Modeling climate suitability for wheat (*Triticum aestivum L.)* distribution inPakistan by Maximum Entropy (Maxent) approach

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Abstract:

Pakistan is one of ten countries in the world which are likely to be strongly affected by climate change and face very serious food security issues. The variability in temperature and precipitation diversifies the geographical expediency of lands for crop cultivation. This research used the (Maxent) model based on maximum entropy approach to predict the climate change impact and land suitability for wheat production in Pakistan. Wheat is by far a significant and major staple food in Pakistan. Wheat occurrence location data and bioclimatic variables for two climatic scenarios Representatives Concentration Pathways (RCP) 4.5 and 8.5 from five general circulation models (GCMs) are used for the year 2070. The main factors that affect the distribution of wheat, according to the study, 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 while a boost in the least suitable area in future scenario. The highly suitable area for future distribution accounts for 26.78% and 19.67% of RCP 4.5 and RCP 8.5 respectively; which shows a negative impact on prospective wheat production in Pakistan. The outcome of this study is of utmost significance for policy makers to create suitable adaptation and mitigation protocols needed to maintain wheat productivity in the face of changing climate.

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Amna Rashid

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Chapter 1: Introduction

Wheat *Triticum aestivum L*. is the most significant and highly nutritious cereal crop, widely grown under various agro-ecological conditions and cropping patterns around the globe (Tiwari & Shoran, 2010; Simmons et al., 2020). It is the second maximum harvested and produced crop around the world. The majority of the people in Pakistan prefer wheat, which is a significant food crop in the country. It is an important agricultural commodity, used as a staple food. It is a significant industrial crop that is used to make savoury snack foods, biscuits, bread, feed, noodles, and confections. Wheat stalk are also used as animal bedding and in construction material (Oyewole, 2016). Wheat as a major staple food provides more nourishment and calories than any other crop in the world (Guarin et al., 2019). Wheat tends to occupy a vital position in the sector of agriculture as it is a primary food crop along with being the fundamental cash crop. The demand of wheat has been increasing with the passage of time as the population has also been increasing around the globe (Gul et al., 2019).

Wheat is grown in 122 countries of the world. The leading wheat-producing countries include China, India, Russia, the United States, Pakistan, Egypt, Turkey, Iran, United Kingdom, Brazil, Algeria, Morocco, Indonesia, Ukraine and Uzbekistan (Fig 1). China has appeared as the biggest wheat producer and accounted for 16% share in global wheat production followed by India, (12.5%) (Fei et al., 2020). Approximately 220 million hectares of farmland around the world and 21% of the world's population relies on wheat crop (Zheng et al., 2020).

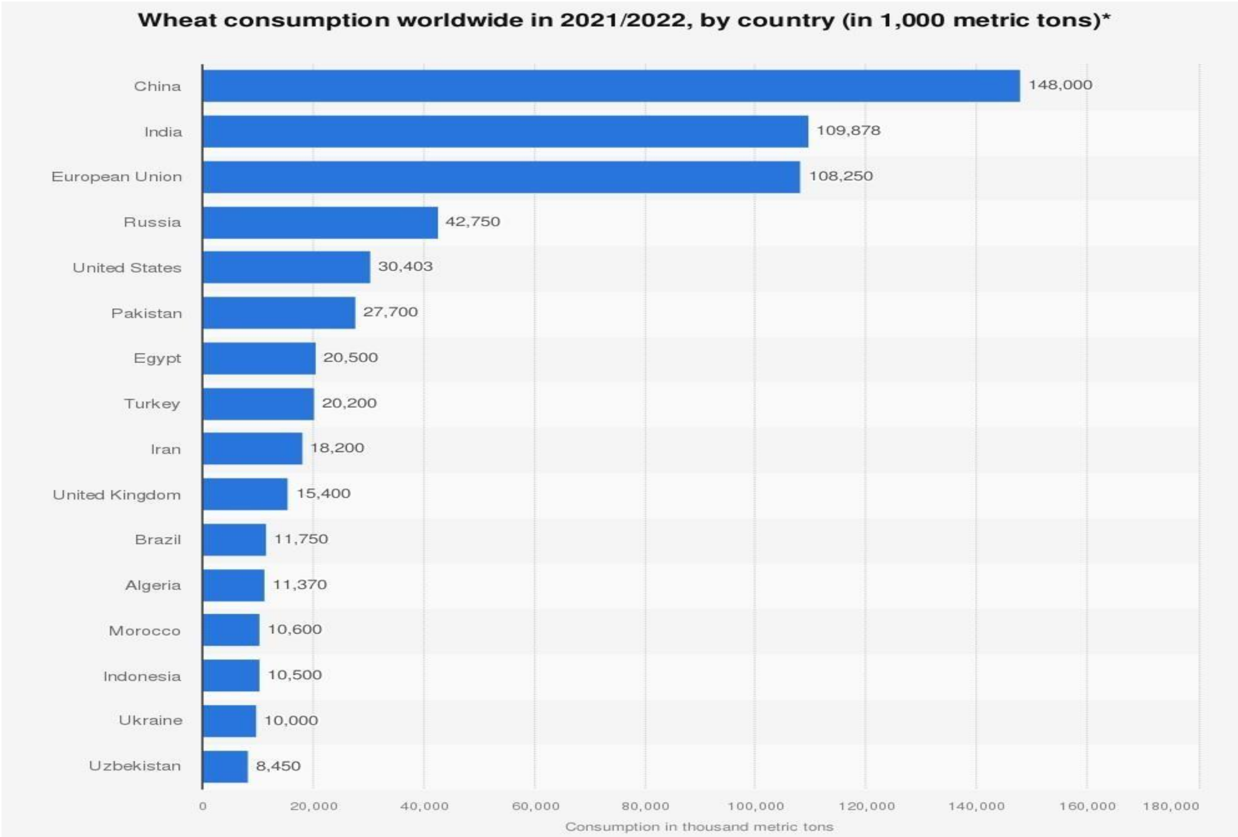

Figure 1.1: Leading wheat producers worldwide in 2021/2022

Source: Statista 2022

It can be seen that China produces the highest amount of wheat (148,000 thousand metric tons TMT) followed by India (109,878 TMT). However, Uzbekistan contributes the least share in the global net wheat production.

The international production of wheat is different around the globe because of the variation in temperature and various climatic conditions throughout the world. Climate is the average weather condition of a particular place which determines not just the yields of cultivated crops but also major cultural practices and occurrence of illnesses and pests (Oyewole, 2016). It poses imperative global environmental impacts and undesirable outcomes in every aspect of human life. According to the United Nation Framework Convention on Climate Change (UNFCCC), climate change is defined as; an alteration occurs in climate of a specific place which is directly and indirectly associated with anthropogenic activities that can change the atmospheric composition (Janjua et al., 2014).

The security of food sources and its long term sustainability will become more challenging for world's growing population as it alters the harvested conditions for crops (Brooks, 2020). According to various scholars climate change has an impact on crop distribution at local, regional and global scales. Throughout history, the majority of populations relied on local or regional food production. Climate change has declined the worldwide wheat and corn production by 5.5 and 3.8 percent, respectively. The production potential of many crops has also been decreased in Europe and other parts of the world as well (Fei et al., 2020).

Although climate change is a worldwide phenomenon but it has more influence on developing countries due to their increased susceptibility and limited capability to reduce the impacts of climate change. Pakistan and other developing countries have agriculture based economies and because of the direct exposure to nature their agriculture sector is most affected (Ali et al., 2017).

Man-made climate change is predicted to have quite a few negative outcomes, amongst them a range shifts and extinction of species and increase in extreme weather events, which ultimately have adverse outcomes on biodiversity and ecosystem functioning (Easterling et al. 2000; Balvanera et al. 2006). However, the consequences on the distribution and productivity of crops will pose the biggest and most immediate threat to human communities and economy (Beck, 2013).

Agriculture being associated with economic activity is extremely responsive to climate change, as its whole procedure relies upon climatic variable. Climate change threatens future agricultural production due to variations in rainfall, temperature and precipitation. Extreme weather events also have adverse effects on agricultural productivity. In order to cope with adverse climate impacts on crops, it is necessary to figure out the potential distribution of crops in a changing climate (Müller et al., 2016).

Furthermore, climatic factors i.e. variation in radiation, precipitation, temperature, greenhouse gas concentrations, and water scarcity have affected agricultural production to a great extent (Dubey & Sharma, 2018). The rise in temperature, increasing droughts, and decreased precipitation, along with reducing soil moisture, has been drastically affecting the agricultural production globally (Syeda, 2017). According to various scholars, future agricultural productivity might decrease as a result of rising temperatures, especially in semi-arid and arid regions like Pakistan (Ahmed & Schmitz, 2011). Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) demonstrated that climate change is probably going to change potential distribution of crops around the globe, which is likely to further increase the amount of land that is suitable for farming in higher latitudes in the Northern Hemisphere and decrease it in tropical regions(Barros & Field, 2014).

Wheat is an adaptive crop towards dynamic climatic conditions. Although, it best thrives under temperate climate, but high temperature limits the crop yield. The prime factors which limit the wheat production are mainly temperature and precipitation. The optimum growing temperature is about 25°C, with minimum and maximum growth temperatures of 3 to 4°C and 30 to 32°C, respectively. Wheat is adaptive to a broad range of moisture conditions and can be grown in most locations where precipitation ranges from 250 to 1750mm (Kumar et al., 2020). The findings of the IPCC display that increase in global temperature during the period 1990 to 2100 will be the most unprecedented as compared to the past 10,000 years (Syeda, 2017). Temperature requirements for wheat play a crucial influence in site selection for wheat cultivation, in addition to temperature requirements, well-drained fertile loam sand to medium texture clay loam and areas with low night temperatures are optimum for growing wheat.

Carbon dioxide is one of the most vital prime factors which drive the climate change. CO_2 concentration has been increasing day by day due to anthropogenic activities (Sabella et al., 2020). There are two significant causes behind this huge Greenhouse gas concentration. This massive greenhouse gas concentration is caused by two important factors.

1. Developed countries increase the growth rate by the exploration of natural resources for expanding shares in international market.
2. UNFCCC does not have legitimate climatic policy framework. Hence, due to these reasons CO_2 concentration has been enhanced from 280 parts per million to 380 parts per million since the industrial revolution (Janjua et al., 2010). Now it is 414 ppm.

Wheat is often grown in Pakistan during the winter, ideally in November. Approximately 90% of wheat is grown on irrigated land and water requirements ranges from 20-21 per acre. In Punjab and Sindh wheat is mostly grown on irrigated land while small amount of winter wheat is also cultivated in northern parts of the country (Janjua et al., 2014).

According to the agricultural experts, loamy and clayey soil is best for growing wheat where ground surface should be smooth to allow for equitable access to all crop fields for agricultural entrances. More than 2/3 of this crop is grown in Pakistan in locations with canal irrigation. It is grown on the following types of land: mountainous regions, semi-desert, deserts, and land irrigated by canals. According to the facts and figures of the economic survey of Pakistan 2013-14, more than 25 million tons of wheat was produced in Pakistan. Wheat is harvested in a number of significant areas in Pakistan, including:

Punjab: Dera Ghazi Khan, Multan, Sahiwal, Faisalabad, Sargodha, Muzaffargarh, Jhang, and Bahawalpur.

Sindh: Hyderabad, Sukkur, Khanpur, Nawabshah.

Khyber Pakhtunkhwa: Mardan, Peshawar, Charsadda, Bannu, Dera Ismail Khan.

Balochistan: Khasdaar, Lorelai, Naseerabad, Kalat.

Irrigation can be taken as a climate adaptation approach to mitigate the unfavorable impacts of climate change and to boost the wheat yield. It is commonly found that crop productivity is higher on irrigated land as compared to the rain-fed crop productivity. Some scholarly articles demonstrated that irrigation is helpful to reduce the harmful impacts of extreme heat. But however, it remains constrained in some parts of the world such as Asia where temperature have harmful effects on irrigated yield and also due to the physical availability of water. Moreover, Irrigation provides a positive response towards changing climate and gives details on how growing water shortage is anticipated to affect future crop yields and also elaborate the relationship between weather and water stress (Zaveri & Lobell, 2019).

Wheat is one of the most important “Rabi” crop and its production has reached over 26.394 million tonnes during 2021-22 which has displayed in the following figure. In Pakistan wheat crop constitutes 7.8% of the additional value in the field of agriculture as well as 1.8% to Gross Domestic Product (GDP) as its demand has been increasing day by day. Moreover, the crop production has been decreased from 27.464 million tonnes to 26.394 million tonnes, showing the decline in the crop production as compared to the previous year 2020-21. During 2021-22, area sown decreased to 8,976 thousand hectares (2.1 percent) against last years of 9,168 thousand hectares (Pakistan Economic Survey 2019-2020).

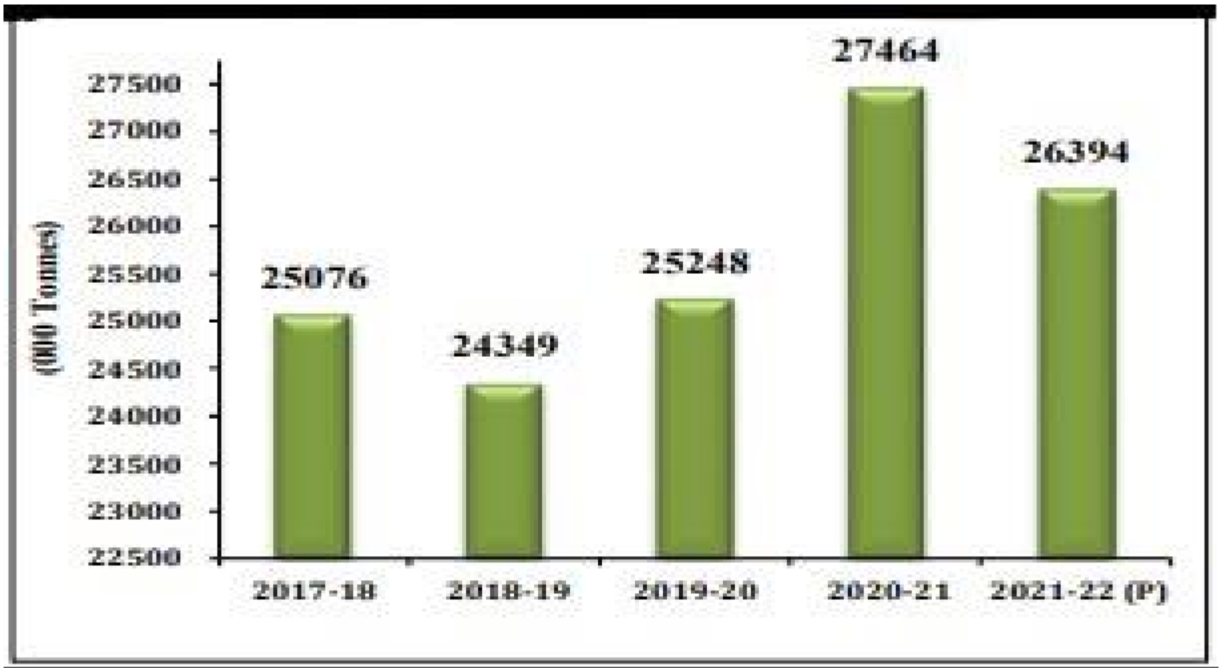

Figure 1.2: Wheat production in Pakistan from year 2017-2022 (000 Tonnes)

Source: Pakistan Economic Survey 2021-2022

In Pakistan per acre land produces approximately 1200 to 1500 kg of wheat nowadays. Punjab (71.17 %) is the major production area, followed by the Sindh province (13.38 %). Wheat is the major cereal crop produced in Punjab, putting Pakistan 8th among the wheat producing countries.

Wheat yield in many regions around the world is expected to decrease under future climate change scenarios. These potential climate change impact assessments can be beneficial for designing adaptation (Araya et al., 2020). Increasing demand of wheat production is a serious challenge for the future so there is a dire need to use such techniques which will amplify the wheat production as a mean to feed the world's growing population (Tiwari & Shoran, 2010).

In order to deal with this issue different scientists have devised various models to gauge the implications of changing climate on the production and distribution of wheat yield. Crop models approaches are regarded as crucial instruments to investigate and evaluate the possible climate change impacts, because they are used to connect the various environmental variables and crop development processes that are specifically susceptible to climate change (Kheir et al., 2019). Recently multiple modeling approaches have been employed to examine the suitability of land for crops production due to advancement in geographic information systems (Kogo et al., 2019).

For determining the potential distribution of crops we use Ecological niche models. These models are proving to be promising. The relationship between a species' known distribution and its environmental parameters is investigated using ENMs (Yue et al., 2019). Ecological niche models have been used to evaluate and map bioclimatic conditions for the distribution of crops under changing environment (Negrini et al., 2020). These models are often used in multiple ways, to predict and estimate the suitable habitat acquired by species in a known region, the estimation of suitable habitat acquired by species in an unknown region and also the changes caused by environmental factors over time and estimate the habitat acquired by those species under such climatic conditions (Warren & Seifert, 2011).

Among these models, the Maxent model, which predicts the prospective distribution of agricultural products, is one of the most effective and widely used model (Jayasinghe & Kumar, 2019). Maxent is a software programme that uses the maximum-entropy principle to estimate species distributions from recent species records. Maxent is a software application supported on the maximum-entropy regulation for modeling species' distributions from current species records (Yue et al., 2019). It has been widely used all around the world on the account of its handy and easy to use software packages for a mixed bag of constructive purposes (Warren & Seifert, 2011).

1.1 Objectives of the Study:

The aims of the study are to:

1. Assess the current distribution of wheat in Pakistan based on the calibrated datasets by using ENM (Maxent)
2. Explain the dynamic changes in wheat distribution and range as a consequence of forthcoming climate change impacts by employing the Maxent model.
3. Evaluate the current and future climatic impacts on wheat production by taking various environmental variables (temperature and precipitation).
4. Delineating the areas for the potential gain and loss in the wheat production with future climate scenarios.

1.2 Significance of the study:

Pakistan is a major wheat producer facing threats towards dynamic climate change. This study will help to evaluate the future potential distribution of *Triticum aestivum L.* by using its current distribution that will assist policy makers and decision makers to deal with future negative climate impacts on wheat crop. Moreover, as an agricultural country Pakistan should be able enough to increase crop production in our region to meet domestic demand and export surplus quantity in order to boost our economy.

Chapter 2: Literature review:

Ecological niche models (ENMs) have been used to assess the future distribution of species in a specific geographical area by evaluating the current distribution of species under changing environment. In order to comprehend the specie distribution of *Triticum aestivum L*, numerous investigations have been carried out using various modeling techniques and ecological niche modeling analysis.

A study was directed by (Araya et al., 2020) to understand the impacts of climate change on wheat production in Ethiopia. They used CROPSIM-CERES wheat model along with GIS tool by taking a variety of environmental variables. The presented results indicate that increase in carbon dioxide concentration and nitrogen fertilizers decrease the negative climatic impacts in most areas of Ethiopia. But, wheat yield reduced in those areas where drought and heat conditions exist regardless of the increase of CO_2 and nitrogen levels. However, Nitrogen fertilizer did not increase yields under low rainfall conditions. So this investigation gives crucial information about climate change impacts and suggests some appropriate recommendations for scientists, professionals experts and policy makers (Araya et al., 2020).

This study was conducted by (Fei et al., 2020) to assess the climate change impacts on China's three main crops (wheat, maize, and rice). They employed the Extreme-Point Symmetric Mode Decomposition (ESMD) model and the Agro-Ecological Zone (GAEZ) for this investigation, which covered the years 1960 to 2010. The findings of the model displays that changing climate increased the rice and maize production potential while reduced the wheat yield in China. This was just because of the difference in maximum and minimum temperature range. Unlike temperature, rainfall had consequential harmful impacts on the production potential of all three crops. These outcomes recommend that preference should be given to such areas that need adjustment in its cultivation zone and provide necessary information for adaptation strategies for rice and maize under changing climate. For the sustainable and ensured food security there is a need to enhance the agricultural infrastructure and mitigate the negative climate change impacts of reduced rainfall and increased daytime temperature (Fei et al., 2020).

Another study was conducted by (Harkness et al., 2020) in UK for the investigation of unfavorable weather events which may have a negative impact on wheat production of UK due to changing climate. They examined 10 unfavorable weather indicators, by taking climate scenarios in combination with global climate models (GCMs) and two greenhouse gas emissions scenarios (RCP4.5 and RCP8.5). The result shows that future adverse weather events decrease in UK which has positive impact on wheat production by mid-20th century. The impact of drier summer improved growth patterns and decreased waterlogging. Although drought severity can remain lower in 2050 but it is recommended to evaluate the drought at a smaller scale. Climate change scenarios and global circulation model displays uncertainty in weather events might cause some climate change issues in future (Harkness et al., 2020).

Wheat and rice are the two fundamental food and cash crops worldwide. This study was carried out by (Kumar et al., 2020) in Uttar Pradesh and Haryana to thoroughly examine the climate change impacts on wheat and rice by using time series analysis. For this analysis they used Ricardian multi-regression approach and Cobb-Douglas production function approach. Different climatic and socio economic variables were taken such as irrigated area, forest area, maximum and minimum temperature range and precipitation, literacy rate of farmers, population density of the area, use of fertilizer, tractor and tools. Generally the result shows that increased rainfall, maximum and minimum temperature had a negative effect on wheat and rice in both states of India. Additionally this is not necessary that climate indicators have similar impacts on both crop yields. In can also be concluded that climate change impacts become more threatening after 1991 due to changes in non-climatic indices. The result based on Ricardian model figure out that there is a nonlinear relationship between variables and crop productivity. So this analysis implied that Ricardian model is found to be a satisfactory and suited approach to investigate the climate change impacts on crops (Kumar et al., 2020).

A detailed study on climate change conducted by (Schierhorn et al., 2020) undermined cereal production globally, specifically in semiarid regions where temperature change or fluctuation in rainfall or extreme heat may have large impact on cereal production. Kazakhstan is the biggest producer and exporter of cereals in Central Asia. The study's primary goal was to assess the effects of climate change on the average temperature, precipitation and heat on barley and wheat yields. Data were taken from 1980 to 2015 by using fixed-effect panel regressions model in the northern part of Kazakhstan. The results indicate that observed changes in climate change have decreased wheat and barley yields in the western part of Kazakhstan which can be compensated by positive effects in the eastern part of Kazakhstan. Extreme heat events had also limited effect on both wheat and barley yields. Policy makers and investors should carefully decide whether to carry on this cereal farming or to take some alternative agricultural practices for the areas that have already been negatively impacted by climate change (Schierhorn et al., 2020).

To determine the negative impacts of ozone concentration on wheat crop, (Guarin et al., 2019) carried out this study in Mexico by using O3-modified DSSAT-N Wheat crop model along with baseline data from 1980 to 2010 and five Global Climate Models (GCMs) under the Representative Concentration Pathway (RCP) 8.5 scenario. They selected thirty-two wheat producing areas for simulation by giving both irrigated and rain-fed conditions. The results shows that the impact of ozone concentration on wheat crop varied but overall simulations show decreased production due to the enhanced ozone concentration in all scenarios. It can be concluded that wheat production loss due to ozone concentration is larger than the loss which is due to change in precipitation, temperature and carbon dioxide concentration in Mexico. Therefore, it is necessary to include the ozone impacts as well in future agricultural impact assessments (Guarin et al., 2019).

This study was presented by (Jayasinghe & Kumar, 2019) to evaluate the suitable tea growing areas in Sri Lanka by using MaxEnt modeling technique. They used 2 climate models MIROC5 and CCSM4 under three representative concentration pathways for the year 2050 and 2070. The study displays that areas with high elevation show better response towards changing climate as compared to the low elevated areas which show loss of crop to a greater extent. The comparison of the suitable areas of current and future scenarios disclosed a decline of 8 percent, 17 percent and 10.5 percent in marginal, medium and optimal suitable areas respectively. This comparison revealed the fact that future climate change would have a negative impact on tea growing areas in Sri Lanka by 2050 and 2070 (Jayasinghe & Kumar, 2019).

A review was carried out by (Kapur et al., 2019) to quantify the climate change impacts on wheat production and soil water balance in the Mediterranean region of Turkey. Wheat production in this region is already affected to a certain extent by irrigation development and water availability issues. To mitigate these issues they used regional climate models and general circulation model. Under future climatic conditions the wheat productivity decreases with the enhanced carbon dioxide concentration, regardless of the model used. It was concluded that due to climate change and increased concentration of CO2 the soil water demand also increased. But due to reduction in rainfall the actual evaporation and soil moisture would decrease 16.5% in future, regardless of its increasing demand. So this study highly recommended that water stress must be handled using appropriate irrigation management approaches for the sustainable production of wheat in future (Kapur et al., 2019).

The Egyptian North Nile Delta is a larger agricultural production area and is also most vulnerable to climate change due to higher temperatures and global sea level rise (Kheir et al. 2019) conducted another study to estimate the impacts of climate change in arid and low elevated areas, i.e. coastal region. They have used CERES and N wheat model and data of two consecutive growing seasons during 2014/2015 and 2015/2016 which were calibrated using a local cultivar grown under irrigated conditions in Egypt. In can be seen that wheat productivity reduced by 17.6% as a result of increased temperature by 1°C to 4°C. However, the crop yield increased due to enhanced carbon dioxide concentration, and this could also offset some of the negative impacts of rising temperature. As this region is on costal area so sea level rise reduce the extent of agricultural land by 60% and put more challenge to wheat productivity in this region (Kheir et al., 2019).

(Kogo et al., 2019) investigated the climate change impacts on the cropping systems and yields, in the state of Kenya by using Maxent (Maximum Entropy Model). This study was done to forecast how the productivity of maize would change in future due to a changing environment. Collected data were split into bioclimatic data and geographic distribution data for two climate change scenarios from two general circulation models for the year of 2070. The yearly mean temperature, annual precipitation, and the average temperature of the wettest quarter were the main variables found in this study. According to the study's findings, under various climate scenarios there would be an average rise in unsuitable areas of 1.9–3.9% and a drop in moderately appropriate areas of 14.6–17.5%. Change in suitable and highly suitable areas may increase. This research will give decision-makers the knowledge they need to develop adaptation plans in response to a changing climate by illuminating the regional and temporal alterations in future maize farming (Kogo et al., 2019).

For the very first time this study was conducted by (Santana Jr et al., 2019) to estimate the climate change impacts on the distribution of Dalbulus maidis (plant pathogen of maize crop) globally by using MaxEnt (specie distribution model). Three GCMs under two Representative Concentration Pathways were used in this study. The result shows that overall climate change will reduce suitability for D. maidis. However, its suitability also increases in some regions of the world. For instance, Peru, Argentina, Colombia, and Venezuela will have a small area that is highly suitable for this pest because it is predicted that these countries will have conditions that are highly suitable for this insect in some areas. This study suggested the policy makers or researchers to produce such varieties of maize crop that tolerate D. maidis in order to reduce their attack on crops (Santana Jr et al., 2019).

Wheat is a prevalent food crop for the whole population of Turkey and uneven distribution of rainfall and the severe temperatures can cause climate change that has an effect on wheat production in this region. This study was carried out by (Vanli et al., 2019) to evaluate the climate change impacts on wheat by utilizing CERES-wheat crop simulation model. Data have been taken from eight surveyed farms from the area of interest for calibration and evaluation. They used climate model by taking two climate change scenarios for mid-century (2036–2065) and end-century (2066–2095). Results indicated that increase in temperature will decrease future crop production. This crop modeling approach gives very crucial information for the quantification of the climatic impacts and may guide stakeholders to take decisions for the reduction of the negative climate change impacts on food crop (Vanli et al., 2019).

(Yue et al., 2019) carried out another research to forecast the global potential distribution of crops under climate change. They used ecological niche models (Maxent) for land suitability and future distribution of wheat crop under various climatic scenarios. The results indicate that increase in temperature mostly affected wheat production globally. Wheat production is more favorable in the RCP 4.5 scenario than it is under the RCP 8.5 scenario. The suitability of land for wheat crop enhanced in some parts of the world included China, the United States, Europe, Canada, Russia, and Pakistan while, decreased land Suitability in Australia, southern India, central and eastern Africa. These outcomes revealed that northern hemisphere (higher latitude) will be more favorable for wheat cultivation and less suitable in tropical regions. We contend that over time, Climate change could alter the worldwide wheat trade and production patterns (Yue et al., 2019).

Another study was conducted by (Zaveri & Lobell, 2019) to calibrate the contribution of irrigation as an adaptation strategies in response to changing climate to increase the wheat yield in India by using historical data across 40 years. Irrigation has been crucial strategy for increasing wheat yield as a significant crop in India. They predicted that yield in 2000s around the country are 13% higher than it would have been without irrigation in 1970s. Additionally, irrigated wheat possesses less sensitivity towards heat as compared to the rain-fed wheat production. However, the production from irrigation expansion in recent time period shows thatthe negative impacts have been increasing regardless of lower heat sensitivity from the widespread expansion of irrigation. It can be argued that improving yield increases in the face of future warming will likely provide a more challenging issue as restrictions on expanding irrigation become more stringent (Zaveri & Lobell, 2019).

Wheat is a major staple food of Pakistan and cultivated on a large scale in the country. The authors of this study (Ali et al., 2017) used feasible generalised least square (FGLS) and heteroskedasticity and autocorrelation (HAC) consistent standard error techniques to estimate the production potential of Pakistan's major crops (sugarcane, wheat, maize, and rice) for the years 1989 to 2015. It can be seen that there was the variation of climatic impact on the major crops of Pakistan. The results show that increase in temperature negatively impacted on wheat production while a decrease in temperature had a favorable effect on all crops. The effect of precipitation on the crop yield is negative for all crops, except for wheat which shows positive response towards increased rainfall. To deal with the detrimental impacts of climate change, there is a dire need to use such techniques that will amplify the crop production in the state and should also develop drought and heat resistant variety for the sustainable food production not just in Pakistan but all over around the world (Ali et al., 2017).

Wheat is the most significant grain crop in Bangladesh and cultivated mostly in parts of Dinajpur. This study was conducted by (Syeda, 2017) who used multiple regression models for the estimation of climate change impacts on wheat crop in this region. Historical climate and yield data were collected for this purpose. Three multiple regression models were used and various climatic variables including a dummy variable during wheat growing period. According to the findings of the model, highly prominent impact is found for the dummy variable. It gives information that better technology have a positive impact on production (Syeda, 2017).

(Tack et al., 2017) carried out this study to elaborate the promising role of irrigation as an adaptation strategy to reduce the negative impacts of enhanced temperature on wheat yield. They have analyzed 180 varieties, and spent 29 years to observe the role of irrigation on crop yield. The result shows that irrigation significantly offsets the negative impacts of extreme heat.

Although 1°C increase in temperature reduces dry land wheat yield about 8% but in their sample irrigation completely reduces this negative impact of temperature. They also analyzed the interaction between heat stress and rainfall for dry land production. It can be concluded that rainfall does not reduce the impacts of heat stress as much as irrigation does. This is because of the volume, intensity and timing of water application on crops, so irrigation has a stronger impact on heat stress as compared to the relying on precipitation alone. The study elaborated that shortage of water not only reduces crop production but can also accelerate the negative impacts of increasing temperature. Thus, it illustrated how important water management is to ensuring future food security around the world (Tack et al., 2017).

A climatic variable such as change in temperature, alternations in precipitation and extreme weather events endanger current and future agricultural productivity around the globe. Therefore, in order to combat the negative detrimental environmental effects of climate change, it is necessary to understand its potential bad implications. (Müller et al., 2016) carried out this study to estimate the impacts of changing weather patterns on winter wheat in Ukraine. This country is particularly appropriate as a large wheat producer in international market because of its suitable agricultural lands. Previous climate data and climate forecasts figure out that increasing temperature in Ukraine and further warming may occur specially in southern parts of Ukraine. They have used statistical approach to find out the relationship between historic yields and predict the changes in winter wheat in response of change in weather patterns by taking two climate scenarios. The study results display minimum effects on future crop yield, however in case of higher emission scenario, for example in todays developed world, the productivity decreases particularly in southern parts of Ukraine. While in northern Ukraine the productivity increased due to increase in temperature and rainfall. It must be suggested that improvements should be taken into consideration to secure food security under changing climate throughout the world (Müller et al., 2016).

Australia's economy depends heavily on two crops: wheat and cotton. This study was conducted by (Shabani & Kotey, 2016) to evaluate the impacts of climate change on wheat and cotton on various places. It combining the A2 emission scenario produced by the CSIRO-Mk3•0 and MIROC-H global climate models with CLIMEX software. The findings of this study were connected to determine the regions in Australia that would be best suited to grow wheat and cotton in the future (2030, 2050, 2070, and 2100). According to the analysis, there would be less land that is suitable for growing wheat and cotton from 2030 to 2050 and from 2070 to 2100. While large sections of the country can still be planted with cotton until 2070, but there will be a dramatic decline in the area planted with wheat throughout that time (Shabani & Kotey, 2016).

Climate change is a global issue and its impact is being discussed in literature in the background of various domains. Pakistan is sensitive towards changing climate because of its geographical location. Due to worldwide anthropogenic activities the concentration of GHGs has been increasing which alters the atmospheric composition. Due to these gases the earth’s temperature has increased by trapping sunlight. The increase in temperature in tropical regions adversely impacted the wheat production. This elaborated study was conducted by (Janjua et al., 2014) in Pakistan to assess the climate change effects on wheat production. They have used Autoregressive Distributed Lag (ARDL) model for this purpose by taking annual data from 1960 to 2009. The conclusion shows that climate change didn’t have the influence on crop yield in Pakistan but it would be having impact in future by increasing warming. However, this study suggested that policy makers and specialists of environment should proposed some suitable measures to confront any harmful effects on wheat crop in Pakistan (Janjua et al., 2014).

(Beck, 2013) carried out this study using ecological niche models to assess species' geographic ranges from occurrence data based on environmental conditions. The geographical changes will be important for the implementation of mitigation strategies. The ecological niche modeling provides a very different and unique approach which is used to relate agriculture to the environment. In this elaborated study ENM-based maps used for crop distribution to assess the land suitability under changing environment for the year 2050. The result demonstrates that agriculture suitability varies extensively in different localities. Some areas show better land suitability while on the other hand some show negative response under changing climate. They also relate the wealth of the nation with their agricultural change and found a positive relation. Some parts of Southern and Eastern Asia, Africa, and Europe were expected to be significantly negatively impacted, while North-Eastern Europe, can anticipate having better and favorable agricultural suitability (Beck, 2013).

One of China's main grain harvests is winter wheat. In order to determine the climate adaptability and geographic spread of winter wheat farming in China, (Jing-Song et al. 2012) used the maximum entropy approach to examine this study. They have taken various climatic variables for the crop distribution and mapped suitable cultivation areas for the winter wheat in China. The Maxent analysis shows that negative accumulated temperature and annual extremely low temperature were the stronger predictors of the winter wheat's northern boundary. This study describes the northern limit of winter wheat cultivation as well as the optimum growing region for winter wheat in China. The outcomes of this research will be useful for policy makers to determine the best winter wheat growing zone and for developing a scientific understanding of how climate change will affect crops(Jing-Song et al., 2012).

Another study was conducted by (Ludwig et al., 2009) to evaluate the current climatic impact on wheat cropping system in Western Australia. They combined historical climatic data with the ASPIM-N wheat model. Two main variables that limit the crop productivity in this area were precipitation and dry land salinity. The results display that significant decrease in rainfall during 1975-2004 did not reduce yield but it has significant impact on farming systems hydrology leading to less waterlogging and deep drainage. The outcomes will give important suggestions for the policy makers to investigate the future impacts of climate change in this area (Ludwig et al., 2009).

Anthropogenic activities and growing agricultural practices altered the entire globe in terms of their land use patterns. Now, in today's world 22% of the total land area is used for pastures and rangelands while only 12% is used for cultivation. In the work being presented, global databases for the distribution of 18 important crops around the world have been constructed using data acquired from satellites and from agricultural censuses. The obtained data elaborate each grid cell containing 18 crops and consistent with agricultural geography. They have analyzed crop diversity across the globe and how different crops are combined to generate significant crop belts. These datasets were not accurate at local scale but can be used at regional and global scale. This analysis can also be used to understand the farming system, food security around the globe and different climate models to deal with environmental consequences of cultivation (Leff et al., 2004).

Another study was conducted by (Easterling et al., 2000) to analyze the observational changes which occur because of potential climate change that will cause extreme events all around the world. This study has been analyzed in many parts of the world, to understand the climate change impacts. The conclusion of this study demonstrated that changes will occur in future climate for extreme events such as increases in intense temperature and precipitation and decreases in extreme low temperatures. Moreover, climate change also poses its impacts on societal infrastructure which would be outraged by climate change. A variety of climate change impacts also documented in many studies at an increasing rate i.e. changes in species range shifts, potential distributional and phonological in many crops and extinction of many species due to climate change. In Addition, biological changes are also linked to extreme weather and climate events (Easterling et al., 2000).

A study was conducted by (Luo et al., 2005) to assess the impacts of climate change on South Australian wheat yield. Using the APSIM-Wheat module and data from the Special Report on Emission Scenarios, they have applied better and refined climate change scenarios. They have taken nine climate models for the period up to 2080. Within every climate change scenario a yield response been constructed. Various climatic variables such as regional rainfall, regional temperature and concentration of CO_2 under combination have also been used for this study. The results indicated that wheat yield has decreased to 13.5 from 32% across all locations within this country under climate change scenario. This study has economic and social significance and would be helpful for policy makers and investors to implement adaptation strategies from local to national level (Luo et al., 2005).

Chapter 3: Methodology

This chapter gives a comprehensive description of the techniques and datasets used in this study including study area, data preparation and the use of Maxent software to obtain results. The data is obtained from different online sources and then this data is prepared and evaluated by using software (MAXENT, ARCGIS and Microsoft Excel).

3.1 Study Area:

The distribution and presence of *Triticum aestivum L.* is analyzed in Pakistan, which is divided into 37 administrative regions of the country. It lies on latitude 23° 35′ to 37° 05′ N and between longitude 60° 50′ to 77° 50′ E as shown in following figure. Pakistan is a South Asian country with diverse agro-ecology. The country is particularly susceptible to climate change because of its geographical location, large population size, and lack of technological resources (Ali et al., 2017). The distribution of precipitation in Pakistan varies widely, mainly in relation to monsoon winds and western disturbances, but there is no precipitation throughout the year. Therefore, Khyber Pukhtonkhuwa and Baluchistan receive the highest rainfall from December to March, and Punjab and Sindh receive 50-75% of the rainfall during the rainy season. The summer monsoon occur from the end of June to 15 September (Salma et al., 2012). Rain fluctuations increased geographically, across the seasons and annually in Asia in recent decades. A declining trend of rainfall across Pakistan's coastal areas and drying level rain pattern was also observed (IPCC, 2007). According to Pakistan's Meteorology Department, the main regions of the country experience a dry climate. Moisture conditions are prioritized, but over the small area in the north. The largest region of Balochistan and Punjab, the main part of the northern area, and the entire Sindh receive less than 250 mm of rainfall in a year.

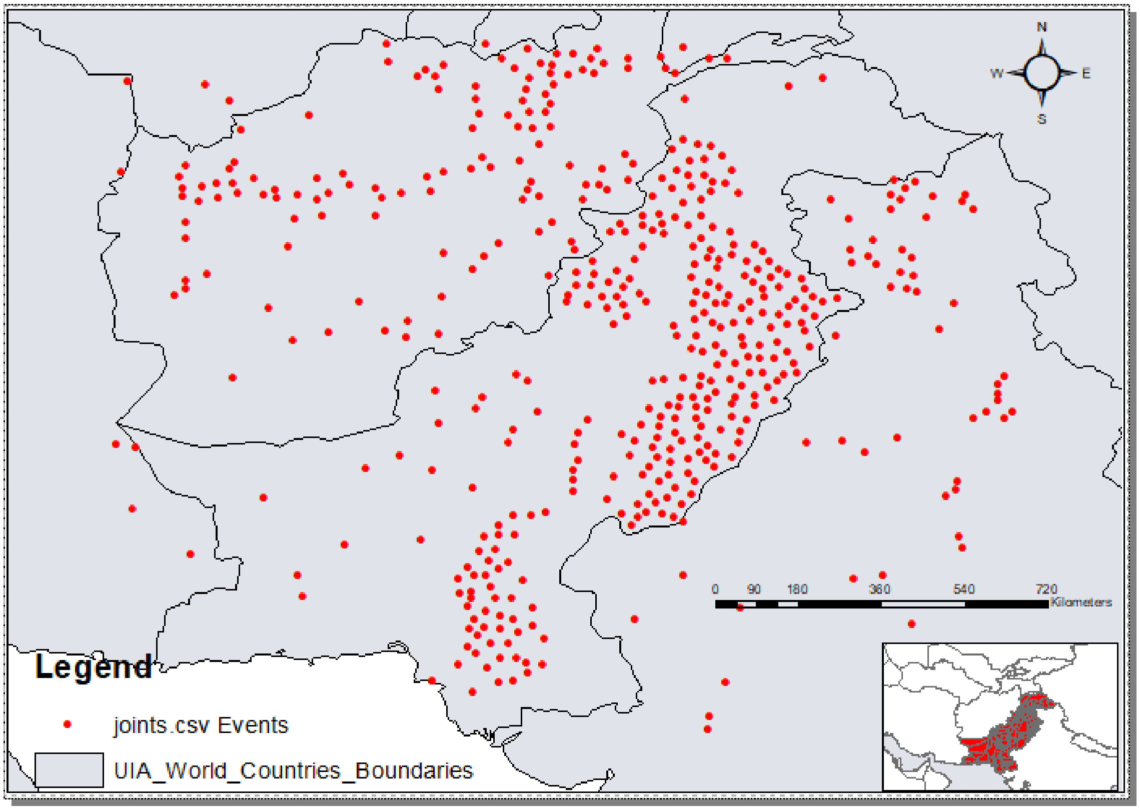

Figure 3.1: Present localities of *Triticum aestivum L.* in Pakistan.

3.2 Data Preparation and Acquisition:

3.2.1 Occurrence Data:

The specie occurrence data used in this study were obtained from Global Biodiversity Information Facility and literature review. Data was included that had latitude and longitude coordinates of wheat crop. Such species occurrence points had specific specie name, longitude, and latitude that determine the geographical location of specie on a map. After acquiring occurrence data for wheat crop, spatial rarefication was performed to reduce autocorrelation. This filtering step was executed by using "spatially rarefy" tool in SDMToolbox so that duplicates, with the same latitude and longitude coordinates, were removed in AcrGIS 10.3 version. This eliminates duplicate points clustered within a radius, which was set to 20km, and removed all those records that occurred in the ocean or great lakes, to prevent statistically over weighting a clustered region. The total of 13236 unique occurrences records was spatially filtered, yielding a final total of 6722 records. When filtering was complete, the data were used as an input for subsequent modeling process. Spatial rarefication can reduce sampling bias and spatial autocorrelation of the specie distribution, and ensure that localities were within 20km resolution. This involved adjusting the occurrence data itself before using it in the model.

3.2.2 Environmental Variables:

The environmental variables used in this study are 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). WorldClim is a collection of high-resolution global environmental layers that can be used for mapping and spatial modeling in a GIS or with other software. Future climate data were acquired from CCAFS Climate Change Agriculture and Food Security (http://www.ccafs-climate.org). The future scenario 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, MIROCMIROC 5, MOHC_HADGEM 2.CC, MPI-ESM-LR and NCAR-CCSM 4 with 2.5 spatial resolution. In the research studies, RCPs are used to determine the future climate scenarios based on the greenhouse gas emissions in the near future (Moss et al., 2010). Together with the occurrence points, the potential distribution regions for *Triticum aestivum L.* in Pakistan were clipped on the study area using ArcGIS. The bioclimatic layers including bio8, bio9, bio18 and bio19 (mean temperature of the wettest quarter, mean temperature of the direst quarter, precipitation of warmest quarter, precipitation of coldest quarter) were removed during analysis as these bioclimatic layers provide the odd special anomalies and artifacts which might affect the results (Samy et al., 2016). The remaining 15 variables were run in Maxent model for further analysis.

Sr.	Bioclimatic variables	Description
1	Bio 1	Annual Mean Temperature
2	Bio 2	Mean Diurnal Range (Mean of monthly (max temp - min temp))
3	Bio 3	Isothermality (BIO2/BIO7) (×100)
4	Bio 4	Temperature Seasonality (standard deviation ×100)
5	Bio 5	Max Temperature of Warmest Month
6	Bio 6	Min Temperature of Coldest Month
7	Bio 7	Temperature Annual Range (BIO5-BIO6)
8	Bio 10	Mean Temperature of Warmest Quarter
9	Bio 11	Mean Temperature of Coldest Quarter
10	Bio 12	Annual Precipitation
11	Bio 13	Precipitation of Wettest Month
12	Bio 14	Precipitation of Driest Month
13	Bio 15	Precipitation Seasonality (Coefficient of Variation)
14	Bio 16	Precipitation of Wettest Quarter
15	Bio 17	Precipitation of Driest Quarter

Table 1: The 15 bioclimatic variables and their description used in Maxent model

3.3 Processing of Data:

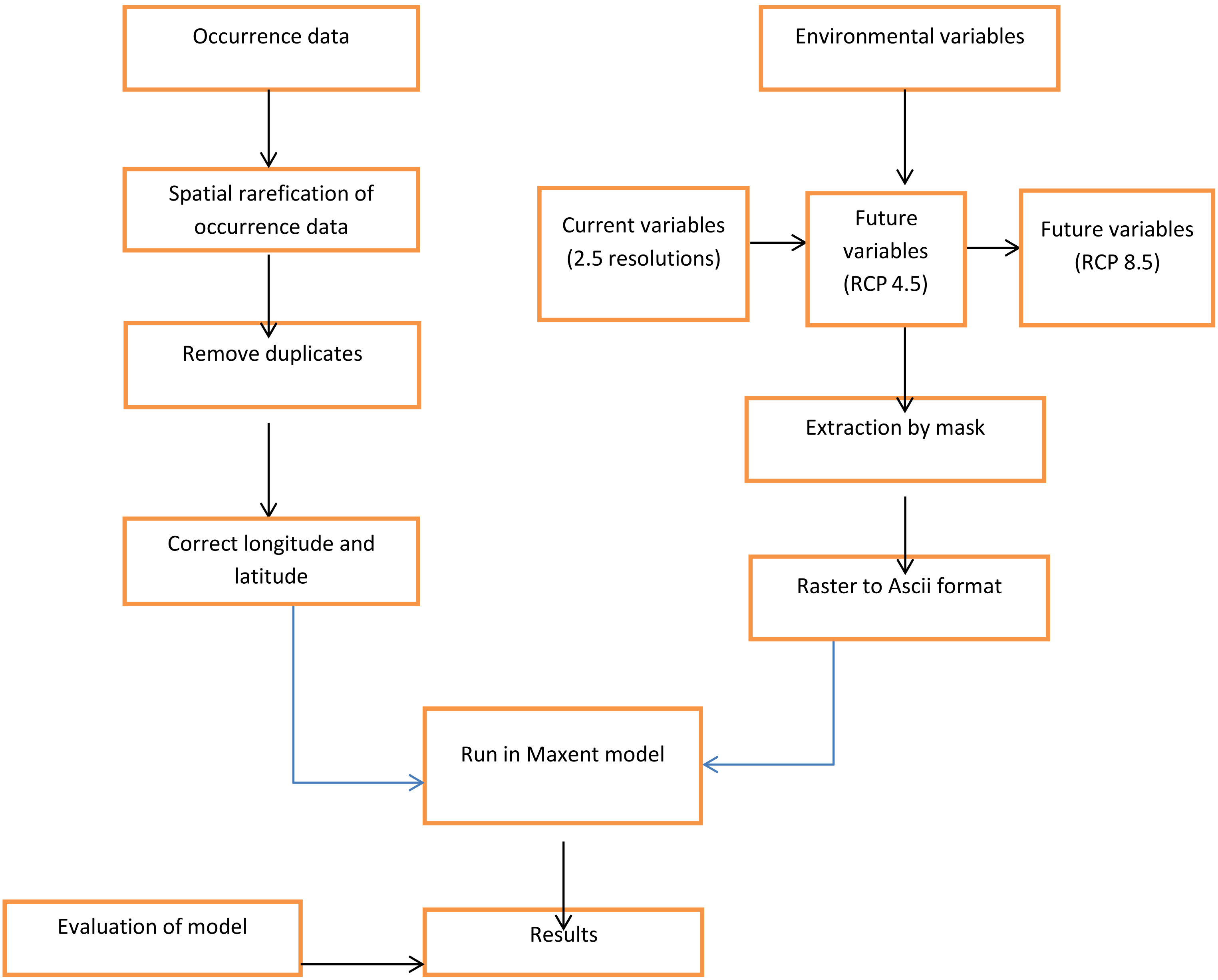

Figure 3.2: The processing of current and future bioclimatic data.

3.4 Maximum Entropy Approach:

Maxent is a software application supported on the maximum entropy approach that is widely used to figure out the probability and suitability of species in a geographic range (Yue et al., 2019). MaxEnt is a multipurpose machine learning technique that was applied using a standalone software programme (Phillips et al. 2006).

Maxent used input data which includes specie present records and environmental variables. For this study and to ascertain the potential distribution of *Triticum aestivum L.* the software was downloaded from **https://biodiversityinformatics.amnh.org/open_source/maxent/**. The version used was Maxent 3.4.4.

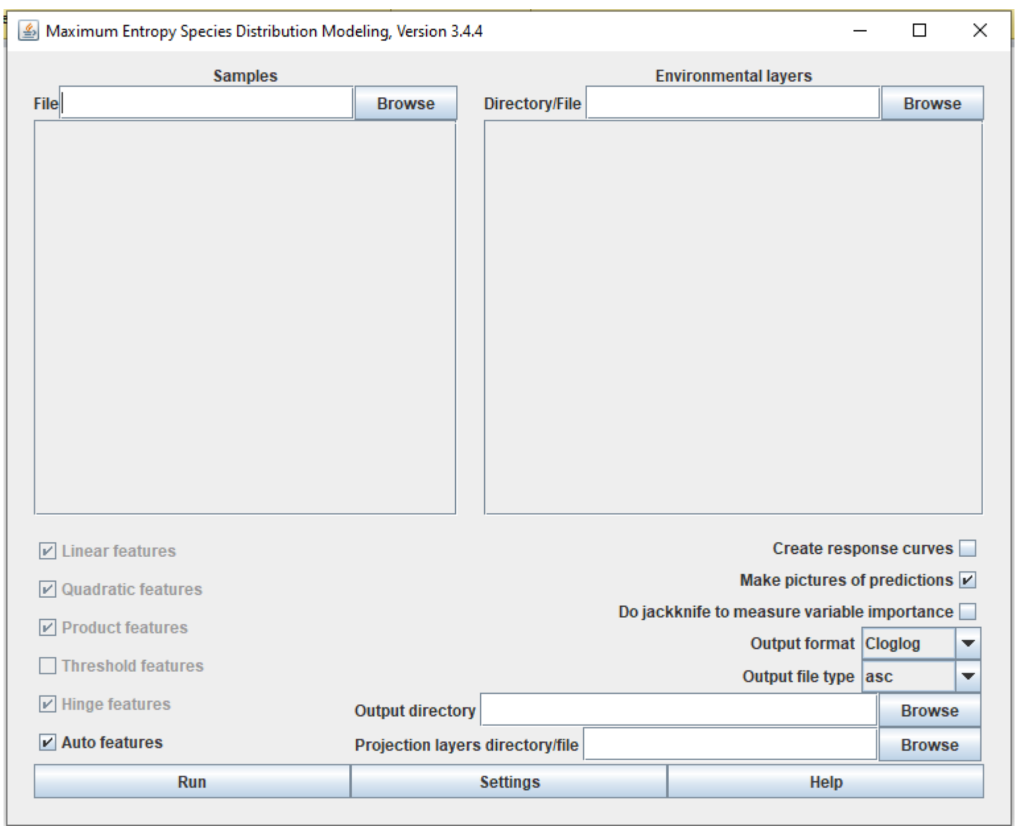

Figure 3.3: The Maxent software version 3.4.4

3.5 Running the Maxent Data:

To run the maxent model it is very necessary to have a specie occurrence data and all environmental layers in CSV format. The specie occurrence file must have three fields: specie name, longitude and latitude in decimal degree. The environmental layers must be in Ascii format and all 15 layers were selected to gain the Maxent results.

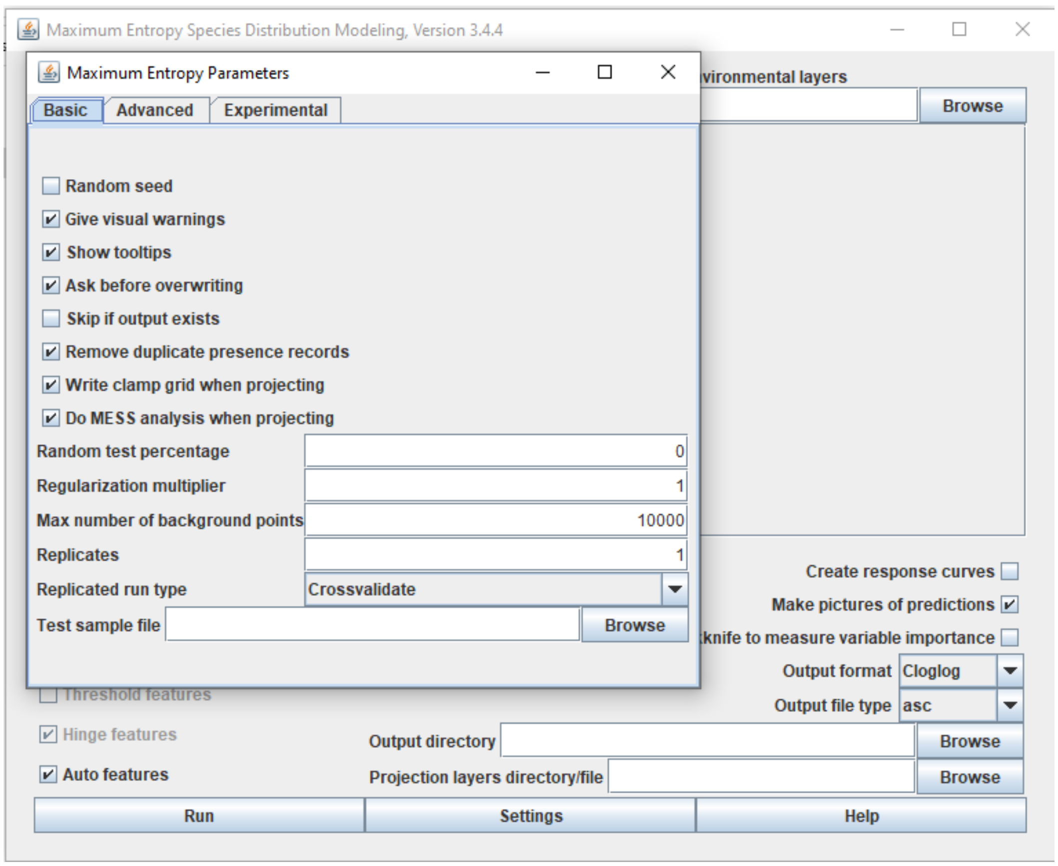

Figure 3.4: The processing of the Maxent (The *Triticum aestivum L* in CSV file and current bioclimatic variables are added to Maxent and were run)

Finally, the resulted Ascii files were converted to raster by using the ArcGIS model builder function and reclassified for area calculation. All categories were used to estimate of medians for area calculation in percentage.

Chapters 4: Results and Discussion:

This chapter includes the results of current and future bioclimatic data.

The results of ENM (Maxent) are presented below.

4.1 Current Bioclimatic Data:

4.1.1 Geographic distribution of *Triticum aestivum L.* under current climatic condition:

The current distribution map shows the distribution area of *Triticum aestivum L.* The map shows three categories which is highly suitable area, moderately suitable area and lowest suitable area. The darker green color shows the highly suitable areas while lighter green to grey color shows the lowest suitable areas.

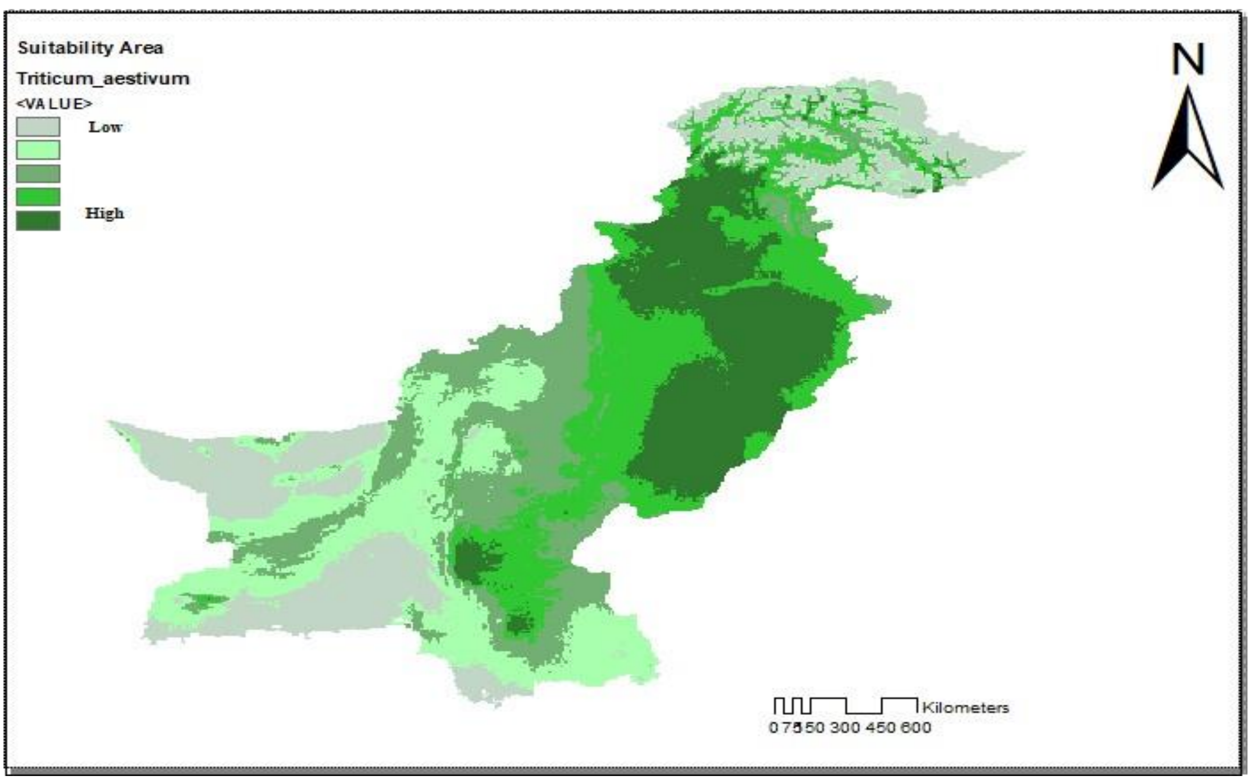

Figure 4.1: The suitable area for the current distribution of *Triticum aestivum L*

Table 2 show the suitable area for *Triticum aestivum L.* under current climatic condition. Suitable area was classified intro three categories; highly suitable, moderate, least suitable. The results show that 39.31% area is highly suitable, 17.06% area is moderately suitable and 43.62% area is least suitable.

Classification	Current distribution Kilometers Square (km^2)	Current distribution Percentage (%)
Highly suitable	389,452 km^2	43.62%
Moderately suitable	152,354.36 km^2	17.06%
Least suitable	350,997.40 km^2	39.31%

Table 2: The suitability analysis and current percent distribution of *Triticum aestivum L*

4.1.2 ROC Curves:

An ROC curve (Receiving operational characteristic curve) is a graph which determines the accuracy of a statistical model (Zou et al., 2007). AUC (Area under the curve), a probability curve, represents the degree of separability. It reveals how well the model can differentiate across classes. The better the model prediction, the higher the AUC (Bhandari, 2020). Sensitivity (also known as the true positive rate) and specificity (also known as the true negative rate) are the basic indicators of model correctness (Zou et al., 2007). If AUC is closest to 1 that means the better the prediction, and AUC is 0 then the poorer the predition and if AUC is higher there are higher chances that positive is separated from negative, if AUC is not higher then there are lower chances of separability of positives from the negatives (Phillips et al., 2006).

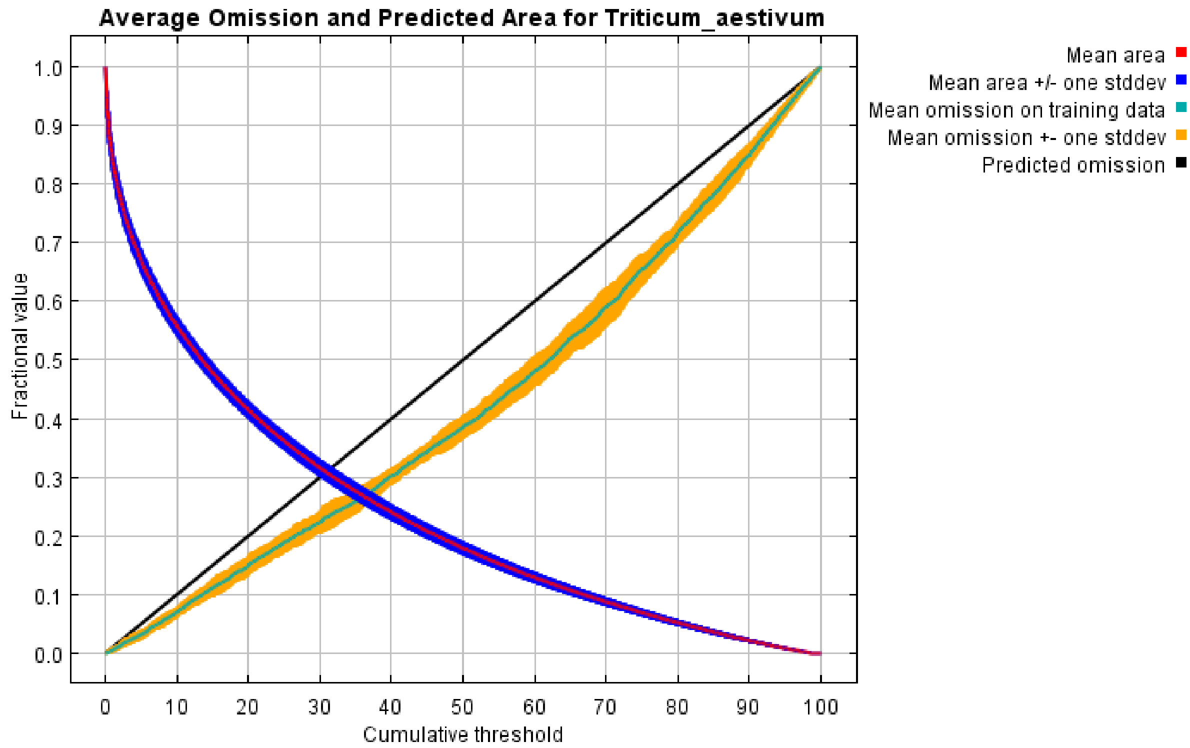

Figure 4.2: The average omission and predicted area for *Triticum aestivum L*

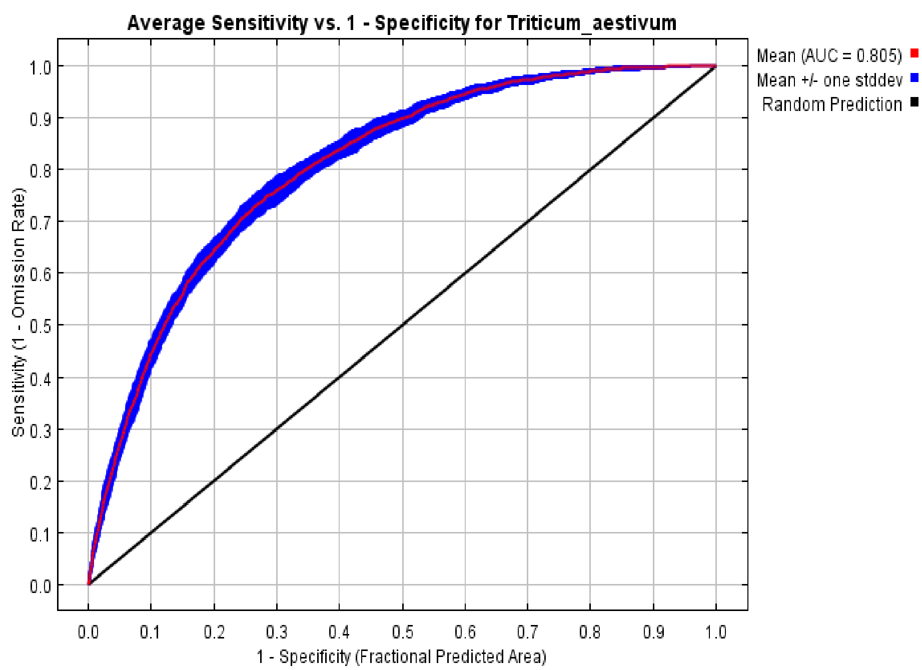

Figure 4.3: The average sensitivity vs specificity for *Triticum aestivum L*

Specie	Maxent AUC-ROC value for current bioclimatic data
Triticum aestivum L	0.805

Table 3: The Area under the ROC Curve (AUC-ROC) value for the current bioclimatic data of *Triticum aestivum L*

The AUC-ROC value for the current bioclimatic data has come out to be **0.805** as shown in table 2 which is closer to 1. Hence, the value shows that better performance of the model and highly suitable areas are highly separated from the lowest suitable areas for the current distribution of the *Triticum aestivum L.*

The relationship between environmental parameters and the predicted likelihood of presence is displayed by a response curve. These curves demonstrate how each environmental factor influences the Maxent prediction; as the environmental variable changes the predicted probability of presence changes accordingly. While maintaining all other environmental factors at their average sample value, the projected probability of presence varies as each environmental variable is altered. In other words, the model may benefit from sets of variables changing simultaneously, whereas the curves reflect the marginal effect of altering just one variable. The curves display the mean response of the 15 replicate Maxent runs in red, and the mean +/- one standard deviation (blue, two shades for categorical variables).

4.1.3 Important bioclimatic variables for assessing the distribution of Triticum aestivum L.

The relative contributions of the environmental factors to the Maxent model are estimated in the table below. The relative percentage contribution of each environmental variable from the jackknife analysis is determined using the Maxent model. The first and the second estimates of the environmental variables are obtained, in the first estimate the increase in the gain value of each iteration is added or subtracted from the corresponding variable only if the lambda is negative in its absolute value, the second estimate is obtained with random permutation. The most contributing variable having the highest percentage is Bio 4 (Temperature seasonality) and Bio 12 (Annual precipitation) having the most important information by itself as shown in the following table.

Variable	Percentage contribution	Permutation importance
Bio4	23.5	10.8
Bio12	11.5	7.3
Bio10	10.6	9.2
Bio13	10.1	6.7
Bio5	9.6	2
Bio14	5.5	1.4
Bio15	5.3	3.1
Bio2	5.1	7.8
Bio1	5.1	20.1
Bio3	4.5	5.6
Bio17	4.3	3.5
Bio16	1.8	4.1
Bio6	1.5	12.4
Bio7	1.2	4.6

Bio11	0.4	1.5

Table 4: Contribution of each environmental variable to the Maxent model

4.1.4 Jackknife analysis of variable importance:

The outcomes of the jackknife test of variable are depicted in the picture below. Bio6 appears to have the most relevant information when utilized alone because it exhibits the largest gain when used alone. Bio12 seems to contain the most information which is not contained in the other variables because it is the environmental variable that reduces the gain when it is eliminated. Values shown are averages over replicate runs.

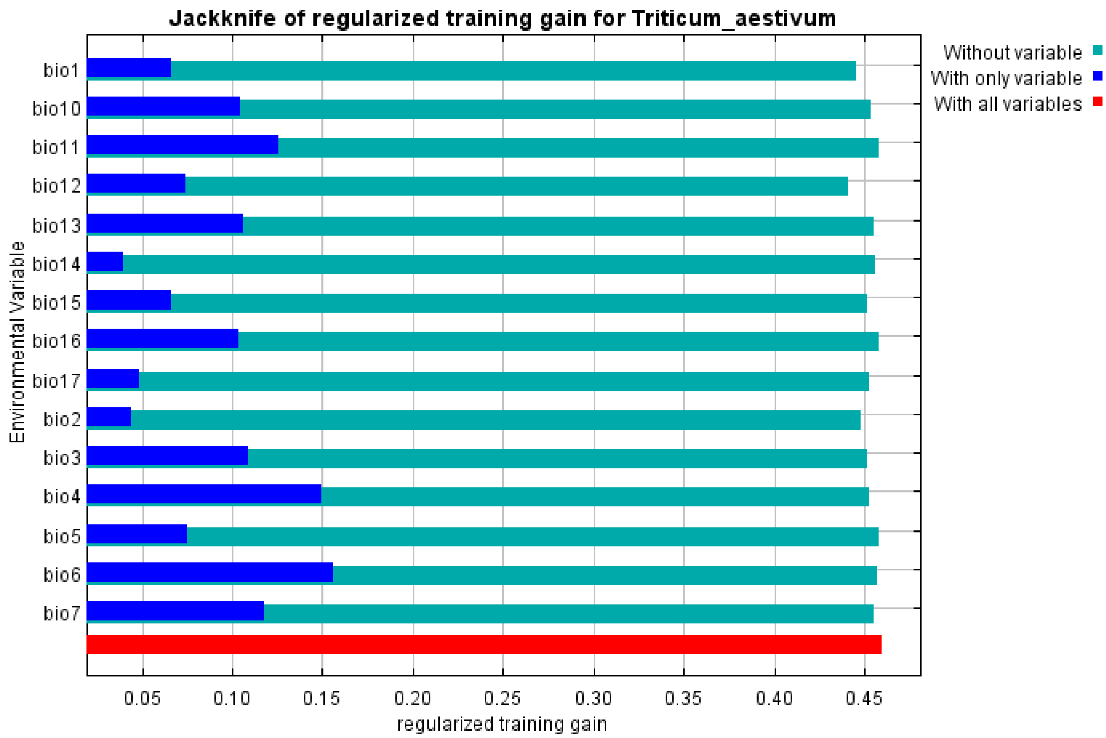

Figure 4.4: The jackknife analysis of training gain for *Triticum aestivum L.*

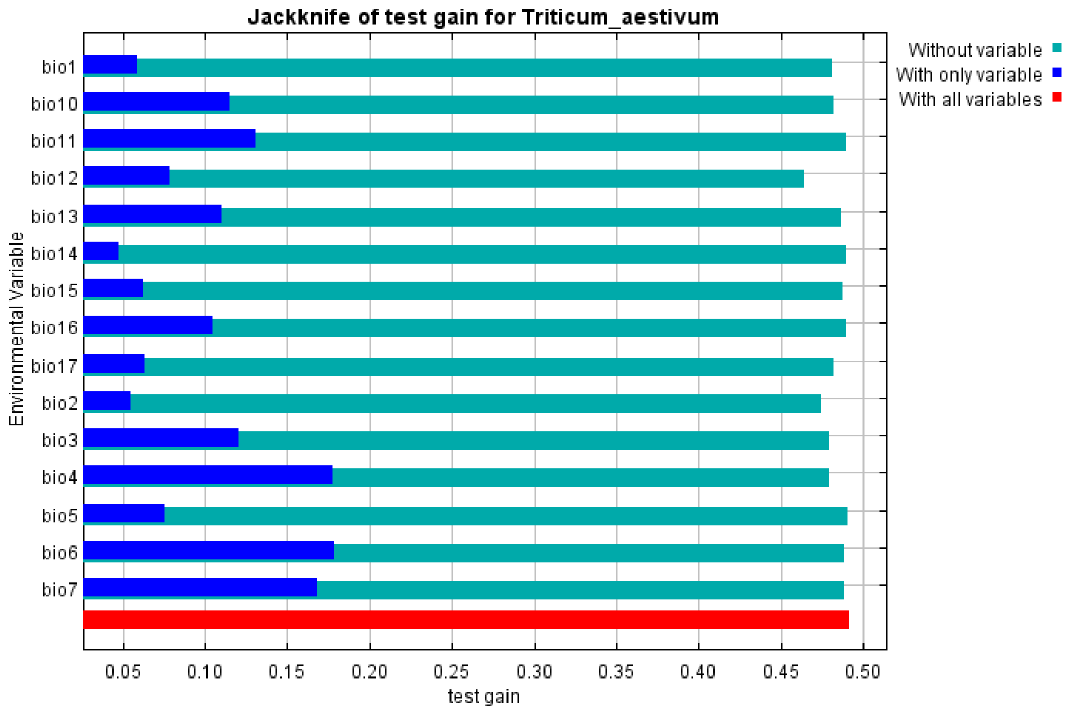

Figure 4.5: The jackknife analysis of test gain for *Triticum aestivum L.*

4.2 Future Bioclimatic Data:

4.2.1 Future Distribution Maps:

The future distribution maps of *Triticum aestivum L.* are shown in the following figures. RCP 4.5 and 8.5 are used of the year 2070s. The dark green color shows the highly suitable areas while the color ranging from light green to grey shows the moderately and least suitable areas for the distribution of *Triticum aestivum L.*

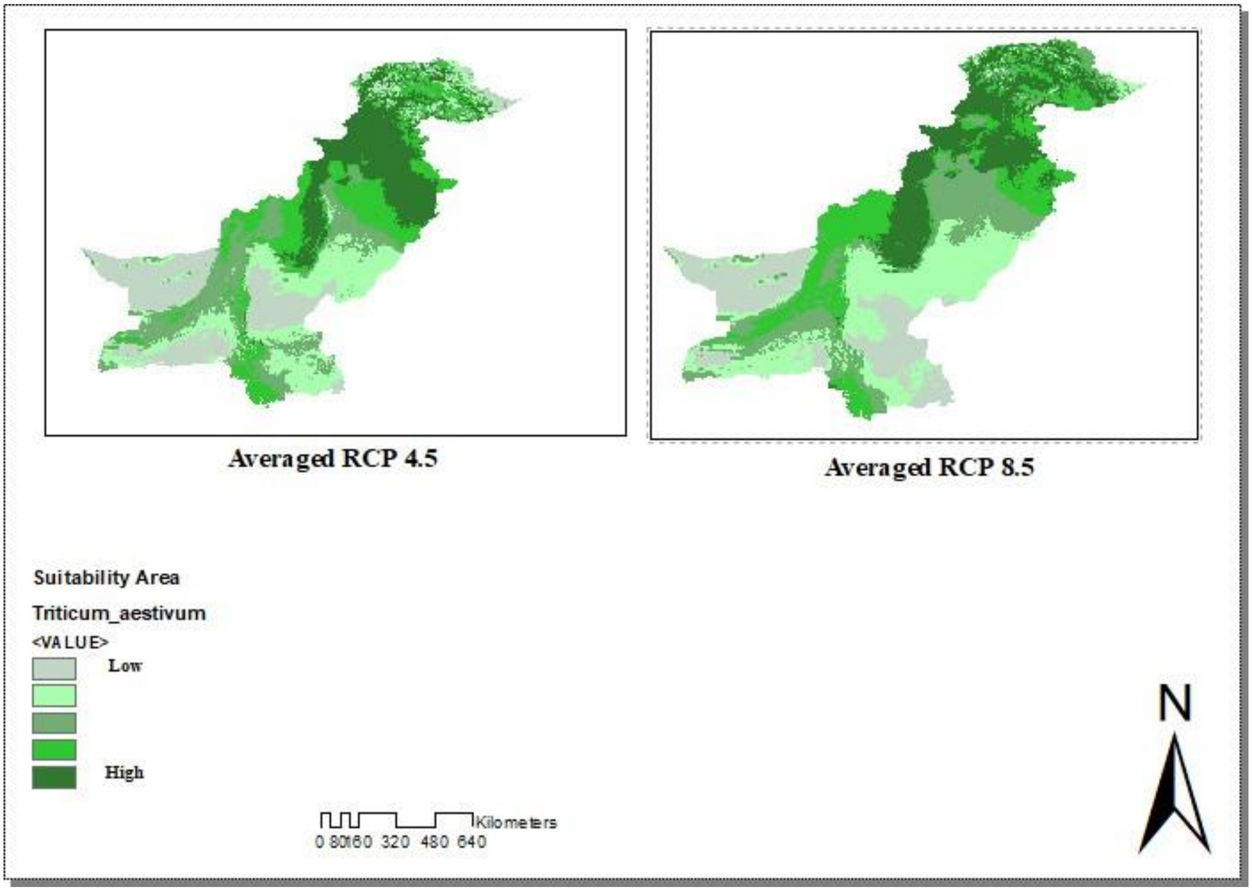

Figure 4.6: The future distribution of Averaged RCP 4.5 and 8.5 of *Triticum aestivum L*

Classification	Future distribution Averaged RCP 4.5 (km^2)	RCP 4.5 (2070) (%)	Future distribution Averaged RCP 8.5 (km^2)	RCP 8.5 (2070) (%)
Highly suitable	237,830.61 km^2	26.78%	174,709.69 km^2	19.67%
Moderately suitable	171,309.42 km^2	19.29%	163,625.95 km^2	18.42%
Least suitable	478,892.41km^2	53.92%	549,696.80 km^2	61.90%

Table 5: The suitability analysis and the future distribution for RCP 4.5 and 8.5 of 2070

This table 5 gives the percentage future distribution for RCP 4.5 and RCP 8.5 of 2070. The highly suitable area is 26.78% and 19.67% for RCP 4.5 and RCP 8.5 respectively. The moderately suitable area is 19.29% for RCP 4.5 and 18.42% for RCP 8.5. The least suitable area is 53.92% for RCP 4.5 and 61.90% for RCP 8.5 of 2070.

4.3 Discussion:

Triticum aestivum L. is a significant and highly nutritious cereal crop around the world. It is cultivated almost everywhere in the world and provides a significant source of food and income for millions of smallholder farmers. It is the need of the hour to understand the climatically suitable area for its cultivation under changing climate. The study focused on the distribution of *Triticum aestivum L.* in Pakistan using current and future bioclimatic variables mainly temperature and precipitation. These are two prominent variables which appeared to be the most affected predicator variables affecting the potential distribution of *Triticum aestivum L.* in current and future scenarios. The model used in this study (Maxent) represents approximation of climatic suitability for *Triticum aestivum L.* and shifts in suitable area is estimated based on the correlative relationship between the predicators and the occurrence localities.

This study aims to determine whether Pakistan's level of wheat production is being affected by the recently discovered threat of climatic change or not. For this purpose the study uses the Maxent model to examine the effects of climate change on wheat production in Pakistan.

The result of ENM in table 3 shows that the AUC value for the raw variable analysis is 0.805 which indicates high accuracy of the model.

The table 2 shows the current suitability percent distribution of *Triticum aestivum L*. The highly suitable area accounts for 43.62% of the total area occupied and the moderately suitable area accounts for 17.06% and the least suitable area accounts for 39.31%. The results showed that the highly suitable area is greater than the least suitable area. The most suitability areas are seen to be in Punjab and some parts of Sindh and KPK. While moderatly and least suitable areas are seen to be in most parts of Balochistan, Sindh and upper KPK.

As compared to the current distribution area of *Triticum aestivum L*, the future averaged RCP 4.5 and 8.5 bioclimatics show less suitability areas than current bioclimatics map. My results imply that climatic changes in the latter half of the 20th century significantly decreased the amount of climatically suitable areas for *Triticum aestivum L.* Under the RCP 4.5 (2070) scenario for the *Triticum aestivum L*, 53.92% of area is least suitable, 19.29% of area is moderately suitable and 26.78% of area is highly suitable. Similarly under the RCP 8.5 (2070) scenario 61.90% of area is least suitable, 18.42% of area is moderately suitable and 19.67% of area is highly suitable. These results show that there is change in the potential suitable ranges of the species over time. A decrease in suitable range can be seen in RCP 4.5 and RCP 8.5.

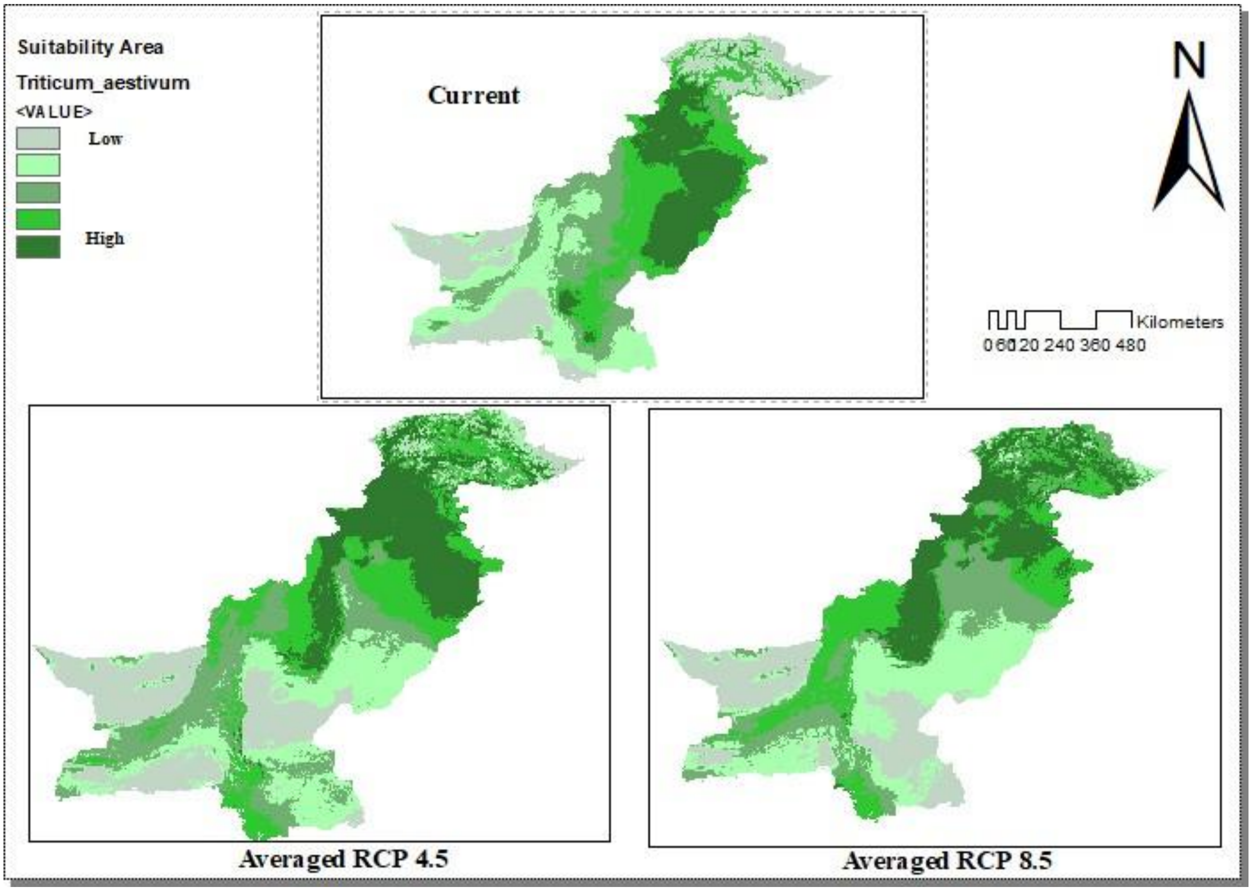

Figure 4.7: The current and future distribution of Averaged RCP 4.5 and 8.5 of *Triticum aestivum L*

Classification	Current distribution	Future distribution Averaged RCP 4.5 (%)	Future distribution Averaged RCP 8.5 (%)
Highly suitable	43.62%	26.78%	19.67%
Moderately suitable	17.06%	19.29%	18.42%
Least suitable	39.31%	53.92%	61.90%

Table 6: The comparison of current and future distribution

According to Table 4, the two most significant climatic factors affecting the distribution of *Triticum aestivum L* are Bio 4 (Temperature seasonality) and Bio 12 (Annual precipitation). These two variables (temperature and precipitation) play a major role in determining the potential distribution of crops. According to various scholars, future agricultural productivity might decrease due to an increase in temperature particularly in semi-arid and arid areas like Pakistan (Ahmed & Schmitz, 2011). In this scenario the temperatures are rising with decreasing precipitation which could ultimately have a detrimental impact on the on the volume of wheat crop. This is a worst scenario and it can be conceived for Pakistan if the level of precipitation decreases as a consequence of climatic change (Janjua et al., 2010).

Chapter 5: Conclusion and Recommendations:

This research is focused on delineating highly suitable, moderately suitable and least suitable areas for wheat production in Pakistan under changing climate scenarios. To better understand the forthcoming distribution of wheat crop under altering climate regimes, it is essential to understand the circumstances that have influenced potential instabilities in the distribution of crops. By using Maxent model it was found that highly and moderately suitable area will decrease while least suitable area will increase under RCP 4.5 and 8.5. The prime production area is in Punjab followed by Sindh and upper KPK. While in the northern parts of Baluchistan, some winter wheat is also cultivated on a small scale. This study reveals that projected heating may lessen this suitable habitat under future climate structure. The results of this study will facilitate the policy makers to comprehend the likely spatial shifts of prospective wheat cultivation and evaluate a basis for the development of ample strategies on mitigation with respect to the impact of climate change.

Recommendations:

Following recommendations may be considered for managing wheat crop under changing climate:

1. This research work should be used to consider future land use changes in the context of climate change and circulation patterns.
2. Suitable areas should be further developed in future in order to increase production.
3. Mitigatory measures should be design to ensure continued sustainable production in areas which are less suitable.

4. Stress tolerant, hybrid and genetically engineered wheat seeds along with sufficient water and fertilizers may be prepared to deal with adverse climatic conditions that these less suitable areas may face.

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