid, Temperate, and Cold.

We observe interesting patterns when comparing the temperature correlations across different climate types. In arid and temperate climates, the correlation between yield and maximum temperature is negative. This suggests that higher maximum temperatures may have a detrimental effect on crop yields in these regions. In contrast, the positive correlation between yield and maximum temperature in cold climates indicates that higher maximum temperatures can benefit crop yields in colder regions. This positive correlation in Cold climates suggests that warming temperatures may extend the growing season or improve growing conditions, thus positively impacting yields. The correlation with minimum temperature is positive in all three climate types, with the strongest correlation observed in the Cold climate, suggesting that higher minimum temperatures may generally favor crop growth, particularly in colder regions.

These results indicate that fertilizer usage consistently correlates strongly with yield across all climate types, underscoring its critical role in agricultural productivity. Precipitation also shows a positive correlation with yield, particularly in Arid and Cold climates, highlighting the importance of an adequate water supply. The influence of temperature on yield varies by climate type, with minimal impact observed in Arid climates, slight beneficial effects of lower temperatures in Temperate regions, and a moderate positive effect of warmer temperatures in Cold climates.

Table 3. Correlation coefficients between yield and climate factors (Prcp, T_{Min}, T_{Max}) and fertilizer (Frtz)for different climate types (Arid, Temperate, Cold).

Yield in Climate Type	Prcp	T_{Min}	T_{Max}	Frtz
Yield/ Arid	0.4081	0.0891	-0.0054	0.5429
Yield/ Cold	0.4371	0.2422	0.1811	0.3760
Yield/Temp	0.2709	0.1333	-0.0515	0.4086

Regression of Yield on Fertilizer and Soil Type

Table 4 illustrates the impact of fertilizers and different soil types on yield across various climate conditions. The results of the regression analyses across Temperate, Cold, and Arid areas reveal that fertilizer usage consistently has a significant positive impact on yield, emphasizing its critical role in agricultural productivity. In Temperate areas, all soil types (Loamy-Soil.2, Loamy-Soil.3, and Sandy-Soil) significantly increase yield compared to the reference soil. In contrast, only Sandy-Soil shows a significant positive effect in Cold areas. In Arid regions, Loamy-Soil.3 and Sandy-Soil contribute significantly to yield, with Sandy-Soil having the most significant effect. Across all models, the intercepts are highly significant, establishing robust baseline yields, and the overall model fits are strong, with predictors collectively explaining substantial yield variability, as evidenced by highly significant F-statistics.

Table 4. Summary of the model predicting Yield with Fertilizer (Frtz) and Soil types for Temperate, Cold, and Arid zones.

Parameter	Estimate	Std. Error	t value	Pr (>|t|)
		Temperate		
Intercept	452.64	43.09	10.504	< 2e-16 ***
Frtz	3.52	0.20	17.599	< 2e-16 ***
Loamy-Soil.2	371.10	74.73	4.966	7.51e-07 ***
Loamy-Soil.3	198.97	37.79	5.266	1.57e-07 ***
Sandy-Soil	360.85	65.01	5.551	3.29e-08 ***
F-statistic:		99.72		
p-value:		< 2.2e-16		
		Cold		
Intercept	656.5679	69.9939	9.380	< 2 × 10−16 ***
Frtz	2.5050	0.4598	5.448	8.58 × 10−8 ***
Loamy-Soil.2	43.3467	88.2041	0.491	*0.6234*
Loamy-Soil.3	22.7419	66.6432	0.341	0.7331
Sandy-Soil	224.8900	112.7241	1.995	0.0467 *
F-statistic:		19.25		
p-value:		1.383e-14		
		Arid		
Intercept	357.4581	35.5290	10.061	< 2.2e − 16 ***
Frtz	4.7307	0.2021	23.413	< 2.2e − 16 ***
Loamy-Soil.2	71.2399	52.2822	1.363	0.173
Loamy-Soil.3	159.9529	34.3569	4.656	3.51e − 06 ***
Sandy-Soil	693.3563	88.4516	7.839	8.38e − 15 ***
F-statistic:		187.3		
p-value:		2.2 e - 16		
		Significance Codes		
0 ‘***’	0.001 ‘**’	0.01 ‘*’	0.05 ‘.’	0.1 ‘ ’

Regression of Residuals on Climate Factors

After completing the initial regression analysis, we extracted the residuals and performed a second regression to examine the impact of climate factors on these residuals. This two-step approach allowed us to isolate and analyse the influence of climate variables on yield variability that the initial model did not explain.

The regression analyses of residuals from initial yield models across Temperate, Cold, and Arid regions, shown in Table 5, highlight the nuanced impacts of climatic factors on agricultural productivity and emphasize the importance of incorporating climate variables into yield predictions. In temperate areas, positive coefficients for Prcp and T_{Min} indicate that these factors enhance yields, while the negative coefficients for their quadratic terms ($Prcp_2$ and T_{Max}^2) reveal diminishing returns or adverse effects at higher levels, underscoring non-linear relationships and the critical role of optimal climate conditions. In cold regions, Prcp positively influences residuals, highlighting the underestimated benefits of moisture in the initial model, while higher T_{Min} shows adverse effects, suggesting overestimated benefits of warming; the T_{Min}^2 further reveals non-linear impacts of extremely low temperatures on yields. Similarly, in arid regions, Prcp and T_{Min} positively affect residuals, with diminishing returns at excessive levels indicated by negative quadratic terms, reflecting risks like waterlogging or salinization and adverse crop responses to extreme temperatures. These findings collectively demonstrate that while initial models based on fertilizer and soil types provide a baseline, integrating detailed climate variables and their non-linear effects is essential for improving yield model precision and developing adaptive strategies for climate variability in diverse agricultural systems.

It is important to note that comprehensive diagnostic tests (such as tests for residual normality, homoscedasticity, and autocorrelation) were meticulously performed across all models developed in this study. Given the inherent structure and characteristics of the climatic and agricultural data, issues such as non-normal residuals, heteroscedasticity, autocorrelation, and multicollinearity (especially in the presence of polynomial terms) were observed. To ensure the validity and robustness of our results, we systematically employed robust statistical methods, including Robust Standard Errors for regression models and variable centering to mitigate multicollinearity in the second-stage models. Therefore, all outputs and results presented in this article reflect the application of these corrections and rigorous statistical approaches to overcome the inherent challenges of the data, thereby ensuring the credibility and reliability of our findings.

Table 5. Summary of the model predicting Residual with Climate Factors for Temperate, Cold, and Arid zones.

Parameter	Estimate	Std. Error	t value	Pr(>|t|)
		Temperate		
Intercept	-3.03374e+02	1.90759e+02	-1.59036	0.1119395
Prcp	1.25171e+00	2.17896e-01	5.74452	1.0890e-08 ***
T_{Max}	1.35803e+01	2.35549e+01	0.57654	0.5643275
T_{Min}	5.17179e+01	1.21359e+01	4.26157	2.1406e-05 ***
Prcp^2	-7.97323e-04	1.89560e-04	-4.20618	2.7318e-05 ***
T_{Max}^2	-1.89702e+00	7.17554e-01	-2.64373	0.0082748 **
T_{Min}^2	-7.20379e-01	1.04585e+00	-0.68880	0.4910422
Multiple R-Squared:		0.71		
		Cold		
Intercept	-6.33916e+02	2.69843e+02	-2.34920	0.019265 *
Prcp	1.97903e+00	4.70445e-01	4.20672	3.1552e-05 ***
T_{Max}	-3.10292e+01	4.46018e+01	-0.69569	0.486996
T_{Min}	-2.83900e+01	1.29129e+01	-2.19858	0.028440 *
Prcp^2	-7.19510e-04	4.27570e-04	-1.68279	0.093142 .
T_{Max}^2	3.37268e+00	2.54750e+00	1.32392	0.186233
T_{Min}^2	-7.61678e+00	1.17554e+00	-6.47938	2.5253e-10 ***
Multiple R-Squared:		0.83		
		Arid		
Intercept	-6.39796e+02	2.72521e+02	-2.34769	0.01901517 *
Prcp	3.19122e+00	4.92547e-01	6.47901	1.2366e-10 ***
T_{Max}	8.13744e+00	2.94383e+01	0.27642	0.78225994
T_{Min}	6.80239e+01	1.48341e+01	4.58566	4.8890e-06 ***
Prcp^2	-2.63468e-03	7.09306e-04	-3.71445	0.00021087 ***
T_{Max}^2	-1.37589e+00	7.06383e-01	-1.94779	0.05161992 .
T_{Min}^2	-1.93440e+00	6.54692e-01	-2.95468	0.00317714 **
Multiple R-Squared:		0.75		

Our findings align with previous research, emphasizing the critical role of temperature and precipitation in determining wheat productivity. For instance, studies by Maddah et al. (2015) and Zarakani et al. (2014) in Iran demonstrated that temperature and precipitation are primary drivers of yield variations in both irrigated and rainfed conditions. Similar conclusions were drawn by Nazari et al. (2021), who found that climate change impacts rainfed wheat yields differently across various climatic regions. Cold semi-arid areas potentially benefit from warmer temperatures, while temperate and hot arid regions face negative impacts.

Future Yield

After completing the estimations, we proceeded to forecast future yields using climate data under three scenarios: SSP1-2.6, SSP2-4.5, and SSP5-8.5. We first used the initial regression model to predict future yields, which relate yield to fertilizer and soil type, to determine the explained yield component. We calculated the mean of this explained component and treated it as a fixed part for each climate scenario. Next, we employed a second regression model, which analyzes the residuals from the first model in relation to climate factors. Using this model, we predicted the residuals for each climate scenario. Finally, we obtained the forecasted yield for each climate scenario by summing the predicted residuals from the second model with the fixed component from the first model.

We also computed prediction intervals to quantify the uncertainty in our model's forecasts. These intervals are crucial as they provide a range within which future observations will likely fall, accounting for model parameter uncertainty and data variability. For instance, a 95% prediction interval means that 95% of such intervals would contain the actual outcome if the experiment were repeated multiple times. Even with additional factors in the model, future yield predictions are expected to fall within these intervals, as they encompass the full range of plausible values, reflecting the overall uncertainty (Nagashima et al., 2019; Nikulchev and Chervyakov, 2023; Tian et al., 2022).

$$Lower/Upper = Predicted\_Yield \pm Z \times Standard\_Error \qquad (5)$$

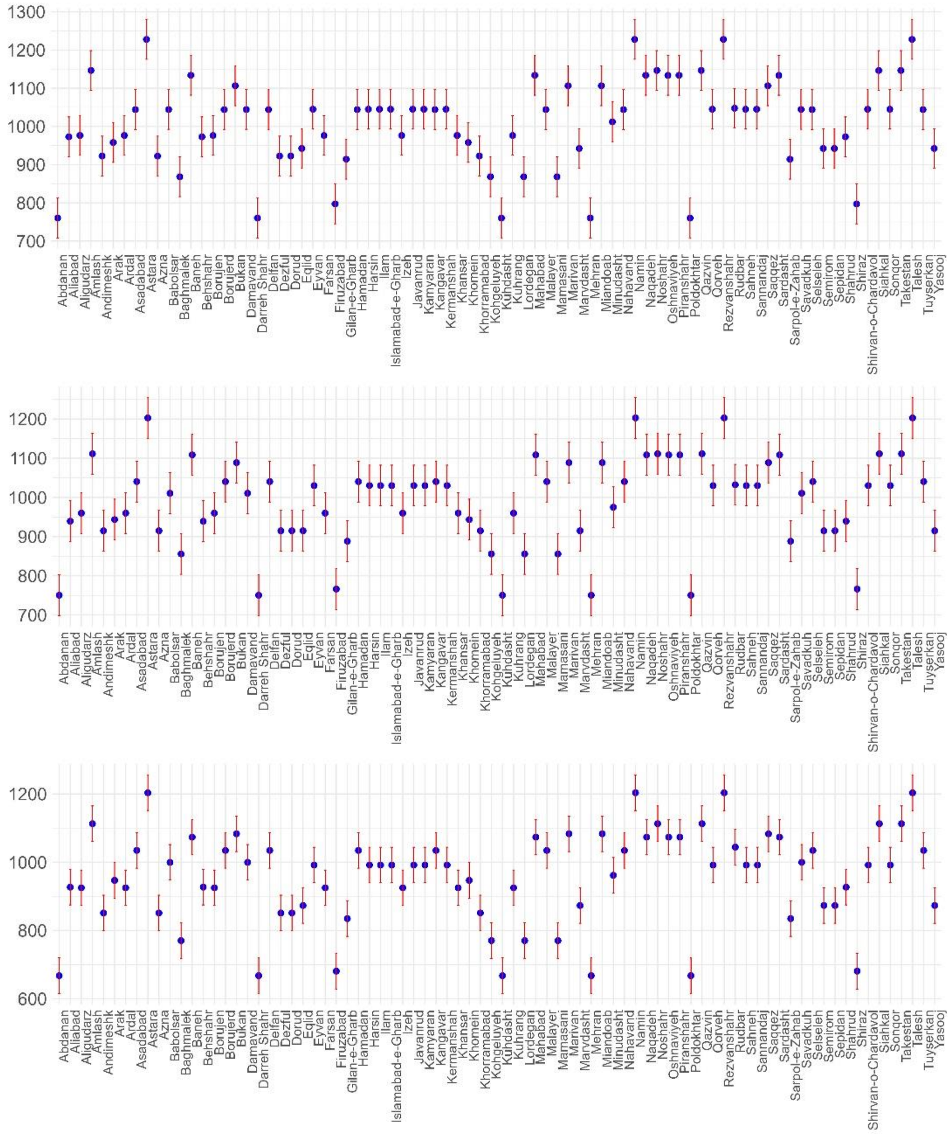
Table 6, provides a comprehensive comparison of observed and projected average crop yields across the Temperate, Cold, and Arid regions, highlighting the impacts of climate change under different emissions scenarios from 1991-2023 to 2051-2073. The observed yields, which are highest in the Temperate region, are followed by the Cold and Arid regions, reflecting the varying climatic conditions that influence agricultural productivity. Under the SSP1-2.6 scenario, characterized by low emissions and moderate temperature increases, all regions show a decline in yields. The Temperate region experiences a 9.6% decrease, attributed to slight temperature increases that could reduce the optimal growing conditions. The Cold region sees a 15.6% reduction, likely due to shorter growing seasons as temperatures rise. In comparison, the Arid region faces a 16.9% drop, exacerbated by potential decreases in precipitation and increased evapotranspiration rates. These changes suggest that temperature and precipitation patterns shifts will adversely affect yields even under a scenario with strong mitigation efforts.

In the SSP2-4.5 scenario, the moderate emissions decline is more pronounced due to greater temperature increases and altered precipitation patterns. The Temperate region's yield decreases by 11.3%, as warmer temperatures could push conditions beyond the optimal range for some crops. The Cold region experiences a 16.4% decline, potentially due to further shortening of the growing season and more erratic precipitation patterns. The Arid region faces a substantial 20.3% drop, likely driven by increased temperatures and decreased rainfall, exacerbating water scarcity and crop stress. The SSP5-8.5 scenario, characterized by high emissions and significant temperature increases, predicts the most severe declines. The Temperate region sees a 14.2% reduction, as higher temperatures could lead to heat stress and reduced yields. The Cold region experiences a 20% decline, reflecting drastic temperature changes and potentially more variable and extreme precipitation events, which can disrupt crop growth. The Arid region suffers the steepest drop, at 24.5%, driven by extreme heat and further reductions in precipitation, severely impacting water availability and crop viability. This comparison illustrates the significant impact of rising temperatures and changing precipitation patterns on crop yields across different regions. While the Temperate region may retain some resilience due to its initially favorable conditions, the Cold and Arid regions are particularly vulnerable to the projected climatic shifts. These findings emphasize the critical importance of addressing temperature increases and precipitation variability through comprehensive mitigation and adaptation strategies, as these factors are key drivers of the potential decline in agricultural productivity under future climate scenarios.

Table 6. Average Yield for Each Scenario (2051-2073) and Average Observed Yield (1991-2023).

	Temperate	Cold	Arid
Observed Yield	1115.37	950.75	938.36
SSP1-2.6	1008.72	802.53	779.88
SSP2-4.5	989.99	795.14	747.70
SSP5-85	957.41	760.67	708.84

Analysing the predicted yield values and their 95% prediction intervals reveals significant insights into the variability and uncertainty inherent in agricultural yield forecasts. As shown in Figs. 4 to 6, the predicted yields for various cities exhibit considerable variation, with corresponding prediction intervals indicating the potential range of yield outcomes. This variability underscores the importance of understanding and managing the factors contributing to yield fluctuations. Policymakers and agricultural stakeholders must consider these prediction intervals when planning and implementing agricultural strategies. In conclusion, the predicted yields and their associated prediction intervals provide valuable information for understanding and mitigating the risks associated with agricultural production. By leveraging this information, stakeholders can make informed decisions to enhance yield stability and ensure food security. Future research should focus on refining prediction models to reduce uncertainty and developing innovative solutions to address the underlying causes of yield variability.



(a)
SSP1-2.6

(b)
SSP2-4.5

(c)
SSP5-8.5

Figure 4. Predicted Yield _ Temperate Areas / Blue point = Predicted Yield, Red line = Intervals.

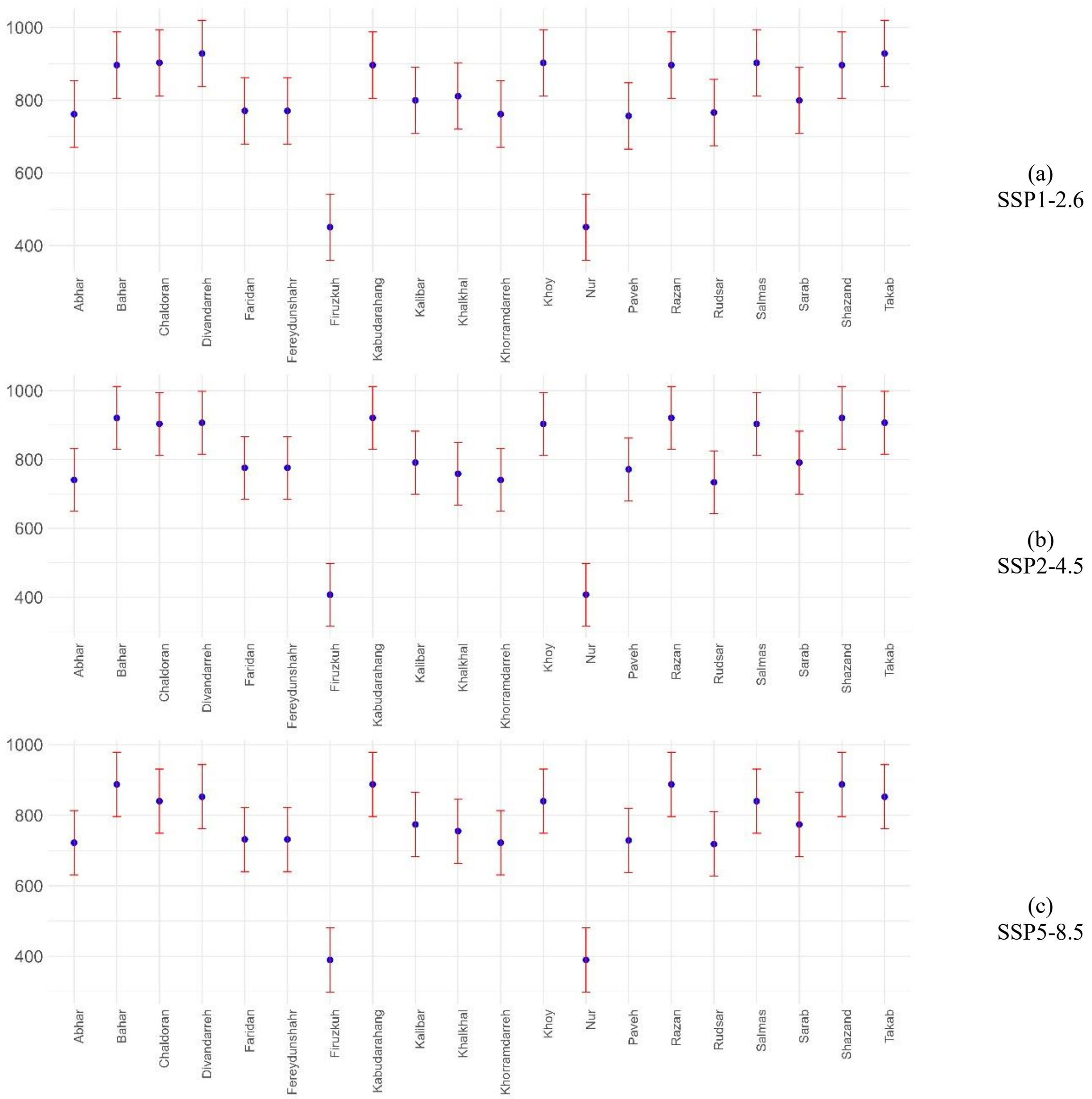


Figure 5. Predicted Yield _ Cold Areas / Blue point = Predicted Yield, Red line = Intervals.

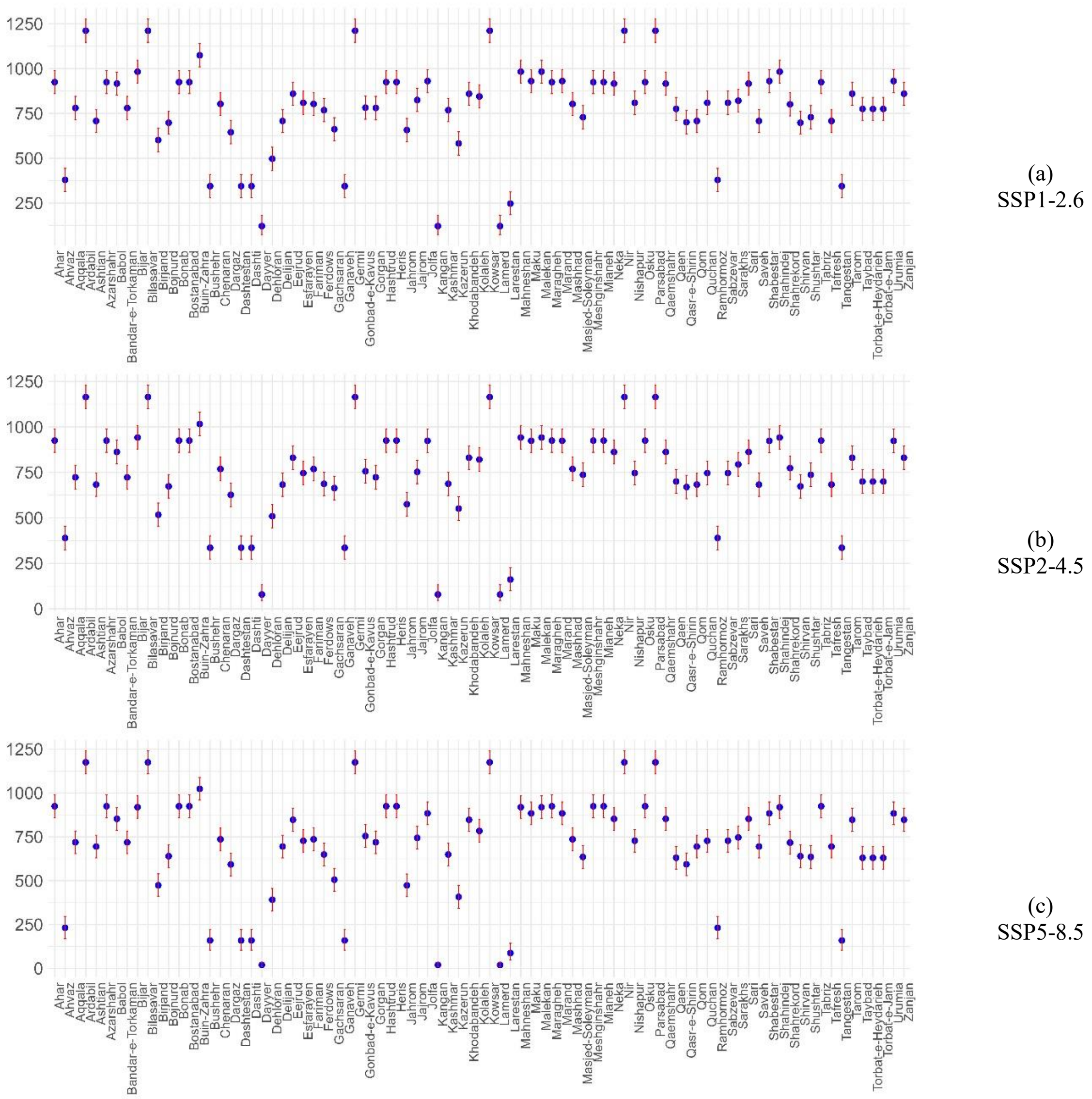


Figure 6. Predicted Yield _ Arid Areas / Blue point = Predicted Yield, Red line = Intervals.

Fig. 7 presents projected volatility in yields across 80 temperate cities from 2051 to 2073 under three climate scenarios: SSP1-2.6, SSP2-4.5, and SSP5-8.5. The results indicate that SSP1-2.6 generally exhibits the lowest yield volatility, suggesting more stable agricultural conditions. In contrast, SSP5-8.5, which is associated with significant climate change impacts, exhibits consistently high volatility, reflecting substantial fluctuations in crop yields and increased uncertainty. The moderate scenario, SSP2-4.5, shows intermediate volatility levels. Across all scenarios, a general trend of increasing volatility over time is observed, particularly pronounced under SSP5-8.5.

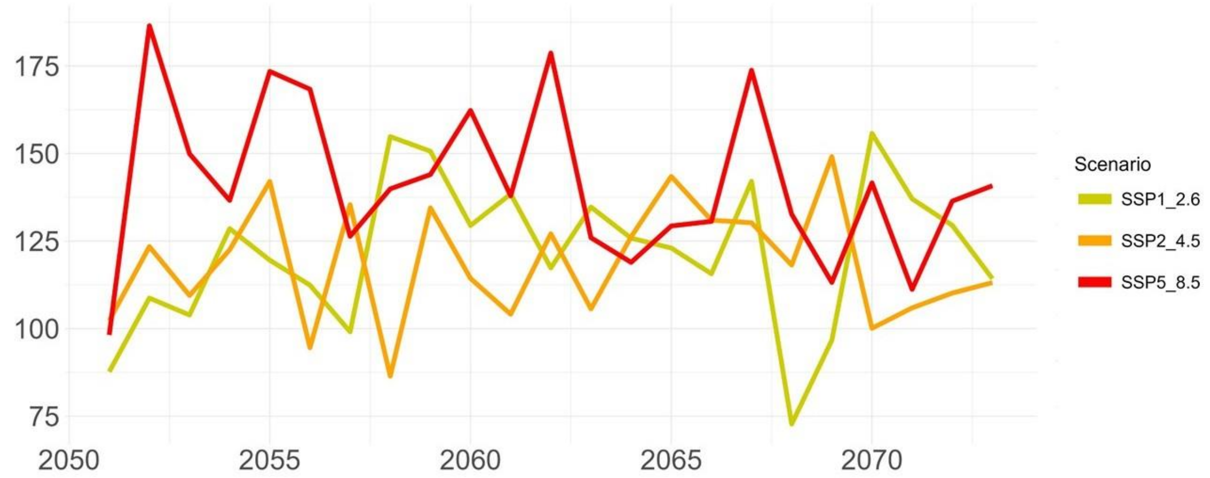


Figure 7. Volatility of the Yield in Temperate Cities over Years in Different Scenarios, y = Volatility, x = Years.

Fig. 8, represents the projected volatility of agricultural yields across 20 cold cities from 2051 to 2073 under three different climate scenarios. The SSP1-2.6 scenario exhibits moderate volatility, with notable peaks, such as 264.9 in 2059, indicating significant variability. SSP2-4.5, a scenario representing moderate emissions, exhibits more consistent volatility, with significant peaks, such as 213.1 in 2054 and 228.3 in 2071, indicating heightened unpredictability in yields. The SSP5-8.5 scenario, characterized by high emissions and substantial climate change impacts, shows fluctuating but generally high volatility, peaking at 230.98 in 2062. Overall, the data suggest that as emissions increase, the volatility of yields becomes more pronounced.

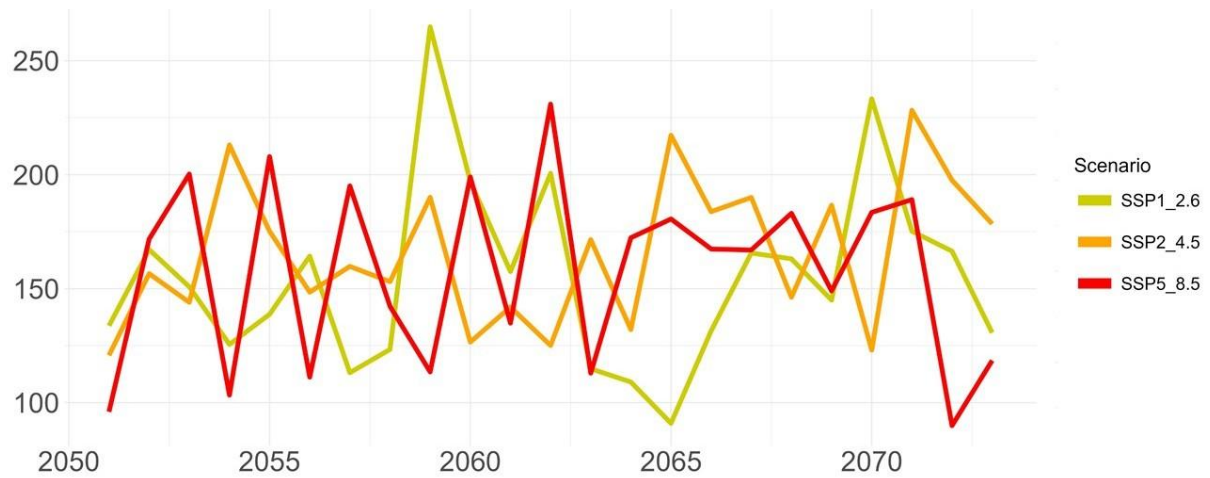


Figure 8. Volatility of the Yield in Cold Cities over Years in Different Scenarios, y = Volatility, x = Years.

Fig. 9 presents projections of agricultural yield volatility across 83 arid cities. Under SSP1-2.6, characterized volatility remains substantial, peaking at 317.4 in 2058, suggesting that even with significant climate mitigation efforts, arid regions may face considerable yield instability. In the SSP2-4.5 scenario, moderate emissions result in pronounced volatility, reaching 333.7 in 2057 and 324.4 in 2069, indicating a high sensitivity of yields to fluctuating climate conditions. The SSP5-8.5 scenario, characterized by high emissions, exhibits the highest volatility, as evidenced by peaks of 368.4 in 2062 and 361.5 in 2070, indicating severe potential disruptions to agricultural production due to the extreme impacts of climate change.

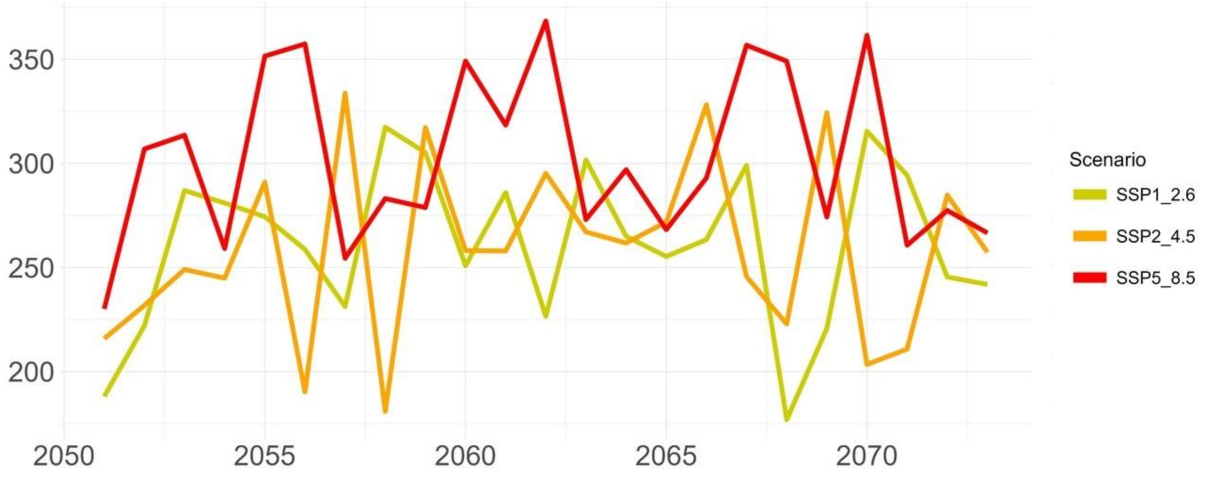


Figure 9. Volatility of the Yield in Arid Cities over Years in Different Scenarios, y = Volatility, x = Years.

Generally, each region exhibits increasing volatility with higher emissions, particularly under SSP5-8.5, which shows the most significant fluctuations. While SSP1-2.6, characterized by low emissions, generally results in lower volatility, especially in arid and cold regions, where the impacts are most pronounced. These findings underscore the critical need for adaptive agricultural strategies in these regions to manage the increased risks and uncertainties associated with future climate scenarios. According to the results, we observe a consistent reduction in wheat yield across all scenarios, aligning with findings from other studies. For instance, Rahmani et al. (2015) demonstrated that wheat yields are expected to decrease by 13% to 28% by 2050 in Birjand. Similarly, Paroon et al. (2020) found that temperature has an inverse relationship with wheat yield, while rainfall has a direct relationship in Hormozgan Province. Their study also indicated that wheat production will experience a significant decline due to climate change by 2100. Moreover, Farajzadeh et al. (2021) projected a 28% to 35% reduction in wheat yield across all stations in northwest Iran by 2100.

Conclusions

This study comprehensively examines the impact of climatic variables and agricultural practices on wheat yield across different climate zones in Iran. Our approach, which employs a two-step estimation process, isolates the effects of climatic variables from other factors, such as fertilizer use and soil type. This method enhances the accuracy of yield predictions by accounting for the nonlinear effects of temperature and precipitation. The significant coefficients for precipitation and temperature in our regression models corroborate the importance of these variables in agricultural productivity, as highlighted by studies using similar statistical approaches (Heil et al., 2020; Kumar and Khanna, 2023). Our results indicate substantial variability in wheat yield based on climate type, with temperate zones showing the highest mean yields due to moderate temperatures and higher precipitation. Conversely, the arid and cold zones face more challenging growing conditions due to temperature extremes and lower, more variable precipitation.

Climate-specific agricultural strategies are crucial for addressing the disparities observed in our analysis. In temperate zones, which showed the highest mean yield and significant effects from multiple soil types and fertilizer usage, policies should focus on sustaining productivity through practices that enhance soil health and improve water-use efficiency. In arid zones, where wheat yield was most sensitive to precipitation variability, adaptation strategies should prioritize investment in modern irrigation infrastructure and adopting drought-tolerant wheat varieties. For cold zones, our regression models revealed strong nonlinear effects of minimum temperature on yield, suggesting that moderate warming may offer benefits. However, extreme cold or sudden shifts may be detrimental. Additionally, fertilizer usage demonstrated a consistently strong and positive impact on wheat yield across all zones, with significant p-values. This finding underscores the importance of policies that ensure equitable access to fertilizers and promote their efficient use. Soil type also plays a critical role, particularly in arid zones, where sandy soils showed the most significant positive effect on yield. As such, soil improvement strategies, including organic matter enhancement and conservation tillage, can be instrumental in boosting yields, especially in more fragile agro-climatic areas.

This study aligns with previous research highlighting the critical role of climate variables in agricultural productivity. For instance, Wu et al. (2021) demonstrated the impact of climate change on maize yields in China, underscoring similar trends in temperature and precipitation effects on crop yields. Similarly, Lobell et al. (2011) analyzed the global impacts of climate change on food production and found that increasing temperatures and changing precipitation patterns have a significant effect on yields. Furthermore, Zhang et al. (2017) emphasized the importance of considering multiple climatic variables in assessing economic impacts on agriculture, which is corroborated by our findings on the intricate interactions between temperature, precipitation, and yield.

Limitations and Implications

This study introduces a novel two-step statistical modeling framework that offers distinct advantages in distinguishing between climatic effects and management-related influences on wheat yield. Unlike previous models that often aggregate all explanatory variables in a single step, our approach enhances interpretability and allows for more precise attribution of yield variability. Applying this method across Iran's temperate, arid, and cold climate zones represents a rare and valuable comparative analysis that few studies have achieved with this level of resolution.

Using a large, long-term dataset and integrating it with CMIP6 climate projections enhances the robustness of our findings and enables forward-looking analysis under multiple emissions scenarios. While the study focuses on key factors such as temperature, precipitation, fertilizer, and soil type, we recognize that future research could incorporate additional dynamic variables such as pest incidence, land-use change, or economic interventions.

Importantly, the modeling framework presented here is transferable to other crops and regions, making it a powerful tool for national and regional agricultural planning. The differentiated findings across climate zones provide concrete guidance for targeted adaptation policies, investment in irrigation systems, and the development of climate-resilient wheat varieties. This work serves as a foundation for both scientific exploration and policy formulation in the face of climate change.

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Appendix

Table A.1. Arid regions in study.

Arid			
Ahar	Dayyer	Khodabandeh	Qaen
Ahvaz	Dehloran	Kolaleh	Qasr-e-Shirin
Aqqala	Delijan	Kowsar	Qom
Ardabil	Eejrud	Lamerd	Quchan
Ashtian	Esfarayen	Larestan	Ramhormoz
Azarshahr	Fariman	Mahneshan	Sabzevar
Babol	Ferdows	Maku	Sarakhs
Bandar	Gachsaran	Malekan	Sari
Bijar	Ganaveh	Maragheh	Saveh
Bilasavar	Germi	Marand	Shabestar
Birjand	Gonbad-e-Kavus	Mashhad	Shahindej
Bojnurd	Gorgan	Masjed-Soleyman	Shahrud
Bonab	Hashtrud	Meshginshahr	Shirvan
Bostanabad	Heris	Mianeh	Shushtar
Buinzahra	Jahrom	Neka	Tabriz
Bushehr	Jajrom	Nir	Tafresh
Chenaran	Jolfa	Nishapur	Tangestan
Dargaz	Kangan	Osku	Tarom
Dashtestan	Kashmar	Parsabad	Taybad
Dashti	Kazerun	Qaemshahr	Torbat-e-Heydarieh
Torbat-e-Jam	Urumia	Zanjan	

Table A.2. Temperate regions in study.

Temperate			
Abdanan	Dezful	Kuhdasht	Rezvanshahr
Aliabad	Dorud	Kuhrang	Rudbar
Aligudarz	Eqlid	Lordegan	Sahneh
Amlash	Eyvan	Mahabad	Sannandaj
Andimeshk	Farsan	Malayer	Saqqez
Arak	Firuzabad	Mamasani	Sardasht
Ardal	Gilan-e-Gharb	Marivan	Sarpol-e-Zahab
Asadabad	Hamadan	Marvdasht	Savadkuh
Astara	Harsin	Mehran	Selseleh
Azna	Ilam	Miandoab	Semirom
Babolsar	Islamabad-e-Gharb	Minudasht	Sepidan
Baghmalek	Izeh	Nahavand	Shahrekord
Baneh	Javanrud	Namin	Shiraz
Behshahr	Kamyaran	Naqadeh	Shirvan-o-Chardavol
Borujen	Kangavar	Noshahr	Siahkal
Borujerd	Kermanshah	Oshnaviyeh	Sonqor
Bukan	Khansar	Piranshahr	Takestan
Damavand	Khomein	Poldokhtar	Talesh
Darreh Shahr	Khorramabad	Qazvin	Tuyserkan
Delfan	Kohgeluyeh	Qorveh	Yasooj

Table A.3. Cold regions in study.

Cold			
Abhar	Bahar	Chaldoran	Divandarreh
Faridan	Fereydunshahr	Firuzkuh	Kabudarahang
Kalibar	Khalkhal	Khorramdarreh	Khoy
Nur	Paveh	Razan	Rudsar
Salmas	Sarab	Shazand	Takab

Table A.4. Full English description for abbreviations.

Abbreviations	Full description
IPCC	Intergovernmental Panel on Climate Change
DSSAT	Decision Support System for Agrotechnology Transfer
WOFOST	World Food Studies
SAFY	Simple Algorithm for Yield estimates
ARIMA	Autoregressive integrated moving average
CMIP	Coupled Model Intercomparison Project (CMIP)
MAE	Mean absolute error
RMSE	Root Mean Squared Error
MAPE	Mean Absolute Percentage Error
SSP	Shared Socioeconomic Pathway

تأثیرات اقلیمی بر عملکرد گندم در ایران: یک تحلیل آماری دو مرحله‌ای در مناطق آب و هوایی متنوع

فاطمه مجتهدی، و بهزاد زکی زاده قریه علی

چکیده

این مطالعه به بررسی تأثیر متغیرهای اقلیمی و شیوه‌های کشاورزی بر عملکرد گندم در مناطق مختلف آب و هوایی ایران می‌پردازد. با استفاده از یک مجموعه داده جامع، ما چگونگی تأثیر دما، بارندگی، نوع خاک و استفاده از کود بر بهره‌وری گندم را تجزیه و تحلیل می‌کنیم. یافته‌های ما نشان‌دهنده تغییرپذیری قابل توجه عملکرد در مناطق معتدل، خشک و سرد است، به طوری که مناطق معتدل به دلیل دمای متوسط و بارندگی کافی، بالاترین میانگین عملکرد را نشان می‌دهند. در مقابل، مناطق خشک و سرد با چالش‌هایی از دمای شدید و بارندگی ناکافی مواجه هستند. این مطالعه از یک فرآیند تخمین دو مرحله‌ای برای جداسازی اثرات متغیرهای اقلیمی از سایر عوامل استفاده می‌کند و دقت پیش‌بینی‌های عملکرد را افزایش می‌دهد. نتایج ما بر نقش حیاتی دما و بارندگی در بهره‌وری کشاورزی تأکید می‌کند و تحقیقات قبلی را تأیید می‌کند و در عین حال بینش‌های جدیدی را از طریق نوآوری‌های روش‌شناختی ارائه می‌دهد. ما چندین توصیه سیاستی، از جمله بهبود زیرساخت‌های آبیاری، ترویج گونه‌های گندم مقاوم در برابر آب و هوا و توسعه استراتژی‌های جامع سازگاری با آب و هوا، ارائه می‌دهیم. هدف این سیاست‌ها افزایش تاب‌آوری و پایداری کشاورزی در مواجهه با تغییرات اقلیمی است. تحقیقات ما به افزایش حجم ادبیات در مورد تغییرات اقلیمی و کشاورزی کمک می‌کند و درک دقیقی از چگونگی تأثیر عوامل اقلیمی بر عملکرد گندم و آگاهی‌بخشی به سیاست‌ها و شیوه‌های کشاورزی مؤثرتر ارائه می‌دهد.