Modeling Climate Suitability for *Triticum aestivum* L. (Common Wheat) in Pakistan Using the MaxEnt Approach

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Received: 27 November 2025 | Revised: 6 January 2026 and 21 January 2026 | Accepted: 23 January 2026

ABSTRACT

Pakistan ranks among the top ten nations globally that are likely to experience severe impacts from climate change and are facing critical food security challenges. Variability in temperature and rainfall alters the geographical suitability of land for crop cultivation. This study employed the Maximum Entropy (MaxEnt) model to forecast the effects of climate change and evaluate land suitability for *Triticum aestivum* L. (common wheat) production in Pakistan, where it is a major staple crop. Bioclimatic variables and occurrence data for two climatic scenarios, Representative Concentration Pathways (RCP) 4.5 and 8.5, from five General Circulation Models (GCMs) were used for the year 2070. The prime factors affecting the *Triticum aestivum* L. distribution are temperature seasonality, annual precipitation, and mean temperature of the warmest quarter. The findings indicate an average decline in highly suitable and moderately suitable areas, whereas an increase is observed in the least suitable areas in future scenarios. The highly suitable area for future distribution accounts for 26.78% and 19.67% under RCP 4.5 and RCP 8.5, respectively, highlighting a negative effect on prospective wheat production in Pakistan. The outcome of this research is of utmost significance for decision-makers to develop suitable adaptation and mitigation protocols to sustain wheat productivity under a changing climate.

Keywords-climate change; spatial rarefaction; Maximum Entropy (MaxEnt) model; Jackknife analysis; potential distribution; Triticum aestivum L.

I. INTRODUCTION

Triticum aestivum L. (common wheat) is the most significant and highly nutritious cereal crop, widely grown under various agro-ecological conditions and cropping patterns around the globe [1, 2]. It is a significant industrial crop that is used to make bread, biscuits, savory snack foods, feed, noodles, and confections. Wheat stalks are also used as animal bedding and in construction material [3]. Thus, *Triticum aestivum* L. occupies a vital position in agriculture as both a primary food crop and a fundamental cash crop [4].

International production of *Triticum aestivum* L. varies due to differences in temperature and climatic conditions worldwide [3]. The security of food sources and their long-term sustainability will become more challenging for the world's growing population as changing climate alters harvested conditions for crops [5].

Although climate change is a worldwide phenomenon, it has a greater influence on developing countries because of their increased vulnerability and limited capability to mitigate its effects [6]. Pakistan and other developing countries have agriculture-based economies, and their agricultural sectors are particularly vulnerable due to direct exposure to environmental conditions [6].

Triticum aestivum L. is grown in 122 countries. Leading wheat-producing countries include China, India, Russia, the United States, Pakistan, Egypt, Turkey, Iran, the United Kingdom, Brazil, Algeria, Morocco, Indonesia, Ukraine, and Uzbekistan. China is the largest producer, accounting for 16% of global wheat production, followed by India (12.5%) [7]. Approximately 220 million hectares of farmland worldwide, supporting 21% of the global population, rely on *Triticum aestivum* L. [8].

Man-made climate change is predicted to have several negative outcomes, including range shifts, species extinctions, and an increase in extreme weather events, which ultimately affect biodiversity and ecosystem functioning [9, 10]. However, the consequences on the distribution and productivity of crops will pose the biggest and most immediate threat to human communities and the economy [11].

Rising temperatures, increasing droughts, decreased precipitation, and reduced soil moisture have drastically affected agricultural production globally [12]. Scholars predict that future agricultural productivity may decrease as a result of rising temperatures, mainly in semi-arid and arid regions like Pakistan [13]. The fifth assessment report from the Intergovernmental Panel on Climate Change (IPCC) indicates that climate change is likely to alter the potential geographic distribution of crops worldwide, potentially expanding suitable land in higher latitudes of the Northern Hemisphere while decreasing it in tropical regions [14].

Triticum aestivum L. is an adaptive crop that can tolerate dynamic climatic conditions. Although it thrives best under temperate climates, high temperatures limit yield. The prime factors limiting wheat production are temperature and precipitation [15]. The ideal temperature for growth is approximately 25 °C, with minimum and maximum values of 3–4°C and 30–32°C, respectively. Since *Triticum aestivum* L. crops can tolerate a wide variety of moisture levels, they can be grown in most places with 250–1750 mm of precipitation annually [16].

In Pakistan, wheat is typically sown in winter, ideally in November. Approximately 90% of wheat is grown on irrigated land, with water requirements ranging from 325–450 mm during the growing season [17]. In Punjab and Sindh, wheat is mostly cultivated on irrigated land, whereas a small amount of winter wheat is grown in northern regions [17]. Loamy and clayey soils are considered ideal, with smooth ground surfaces to allow equitable access for agricultural operations. More than two-thirds of wheat in Pakistan is grown in areas with canal irrigation, including mountainous regions, semi-deserts, deserts, and canal-irrigated lands. According to the economic survey of Pakistan 2013–14, more than 25 million tons of wheat were produced.

To reduce the negative effects of climate change and enhance wheat productivity, irrigation may be considered a form of climate adaptation. Crop productivity is generally higher on irrigated land than on rain-fed land. Studies have shown that irrigation helps reduce the harmful impacts of extreme heat. However, in some regions, particularly in Asia, its effectiveness is limited by water availability and temperature extremes. Moreover, irrigation provides a positive response to changing climates and helps evaluate how water scarcity and weather variability impact future crop production [18].

Under future climate change scenarios, *Triticum aestivum* L. yields are anticipated to decrease in many regions worldwide [19]. Increasing demand for wheat production is a serious challenge; hence, it is imperative to employ methods that enhance production to feed the world's growing population [1].

To address this issue, scientists have developed various models to assess the impact of climate change on wheat production and distribution. Crop modeling approaches are crucial for evaluating climate change impacts because they integrate environmental factors with agricultural growth procedures that are sensitive to climate variability [20]. Advances in Geographic Information Systems (GIS) have facilitated multiple modeling approaches to assess land suitability for crop production [21].

Ecological Niche Models (ENMs) are widely used to determine potential crop distributions [22]. These models can predict suitable habitats in known regions, estimate habitats in unknown regions, and assess changes caused by environmental factors over time [23]. Among these, the Maximum Entropy (MaxEnt) model, which forecasts the prospective distribution of agricultural products, is one of the most effective and commonly employed models [24]. MaxEnt is a software program that uses the maximum-entropy principle to estimate species distributions from recent occurrence records [22]. It has been widely used worldwide due to its handy and easy-to-use software packages for diverse applications [23].

A. *Objectives of the Study*

The objectives of this study are:

- Evaluate the present distribution of *Triticum aestivum* L. in Pakistan using calibrated datasets with the ENM (MaxEnt)
- Describe changes in wheat distribution and range under projected climate change using the MaxEnt model.
- Analyze current and future climate effects on wheat production by considering environmental factors, including temperature and precipitation.
- Delineate areas of potential gain and loss in wheat production under future climate scenarios.

B. Novelty of the Work

This study introduces a novel framework that integrates downscaled climate projections with machine learning-based crop yield modeling. Combining process-based crop models with data-driven techniques improves local-scale prediction accuracy for climate-smart agricultural planning.

II. MATERIALS AND METHODS

A. Description of the Study Area

The distribution and presence of *Triticum aestivum* L. were analyzed in Pakistan, which is divided into 37 administrative regions. The country is located between longitudes 60° 50′ and 77° 50′ E and latitudes 23° 35′ to 37° 05′ N, as shown in Figure 1. Pakistan is a South Asian country with diverse agroecology. The country is particularly susceptible to climate change because of its geographic location, substantial population, and limited technological resources [6]. Precipitation in Pakistan varies widely, mainly in relation to monsoon winds and western disturbances, but there is no uniform rainfall throughout the year. From December to March, Khyber Pakhtunkhwa (KPK) and Baluchistan receive the most rainfall, whereas Punjab and Sindh receive 50–75% of the total during the rainy season. The summer monsoon occurs from the end of June to 15 September [25].

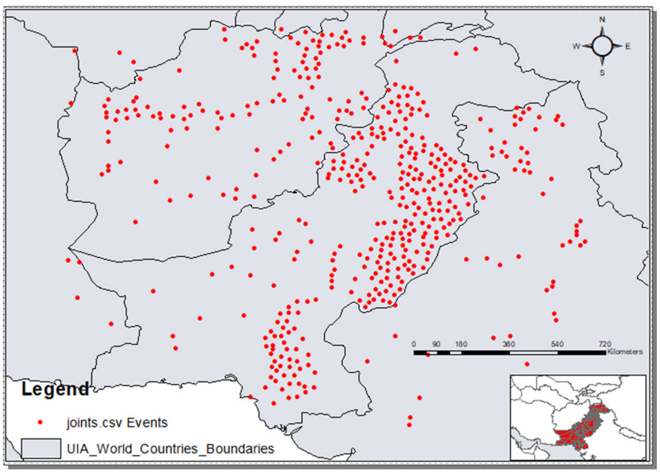

Fig. 1. Present localities of *Triticum aestivum* L. in Pakistan.

Rain fluctuations have increased geographically, across seasons, and annually in Asia in recent decades. A declining trend of rainfall along Pakistan's coastal areas and a reduction in overall rainfall levels was also observed (IPCC, 2007).

According to Pakistan's Meteorology Department, the main regions of the country experience a dry climate. Moisture conditions exist only over a small area in the north. The largest regions of Punjab and Baluchistan, the main part of the northern area, and the entire Sindh receive less than 250 mm of rainfall annually.

B. Data Collection

Occurrence data with latitude and longitude were obtained from the Global Biodiversity Information Facility (GBIF) and a literature review. Spatial rarefaction was performed to reduce autocorrelation, removing duplicate points clustered within a radius of 20 km. Using ArcGIS 10.3, a map of occurrence points was created. For MaxEnt modeling, a total of 447 points were utilized.

The environmental variables used in this study included current and future bioclimatic variables. The 19 current bioclimatic variables were downloaded in raster format at a spatial resolution of 2.5 from WorldClim (http://www.worldclim.org). Future climate data were acquired from the Climate Change, Agriculture and Food Security (CCAFS) database (http://www.ccafs-climate.org). The future scenarios were based on two Representative Concentration Pathways (RCPs), RCP 4.5 and RCP 8.5, for the year 2070.

The General Circulation Models (GCMs) selected for this study were GISS-E2-R, MIROC5, MOHC-HADGEM2-CC, MPI-ESM-LR, and NCAR-CCSM 4, all with 2.5 spatial resolution. Bioclimatic layers were created by integrating historical trends of temperature and precipitation. These layers are crucial for estimating the differences between present and future climatic patterns, and consequently, for predicting the potential distribution of species.

C. Data Processing

Figure 2 provides a clear view of the data processing methodology. For *Triticum aestivum L.* crop, spatial rarefaction was performed to reduce autocorrelation. Using ArcGIS, the occurrence points and potential distribution regions of *Triticum aestivum* L. in Pakistan were clipped to the study area.

The bioclimatic layers Bio8, Bio9, Bio18, and Bio19 (mean temperature of the wettest quarter, mean temperature of the driest quarter, precipitation of the warmest quarter, precipitation of the coldest quarter) were removed from the MaxEnt analysis because these layers contain unusual anomalies and artifacts that could affect the results [26]. The remaining 15 variables were used in the MaxEnt model for further analysis, as presented in Table I.

D. Maximum Entropy Approach

MaxEnt is a software application based on the maximum entropy approach, which is widely used to estimate the probability and suitability of species in a geographic range [27]. It requires input data, including species presence records and environmental variables. The version used in this study was MaxEnt 3.4.4.

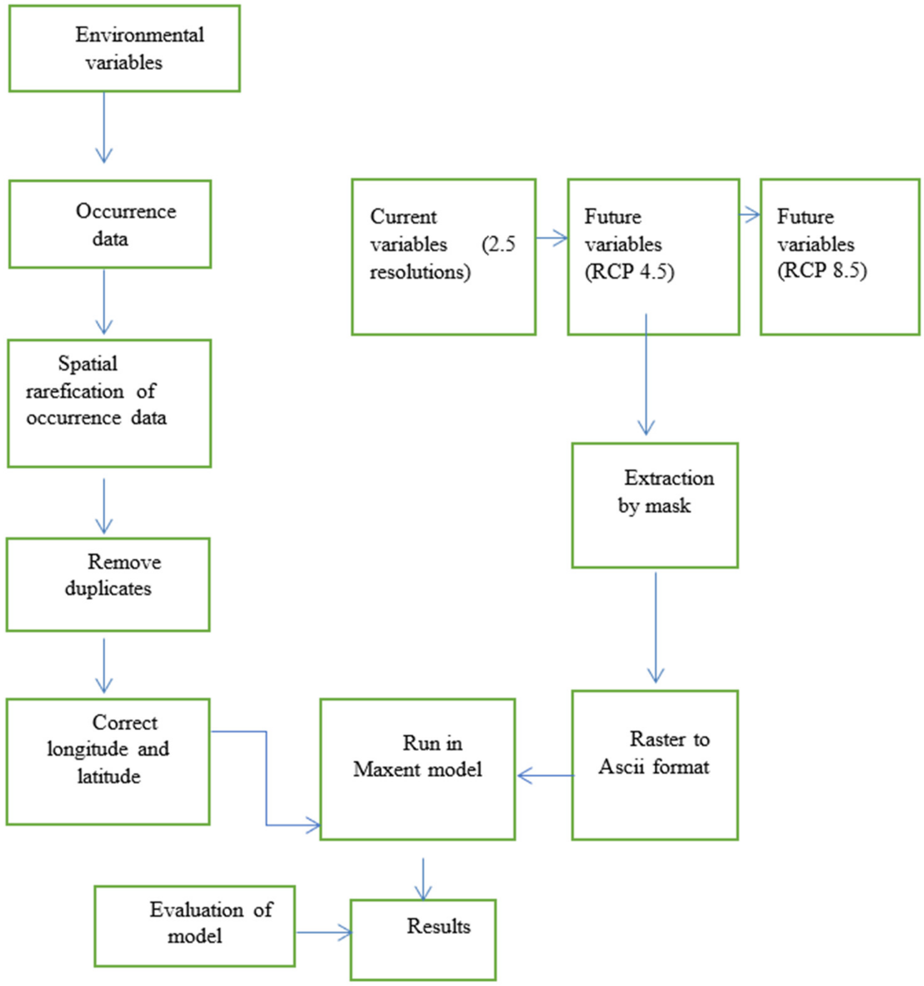

Fig. 2. Flow diagram of the processing methodology.

TABLE I. BIOCLIMATIC VARIABLES USED IN MAXENT MODELING AND THEIR DESCRIPTIONS

No.	Bioclimatic variable	Description
1	Bio1	Annual mean temperature
2	Bio2	Mean diurnal range (mean of monthly max temp – min temp)
3	Bio3	Isothermality (Bio2/Bio7 × 100)
4	Bio4	Temperature seasonality (standard deviation ×100)
5	Bio5	Max temperature of warmest month
6	Bio6	Min temperature of coldest month
7	Bio7	Temperature annual range (Bio5 – Bio6)
8	Bio10	Mean temperature of warmest quarter
9	Bio11	Mean temperature of coldest quarter
10	Bio12	Annual precipitation
11	Bio13	Precipitation of wettest month
12	Bio14	Precipitation of driest month
13	Bio15	Precipitation seasonality (coefficient of variation)
14	Bio16	Precipitation of the wettest quarter
15	Bio17	Precipitation of the driest quarter

E. Running the MaxEnt Model

To run the MaxEnt model, species occurrence data and environmental layers must be prepared in the correct formats. The species occurrence file must include three fields: species name, longitude, and latitude in decimal degrees. The environmental layers must be in ASCII format, and all 15 layers were selected for the MaxEnt analysis. The resulting ASCII files were then converted to raster using the ArcGIS ModelBuilder function and reclassified for area computation. All categories were used to estimate median values for area calculations expressed as percentages. Jackknife tests and the Area Under the Curve (AUC) were computed in MaxEnt to assess model accuracy using both training and test datasets. The MaxEnt 3.4.4 parameters window is shown in Figure 3.

III. RESULTS AND DISCUSSION

The relative percentage contributions of the predictor variables are presented, followed by an assessment of the model's performance using AUC values, and finally, current and future hypothetical habitat suitability maps are shown and contrasted. The contributions of environmental variables to the MaxEnt model are estimated and listed in Table II.

TABLE II. CONTRIBUTION OF ENVIRONMENTAL VARIABLES TO THE MAXENT MODEL

Variable	Contribution (%)
Bio4	23.5
Bio12	11.5
Bio10	10.6
Bio13	10.1
Bio5	9.6
Bio14	5.5
Bio15	5.3
Bio2	5.1
Bio1	5.1
Bio3	4.5
Bio17	4.3
Bio16	1.8
Bio6	1.5
Bio7	1.2
Bio11	0.4

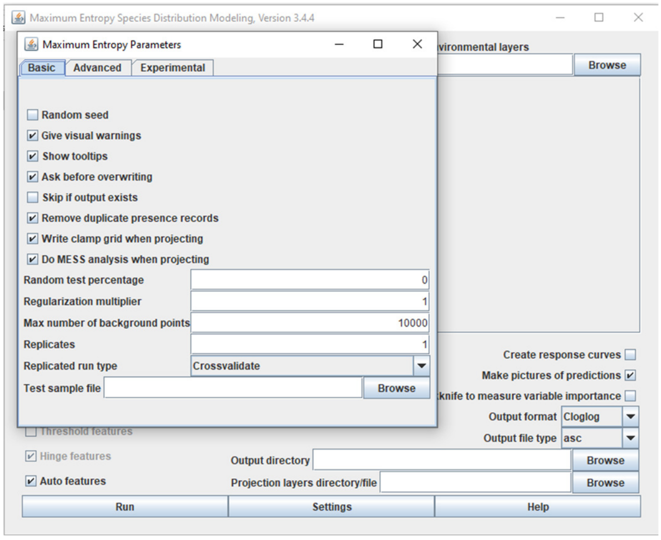

Fig. 3. The processing window of MaxEnt.

The main variables predicting the potential distribution of *Triticum aestivum* L. in Pakistan are temperature seasonality (Bio4) and annual precipitation (Bio12) for the current scenario, with respective contributions of 23.5% and 11.5% (Table II). The relative importance of all environmental variables was further assessed using Jackknife tests, which evaluate the effect of each variable on model performance by measuring changes in regularized training gain and test gain when excluded from the model (Figure 4). The MaxEnt model's predictive performance was evaluated using the AUC, which was 0.805 for *Triticum aestivum* L. (Figure 5), indicating high predictive accuracy. AUC values measure how well the model distinguishes between classes; the higher the AUC value, the better the model's predictions [28, 29].

The current and future distribution maps of *Triticum aestivum* L. are shown in Figures 6 and 7, using RCP 4.5 and RCP 8.5 for 2070. Dark green indicates highly suitable areas, whereas light green to grey indicates moderately and least suitable areas.

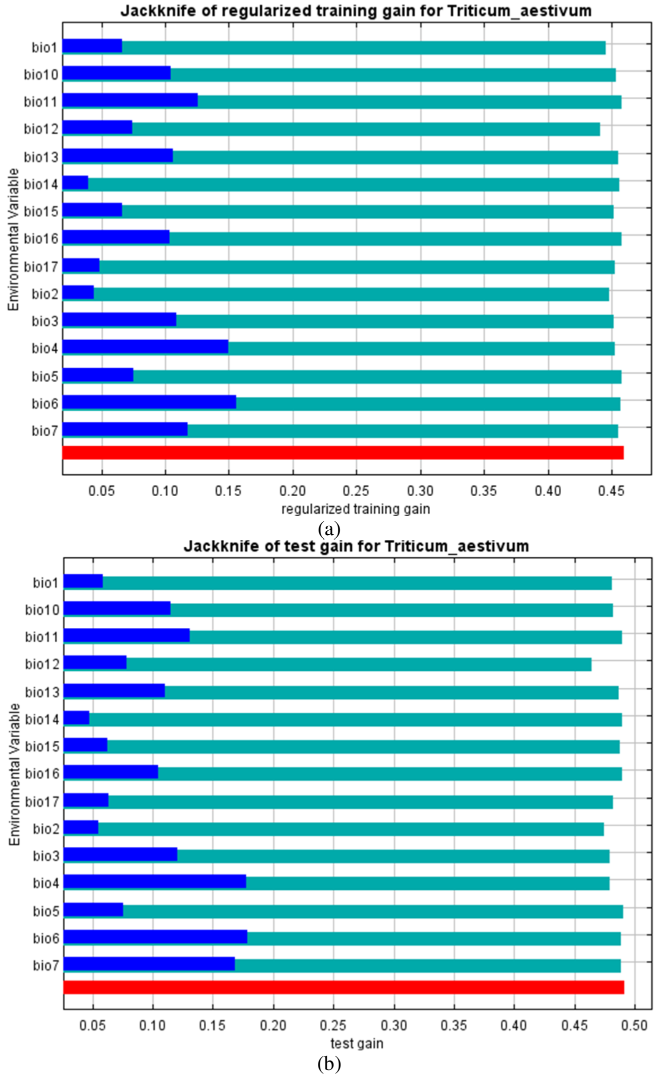

Fig. 4. Jackknife tests for *Triticum aestivum* L.: (a) regularized training gain, (b) test gain.

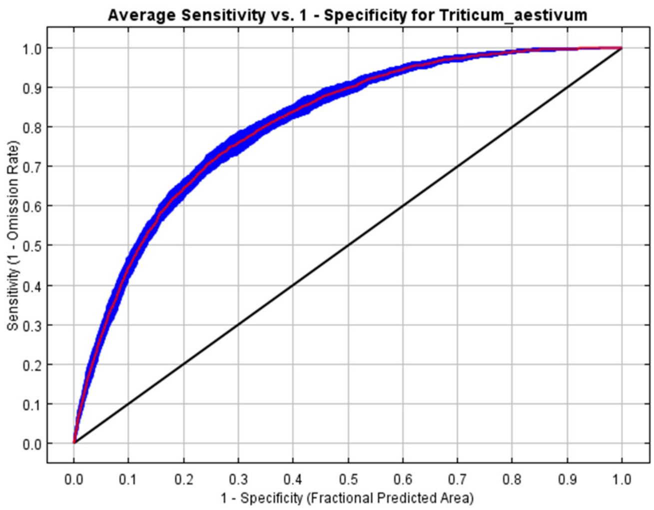

Fig. 5. Receiver Operating Characteristic (ROC) curve showing the AUC for Triticum aestivum L.

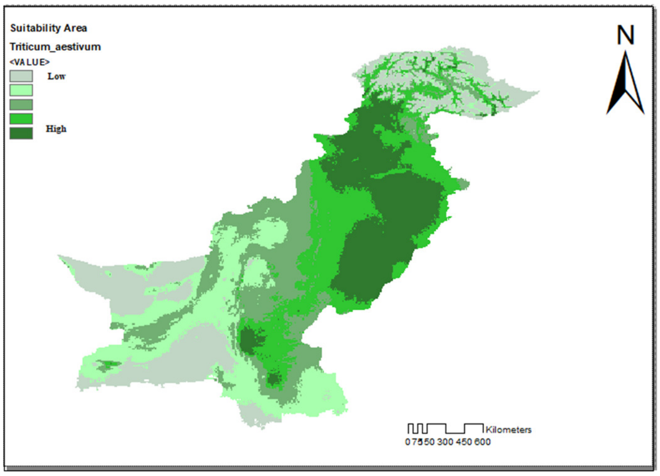

Fig. 6. Current potential distribution of *Triticum aestivum* L. in Pakistan.

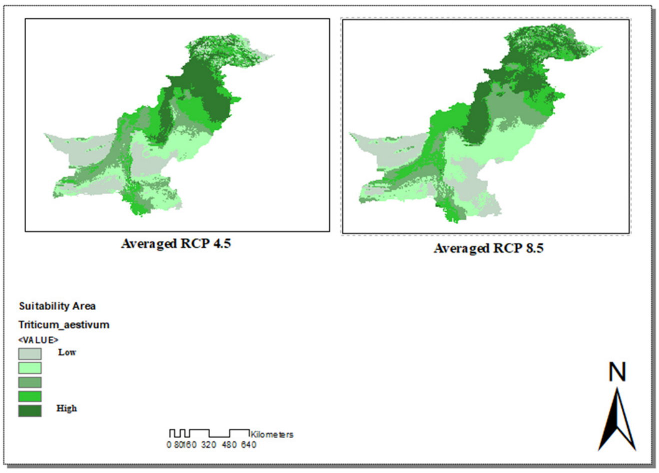

Fig. 7. Future potential distribution of *Triticum aestivum* L. in Pakistan under averaged RCP 4.5 and RCP 8.5 scenarios.

Table III presents the suitable area for *Triticum aestivum* L. under current climatic conditions. Habitat suitability was classified into three categories: highly suitable, moderately suitable, and least suitable. The results indicate that 39.31% of the area is highly suitable, 17.06% is moderately suitable, and 43.62% is least suitable.

TABLE III. CURRENT DISTRIBUTION OF *TRITICUM AESTIVUM* L.

Classification	Current distribution (km²)	Current distribution (%)
Highly suitable	389,452	43.62
Moderately suitable	152,354.36	17.06
Least suitable	350,997.40	39.31

The highly suitable areas decrease to 26.78% and 19.67% under RCP 4.5 and RCP 8.5, respectively, in 2070. Moderately suitable areas cover 19.29% and 18.42%, whereas least suitable areas expand to 53.92% and 61.90% under the two scenarios (Table IV).

TABLE IV. FUTURE DISTRIBUTION OF *TRITICUM AESTIVUM* L. UNDER RCP 4.5 AND RCP 8.5 (2070)

Classification	Future distribution RCP 4.5 (km²)	RCP 4.5 (%)	Future distribution RCP 8.5 (km²)	RCP 8.5 (%)
Highly suitable	237,830.61	26.78	174,709.69	19.67
Moderately suitable	171,309.42	19.29	163,625.95	18.42
Least suitable	478,892.41	53.92	549,696.80	61.90

IV. CONCLUSION

This research focuses on identifying highly suitable, moderately suitable, and least suitable areas for wheat production in Pakistan under changing climate scenarios. To better understand the future distribution of *Triticum aestivum* L., it is essential to understand the factors influencing potential instability in its distribution. By using the Maximum Entropy (MaxEnt) model, it was found that highly and moderately suitable areas are projected to decrease, whereas the least suitable areas are projected to increase under Representative Concentration Pathways (RCP) 4.5 and 8.5. Punjab is the primary production region, followed by Sindh and upper Khyber Pakhtunkhwa (KPK), whereas winter wheat is grown on a smaller scale in the northern regions of Balochistan. This study indicates that projected temperature increases may reduce suitable habitats. The results of this research will help decision-makers understand potential changes in the geographical distribution of *Triticum aestivum* L. production and provide a basis for developing effective strategies to mitigate the effects of climate change.

V. RECOMMENDATIONS

The following recommendations may be considered for managing wheat production under a changing climate:

1. This research may be used to consider future land-use changes in the context of climate change and atmospheric circulation patterns.
2. Suitable areas should be further developed to enhance wheat production.
3. Mitigation measures should be designed to ensure sustainable production in less suitable areas.
4. Stress-tolerant, hybrid, and genetically engineered wheat varieties, along with sufficient water and fertilizers, may be developed to cope with adverse climatic conditions in these less suitable areas.

ACKNOWLEDGMENT

The authors extend their appreciation for the support provided by the University of Business and Technology, Jeddah, Saudi Arabia.

DATA AVAILABILITY STATEMENT

The data supporting the findings of this study are included in this paper.

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