Predicting the Distribution of Wheat and Maize in Pakistan under Climate Change

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Certificate

This dissertation submitted by Ms. Nusaiba Khubaib is accepted in its present form, by the Institute of Environmental Sciences and Engineering (IESE), School of Civil and Environmental Engineering (SCEE), National University of Sciences and Technology (NUST), Islamabad, Pakistan as satisfying the partial requirement for the degree of Master of Science in Environmental Science.

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THESIS ACCEPTANCE CERTIFICATE

It is certified that the contents and forms of the thesis entitled "**Predicting the Distribution of Wheat and Maize in Pakistan under Climate Change**" submitted by Ms. Nusaiba Khubaib, Registration # 00000205220 has been satisfactory, free of errors and plagiarism for the requirements of the degree of Master of Science in Environmental Science. It is further certified that necessary amendments as pointed out by the GEC members of the scholar have also been incorporated in the said thesis.

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Abstract

Climate change has various and wide-ranging impacts on different physical and biological systems of Earth. One such system is agriculture that is impacted vastly by climate change and gives rise to the situation of food security or insecurity at both the local and global level. Pakistan is an agrarian country, still faces food security issues. Pakistan is predicted to be highly susceptible to go through area reduction and geographical shifting of major crops within the country. In such scenario, keeping in view the pressure of rapidly increasing population of the country, it is of utmost importance to assess the food vulnerability to climate change. For this purpose, the potential distribution of Wheat and Maize, which are staple food crop, are going to be assessed in this study. To assess the impact of climate change on these crops in Pakistan, Species Distribution Model 'MaxEnt' is used. Results from the model show that there is an area decline under both future climate change scenarios (RCP 4.5 and RCP 8.5) compared to the current climate for both the crops. The important climate variables for maize distribution were precipitation of the wettest quarter and isothermally, whereas irrigation and elevation were the most important factors for wheat distribution in current climate. While for future distribution, bioclimatic factor of mean temperature of the warmest quarter had the most importance for maize crop, and precipitation of the warmest quarter was important factor for wheat. The results of the study are beneficial in understanding the effects of habitat distribution of crops as well as climate change on the production and yield of crop, and can help policy makers in lessening the imminent threat of food insecurity in future.

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Chapter 1

INTRODUCTION

1.1 Background and Scope

Climate plays a great role in controlling the structure and function of important terrestrial ecosystems (Wu et al., 2010). Even the smallest change in climate, either natural or man-made, can cause loss of biodiversity and other disturbances like habitat fragmentation, distribution in habitat and extreme event like extinction of a plant or food crop. In such scenario, there have been many studies conducted that closely observe the impacts and the response of species to these impacts, they suggest that both animals and plants species have shifted to higher elevations in response to the recent changes induced by climate change (Root et al., 2003). If the climate change continues at the predicted rate, it can be assumed that the geographical shifts of the species will also continue causing changes in distribution range and even extinction of some highly sensitive species (Ferrier et al., 2002). Climate change has a number of wide-ranging impacts on different physical and biological systems of Earth including health, water availability, temperatures, forests and species. One such impact is on the field of agriculture.

Climate is one of the primary factors on which agriculture is dependent. Sustainability of various sectors like agriculture, economy, society and environment is heavily affected by climatic factors that are not in human control such as, temperature, precipitation, soil moisture and natural disasters like floods and droughts etc. (Warren et al., 2006). As mentioned earlier, climate change influences various elements in agriculture, e.g. yield, crop area and crop value etc. that in turn affects the agricultural sustainability. Every crop has its own morphology and corresponding response to climate change and climate affects the productivity of each crop differently. Due to this reason, impact on the output and crop value of different crops can vary significantly from each other which influences the judgment of crop selection. Changes in climate also give rise to the situation of food security or insecurity at both local and global level (Parry et al., 2004).

Climatic conditions largely shape the ecosystems of agriculture. Since agriculture plays a vital role in human sustainability and economy, it is very crucial to determine the potential impact of climate change on the agriculture in terms of crop production. This has caused researchers worldwide to study the impacts of climate change on physical aspects of agriculture such as crop and/or livestock yield change and the consequence of this potential change in yield on the economy (FAO, 2019). The World Food Summit of 1996 defines food security as, “when all people at all times have access to sufficient, safe, nutritious food to maintain a healthy and active life”. The definition is valid at all levels including national, provincial and individual (FAO, 2019).

The changes or potential decrease in crop supply due to climate variability and change can alter the constancy of entire food availability system. The areas already vulnerable to hunger or malnutrition will be the ones most affected by climate change as it will intensify food insecurity in such areas (Hossain et al., 1998). Similarly, it can be assumed that economic effects on incomes of households as well as individuals can indirectly affect food access and food consumption. Loss of or reduced access to drinking water and deterioration of health can partially or completely impair food utilization. This theory highlights the importance of a wide research and investment in planning adequate adaptation and mitigation measures to actively tackle food insecurity and the related issues (Hossain et al., 1998).

Climate change has the potential to impact food security and all of its four dimensions through the predicted impacts that are discussed as follows (Gregory et al., 2005).

1.1.1 Food Production and Food Availability:

Agro-ecological conditions and income growth and distribution are the two main factors through which climate affects production and availability of food directly and indirectly by affecting demand for agricultural products (Islam & Wong, 2017).

1.1.2 Stability of Food Supplies:

Stability of food supplies can be impaired due to change or decrease in crop yield and in turn communal food supplies. Arid and semi-arid areas are most vulnerable to climatic changes and have a potential to reduce their crop and livestock production and yield (Islam & Wong, 2017).

1.1.3 Food Access

In several developing countries, governments have taken initiative of decreasing food prices and increasing households and induvial incomes which has led to significant betterment in food access over the last three decades. However, climate change can reverse this trend by inducing increase in food prices and decrease in rate of incomes (Gregory et al., 2005).

1.1.4 Food Utilization

Climate change can alter the situation of food safety and dynamics of disease pressure caused by vectors, food and other water-borne diseases thus shaping the individual's capability of food utilization effectively (Islam & Wong, 2017).

The above mentioned damaging effects of climatic changes on food insecurity compeled to bring forward the approaches and studies that shed light on effect of climate change on suitable environments of the crop species in current and future climate change scenarios. Predictive modeling of species geographic distribution is one such approach.

1.2 Species Distribution Modeling

A wide variety of models have been developed to predict species potential distribution. Although there are differences that occur between different algorithms being used by different models, predictions generated by all the models are in ecological space with multi dimensions. It is not possible to predict accurate species geographic occurrences as it is, but a probability can be derived which shows the habitat suitability in an ecological space using some bioclimatic variables and interactions among them (Rosenzweig, 1995). As the Species Distribution Models (SDMs) rely solely upon principles of ecology, they prove to be a useful tool for providing solutions for applied ecology, natural conservation of species and biogeography (Guisan & Thuiller 2005).

To understand the various biotic and abiotic factors of the environment and ecology of a species' habitat, a number of models can be utilized. The most common and useful models among a wide array of such SDMs include; BIOCLIM, which is deemed as an algorithm consisting of climatic envelop (Busby, 1991); Genetic Algorithm for Rule Set Production (GARP), consisting of a genetic algorithm (Peterson et al., 2002) and maximum entropy (MAXENT) algorithm (Phillips et al., 2006). In this study MaxEnt species distribution model has been used which will be described in detail.

1.2.1 MaxEnt

MaxEnt is an SDM that follows a general-purpose approach developing predictions that utilize information which is only partially available. It is based on statistical mechanics (Jaynes, 1957), and can also be termed as a general-purpose method which can be used for presence only modeling of distribution of a given species. Thus, it is suitable for all such applications that involve presence only datasets. MaxEnt works on predicting a specific targeted probability distribution by determining the probability distribution of maximum entropy for that species, which means the distribution that is most spread out or even, while dealing with a set of limitations i.e. availability of only partial information about the distribution of target species. This partial information of the target species distribution mostly is present in the form of real-valued variables (features) while the limitations are the anticipated values of every feature which should be comparable to the average of all the sample points taken from the distribution of target species. When MaxEnt is used for species distribution modelling using presence-only approach, the coordinates of the study area define the MaxEnt probability distribution, coordinates that have known species presence records make up the sample points while the features consist of climatic conditions like environmental or bioclimatic variables, elevation, soil or vegetation type and their functions (Phillips et al., 2006).

The prediction can be of both scenarios; current and future. While the current prediction of suitable habitat of a species shown by MaxEnt only utilizes the current (present environment) environmental and bioclimatic variables, the future scenarios typically include the environmental variables that are derived for future years (e.g. 2050 or 2070) using various global circulation models that predict different representative concentration pathways (RCPs). Environmental or bioclimatic variables will behave differently under different RCPs.

1.2.2 Representative Concentration Pathways (RCPs)

Inter Governmental Panel on Climate Change (IPCC) published its 5th Assessment Report (AR 5) in which they made use of RCPs that are concentration pathways. These pathways describe concentrations of Greenhouse Gas (GHGs) and aerosol along with the change in land use and the results are in accordance with the diverse climatic outputs which the climate modelling experts use. The radiative forcing that will be generated up until the end of 21st century. Radioactive forcing, by definition, is the additional temperature the atmosphere captures due to the presence of extra GHGs. It is measured in Watts per Meter square(W/m^2). The RCPs have been grouped into four types to forecast the emissions (van Vuuren et al., 2011).

RCPs consider the effects of carbon dioxide and the environmental concentration of greenhouse gases and aerosols. Each RCPs covers a period of 1850 to 2100. Each of the RCPs signifies a huge set of situations in the scientific world. The full range of scenarios, featuring or not featuring, is within the scope of the RCP. These involve a mitigation scenario that results in a very low radiative forcing level (RCP 2.6), two comparatively stabilized moderate scenarios (RCP 4.5 and RCP 6) and a very high surface emission scenario (RCP 8.5) is included (Kawase et al., 2011).

The RCP 8.5 basically portrays a scenario where minimum to no effort is made to curb the emissions and the resultant warming by the year 2100. RCP 6 is a moderate scenario showing a stable radiative forcing scenario after the year 2100 due to steps taken to curb the GHG emissions. RCP 4.5 shows B1, a lowest emission scenario, evaluated in the Assessment Report 4 of IPCC. Whereas the most sustainable pathway is RCP 2.6 which shows the maximum curve of emissions earlier than other scenarios and then its fall because of the steps taken to remove CO_2 from atmosphere. This RCP calls for early interventions from all the countries that are currently emitting CO_2 into the air (van Vuuren et al., 2011).

1.3 Significance of the Study

Agriculture has been in practice in Pakistan since Neolithic times. It used to have high contribution in Gross Domestic Products (GDP) even after independence of the country but gradually, due to rise of other sectors e.g. industry and manufacturing, its share decreased from 52% in 1950-51, to just about 21.9% in 2001-02. Currently agriculture makes up 19.5% gross domestic product (GDP) and utilizes 42.3% labor force of Pakistan. It supplies raw materials for various value-added industries (Economic Survey, 2017). Although the share of agriculture sector in the national GDP has decreased, it still remains a vital component of Pakistan's economy. Furthermore, it also provides largest means of foreign exchange earnings as it contributes as a raw material for major industries like textile and sugar. Pakistan today owns the highest production of kinnow (mandarin-type citrus) in the world. It has a leading animal herd, 3rd biggest production of dates, 5th biggest production of mangoes, cotton and milk and 10% of rice barter globally. The sector is a source of food and livelihood for around 68% of population that inhibits rural areas. It therefore plays an essential role in national development, food security and poverty reduction (Economic Survey of Pakistan, 2017).

1.3.1 Agro-ecological Zones of Pakistan

For agricultural purpose, Pakistan has been distributed into ten distinct agro-ecological zones namely; Indus Delta, Southern Irrigated Plain, Sandy Desert, Northern irrigated Plain, Barani (rainfall), Wet Mountains, Northern dry mountains, Western Dry Mountains, Dry western Plateau and Sulaiman Piedmont. Figure 1.1 shows the zones and their locations all across the country. The most productive agro-ecological zones are situated within the province of Punjab. Most of the crops are grown all over the country, however, some agro-ecological zones are more favorable for some specific crops. For example, the major crops of Pakistan i.e. cotton, sugar cane, rice and wheat are mostly grown in the agro-ecological zones of Indus Basin and Delta and northern and southern irrigated plains (CIAT; World Bank, 2017).

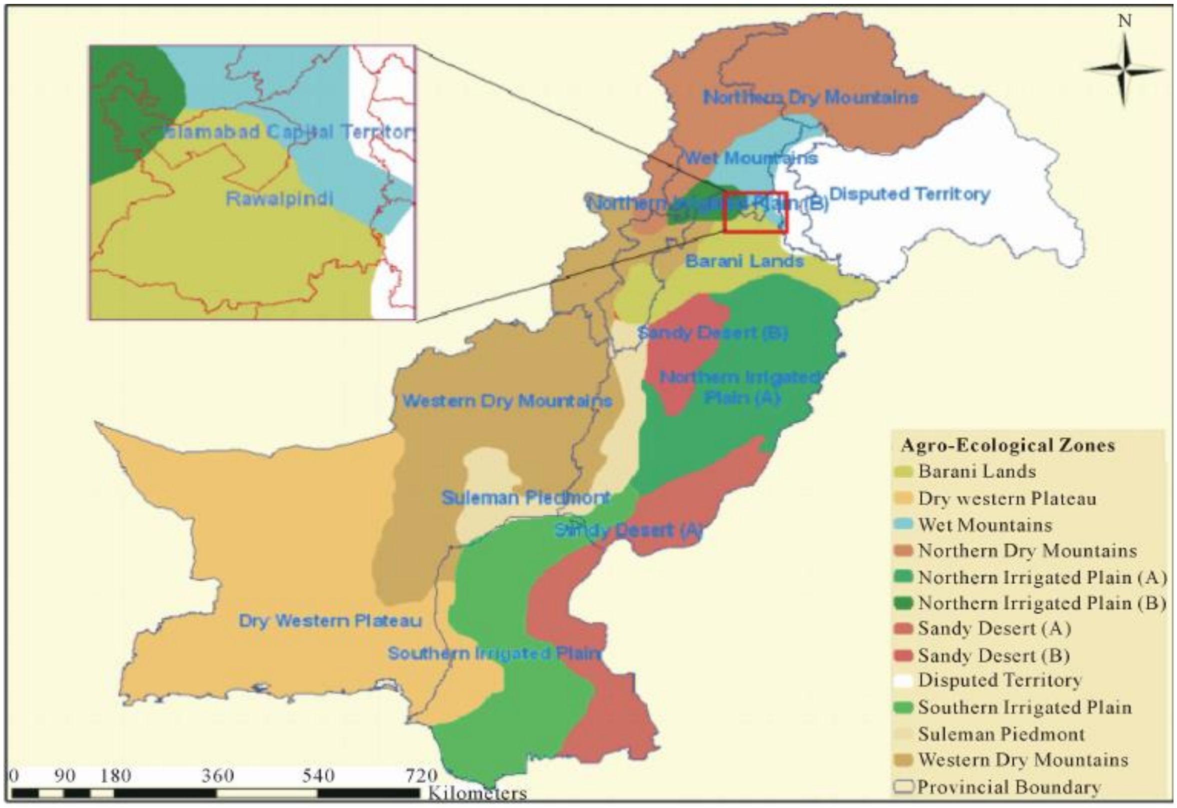


Figure 0.1: Agro-ecological zones of Pakistan. Source: (Kazmi, 2012)

1.3.2 Food Security Situation in Pakistan

Despite being an agrarian country and having substantial increase in yields of staple crops, factors like natural disasters, financial unsteadiness and peace and stability issues have given rise to food insecurity in the country over the past years. According to Global Food Security Index, Pakistan holds 78th position in a list of 113 countries and 60% of its population is food insecure. A country that possesses an index score of 39.7 and a supply sufficiency of 100, an estimated food supply of 2,440 kcal/person/day, fails to meet the demand of food because of high geographical differences in food production and supply. More than 22% of Pakistani population is undernourished, 31% of children are underweight, 15% affected by wasting and high levels of severe stunting i.e. around 45%, is reported. Diets in Pakistan usually lack diversity as on the food diversity index, score of Pakistan is 53.60 (MNFSR, 2017; CIAT; World Bank, 2017). Issues like malnourishment are more prevalent in rural areas (46%) than urban areas. Highest percentage of malnourishment is found in FATA (58%), then Gilgit-Baltistan (51%) and then Balochistan (52%) (MNFSR, 2017).

1.4 Selected Crops for the Study

1.4.1 Wheat

Wheat contributes 9.9% value in agriculture and makes up 2% of GDP (Economic Survey of Pakistan, 2017). As it is a staple diet, it holds a vital position in agriculture. Wheat is a widely grown crop that is mostly considered suitable for climates prevailing in the temperate and tropical regions, however, it is still widely grown under diverse climates ranging from the equator to higher elevations near and even within the Arctic circle. The temperature most suitable for growing wheat lies at about 25°C. The minimum temperature required for its growth lies between 3° and 4°C while the maximum temperature is between 30° and 32°C. For the required moisture, wheat is quite adaptative as it can grow at any location receiving precipitation within the range of 250 to 1750 mm. Wheat is usually broadly classified into spring and winter wheat, characterized by the season it is grown in. Spring wheat is usually sown in spring season and it grows and matures in summer season while winter wheat is harvested in winter season after the crop has endured some low winter temperature between 0° to 5°C. Figure 1.2 shows the harvesting (in yellow) and sowing (in green) months of wheat crop in Pakistan across all the provinces (PARC, 2015).

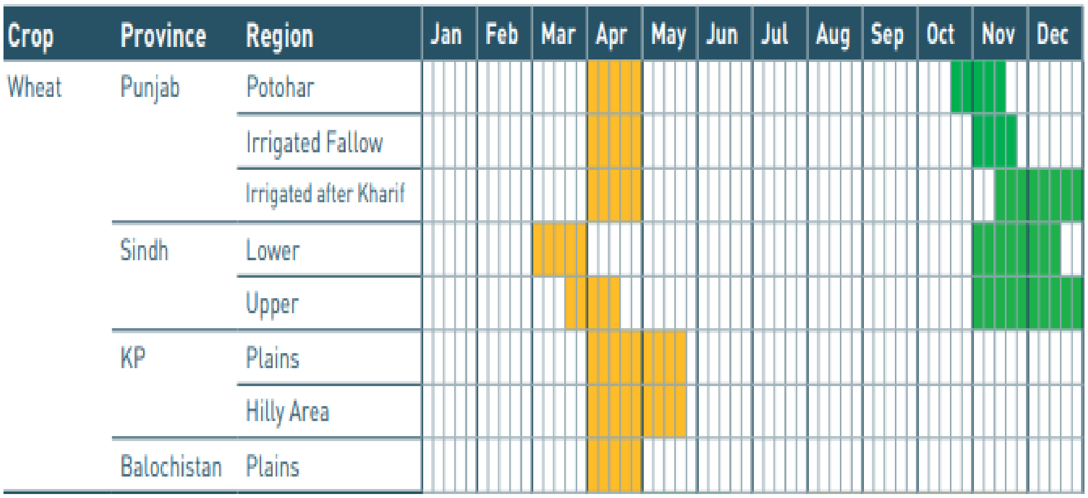


Figure 0.2: Sowing and Harvesting months of Wheat crop in Pakistan (FAO, 2019)

1.4.1.1 Trend of Wheat Area and Production

Production of the wheat has generally increased over the years, but not without recurring fluctuations in the yield (figure 1.3). Cropped area under wheat covers more hectares than any other agricultural crop, however, it still fails to achieve its potential and meet the gap between demand and supply on a national level. We are witnessing a decline in both the area and production of wheat. This insufficiency is a result of many factors such as, unexpected changes in weather, land fragmentation due to transfer and distribution of land property among heirs, which limits investment in modern equipment and input. Trade and pricing policies which discourage investments, pests and disease attack, unaffordability as well as ill-usage of pesticides that leads to wastage and health problems are all those factors that contribute to low supply of wheat according to its demand (Planning Commission, 2017).

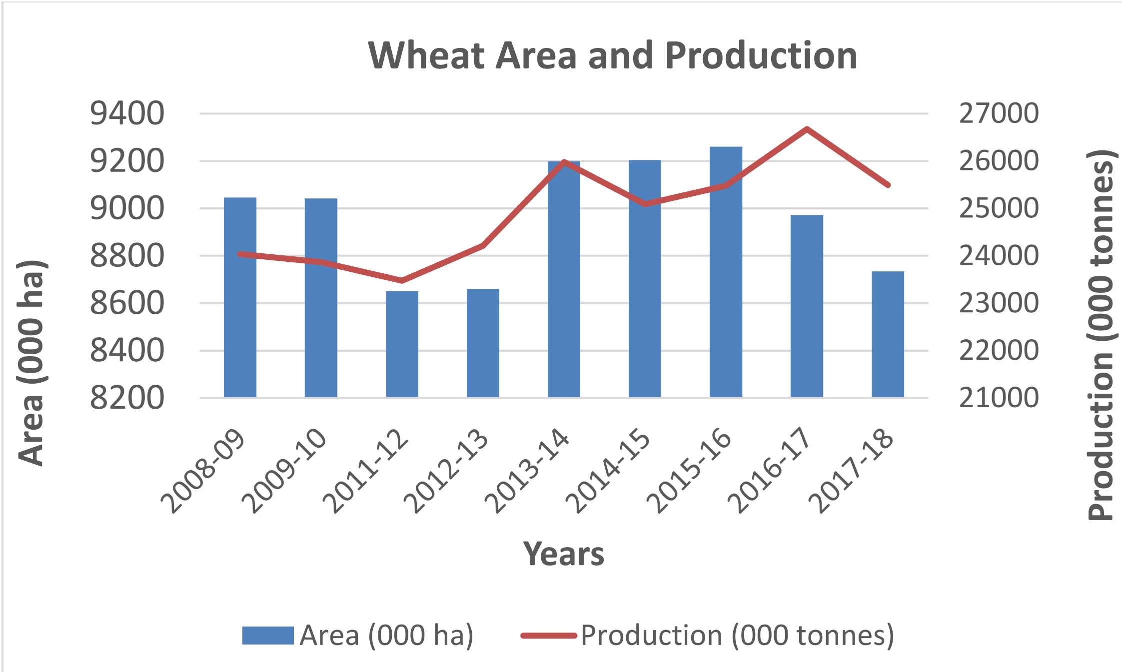


Figure 0.3 Trend in area and production of wheat crop (Pakistan Bureau of Statistics, 2018)

1.4.2 Maize

Maize, also commonly known as corn, is the second most widely grown crop after rice worldwide due to its ease of sowing and harvesting and high yield. It needs a good deal of moisture and temperature for growth from sowing stage to harvesting stage. It requires a temperature of about 21°C for sowing and for growth, it needs around 32°C. It cannot sustain high temperatures and low humidity as extreme conditions interfere with its pollination and damage the foliage of the crop. Maize is also quite sensitive to standing waters during the early growth period (Arain, 2013). Maize is a high yielding crop and is of a particular importance in a country like Pakistan where there is rapidly increasing population and limited food supply. It is the fourth most abundantly grown crop in the country, exceeded by wheat, cotton and rice. Maize covers above one million hectares in Pakistan and has a total production of around 3.5 million metric tons (Planning Commission, 2017).

Figure 1.4 shows the sowing and harvesting months of maize crop in Pakistan across all the provinces. Green color shows the sowing period while yellow denotes harvesting months.

Figure 0.4 Sowing and harvesting months of Maize crop in Pakistan (FAO, 2019)

1.4.2.1 Trend of Maize Area and Production

Maize is among the five major crops and one of the main Kharif crops in Pakistan. Compared to the average crop production of last year, Maize production stood at 5.702 million tonnes which is a drop of 7% from the production of last year that stood at 6.134 million tonnes. The drop in yield arose owing to the reduction in area. Maize growing farmers shifted from cultivating maize to cultivating sugarcane and rice crops (Economic Survey, 2017-18).

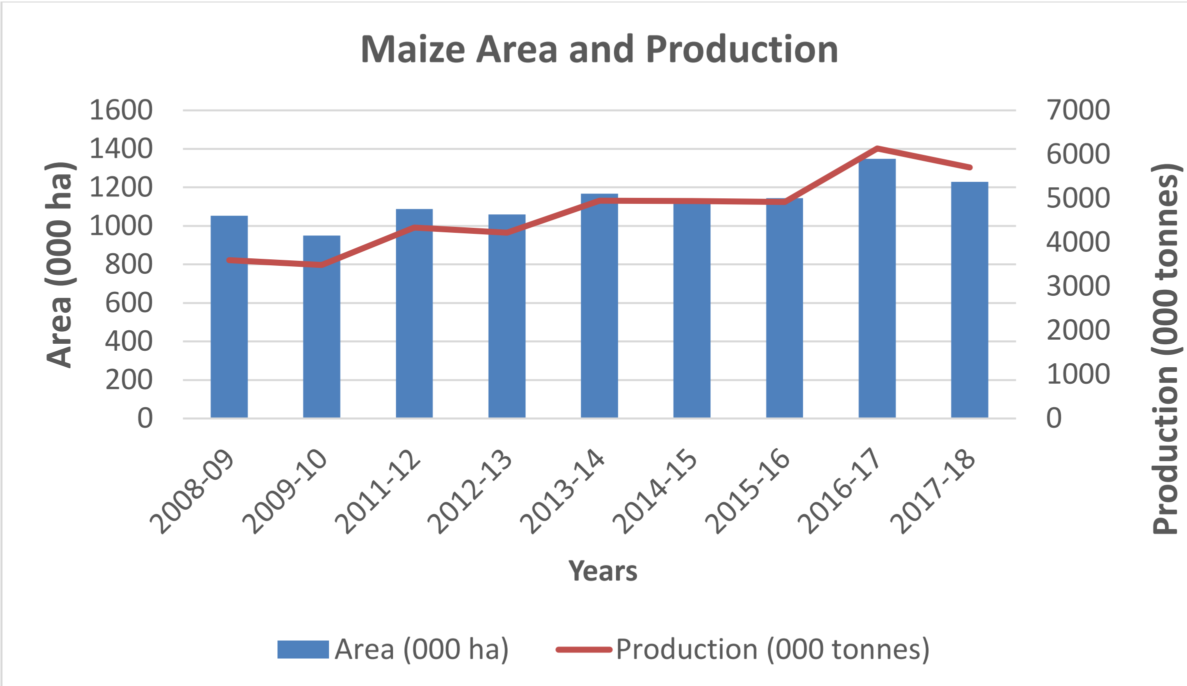


Figure 0.5 Trend in area and production of maize crop (Pakistan Bureau of Statistics, 2018)

Since the maize crop is sensitive to high temperatures, it is very much susceptible to changing climate in the study area, Pakistan. This decline is further anticipated to rise in future under extreme and moderate climate change scenarios. Due to the importance and vulnerability of such crucial major crops of Wheat and Maize to the climate change, it was decided to predict the suitable habitats of both the crops under different climate change scenarios. The objectives of this study were:

1. To predict and compare the effect of two Climate Change scenarios RCP (4.5 and 8.5) on wheat and maize distribution.
2. To identify key environmental variables that are highly correlated with spatial distribution of wheat and maize in Pakistan.

Chapter 2

LITERATURE REVIEW

2.1 Species Distribution Models (SDMs)

Species Distribution Models (SDMs) are governed by the interrelation of bioclimatic or environmental variables and species presence records as they determine habitat suitability on a wide scale by taking a look at ecological drivers (Elith & Leathwick, 2009). There have been developed a diverse range of modelling methods that typically range from instructions-based models to machine learning models. The quality and quantity of input information defines the accuracy of the model. The information can be random occurrence data sampling as well as more precise presence-absence records (Kramer-schatd et al., 2013).

2.1.1 Types of Species Distribution Models SDMs

In order to determine a species distribution, two approaches can be followed. First approach is mechanistic, which runs on incorporating environmental factors with a species' tolerance that is already established, e.g. the species maximum temperature tolerance limit. This is usually done by observing species response to different environmental conditions but most of the times such data is impossible to find (Franklin, 2010). The second approach called correlative approach; it is the approach one usually resorts to after failing to find any extensive data on species tolerances with respect to the environmental conditions. This approach assumes that the present occurrence of the species is evident of the conditions it normally requires for survival. Most of the SDMs employ this approach (Guisan & Zimmermann, 2000) and it is also used in the present study.

The algorithms used for species distribution models following correlative approach can be largely grouped into profile, regression, and machine learning methods. These three methods can be differentiated on the basis of type of input data they use as profile method only require species presence data while regression and machine learning methods needs species absence data or background data as well in addition to the presence data. The difference among the regression and machine learning model is not that prominent but still can be used to classify models. While profile method only use presence-only data, the other two methods can use either survey-absence data or pseudo-absence (background) data. There is another class of model that is totally different and makes use of geographic location of occurrences that are known. They do not take into account the environmental variables at those locations (Hui et al., 2013).

One example of model employing machine learning method is MaxEnt, which is used in this study. MaxEnt has a dinstict feature and position among different models and has been ranked as the best perfoming model in 16 other modeling methods. Its better performance is due to the fact that it uses a complicated underlying algorithm compared to other models and with its ability to use presence-only data, can directly relate the response of a given species to the environmental factors of the habitat its currently present in (Elith et al., 2006). In comparison to the models that use presence as well as absence data for modeling e.g., logistic regression or CART, MaxEnt has the ability to perform equally well or even better in case of species where absence data is hard to find and only presence data is made available. This performance and accuracy in the prediction of a species can further be increased by correcting or validating the data of species presence using ground truthing or satellite based observations (Ray et al., 2015).

2.1.2 MaxEnt

Maximum Entropy Model (MaxEnt) hasproved to be very useful for modeling the likely distribution of sensitive species in need of conservation (Kramer-schatd et al., 2013). MaxEnt basically uses the maximum entropy principal to evaluate environmental niche and determine a species' future distribution under the changing climate, by linking presence data to the given bioclimatic variables (Phillips et al., 2006). It is widely used all over the world owing to its ease in use and generating reliable outputs with incomplete or irregular input data and small sampling errors (Elith et al., 2006).

For this study, MaxEnt model was used due to its advantages over other SDMs which include;

(i) It only needs presence data of the species and information on environmental factors while still performing great with partial records (Pearson et al., 2007)

(ii) Has the ability to utilize continuous as well as categorical variables

(iii) Makes efficient use of algorithms that are deterministic in nature and ensure convergence with an optimal probability distribution.

(iv) Moreover, MaxEnt was rated the best performing algorithm in a contest of 16 different SDM methods (Elith et al., 2006; Phillips et al., 2006).

2.1.3 MaxEnt Model Predictions

2.1.3.1 AUC Curve

In the evaluation stage, Area Under Curve (AUC) was used for authentication of model. It basically evaluates the model by estimating its ability to differentiate between presence and absence points that are observed in a test dataset. If the AUC value is high, it usually means model is accurate in differentiating between the species' presence or absence locations. So higher the AUC, more accurate is the model.

True positive rate (TPR) as well as false positive rate (FPR), both are needed, as functions of classifier factor, in order to obtain an AUC curve. The TPR includes the number of correct positive results between all the positive results in the test while FPR in contrast, suggests the number of false positive results that show in the midst of negative samples in the test dataset. AUC is measured on the scale of 0 to 1 with 0 to 0.4 showing the lowest accuracy and worst performance of the model, 0.5 is random performance, 0.6 to 0.7 good, 0.8 to 0.9 very good and 0.9 to 1 shows excellent performance of the model with highest accuracy in the results (Peavey, 2010).

2.1.3.2 Jacknife Test

To determine, which of the variables contribute more to our model for wheat crop in the current climate, jackknife test was applied. Jackknife performs resampling of data. It basically picks up each variable and then calculate the estimate of the model with only that variable and without that variable. The red bar indicates the score of a variable in the model using only that climatic variable, length of the bar would represent the importance of the factor hence a long bar indicates the more contribution of the bioclimatic variable to the model. The blue bar estimates the score of a model without that variable (Song et al., 2012).

2.1.3.3 MaxEnt Studies on Crops

The possible global distribution and dynamics of wheat was predicted by Yue et al. (2019) under various scenarios of climate change. Based on the large occurrence datasets of wheat and the major environmental factors affecting wheat growth, they made use of MaxEnt to determine the possible future distribution of wheat for cultivation under multiple scenarios of global climate change as well as predicting the suitability of the land. Their results show that wheat suitability is mainly affected by environmental factors and on the fact that the accumulated temperature is ≥0°C is particularly important. Their mean AUC value for the results was 0.75. They determined that RCP 4.5 future climate scenario is more favorable for growth of wheat compared to RCP 8.5 which is the least favorable. In general, climate change is expected to boost the land suitability for cultivation of wheat in the middle and high latitudes and reduce the suitability in low latitudes. Although the climate change will not significantly change the presence of wheat crop all over the world, the risks of future wheat cultivation could be substantially higher because of increased natural disasters caused by climate change such as extreme temperature, heat wave and drought.

In China, winter wheat is considered to be the primary food crop. Gansu Province is a traditional area for growing winter wheat, and its cultivation range is constrained due to thermal conditions in winter. The typical temperature of Gansu Province grew by 0.28°C per decade, which is greater than the Chinese and global average, and the greater temperatures in winter are more pronounced. Hence, it is essential to review the aptness and susceptibility of winter wheat cultivation in Gansu under climate change. To build a relationship model between winter wheat cultivation and the climate that can assess the suitability and susceptibility of wheat during 1961 to 2015, Wang et al. (2019) used MaxEnt and ArcGIS to choose main climatic variables. These included total annual radiation, annual precipitation, annual average temperature, annual extreme minimum temperature, the warmest monthly average temperature and the coldest monthly average temperature. Results indicated that the average low temperatures and annual minimum temperature make up two most vital climatic factors that influence winter in province of Gansu. This shows that winter heat can tolerate low temperatures. However, since it is present mostly in arid and semi-arid areas of Gansu, precipitation is also a deciding factor in its distribution. They determined that climate change does not have a significant impact on Gansu as the suitable areas change only slightly under climatic changes and exhibit moderate adaptation. The AUC of their study was 0.90 which showed the accuracy of the model used in the study.

Song et al. (2012) determined the climatic suitability of winter wheat planting zone in China. They took into account the climatic data, geographical occurrence of species and fed them into MaxEnt model to establish relationship between the suitable area for wheat cropping and the climate. The key environmental factors playing role in the suitability of winter wheat cultivation in an area were assessed to determine climatic favorability. These key factors included negative accumulative temperature, annual rainfall, annual mean minimum temperature, and evapotranspiration. A negatively accumulated temperature of -700°C and annual mean minimum temperature higher than -30°C is required for survival of winter wheat. The suitability area map for winter wheat was then mapped on the basis of MaxEnt distribution model. The results, with an AUC of 0.87, determine the northeast boundary of winter wheat to be in north Heilongjiang Province while northwest boundary of the crop to be in north Xinjiang Autonomous Region. The output of the study can be helpful as it describes suitable winter wheat cropping areas which will be effective in guidance of cultivation of this crop and understanding the effects of climate change on it.

Maize is included in the major staple food crop in Kenya. Kogo et al. in 2019 modelled the suitability of plantation of maize in Kenya with respect to the climate required. The impact of climate change on suitable rainfed maize areas was modelled using MaxEnt model. The made use of environmental or bioclimatic factors for a couple of difference RCPs which included RCP 4.5 and RCP 8.5 from two general circulation models (GCMs) namely HadGEM2-ES and CCSM4 for the year 2070. The found out the major variables affecting maize distribution to be annual rainfall, annual temperature and wettest quarter. The results revealed the unsuitable areas to increase by 1.9–3.9% and moderately suitable areas to decrease by 14.6–17.5%. however, the suitable areas and highly suitable areas increase by 17–20% and 9.6% respectively.

He & Zhou (2011) assessed the climatic suitability for maize cultivation in China in order to gain scientific understanding of maize production and how is it being impacted by climate change. The study took into account the climatic factors on national level that decide the presence of the maize species in a given area. The occurrence location of Maize along with climatic data was fed into MaxEnt model and ArcGIS tool was used to assess and determine the maize distribution. The results proved that to study the impacts of climate change and determine the habitat suitability of maize, MaxEnt can be used. the key factors that had an impact on maize distribution included, annual average temperature, annual precipitation, humidity index, frost-free period, ≥10°C accumulated temperature, ≥0°C accumulated temperature, ≥10°C accumulated temperature and the warmest month average temperature. They also categorized the suitability zones of maize on the basis of climate using MaxEnt method. Using the relation between suitable maize areas and climatic indices, they were also able to determine the climatic thresholds for maize cropping zones. It was found out that different maize species have different climatic thresholds and different climatic suitability which should be studied in detail to assess the optimum cropping zones for maize. Their AUC of their model was 0.81 which showed very good performance of the model.

In Pakistan, to determine the impact on medicinal asclepiads of climatic changes, Khanum et al. (2013) use MaxEnt modelling. It was utilized to forecast the possible suitable climatic zones of three medicinally vital plant species namely; *Pentatropis spiralis, Tylophora hirsuta, and Vincetoxicumarnottianum.* Despite being all of them a member of Asclepiad species family, they require different ecologic biogeographic parameters and have different conservation value.

They collected the presence location data was from major herbaria of the country and field surveys. They determined that MaxEnt was a very suitable method for predicting the environmental niche of these herbs as it performed better than average with an Area under Curve (AUC) of 0.74 for *P. spiralis* while 0.84 and 0.59 for *V. arnottianum* and *T. hirsute* respectively.

The results indicated an increase of suitable area for *P. spiralis* in south Punjab and Balochistan while a decrease in suitable areas in south eastern Sindh. For *Vincetoxicum arnottianum* as well as *T. hirsute,* the results indicated decline in suitable area in northern Punjab and lower peaks of mountainous area (Galliat, Zhob and Qalat etc) while an increase in upper peaks of country's northern areas. They recommended that the same modeling approach presented an also be applied to other rare Asclepiad species to determine their vulnerability to climate change, especially those who are threatened.

The potential habitat distribution of *Olea ferruginea* was predicted by Ashraf et al., 2016 using the method of MaxEnt for current and future climate (2050). Potential distribution *Olea ferruginea*, an economically important plant, was assessd using bioclimatic variables (both current and future climate), digital elevation model (DEM) slope and occurrence location data. Using 219 occurrence points in their study, they achieved an AUC of 0.98 which showed model performed much better than average. The study determined a substantial impact of future climate scenario on *Olea ferruginea* under global climatic changes. A considerable reduction in the suitable areas of *Olea ferruginea* was noticed under current climate but the model predicted an increase in the suitable areas in the future climate at higher altitudes, a phenomenon known as habitat shift. The study recommended to make use of the potential suitable areas of *Olea ferruginea* that are predicted and restoration of deforested lands.

Swat is a district in Pakistan that is considered a hub of biodiversity. However, growing impacts of climate pose a serious threat to, especially, plant species in the district and can cause extinction of many species. To analyze the impacts of these climatic changes in detail on the plant species *Abies pindrow*, Ali et al. (2012) carried out a study using MaxEnt modelling by combining HADCM3 A2a international climate change future climate scenario and the occurrence location of *Abies pindrow*. They estimated a significant change in the future distribution of the said species with model showing an AUC of 0.97 for present and 0.98 for future climatic distributions of the species. The key environmental factors affecting the distribution of *Abies pindrow* and contributing significantly to the model include mean temperature of warmest quarter and annual temperature range. The study predicted a decline in suitable areas and the population density of the species by the year 2080. It was also noted that the change in population and suitable areas of *Abies pindrow* will not only affect the species itself but also the associated subflora will be impacted.

Chapter 3

METHODS AND MATERIALS

3.1 Study area

Pakistan lies at latitude of 30.3753° N and longitude of 69.3451° E. It is geographically located in South Asia with area of about 881,913 Km^2. The neighbouring countries include India in East, Afghanistan and Iran in West, China at its north and a coastline along Arabian Sea in the South. The climate of Pakistan is a very diverse one and it features four season; spring, summer, autumn and winter. Figure 3.1 shows map of Pakistan.

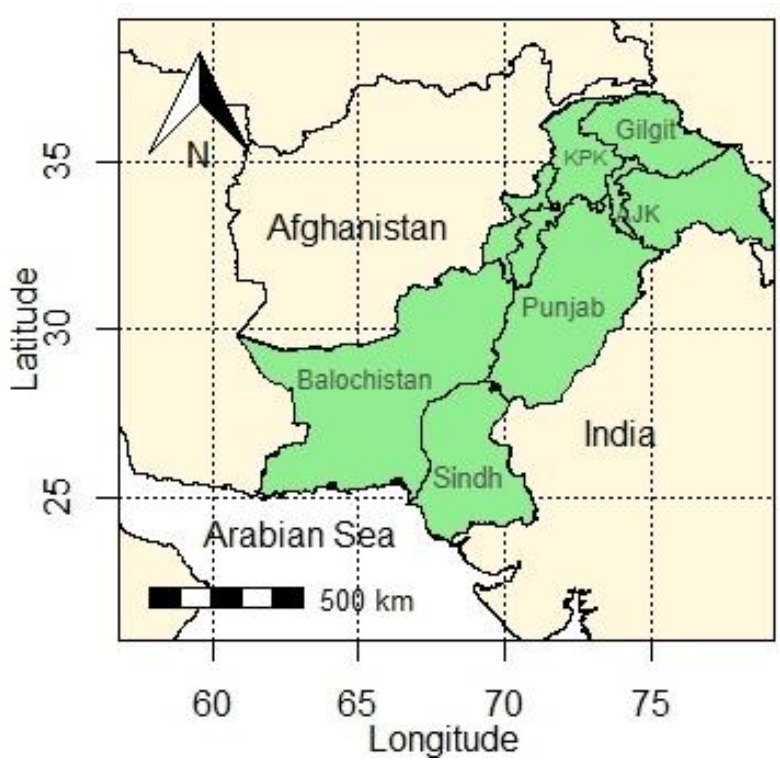


Figure 0.1 Study Area Pakistan

3.2 Datasets Used

3.2.1 Species Observation Data

Species occurrence data for the analysis of wheat and maize crops was obtained from Pakistan Bureau of Statistics (PBS). The agricultural statistical department within PBS provided the crop observational data for the year 2008-09, 2011-12, 2013-14, 2016-17 and 2018. The data included production and area for each crop. Since the data was spread over the span of 4 years, an average of production per hectare was derived and all the districts with above 50% crop yield were selected. The selected data points of dsitricts consisted of 46 records for maize and 59 records for wheat. These areas of high crop yield were then utilized in the form of geographical latitudes and longitudes for further analysis. This data was fed directly into the species distribution model as presence-only data.

3.2.2 Climate Data

MaxEnt model requires bioclimatic data which is used to determine the habitat suitibilty for a given species and thus climatic suitability for a species for both present as well as future scenario. For the present study, 19 bioclimatic variables (Bioclim) were obtained from WorldClim at a resolution of 0.5 km (Hijmans et al., 2005). Table 3.1 shows these 19 bioclimatic variables along with their description. Global temperature and precipitation data are the main factors that drive bioclim variables (Hijmans et al., 2005). The bioclimatic variables that were downloaded accounted for current and future (year 2070) climatic scenarios. Current bioclimatic include average climatic data for years 1970-2000 (Hijmans et al., 2005). For future bioclimatic data, worldClim offers projections using Global circulation models (GCMs) for four representative concentration pathways (RCPs).

RCPs include worst-case, moderate and best-case scenarios. For this study, moderate and worst-case scenarios were chosen to include in the model which consist of RCP 4.5 W/m^2 and RCP 8.5 W/m^2 respectively. Future climatic data for year 2070 for both the RCPs is an average of projected values for the years 2061 to 2080 (Booth et al. 2014). RCP 4.5 is a moderate- case scenario in which greenhouse gases are projected to rise and reach at their peak by mid-century, they are then predicted to decline quickly over the next thirty years shortly before stabilizing (Vuuren et al., 2011). RCP 8.5, being the worst-case scenario, features high emissions of greenhouse gases where the emissions are only projected to rise with passing years with no stabilization or decline (Vuuren et al., 2011).

The GCM model applied in the study is Coupled Model Intercomparison Project, Phase 5 (CMIP5) which is simulated using Max Planck Institute for Meteorology (MPI-M) based on the MPI-ESM-LR model. It is a project of the World Climate Research Programme (WCRP) for providing IPCC AR5 (Fifth Assessment Report, IPCC 2013) with time-projected environmental variables. It is made available to the scientific community, and can be accessed from the ESGF portal (Program for Climate Model Diagnosis and Intercomparison (PCMDI). The computing for these projections is done via different representative pathways such as RCP 2.5, 4.5, 6 and 8.5. Every representative pathway includes the same category of the data with different values projecting different levels of carbon emissions over a time as a result of human activities (Combal and Caumont, 2016). It also analyses the predicatblity of climate and determines the predictive accuracy of forecast systems based on decadal timelines. Another feature of the model is its ability to determine the reason behind a range of responses from models that are similarly forced (Taylor et al., 2012)

Table 0.1 Bioclimatic variables used in the study (www.WorldClim.org)

Bioclimatic Index	Description
Bio1	Annual Mean Temperature
Bio2	Mean Diurnal Range
Bio3	Isothermality
Bio4	Temperature Seasonality
Bio5	Max Temperature of Warmest Month
Bio6	Min Temperature of Coldest Month
Bio7	Temperature Annual Range
Bio8	Mean Temperature of Wettest Quarter
Bio9	Mean Temperature of Driest Quarter
Bio10	Mean Temperature of Warmest Quarter
Bio11	Mean Temperature of Coldest Quarter
Bio12	Annual Precipitation
Bio13	Precipitation of Wettest Month
Bio14	Precipitation of Driest Month
Bio15	Precipitation Seasonality
Bio16	Precipitation of Wettest Quarter
Bio17	Precipitation of Driest Quarter
Bio18	Precipitation of Warmest Quarter
Bio19	Precipitation of Coldest Quarter

All the 19 bioclimatic variables were used in the study as environmental predictors. Other than the bioclimatic variables, co-variates such as elevation, irrigation and soil types were also included in the model to best predict the suitable habitat for wheat and maize for predicting all the relevant factors that influence climatic suitability for both the crops. Data for elevation (DEM) was downloaded from USGS (www.usgs.org) and for irrigation and soil types, the data was downloaded from FAO website (www.fao.org).

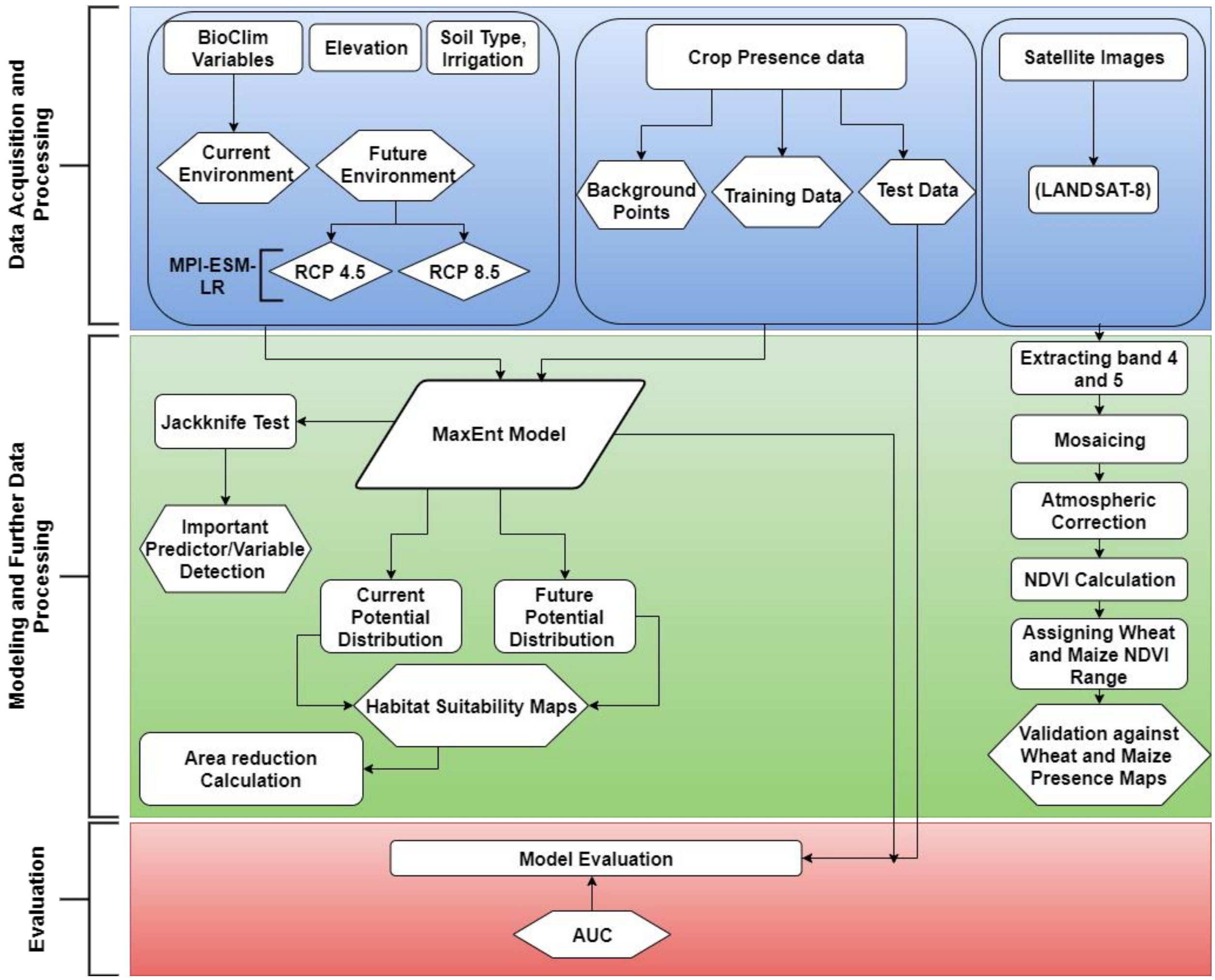


Figure 0.2 Research flow diagram of the study

3.2.3 Environmental Variables

To be able to better predict the effect of climatic changes on proposed crops, environemnetal variables as well as co-variates were taken into account to run the model (as discussed above). A specific range of suitable environmental variables can be selected and used in predicting the habitat suitability of a species while running MaxEnt model (Pearson, 2007). For this study, the environmental variables or the co-variates that were selected include soil type, irrigation and elevation. All these variables perform a crucial part in defining the habitat suitability of Maize and Wheat crop (Pearson, 2007).

3.2.4 Remote Sensing Data

To compare and validate the climatic suitability map that was generated using MaxEnt model for the current environment, remote sensing data, LANDSAT 8-Level 1, for the year 2018 was downloaded. As the study area was whole of Pakistan, 66 tiles in total had to be downloaded. The path and row numbers of these tiles were identified using Pakistan shapefile in ArcMap 10.5. The data was then downloaded from USGS Earth explorer official website (www.usgs.org). For this particular study, there were two crops Wheat and Maize; that were needed to be assessed and predicted the current and future climatic suitability. Since the crops were to be identified using their assigned Normalized Difference Vegetation Index (NDVI) value from the satellite images, it was made sure that the months chosen for downloading the images are the ones when the crop is at full bloom and is ready to be harvested. In Pakistan, Maize crop is harvested in the months of October to November and Wheat crop is harvested in the months of March to April in a large part of the country (Rehman et al., 2015). Therefore, two separate datasets were downloaded for the months October to November and March to April. Cloud cover was kept minimal for the images downloaded i.e. between 10% to 20%. Once all the tiles for both the crops were downloaded, further data processing was carried out which included stacking of raster bands, making a mosaic of all the downloaded tiles, atmospheric correction and finally NDVI calculation for the raster dataset. Specific NDVI ranges for wheat and Maize crop were derived using literature review (Damian et al., 2020; Filgueiras, 2019). The range for Wheat was found to be from 0.3 to 0.8 and for Maize it was from 0.25 to 0.75.

3.3 Methodology

3.3.1 Softwares Used

a) R programming

b) ArcMap 10.5

c) Linux

d) QGIS

3.3.2 Maximum Entropy (MaxEnt): Species Distribution Modeling

Figure 3.2 shows the flow diagram research steps taken in this study. Once the datasets were prepared, it was run in R program (www.rstudio.com). In the MaxEnt modelling, using the association between the present habitat distribution of the specie and the current climatic conditions, future habitat distribution ranges are predicted. MaxEnt model basically uses an algorithmic technique for prediction of species distribution in future (Phillips et al., 2006). As mentioned above, MaxEnt uses presence records as well as background points to be run under the model. Occurrence records are mostly obtained by secondary sources but are also collected primarily through field visiting. However, there can b a bias in presence records as they tend to be more from the site which is easily accessible such as roads etc (Phillips et al., 2006) this can lead to inaccurate predictions. MaxEnt picks the random background point with a similar bias to improve the predictive accuracy (Phillips et al., 2006).

To run the model, occurrence records in a text file, were imported into R. following which, climatic data along with environmental variables (co-variates) were also fed into the model.
The model was validated by dividing the presence records into two data sets; training data and testing data. Training data comprised of 80% data while testing data is comprised of 20% of

occurrence data. The training data trained the model while the testing data tested the data on the basis of the training. After inclusion of all the steps, model was run and relevant maps were generated for each category. The results generated by the model for each climatic scenario were evaluated and validated by the Area Under Curve (AUC) curve value in receiver operating characteristic (ROC) curve. AUC values range from 0 to 1 (Phillips et al., 2006) with 1 being the highest and 0 the lowest value for the AUC.

Once the maps for each crop in all current, future 4.5 and future 8.5 scenarios were generated, the respective areas of each crop were calculated for the current and future scenarios. This was done for not only the suitable area of whole Pakistan but for also for each province of the country.

Jackknife test was also used in the study to identify the importance of every bioclim variable that is fed into MaxEnt model. The jackknife procedure ignores each variable, builds a model without that variable, then create a model using only the omitted variable (Baldwin, 2009).

Current climate specie distribution map was validated and compared with satellite images data that was processed earlier.

Pearson's correlation was also used on the most important variables to determine their negative or positive correlation with other variables.

Chapter 4

RESULTS AND DISCUSSION

4.1 Wheat

4.1.1 Presence Points of Wheat distribution

Figure 4.1 shows the locations of wheat crop with presence points encompassing mostly central Punjab, Sindh and some parts of KPK.

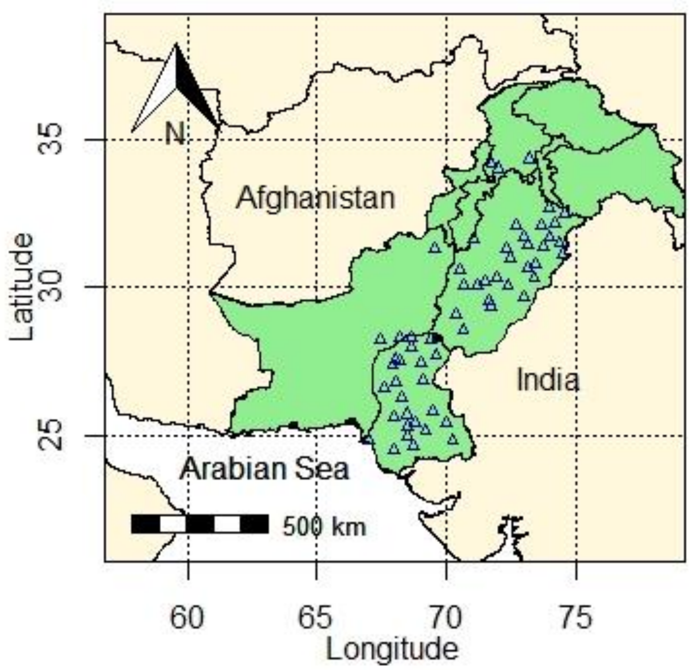


Figure 0.1 Present locations of Wheat in Pakistan

4.1.1.1 Comparison and Validation against NDVI Map

The downloaded satellite images were compared with the field observed map of wheat occurrence data as shown in figure 4.1 (a & b). The comparison showed an insignificant difference between the two maps (figure 4.2). All those areas, where the field observed data showed wheat presence, were identified by the NDVI map having assigned NDVI range as well and hence this validated the wheat crop presence data.

(a) (b)

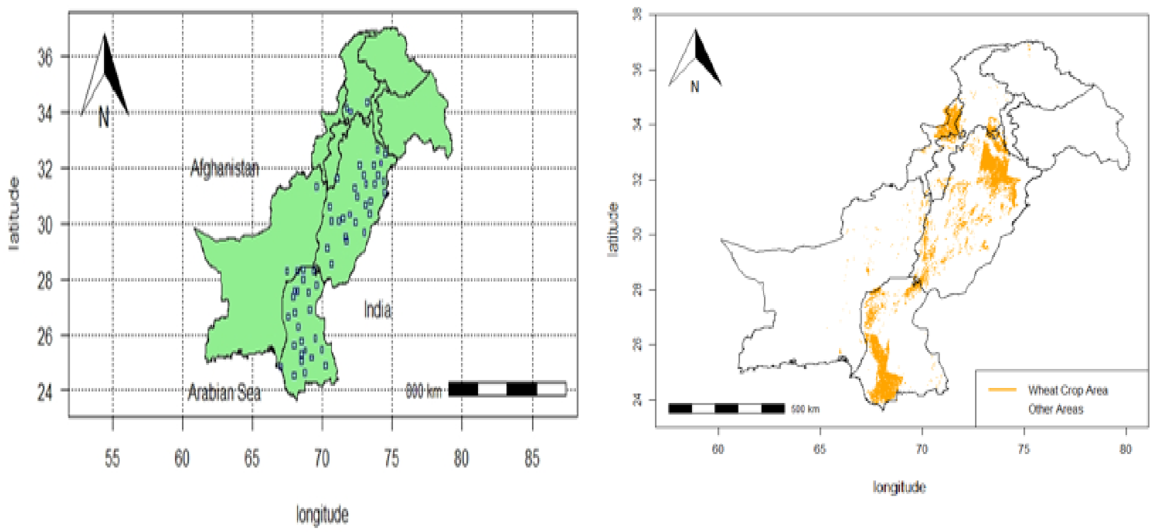


Figure 0.2 Comparison between (a) field observed wheat locations and (b) NDVI based locations

4.1.2 Current Climatic Suitability of Wheat

4.1.2.1 Raw Values and Threshold Maps

The raw value map forms the basis of the output from a MaxEnt model as it determines the importance of each feature and suggests the suitability of different areas in comparison with each other. Darker shaded areas show more suitable area while lighter colored areas show less suitable areas.

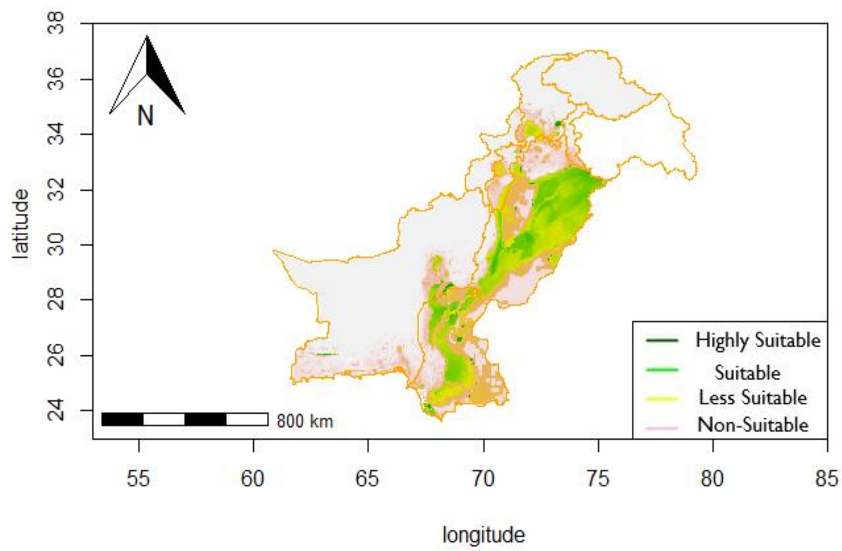


Figure 0.3 MaxEnt raw values map showing current climatic suitability of Wheat

However, raw values maps are graded and since a more binary output is desired with just presence and absence to calculate the area of species distribution a different output was selected than raw values where MaxEnt assigns threshold values to the data and allows to make binary maps. Figure 4.4 shows the threshold map of wheat current distribution where it can be observed that the major suitable areas lie in Punjab and Sindh with some parts of KPK, Balochistan and AJK.

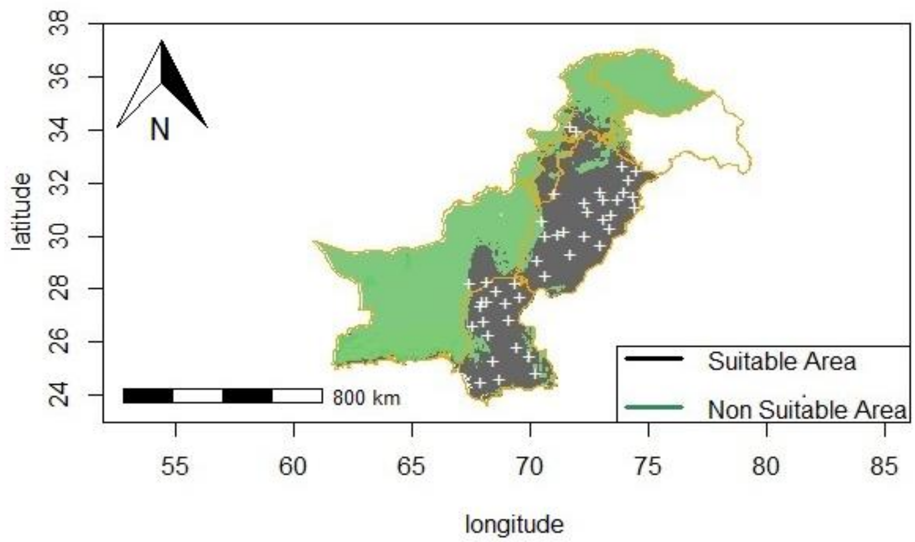


Figure 0.4 Threshold map showing current climatic suitability of wheat

Area calculation was also performed using the threshold maps. The method performed in the study for determining area included calculation on the basis of the raster image. This basically requires cell sizes which can be obtained from raster object/image using the function of area in the raster package of R in Km^2. It changes from north to the south. By adding together all cell sizes that have a similar value or by extracting a median cell size of all the cells and then multiplying it by number of cells can provide the size of the entire area. Currently 386,148 km^2 (38,614,800 ha) area is suitable for wheat growth.

4.1.2.2 Evaluation of Model Accuracy

The MaxEnt model results evaluated the AUC of 0.93 (figure 4.5) which predicts that the model is very affective and accurate in distinguishing between the presence and absence of wheat crop.

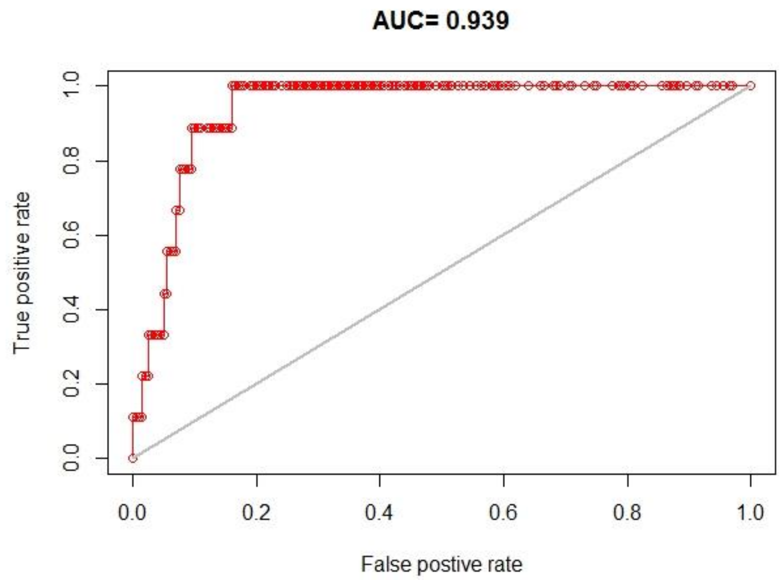


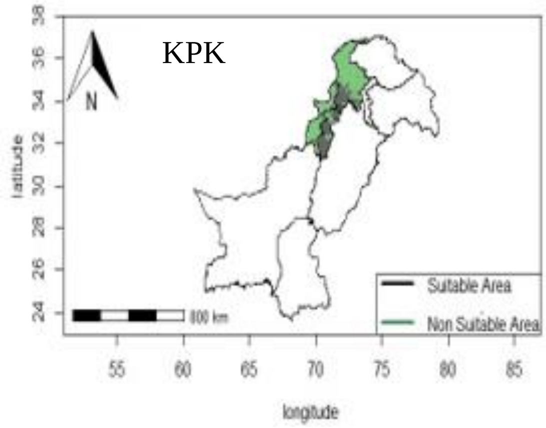
Figure 0.5 Area Under Curve (AUC) for model evaluation under current climate scenario for Wheat

4.1.2.3 Province-Wise Breakdown of Wheat Under Current Climate Scenario

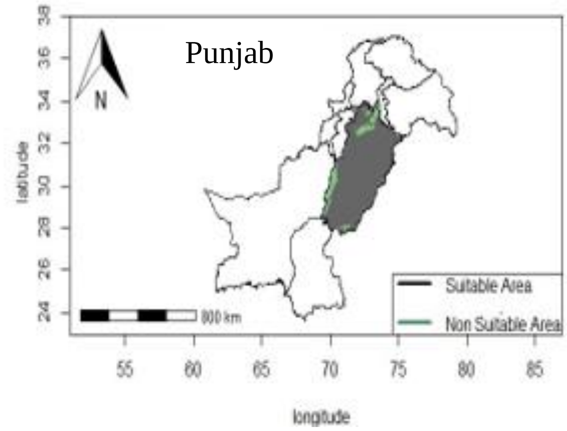
Further calculations were performed to determine the province wise area of Wheat under the current climatic scenario (figure 4.6).

Punjab holds the highest suitable area for wheat cultivation owing up to 184,730 km^2 (18,473,000 ha) (figure 4.6 b). It is followed by 122,035.9 km^2 (12,203,590 ha) of area in Sindh (figure 4.6 c), 31,218.2 km^2 (3,121,820 ha) in KPK (figure 4.6 a) and 44,678.3 km^2 (4,467,830 ha) in Balochistan (figure 4.6 d).

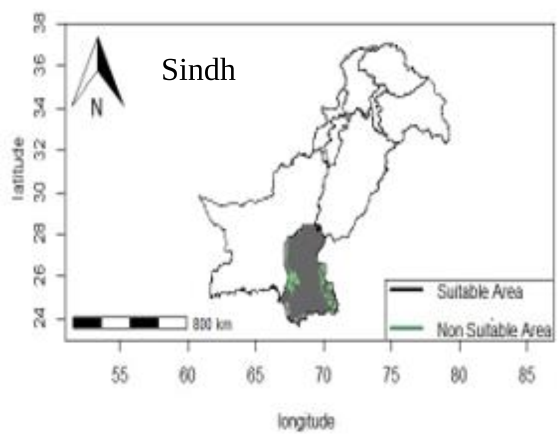
(a)



(b)



(c)



(d)

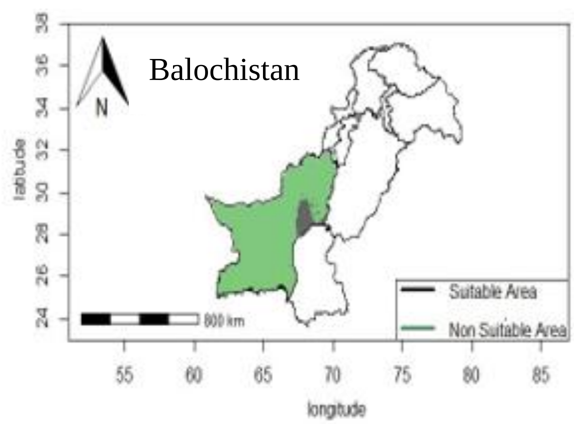


Figure 0.6 (a) Suitable area for wheat cultivation under current climate in KPK (b) Suitable area for wheat cultivation in Punjab (c) Suitable area for wheat cultivation in Sindh (d) Suitable area for wheat cultivation in Balochistan

4.1.2.4 Variable Contribution (Current Climate)

The jackknife test revealed that for the wheat crop habitat suitability, under current climatic scenario, the variables contributing most in current scenario are irrigation and elevation. The length of the red bar represents the score using only one of the climatic indices; the longer the bar, the more important is the climatic factor. The length of the light gray bar represents the score of a model created with the remaining indices.

Figure 0.7 The bar graph of Jackknife Test for wheat (current climate). The red bar shows the gain when the specific variable is used in isolation and the light blue bar shows the gain when that specific variable is excluded from analysis.

4.1.2.5 Pearson's Correlation

Pearson's correlation showed that irrigation is most positively correlated with Mean Temp. of Wettest Quarter and negatively correlated with elevation and soil type. Elevation is most positively correlated with minimum temperature of coldest month and most negatively correlated with Temperature Seasonality (figure 4.8).

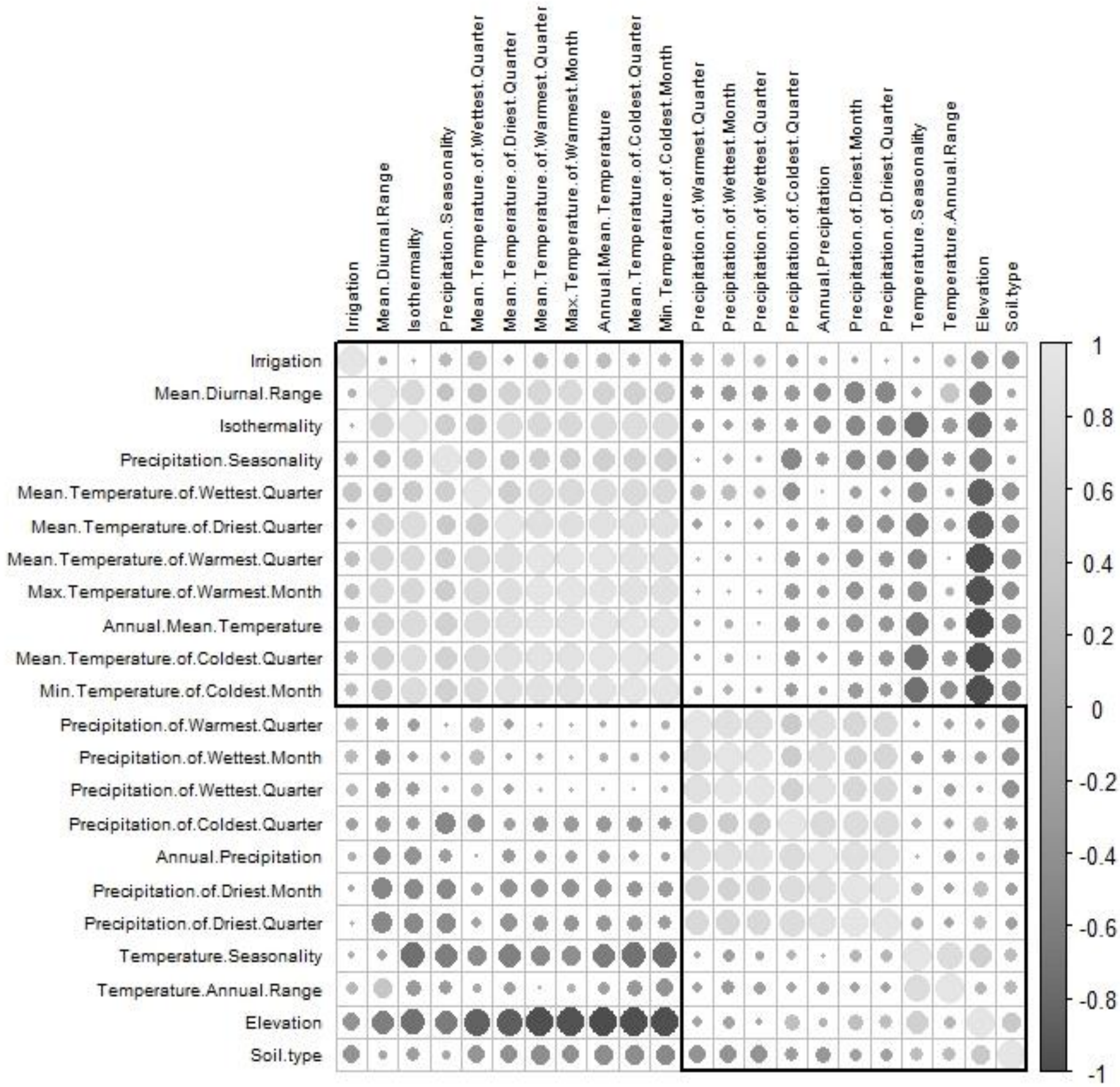


Figure 0.8 Pearson correlation coefficient graph for wheat under current climate scenario

4.1.3 Climatic Suitability of Wheat Under Future Climate RCP 4.5

4.1.3.1 Raw Values and Threshold Maps

Under future climatic scenario, RCP 4.5, a considerable shrinkage of area was identified in the MaxEnt raw values and threshold map. The suitable area reduced to 269,634.7 km^2 (26,963,470 ha). Major suitable areas were identified in Punjab and Sindh with very few parts of KPK, Balochistan and AJK (figure 4.9 & 4.10).

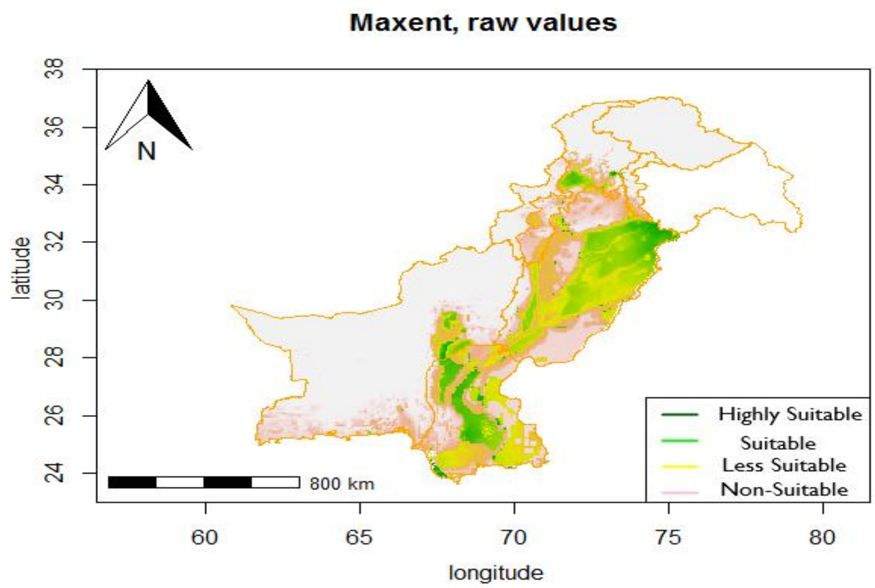


Figure 0.9 MaxEnt raw values map showing climatic suitability of wheat under RCP 4.5

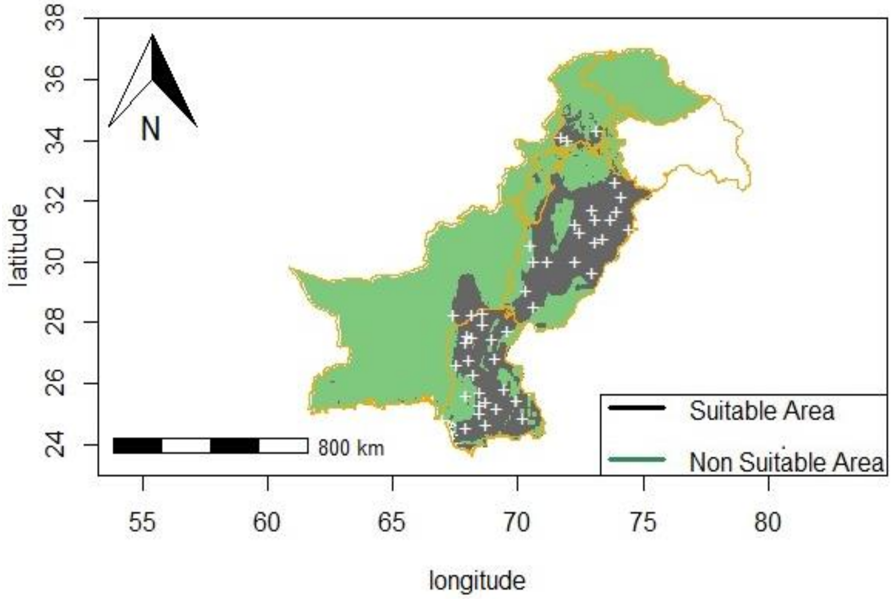


Figure 0.10 Threshold map showing climatic suitability of wheat under RCP 4.5

4.1.3.2 Evaluation of Model Accuracy

The AUC value of the model evaluated for RCP 4.5 is 0.89 which shows the model performed above average and its results are very accurate (figure 4.11).

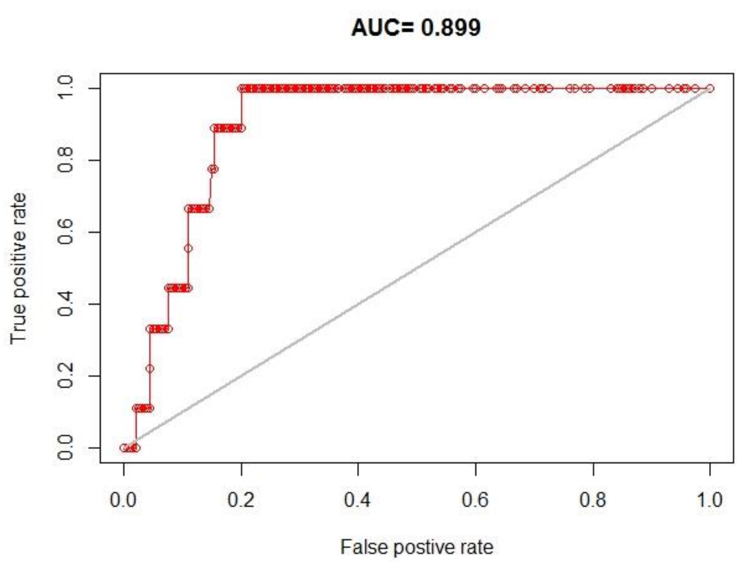


Figure 0.11 AUC model evaluation for Wheat under RCP 4.5

4.1.3.1 Province-Wise Breakdown of Wheat Under Future Climate Scenario RCP 4.5

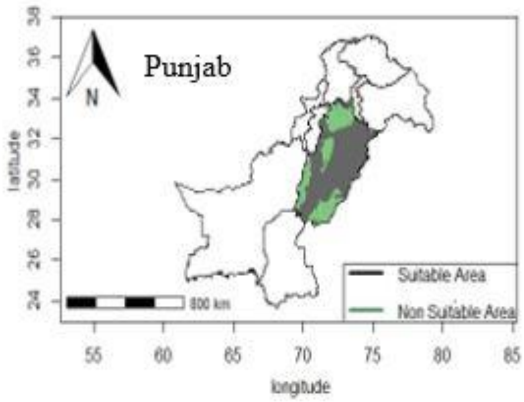
Further calculations were performed to determine the province wise area of Wheat under RCP 4.5.

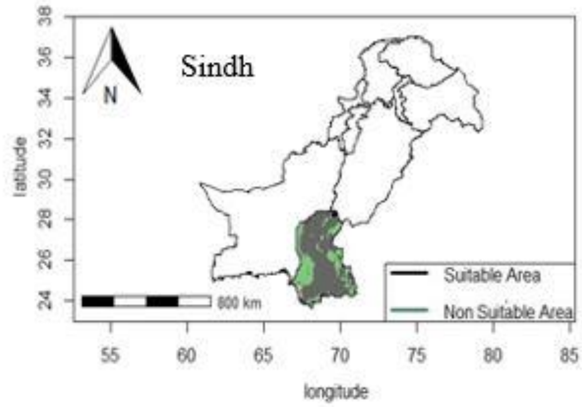
Punjab observed reduction of suitable area but still holds the highest suitable area for wheat cultivation owing up to 136,535 km^2 (13,653,500 ha) (figure 4.12 a). It is followed by 97,981.5 km^2 (9,798,150 ha) of area in Sindh (figure 4.12 b), which also got reduced from 122,035.9 km^2 (979,815,000 ha). 15,751.6 km^2 (1,575,160 ha) was calculated in KPK (figure 4.12 d) and 17,864.2 km^2 (1,786,420 ha) in Balochistan (figure 4.12 c). The overall trend of model output of wheat crop for all the provinces showed decline in area suitability.

4.1.3.2 Variable Contribution (RCP 4.5)

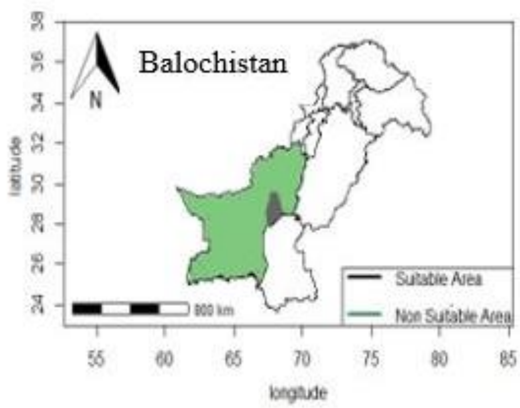
For the wheat crop habitat suitability, under future climatic scenario (RCP 4.5), the variables contributing most in future RCP 4.5 scenario are irrigation and Precipitation of Warmest Quarter. The length of the red bar represents the score using only one of the climatic indices; the longer the bar, the more important is the climatic factor. The length of the light gray bar represents the score of a model created with the remaining indices (figure 4.13).

(a) (b)





(c) (d)



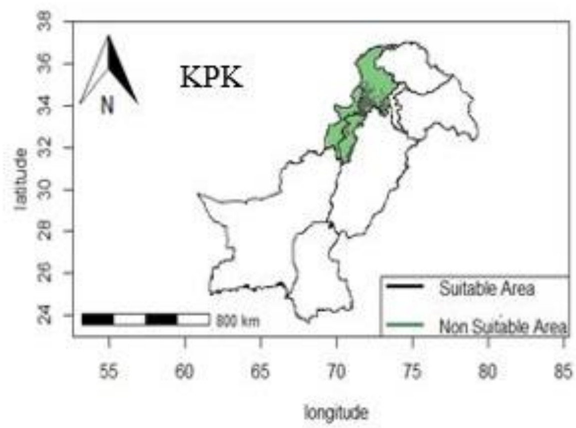


Figure 0.12 (a) Suitable area for wheat cultivation in Punjab under RCP 4.5 (b) Suitable area for wheat cultivation in Sindh under RCP 4.5 (c) Suitable area for wheat cultivation in Balochistan under RCP 4.5 (d) Suitable area for wheat cultivation in KPK under RCP 4.5

Figure 0.13 The bar graph of Jackknife Test for wheat (RCP 4.5). The red bar shows the gain when the specific variable is used in isolation and the light blue bar shows the gain when that specific variable is excluded from analysis.

4.1.3.3 Pearson's Correlation

Pearson's correlation was applied on the most important variables to determine their negative or positive correlation with other variables. It was found out that irrigation is most positively correlated with Mean Temp. of Wettest Quarter and negatively correlated with elevation and soil type. Precipitation of Warmest Quarter is most positively correlated with annual precipitation and negatively correlated with soil type (figure 4.14).

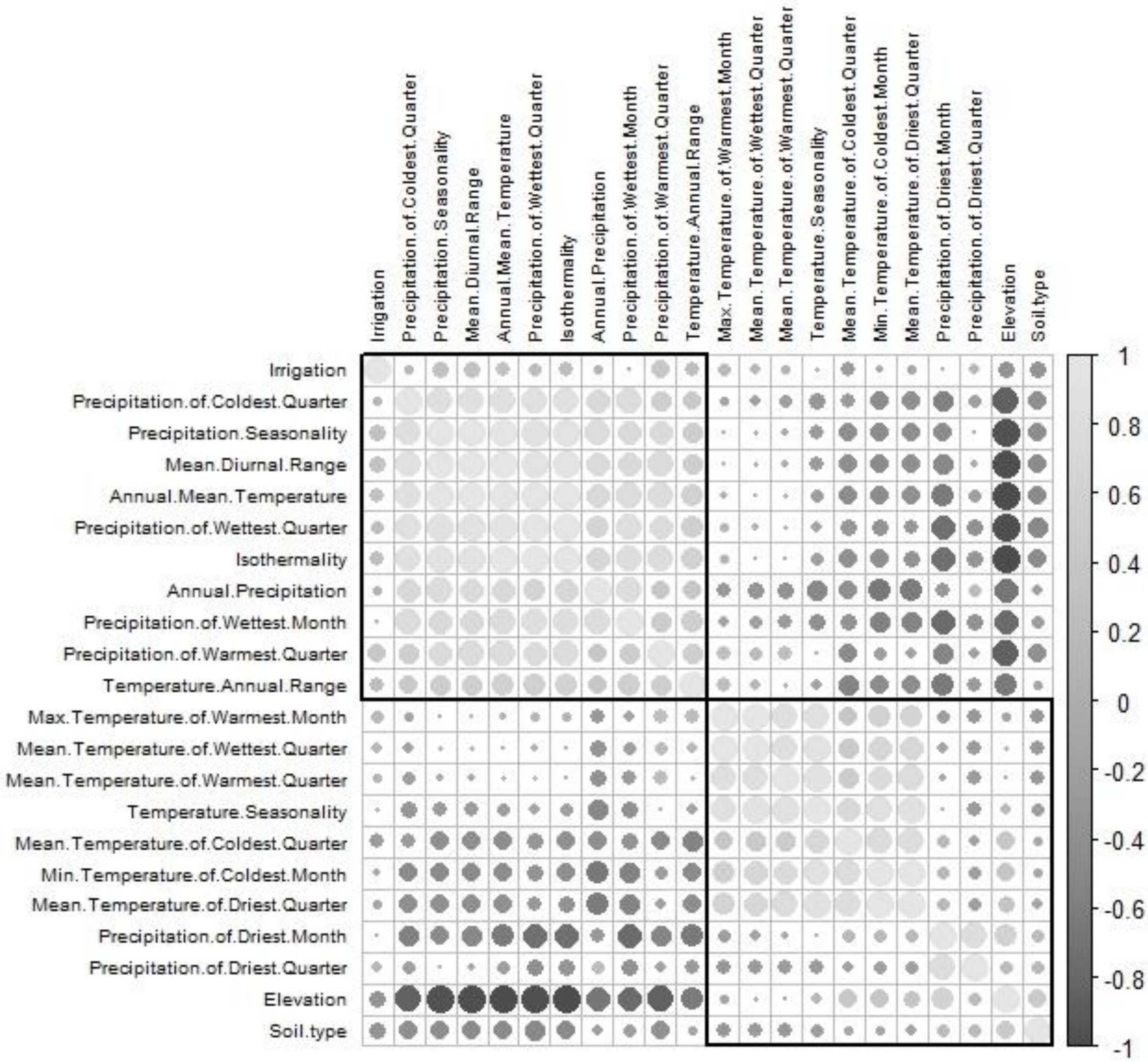


Figure 0.14 Pearson correlation coefficient graph for wheat under RCP 4.5

4.1.4 Climatic Suitability of Wheat Under Future Climate RCP 8.5

4.1.4.1 Raw Values and Threshold Maps

Under future climatic scenario, RCP 8.5, a considerable shrinkage of area was identified in the MaxEnt raw values and threshold map. The suitable area reduced to

248,174 km^2 (24,817,400 ha). Major suitable areas were identified in Punjab and Sindh with very few parts of KPK (figure 4.15 & 4.16).

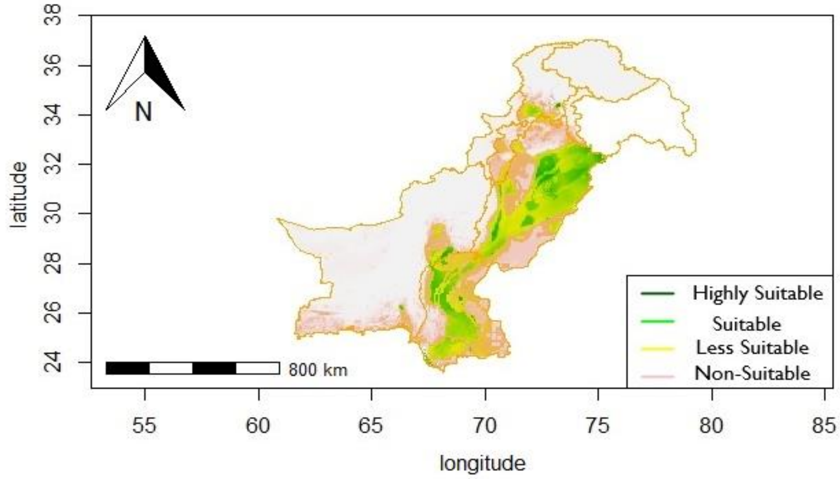


Figure 0.15 MaxEnt raw values map showing climatic suitability of Wheat under RCP 8.5

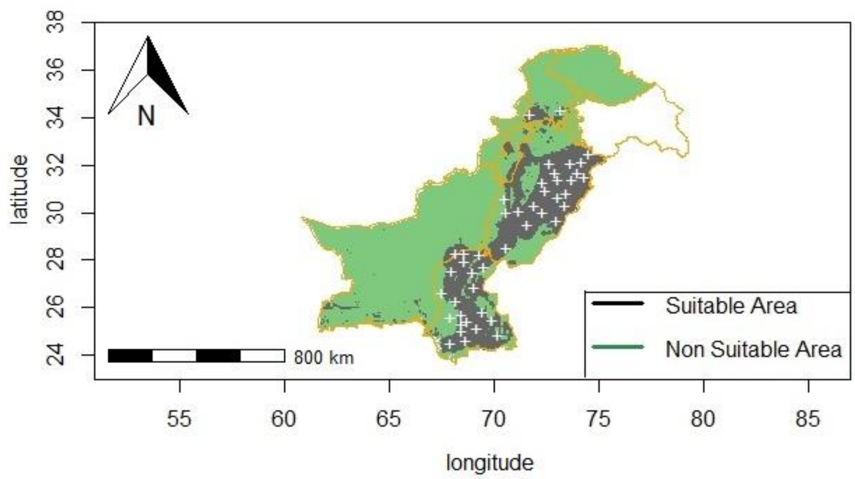


Figure 0.16 Threshold map showing climatic suitability of wheat under RCP 8.5

4.1.4.2 Evaluation of Model Accuracy

The AUC value evaluated from the model for RCP 8.5 is 0.83 which shows the model performed above average and its results are close to accurate.

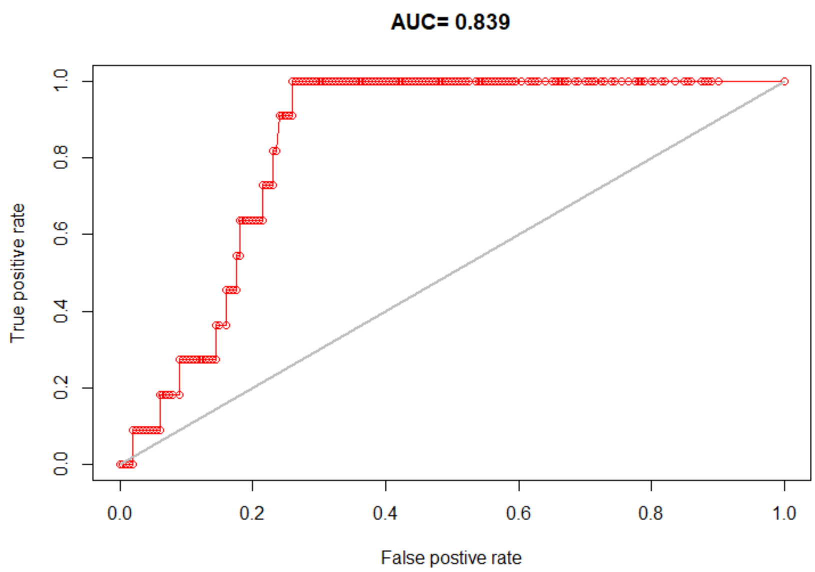


Figure 0.17 AUC for model evaluation for Wheat under RCP 8.5

4.1.4.3 Province-Wise Breakdown of Wheat Under Future Climate Scenario RCP 8.5

Further calculations were performed to determine the province wise area of Wheat under RCP 8.5.

Punjab observed acute reduction of suitable area but still holds the highest suitable area for wheat cultivation owing up to 134,910.5 km^2 (13,491,050 ha) (figure 4.18 a). It is followed by 90,750.5 km^2 (9,075,050 ha) of area in Sindh (figure 4.18 b), which also got reduced. 12,248.9 km^2 (1,224,890 ha) was calculated in KPK (figure 4.18 c) and 9,959.2 km^2 (995,920 ha) in Balochistan (figure 4.18 d) which lost even more area under RCP 8.5 than KPK. The overall trend of wheat crop for all the provinces showed decline in climatic suitability.

4.1.4.4 Variable Contribution (RCP 8.5)

To determine, which of the variables contribute more to our model for wheat crop in the future climate (RCP 8.5), jackknife test was applied. For the wheat crop habitat suitability, under future climatic scenario (RCP 8.5), the variables contributing most in the future RCP 8.5 scenario are irrigation and annual mean temperature (figure 4.19).

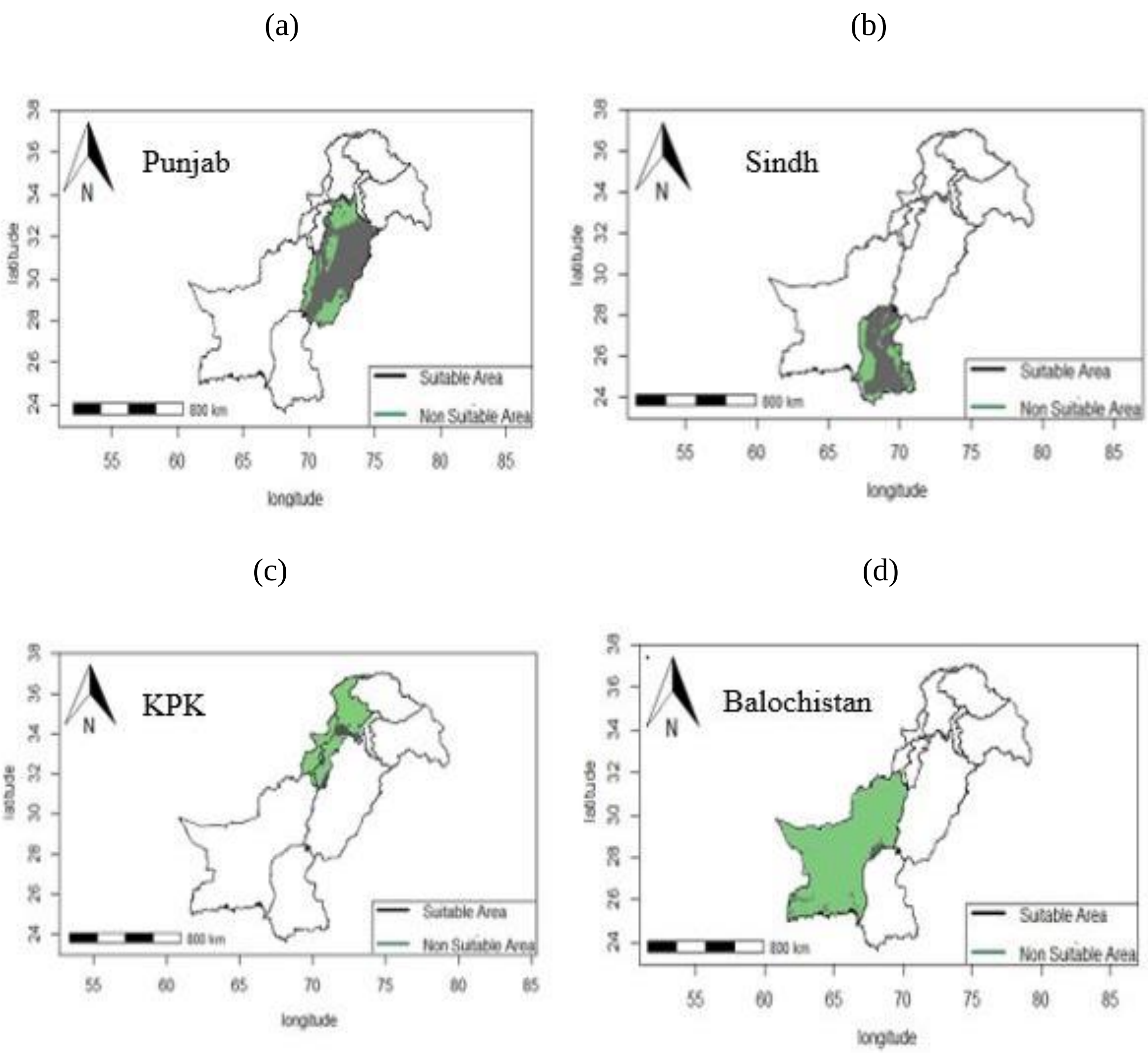


Figure 0.18 (a) Suitable area for wheat cultivation in Punjab under RCP 8.5 (b) Suitable area for wheat cultivation in Sindh under RCP 8.5 (c) Suitable area for wheat cultivation in KPK under RCP 8.5 (d) Suitable area for wheat cultivation in Balochistan under RCP 8.5

Figure 0.19 The bar graph of Jackknife Test for wheat (RCP 8.5). The red bar shows the gain when the specific variable is used in isolation and the light blue bar shows the gain when that specific variable is excluded from analysis.

4.1.4.5 Pearson's Correlation

Pearson's correlation was applied on the most important variables to determine their negative or positive correlation with other variables. It was found out that irrigation is most positively correlated with Precipitation of Warmest Quarter and negatively correlated with elevation. Annual mean temperature is most positively correlated with Precipitation of Wettest Quarter and negatively correlated with elevation (figure 4.20).

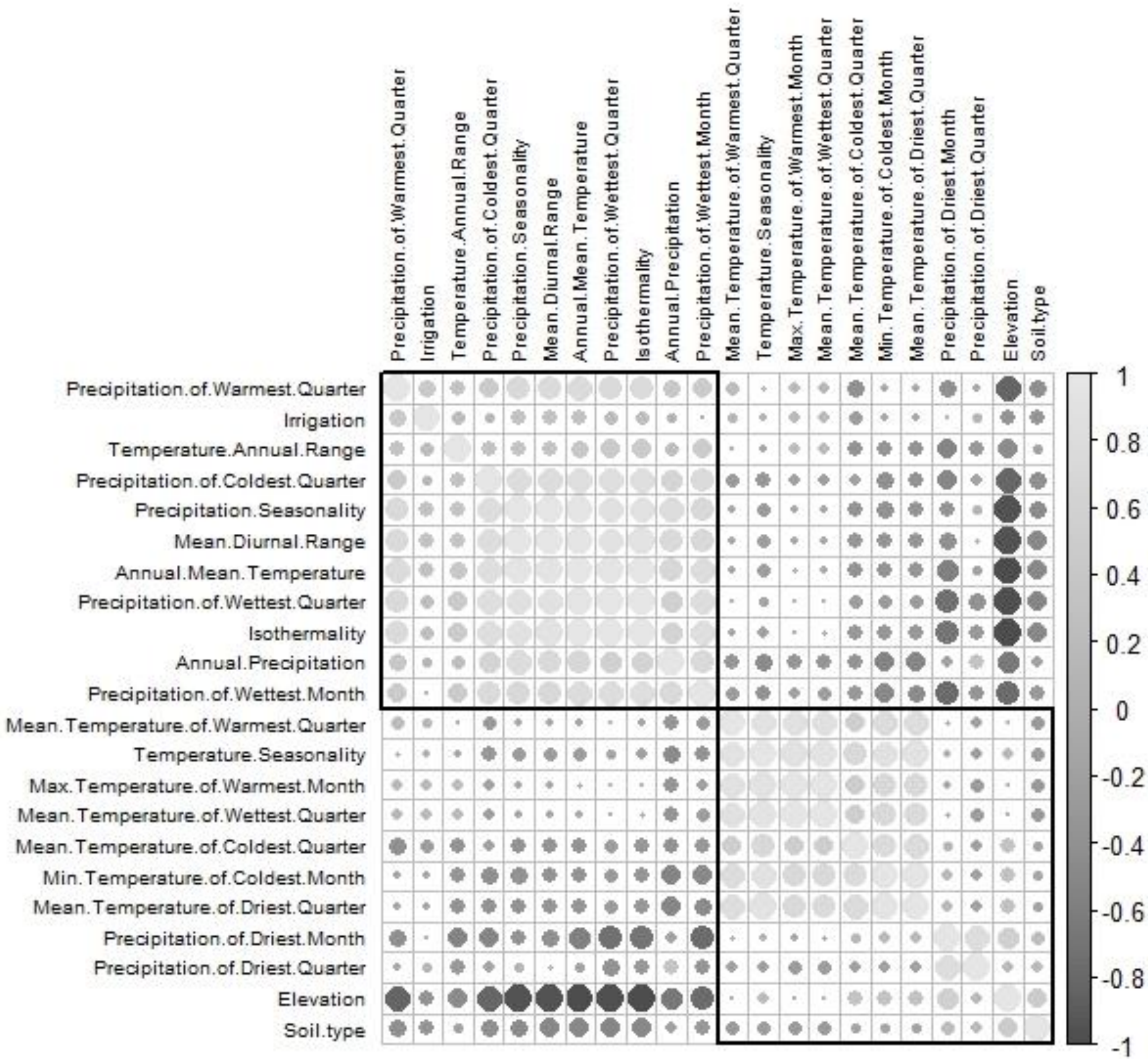


Figure 0.20 Pearson correlation coefficient graph for wheat under RCP 8.5

4.1.5 Wheat Prediction Areas Current & Future Climate (RCPs 4.5 & 8.5)

A comparion of each model outcome for presnt and future scenarios showed that area continues to shrink in both the future scenarios (figure 4.21). As the area under Current climatic scenario is 386,148.3 km^2 (38,614,830 ha), under Future climatic Scenario RCP 8.5 it reduces to 269,634.7 km^2 (26,963,470 ha) and in Future Scenario RCP 8.5, area further reduces to 248,174.6

km^2 (24,817,460). There was a total of 30% reduction in suitable area under RCP 4.5 and 35% under RCP 8.5.

Suitable area for wheat cultivation almost disappears in Balochistan while it reduces considerably in Punjab, Sindh and KPK. Table 4.1 shows a summarized table of suitable wheat area calculated under all climate scenarios along with the area reduction under RCP 4.5 and RCP 8.5.

(a) (b) (c)

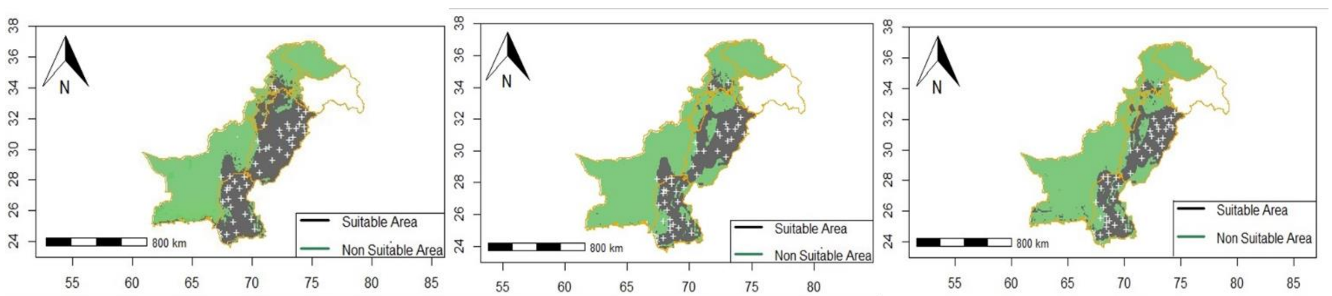


Figure 0.21 (a) Wheat prediction areas under current climatic scenario (b) Wheat prediction areas under RCP 4.5 and (c) Wheat prediction areas under Future RCP 8.5.

Table 0.1 Wheat area Reduction Calculation under RCP 4.5 and RCP 8.5

Province	Current Area (Km^2)	Area under RCP 4.5 (Km^2)	Area under RCP 8.5 (Km^2)	Reduction in Area (4.5) (Km^2)	Reduction in Area (8.5) (Km^2)
Punjab	184,730	136,535	134,910	48,195	49,820.0
Sindh	122,035	97,981.50	90,750	24,054	31,285
KPK	31,218.20	15,751.60	12,248.90	15,467	18,969
Balochistan	44,678	17,864	9,959	26,814	34,719
Azad Jammu Kashmir	2,855	1,281	306.5	1,574	2,549
Total	386,148.30	269,634.70	248,174.60	116,514	137,974

Figure 4.22 shows the graphical representation of area reduction.Drastic area change in Punjab and Balochistan can be identified under RCP 4.5 and RCP 8.5.

The results of the study correlate with previous studies (Song et al., 2012, Yue et al., 2019, Wang et al., 2019). Yang et al., 2017 predicted the impact of inclined heat stress occurrences due to climate change on the yield and production of wheat in China. Their results suggested that in next 50 years, a decrease in the yield of wheat is expected by a percentage of -7.1 for winter wheat and -17.5 for spring wheat keeping the irrigation conditions under consideration. Another study conducted in 2019 by Wang et al. (Wang et al 2019) predicted the impact of global warming on winter wheat in Gansu Province of China. The results showed little to moderate effect on the suitable area for winter wheat cultivation in Gansu under different climate change scenarios.

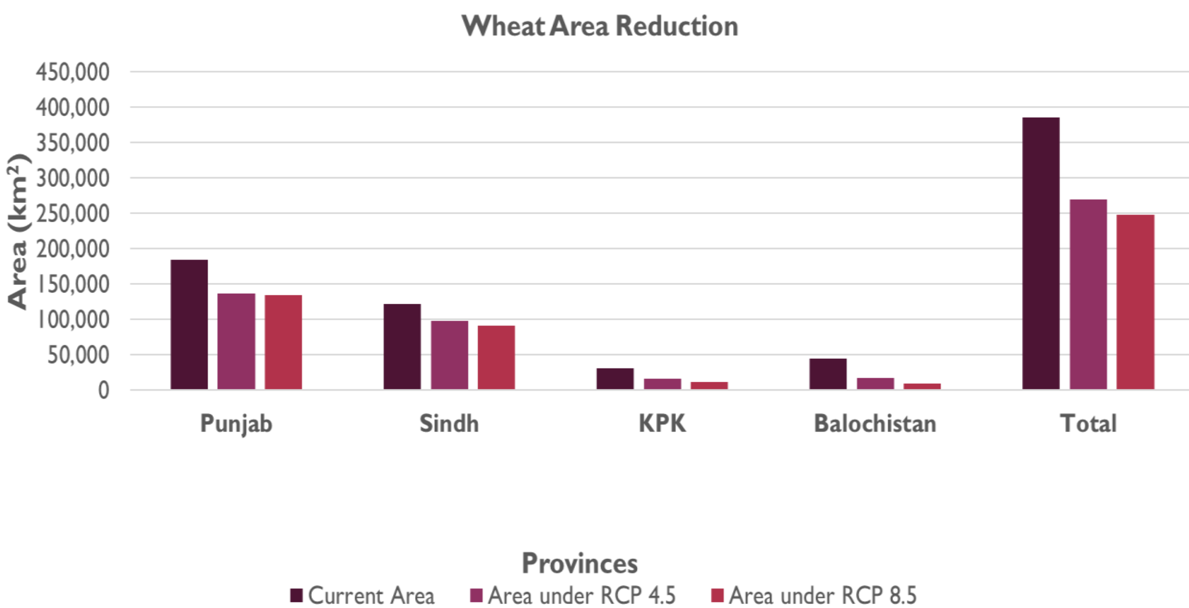


Figure 0.22 Graphical representation of wheat area reduction

4.2 Maize

4.2.1 Presence Points of Maize distribution

Figure 4.23 shows the locations of maize crop with presence points in Punjab, KPK and in some parts of Sindh.

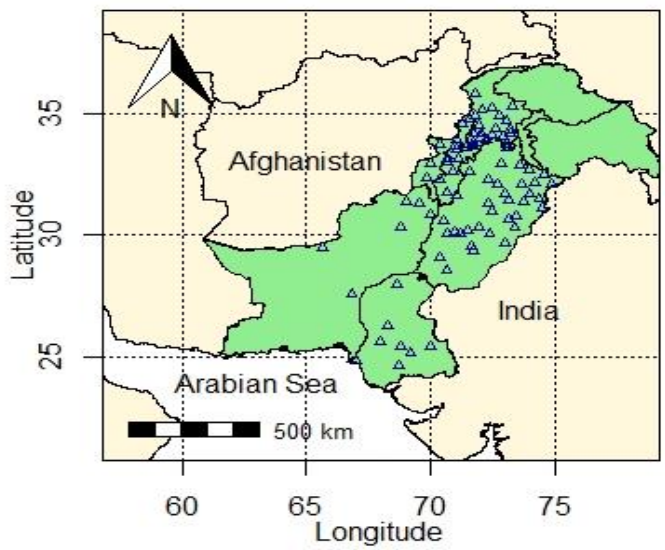


Figure 0.23 Present locations of Maize in Pakistan

4.2.1.1 Comparison and Validation against NDVI Map

The downloaded satellite images were compared with the field observed map of maize occurrence data as shown in figure 4.23. The comparison showed an insignificant difference between the two maps (figure 4.24). Both the maps show almost similar areas where the maize is grown with a little variability in Sindh which could be because of the fact that the NDVI range assigned to maize also includes range of some other vegetation.

(a) (b)

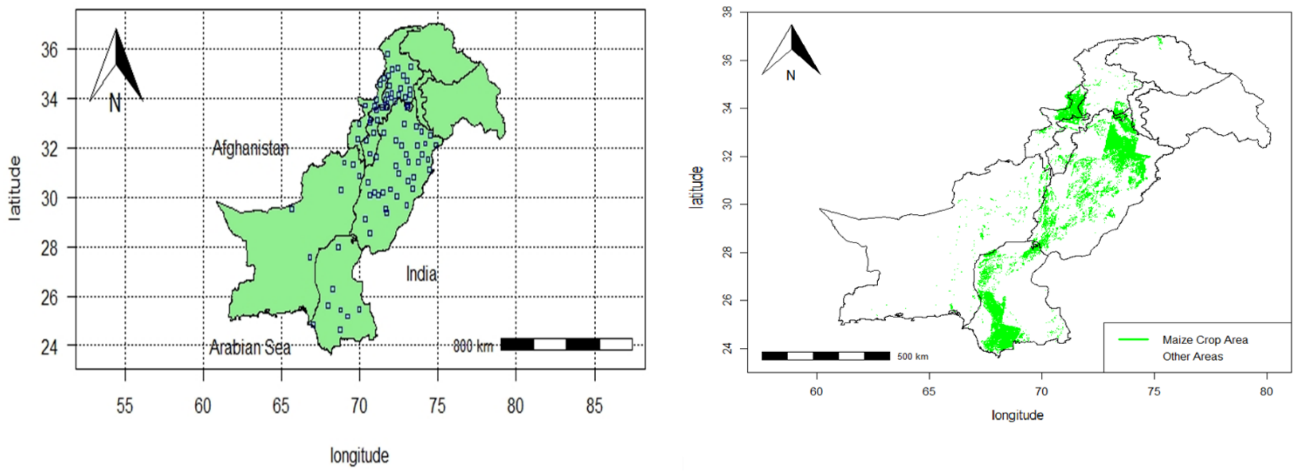


Figure 0.24 Comparison between (a) field observed Maize location and (b) NDVI based locations

4.2.2 Current Climatic Suitability of Maize

4.2.2.1 Raw Values and Threshold Maps

MaxEnt model was run along with the wheat occurrence data and current climatic data to generate the suitability raw values map.. Darker shaded areas show more suitable area while lighter colored areas show less suitable areas.

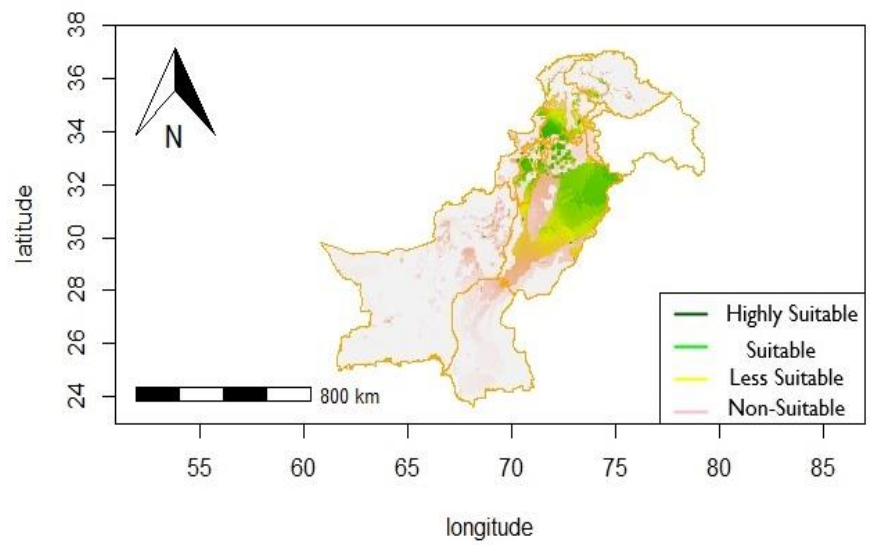


Figure 0.25 MaxEnt raw values map showing current climatic suitability of Maize

However, raw values maps are graded and since a more binary output is desired with just presence and absence to calculate the area of species distribution a different output was chosen than raw values where MaxEnt assigns threshold values to the data and allows to make binary maps. Figure 4.26 shows the threshold map of maize current distribution where it can be observed that the major suitable areas lie in Punjab and KPK with some parts of Gilgit-Baltistan and a minor part of balochistan.

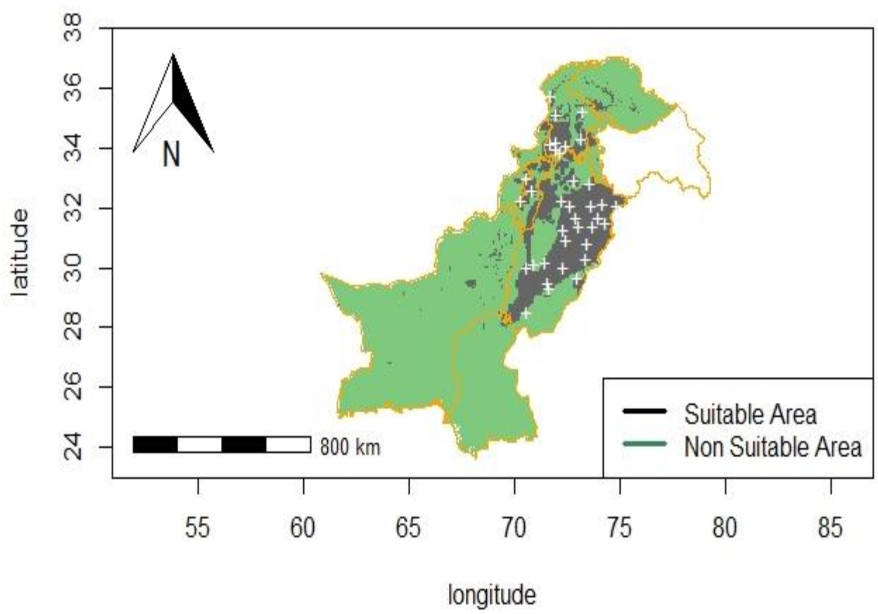


Figure 0.26 Threshold map showing current climatic suitability of maize

Area calculation was also performed using the threshold maps with the same method as described in section 4.1.2.1 above. Currently 179,699 km^2 (17,969,900 ha) area is suitable for maize growth.

4.2.2.2 Evaluation of the Model Accuracy

In the evaluation stage, Area Under Curve (AUC) was used for authentication of model. It measures the capability of model predictions to distinguish between observed presence and absence locations for a test dataset. The model calculated the AUC of 0.89 which shows the model is very affective and accurate in distinguishing between the presence and absence of maize crop.

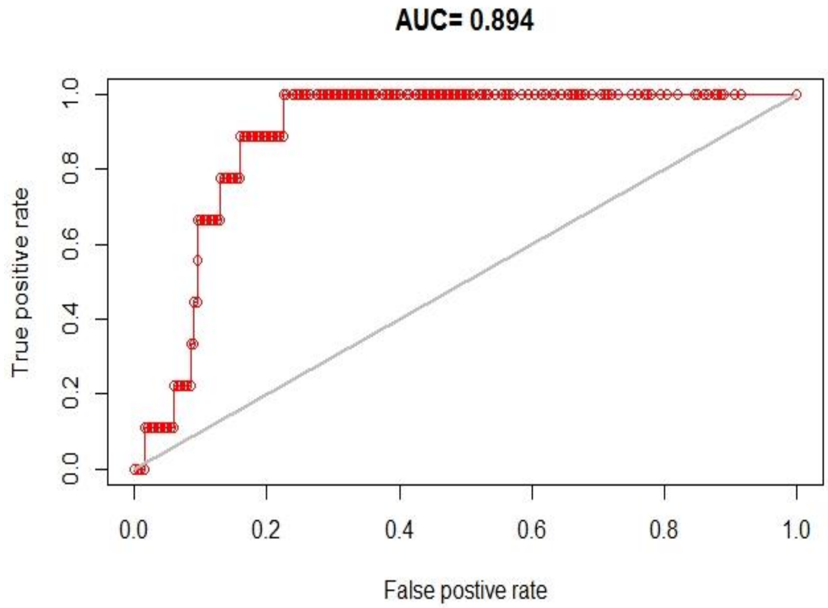


Figure 0.27 Area Under Curve (AUC) for model evaluation under current climate scenario for maize

4.2.2.3 Province-Wise Breakdown of Maize Under Current Climate Scenario

Further calculations were performed to determine the province wise area of Wheat under the current climatic scenario.

Punjab holds the highest suitable area for maize cultivation owing up to 127,391.3 km^2 (12,739,130 ha) (figure 4.28 a) . It is followed by 39,825.3 km^2 (3,982,530 ha) of area in KPK (figure 4.28 b)and 4,001 km^2 (400,100) in Gilgit-Baltistan (figure 4.28 c) and 4,052 km^2 (405,200 ha) area in Balochistan (figure 4.28 d).

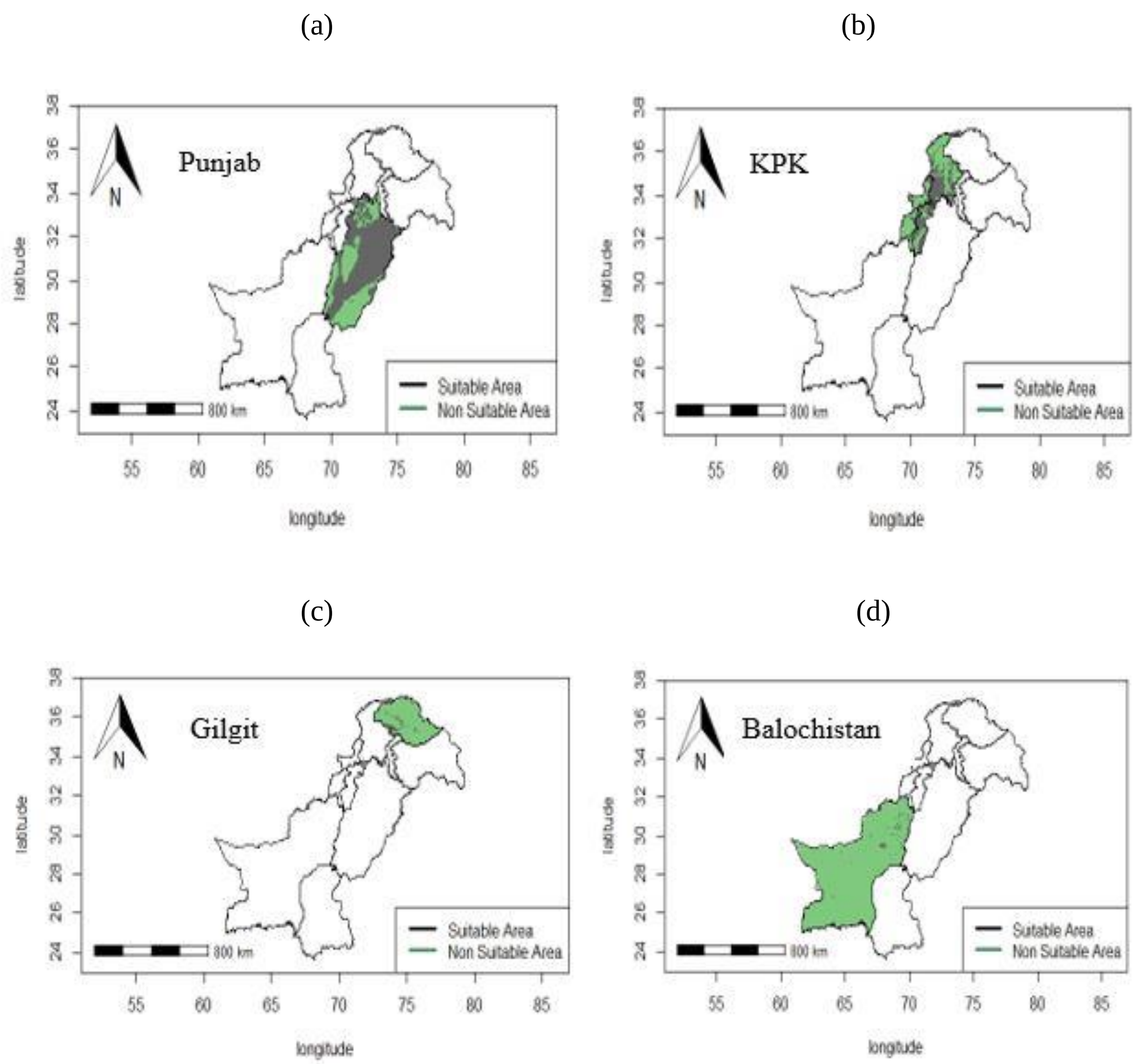


Figure 0.28 (a) Suitable area for maize cultivation in Punjab under current climate (b) Suitable area for maize cultivation in KPK under current climate (c) Suitable area for maize cultivation in Gilgit under current climate (d) Suitable area for maize cultivation in Balochistan under current climate

4.2.2.4 Variable Contribution (Current Climate)

To determine, which of the variables contribute more to our model for maize crop in the current climate, jackknife test was applied. The length of the red bar represents the score using only one of the climatic indices; the longer the bar, the more important is the climatic factor. The length of the light gray bar represents the score of a model created with the remaining indices For the maize crop habitat suitability, under current climatic scenario, the variables contributing most in current scenario are isothermality and Precipitation of Wettest Quarter.

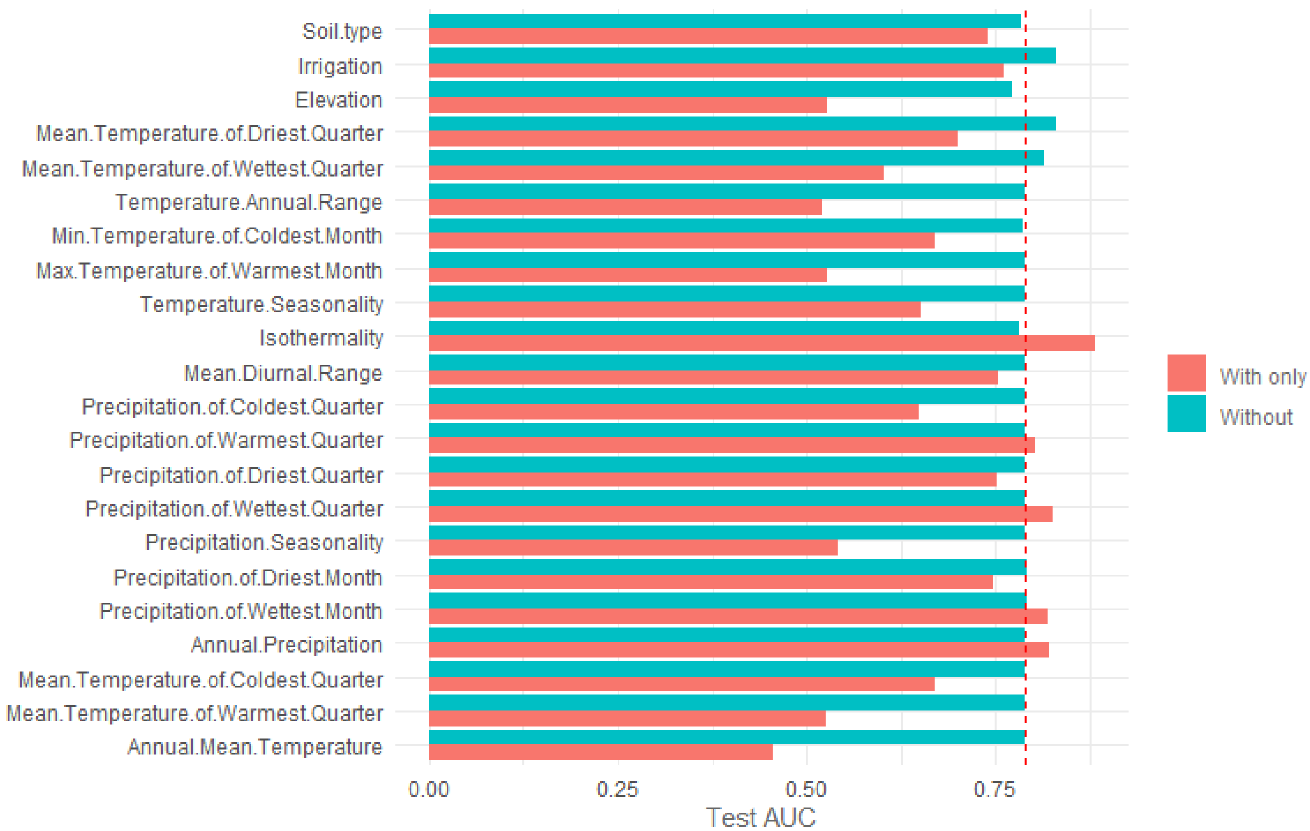


Figure 0.29 The bar graph of Jackknife Test for maize (current climate). The red bar shows the gain when the specific variable is used in isolation and the light blue bar shows the gain when that specific variable is excluded from analysis.

4.2.2.5 Pearson's Correlation

Pearson's correlation was used on the most important variables to determine their negative or positive correlation with other variables. It was found out that isothermality is most positively correlated with annual mean temperature and negatively correlated with elevation. Precipitation of Wettest Quarter is most positively correlated with annual precipitation and most negatively correlated with soil type.

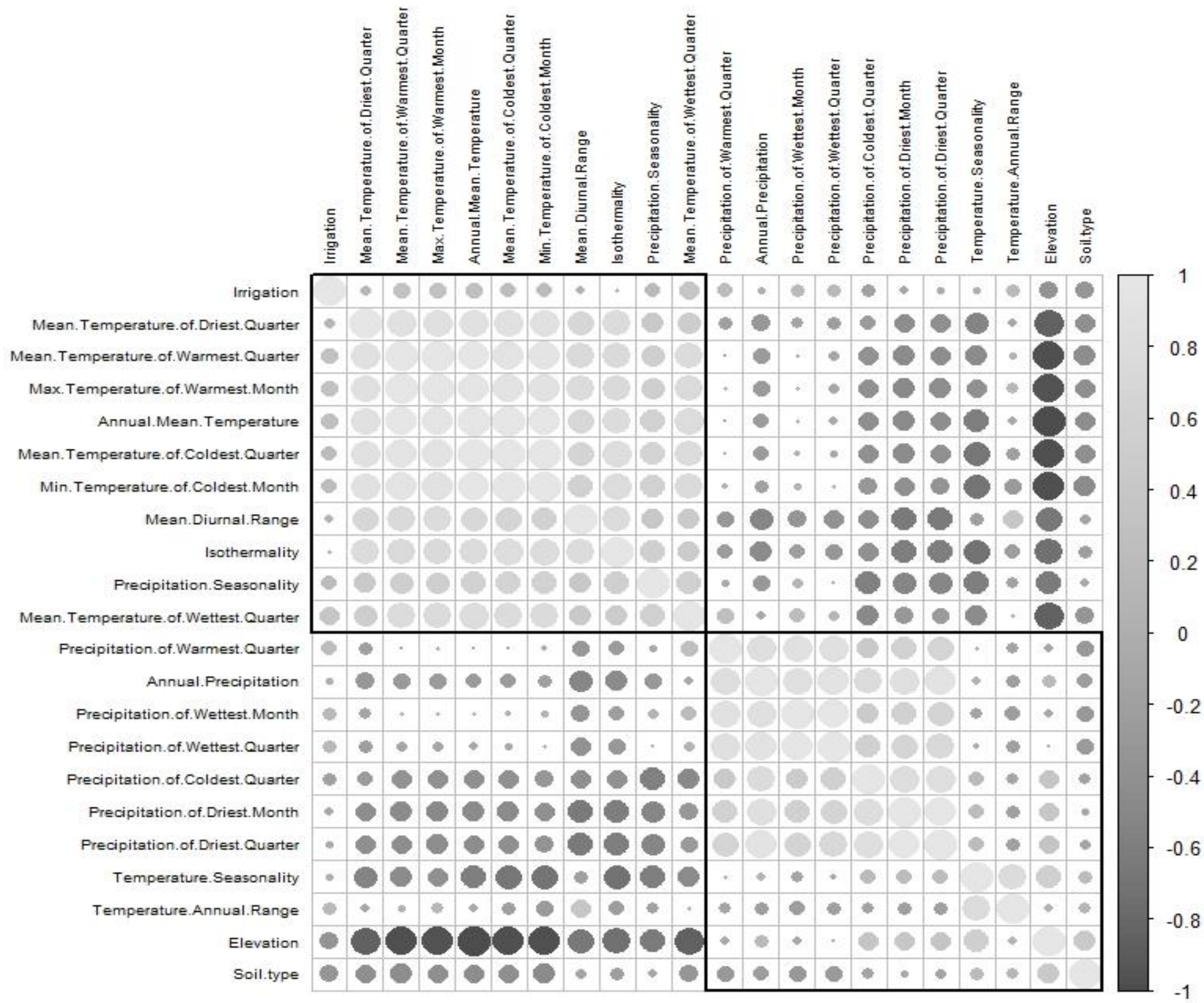


Figure 0.30 Pearson correlation coefficient graph for maize under current climate scenario

4.2.3 Climatic Suitability of Maize Under Future Climate RCP 4.5

4.2.3.1 Raw Values and Threshold Maps

Under future climatic scenario, RCP 4.5, a considerable shrinkage of area was identified in the MaxEnt raw values and threshold map. The suitable area reduced to 137,628 km^2 (13,762,800 ha). Major suitable areas were identified in Punjab and KPK with some parts of Gilgit-Baltistan (figure 4.31 & 4.32).

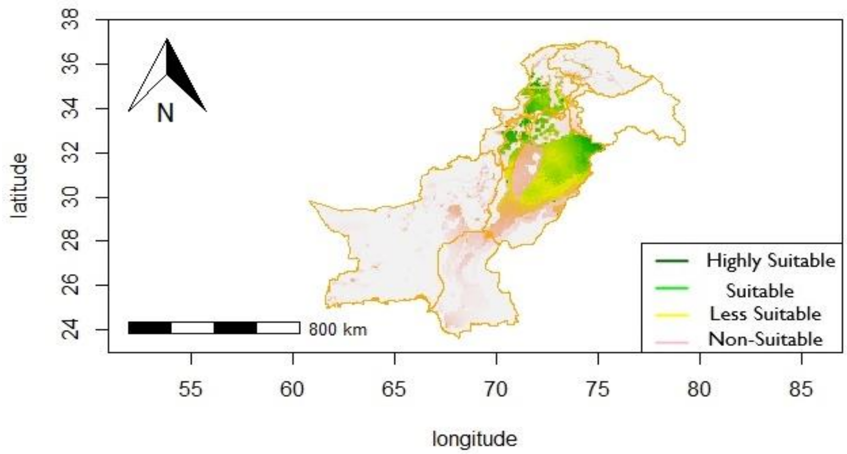


Figure 0.31 MaxEnt raw values map showing climatic suitability of Maize under RCP 4.5

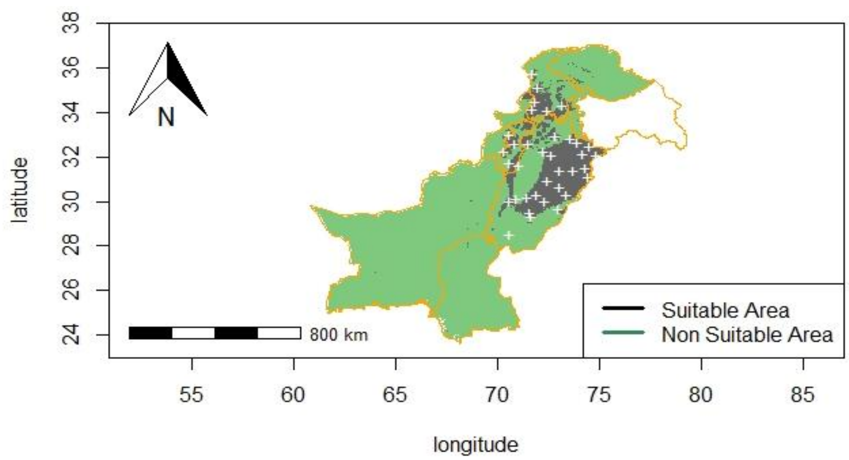


Figure 0.32 Threshold map showing climatic suitability of Maize under RCP 4.5

4.2.3.2 Evaluation of Model Accuracy

The AUC value of the maps generated for RCP 4.5 is 0.90 which shows the model performed way above the average and its results are very accurate.

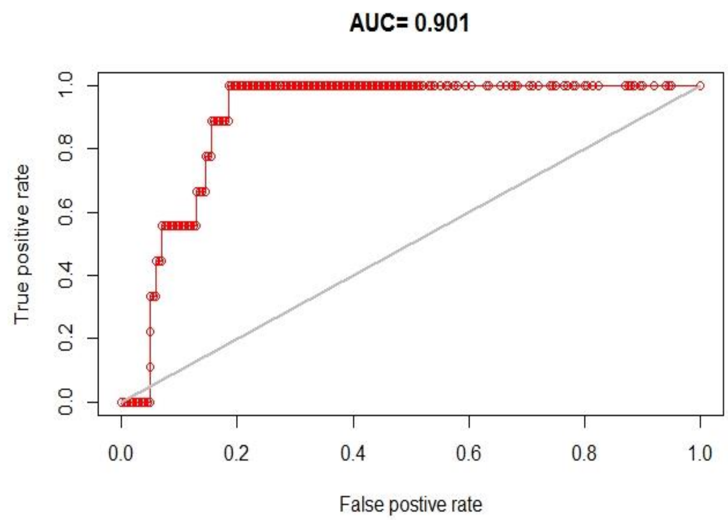


Figure 0.33 AUC for model evaluation for Maize under RCP 4.5

4.2.3.3 Province-Wise Breakdown of Maize Under Future Climate Scenario RCP 4.5

Further calculations were performed to determine the province wise area of Maize under RCP 4.5. The area breakdown is as follows.

Punjab observed reduction of suitable area but still holds the highest suitable area for maize cultivation owing up to 99,802.1 km^2 (9,980,210 ha) (figure 4.34 a). It is followed by 34,060.3 km^2 (3,406,030 ha) of area in KPK, which also got reduced from 39,825.3 3 km^2 (3,982,533 ha) (figure 4,34 b). 1464.5 km^2 (146,450 ha) area was calculated in Gilgit Baltistan which also shows reduction compared to the current climate (figure 4.34 c). The overall trend of climate suitability for maize crop for all the provinces showed a decline.

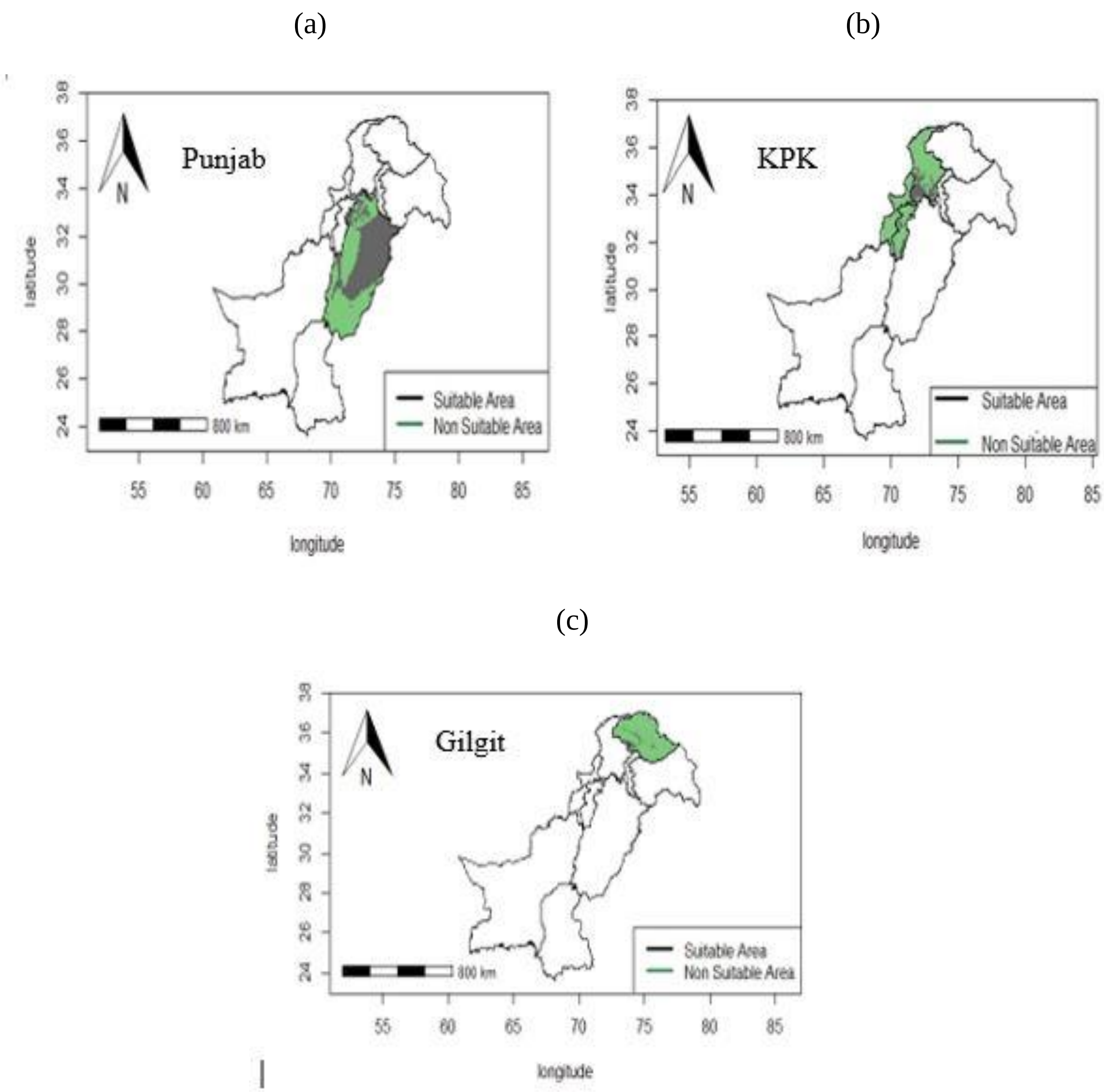


Figure 0.34 (a) Suitable area for maize cultivation in Punjab under RCP 4.5 (b) Suitable area for maize cultivation in KPK under RCP 4.5 (c) Suitable area for maize cultivation in Gilgit under RCP 4.5

4.2.3.1 Variable Contribution (RCP 4.5)

To determine, which of the variables contribute more to our model for maize crop in the future climate (RCP 4.5), jackknife test was applied.For the maize crop habitat suitability, under future climatic scenario (RCP 4.5), the variables contributing most in future RCP 4.5 scenario are irrigation and Mean Temp. of Warmest Quarter.

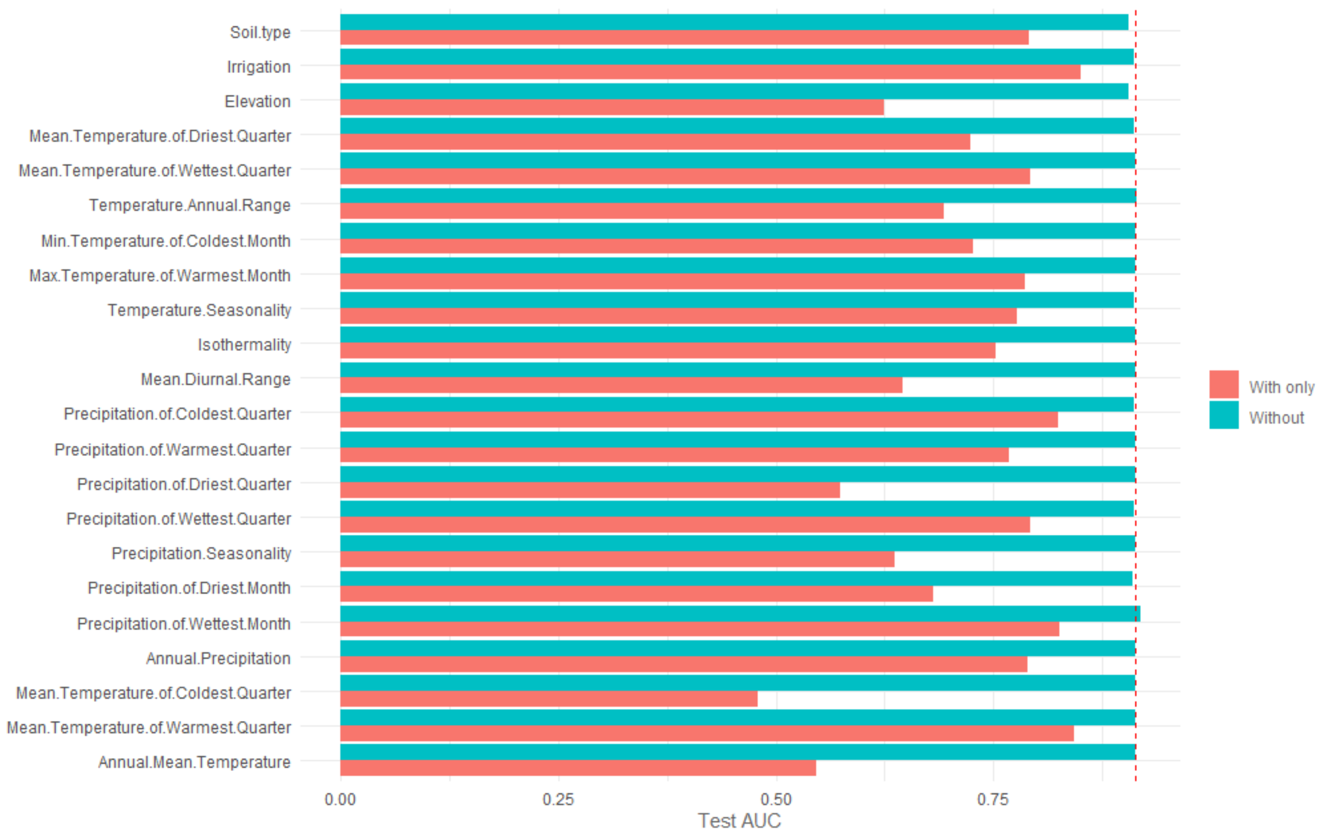


Figure 0.35 The bar graph of Jackknife Test for maize (RCP 4.5). The red bar shows the gain when the specific variable is used in isolation and the light blue bar shows the gain when that specific variable is excluded from analysis.

4.2.3.2 Pearson's Correlation

Pearson's correlation was applied on the most important variables to determine their negative or positive correlation with other variables. It was found out that irrigation is most positively correlated with Precipitation of Warmest Quarter and negatively correlated with elevation and soil type. Mean Temp. of Warmest Quarter is most positively correlated with Max. Temp. of Warmest and negatively correlated with Month annual precipitation.

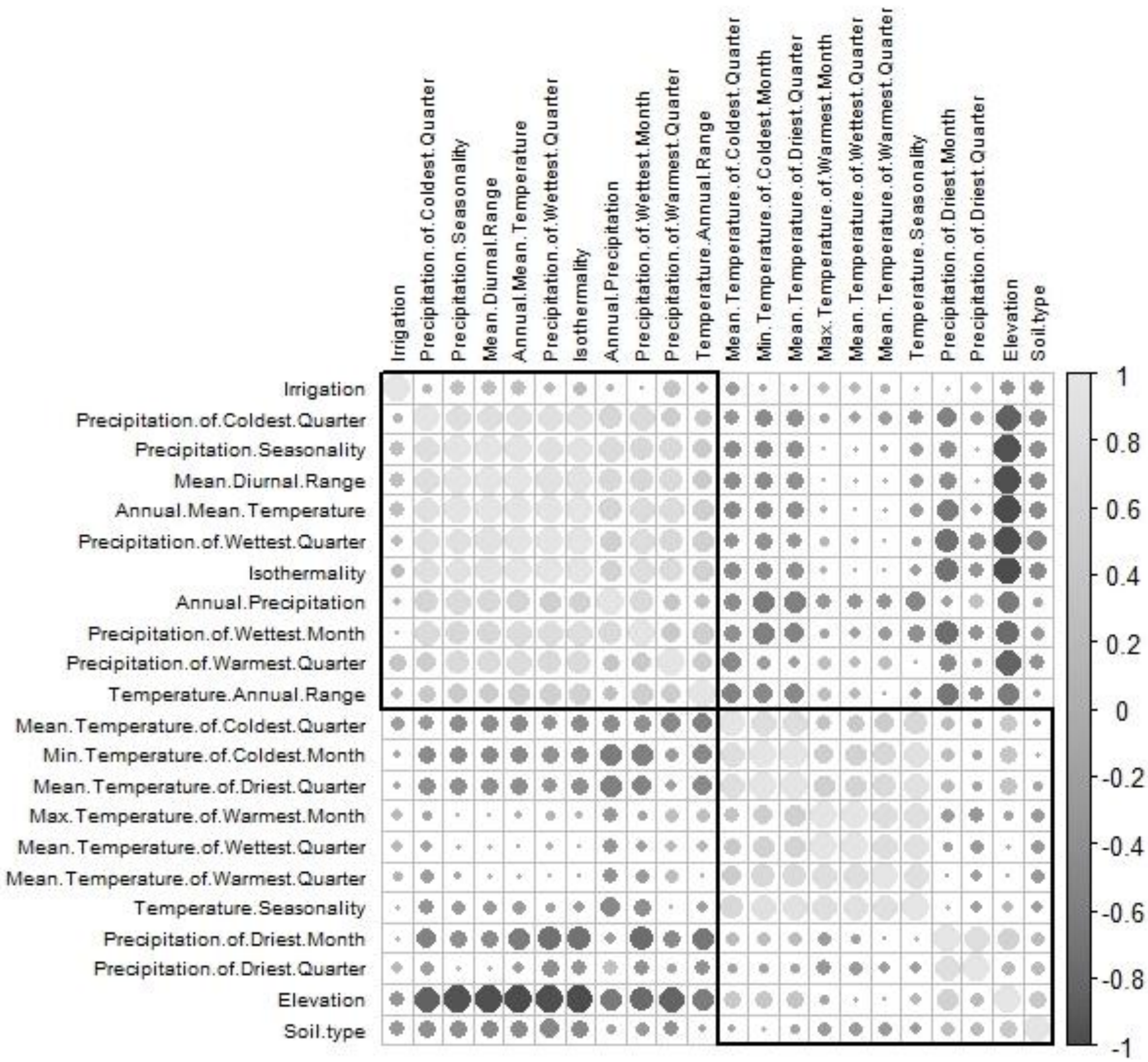


Figure 0.36 Pearson correlation coefficient graph for maize under RCP 4.5

4.2.4 Climatic Suitability of Maize Under Future Climate RCP 8.5

4.2.4.1 Raw Values and Threshold Maps

Under future climatic scenario, RCP 8.5, a considerable shrinkage of area was identified in the MaxEnt raw values and threshold map. The suitable area reduced to 113,959.8 km^2 (11,395,980 ha). Major suitable areas were identified in Punjab and KPK with considerable shrinkage. There is Area loss in Gilgit-Baltistan and AJK (figure 4.37 & 4.38).

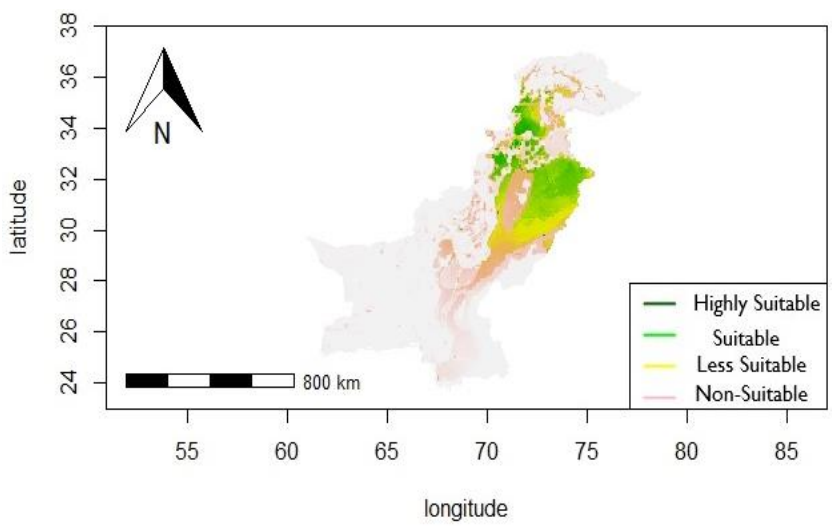


Figure 0.37 MaxEnt raw values map showing climatic suitability of Maize under RCP 8.5

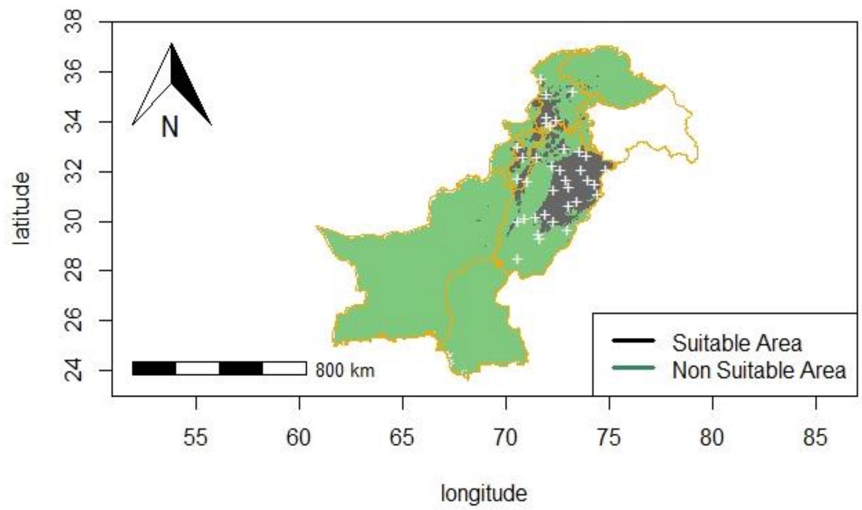


Figure 0.38 Threshold map showing climatic suitability of Maize under RCP 8.5

4.2.4.2 Evaluation of Model Accuracy

The AUC value of the maps generated for RCP 8.5 is 0.93 which shows the model performed way above average and its results are very accurate.

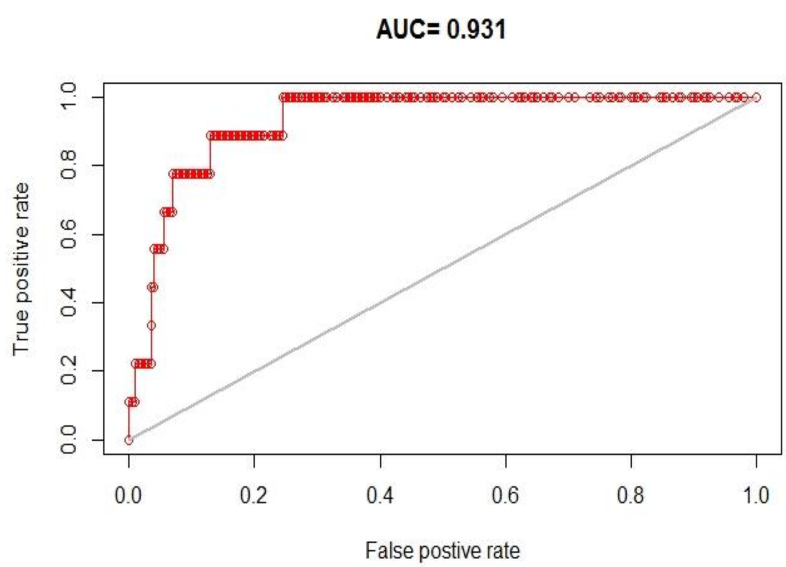


Figure 0.39 AUC for model evaluation for Wheat under RCP 8.5

4.2.4.3 Province-Wise Breakdown of Maize Under Future Climate Scenario RCP 8.5

Further calculations were performed to determine the province wise area of Wheat under RCP 8.5. The area breakdown is as follows.

Punjab observed acute reduction of suitable area but still holds the highest suitable area for wheat cultivation owing up to 84294.4 km^2 (8,429,440 ha) (figure 4.40 a). It is followed by 27561 km^2 (2,756,100 ha) of area in KPK, which also got reduced significantly (figure 4.40 b). The overall trend of climate suitability for maize crop for all the provinces showed a decline.

(a) (b)

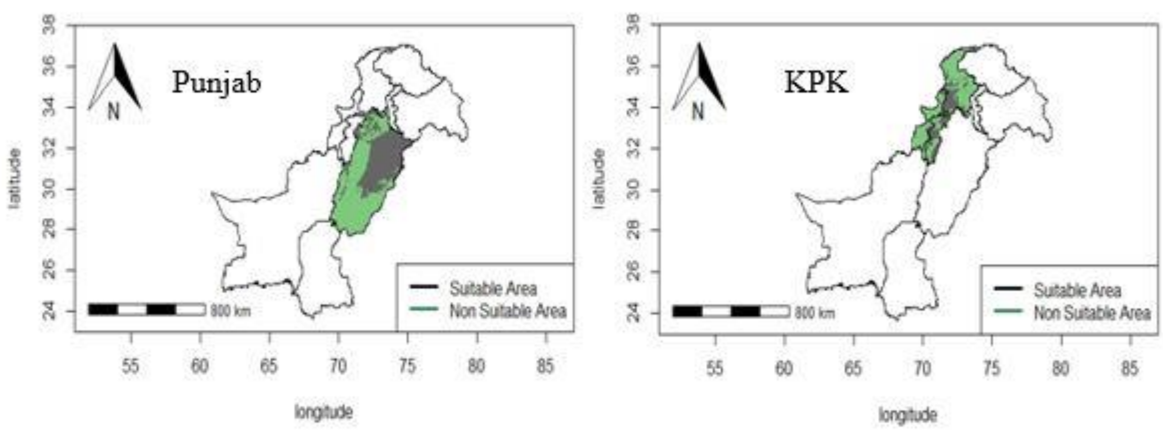


Figure 0.40 (a) Suitable area for maize cultivation in Punjab under RCP 8.5 (b) Suitable area for maize cultivation in KPK under RCP 8.5

4.2.4.1 Variable Contribution (RCP 8.5)

To determine, which of the variables contribute more to our model for maize crop in the future climate (RCP 8.5), jackknife test was applied. For the maize crop habitat suitability, under future climatic scenario (RCP 8.5), the variables contributing most in future RCP 8.5 scenario are irrigation and preciptation of wettest month (figure 4.41).

4.2.4.1 Pearson's Correlation

Pearson's correlation was applied on the most important variables to determine their negative or positive correlation with other variables. It was found out that irrigation is most positively correlated with Precipitation of Warmest Quarter and negatively correlated with elevation Precipitation of Wettest Month is most positively correlated with Precipitation of Driest Monthand negatively correlated with annual mean temperature (figure 4.42).

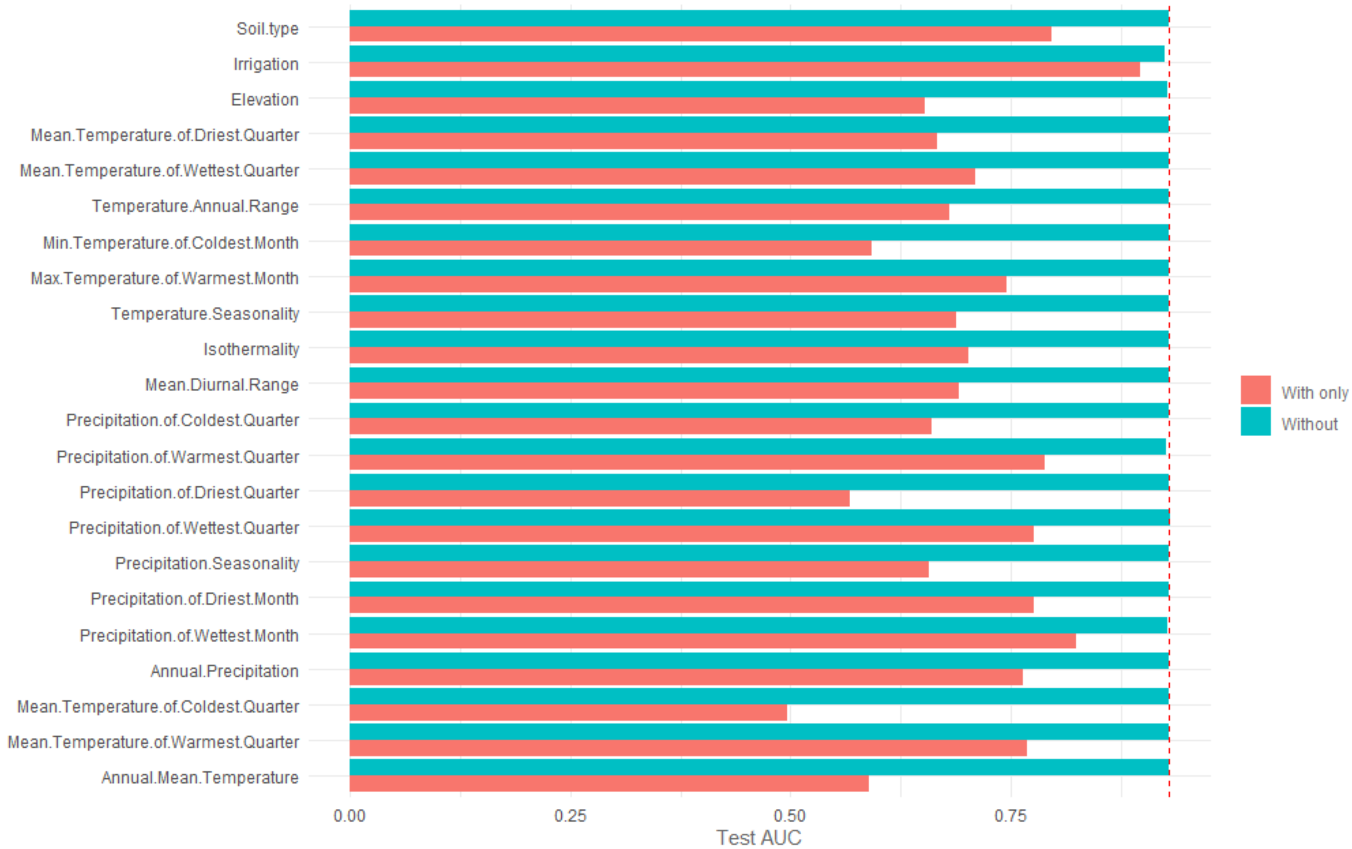


Figure 0.41 The bar graph of Jackknife Test for maize (RCP 8.5 climate). The red bar shows the gain when the specific variable is used in isolation and the light blue bar shows the gain when that specific variable is excluded from analysis.

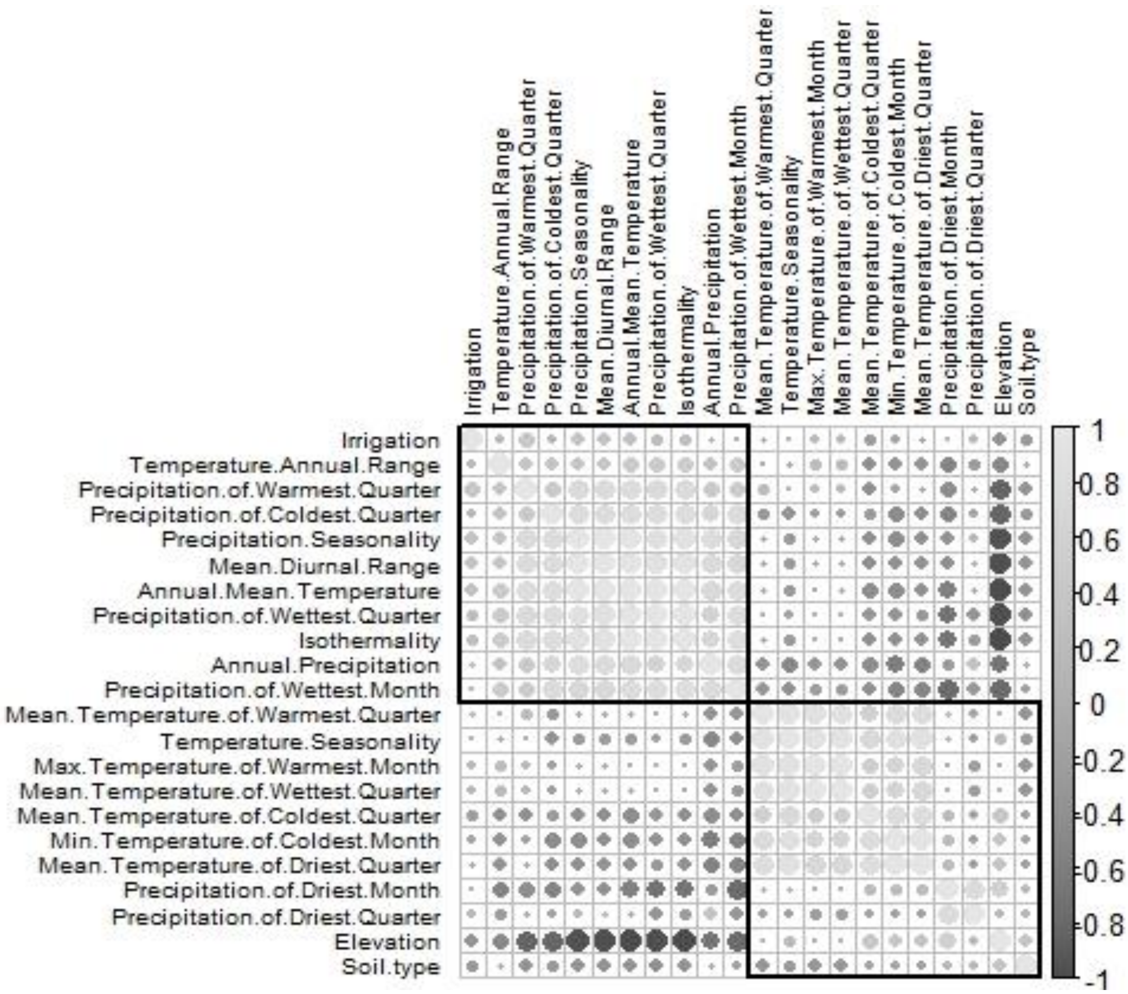


Figure 0.42 Pearson correlation coefficient graph for maize under RCP 8.5

4.2.5 Maize Prediction Areas Current & Future Climate (Rcp 4.5 & Rcp 8.5)

If a comparison is made of all three climatic scenario and a trend is tried to be established, it can be easily observed that area continues to shrink in both the scenarios (figure 4.43). As the area under Current climatic scenario is 179,699.5 km^2 (17,969,950 ha), under Future climatic Scenario RCP 4.5 it reduces to 137,628.3 km^2 (13,762,830 ha) and in Future Scenario RCP 8.5, area further reduces to 137,628.3 km^2 (13,762,830 ha). There was a total of 23% reduction in suitable area under RCP 4.5 and 37% under RCP 8.5.

Suitable area for maize disappears in Sindh and Gilgit Baltistan and there is an area loss in KPK and Punjab as the temperature and precipitation will see fluctuations and sudden increase or decrease in the two future climate scenarios. Table 4.2 shows a summarized table of suitable wheat area calculated under all climate scenarios along with the reduction taken place under RCP 4.5 and RCP 8.5. It can be seen that Punjab underwent the largest reduction with area of 27,589 km^2 (2,758,900 ha) under RCP 4.5 and 43,096 km^2 (4,309,600 ha) under RCP 8.5.

(a) (b) (c)

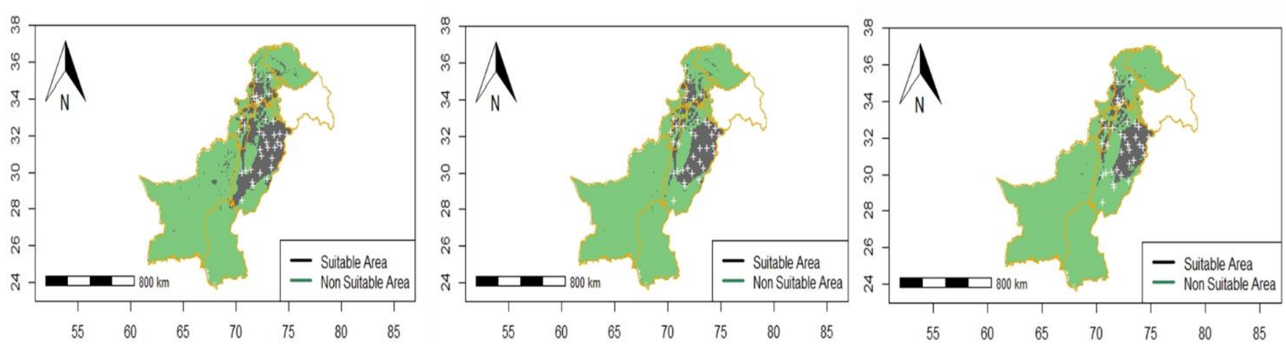


Figure 0.43 (a) Maize prediction areas under current climate scenario (b) Maize prediction areas under future RCP 4.5 (c) Maize prediction areas under Future RCP 8.5.

Table 0.2 Maize area Reduction Calculation under RCP 4.5 and RCP 8.5.

Province	Current Area (Km^2)	Area under RCP 4.5 (Km^2)	Area under RCP 8.5 (Km^2)	Reduction in Area (4.5) (Km^2)	Reduction in Area (8.5) (Km^2)
Punjab	127,391	99,802	84,294	27,589	43,096.6
Sindh	1,615	0	0	1,615	1,615
KPK	39,825.30	34,060.30	27,561.00	5,765	12,264
Balochistan	4,052	0	0	4,052	4,052
Gilgit-Baltistan	4,002	1,464	754	2,538	3,248
Azad Jammu Kashmir	2,014	1,273	622.6	741	1,391
Total	179,699.50	137,628.30	113,959.80	42,071	65,740

Figure 4.44 shows the graphical representation of area reduction where drastic change in punjab and KPK can be identified in terms of area reduction under RCP 4.5 and RCP 8.5.

Furthermore, maize distribution studies have been carried out around the world using MaxEnt (Nabout et al., 2012, Hufford et al., 2012, Kogo et al., 2019, He et al., 2019). Kogo et al., 2019. identified the most important variables for maize crop growth in Kenya were mean temperature of wettest quarter, annual precipitation and annual mean temperature. The study indicates a decrease in the suitable areas for maize production by 1.9% to 3.9% and a decrease in moderately suitable areas by 14.6% to 17.5% under various climate change scenarios. He et al., 2019 also identified a decrease in suitable and highly suitable regions that produce Summer Maize in China. Their study indicated a shift of maize highly suitable area to North-East China under both RCP 4.5 and 8.5 climate scenarios while in case of suitable and less suitable areas, the shift was more towards North-West. Our study shows similar shift of suitable areas towards North-West for maize crop (figure 6b). The present study however contradicts with the findings of Ji et al., (2018). They predicted a suitable area expansion of spring maize under global warming scenarios in future although they observed a detrimental effect of climate change on spring maize under historic climate change observation from 1961–1990 and 1981–2010.

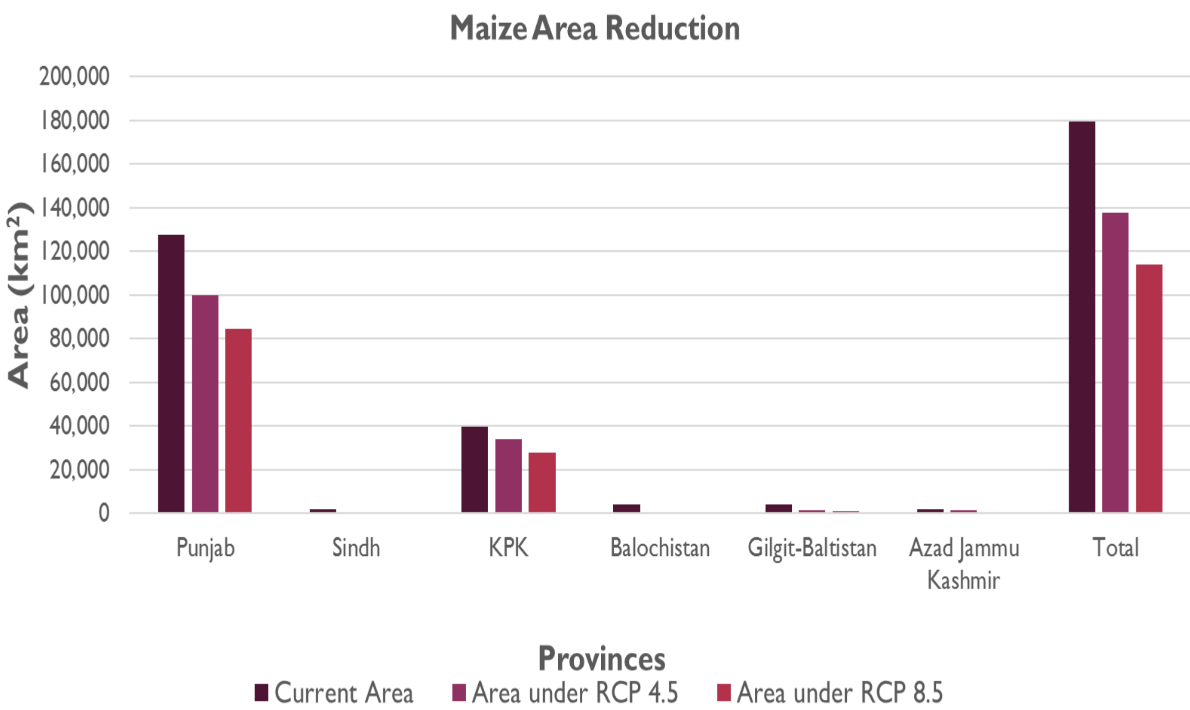


Figure 0.44 Graphical representation of maize area reduction

Chapter 5

CONCLUSION AND RECOMMENDATIONS

In present climate, wheat and maize both are distribution majorly in Punjab and KPK. Results of the model reveal that moderate to severe impact is expected on the distribution of wheat and Maize crop in RCP 4.5 and 8.5 climate change scenarios. Wheat cultivation area is predicted to undergo 30% to 35% reduction under RCP 4.5 and RCP 8.5 and maize growth area is predicted to undergo 23% and 37% reduction under RCP 4.5 and RCP 8.5 respectively. Punjab Sindh and KPK are going to be severely affected in both the scenarios in next 50 years. Environmental factor that contribute the most in determining the current climatic suitability of maize include precipitation of wettest quarter and isothermality. While for wheat these are, irrigation and elevation. For future 4.5, most contributing environmental variables for Maize include irrigation and mean temperature of warmest quarter. For wheat these include irrigation and precipitation of warmest quarter. For future 8.5, environmental variables having most impact on the maize crop include irrigation and precipitation of wettest month. For wheat crop: irrigation and annual mean temperature.

The use of species distributions models for determining impacts and assessing risk to various species distribution as well as for the development of spatial databases can pave way for the formulation of science-based conservation strategies that would be beneficial for both the species and their ecosystems. Proactive measures are needed to cope with the impact of climate change on food crops of Pakistan. Mapping the habitat suitability area for wheat and Maize can help policy makers to take precautionary measures and introduce novel techniques in their cultivation so as to increase the production and reduce the risk of food security. These novel techniques can include crop diversification, changes in cropping pattern, conserving soil moisture through appropriate tillage methods, improving irrigation efficiency, and afforestation. The identification of such variety of crop seeds is needed that can endure effects of rapidly changing climate.

REFERENCES

Ali, K., Ahmad, H., Khan, N. and Jury, S., 2014. Future of Abies pindrow in Swat district, northern Pakistan. Journal of forestry research, 25(1), pp.211-214.

Ashraf, U., Ali, H., Chaudry, M., Ashraf, I., Batool, A. and Saqib, Z., 2016. Predicting the potential distribution of Olea ferruginea in Pakistan incorporating climate change by using MaxEnt model. Sustainability, 8(8), p.722.

Baldwin, R.A., 2009. Use of maximum entropy modeling in wildlife research. Entropy, 11(4), pp.854-866.

Booth, T.N., Henry, N., Busby, J., & Hutchinson, M.F., 2014. BIOCLIM: the first species distribution modelling package, its early applications and relevance to most current MAXENT studies. Diversity and Distributions. 20. 10.1111/ddi.12144.

Busby, J., 1991. BIOCLIM-a bioclimate analysis and prediction system. Plant protection quarterly, 61, pp.8-9.

Chakraborty, A., A. E. Gelfand, A. M. Wilson, A. M. Latimer, and J. A. Silander, Jr., 2010. Modeling large scale species abundance with latent spatial processes. Annals of Applied Statistics 4:1403–1429

Combal, B., & Caumont, H. (2016). Supporting Marine Sciences With Cloud Services: Technical Feasibility and Challenges. In Cloud Computing in Ocean and Atmospheric Sciences (pp. 59-88). Academic Press.

Damian, J.M., Pias, O.H.D.C., Cherubin, M.R., Fonseca, A.Z.D., Fornari, E.Z. and Santi, A.L., 2020. Applying the NDVI from satellite images in delimiting management zones for annual crops. Scientia Agricola, 77(1).

Despland, E. and Houle, G., 1997. Climate influences on growth and reproduction of Pinus banksiana (Pinaceae) at the limit of the species distribution in eastern North America. American Journal of Botany, 84(7), pp.928-937.

Economic Survey of Pakistan 2017. Finanace Division, Government of Pakistan

Elith, J. & Leathwick, J.R., 2009. Species distribution models: ecological explanation and prediction across space and time. Annual Review of Ecology and Systematics, 40, 677–697.

Elith, J., Graham, C.H., Anderson, R.P. et al., 2006. Novel methods improve prediction of species' distributions from occurrence data. Ecography, 29, 129–151.

Ferrier, S., Drielsma, M., Manion, G. and Watson, G., 2002. Extended statistical approaches to modelling spatial pattern in biodiversity in northeast New South Wales. II. Community-level modelling. Biodiversity & Conservation, 11(12), pp.2309-2338.

Filgueiras, R., Mantovani, E.C., Althoff, D., Fernandes Filho, E.I. and Cunha, F.F.D., 2019. Crop NDVI Monitoring Based on Sentinel 1. Remote Sensing, 11(12), p.1441.

Food and Agricultural Organisation (FAO) of the United Nations. Available online at: http://www.fao.org/hunger. Accessed: October 15th, 2019

Franklin J, 2010. Mapping species distributions: spatial inference and prediction. Cambridge University Press.

Garcia, K., Lasco, R., Ines, A., Lyon, B. and Pulhin, F., 2013. Predicting geographic distribution and habitat suitability due to climate change of selected threatened forest tree species in the Philippines. Applied geography, 44, pp.12-22.

Ghulam Nabi Arain, 2013. Maize (Corn) cultivation in Pakistan, Valley Irrigation Pakistan.

Gregory, P.J., Ingram, J.S. and Brklacich, M., 2005. Climate change and food security. Philosophical Transactions of the Royal Society B: Biological Sciences, 360(1463), pp.2139-2148.

Guisan A & Zimmermann NE, 2000. Predictive habitat distribution models in ecology. Ecological modelling, 135(2), 147-186.

Guisan, A. and Thuiller, W., 2005. Predicting species distribution: offering more than simple habitat models. Ecology letters, 8(9), pp.993-1009.

Hastie, T., and R. J. Tibshirani. 1990. Generalized additive models. Chapman and Hall, London, UK.

He, Q. and Zhou, G., 2012. The climatic suitability for maize cultivation in China. Chinese Science Bulletin, 57(4), pp.395-403.

He, Q., Zhou, G., Lü, X. and Zhou, M., 2019. Climatic suitability and spatial distribution for summer maize cultivation in China at 1.5 and 2.0° C global warming. Science Bulletin, 64(10), pp.690-697.

Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.G., & Jarvis, A., 2005. “Very high resolution interpolated climate surfaces for global land areas”, International Journal of Climate, 25, 1965-1978.

Hossain, M.S., Setu, N.N. and Rahman, R., 1998. Climate Change And Its Impact On Food Security In South Asian Countries.

Hufford, M.B., Martínez-Meyer, E., Gaut, B.S., Eguiarte, L.E. and Tenaillon, M.I., 2012. Inferences from the historical distribution of wild and domesticated maize provide ecological and evolutionary insight. PLoS One, 7(11), p.e47659.

Hui, F.K., Warton, D.I., Foster, S.D. and Dunstan, P.K., 2013. To mix or not to mix: comparing the predictive performance of mixture models vs. separate species distribution models. Ecology, 94(9), pp.1913-1919.

Islam, M. and Wong, A., 2017. Climate change and food in/security: A critical nexus. Environments, 4(2), p.38.

Jaynes, E.T., 1957. Information theory and statistical mechanics. Phys. Rev. 106, 620–630.

Ji, Y., Zhou, G., He, Q. and Wang, L., 2018. The Effect of Climate Change on Spring Maize (Zea mays L.) Suitability across China. Sustainability, 10(10), p.3804.

Song-Jing, S., Guang-Sheng, Z. and Xing-Hua, S., 2012. Climatic suitability of the distribution of the winter wheat cultivation zone in China. European Journal of Agronomy, 43, pp.77-86.

Kawase, H., Nagashima, T., Sudo, K. and Nozawa, T., 2011. Future changes in tropospheric ozone under Representative Concentration Pathways (RCPs). Geophysical Research Letters, 38(5).

Kazmi, D. H., 2012. Agrometeorological wheat yield prediction in rainfed Potohar region of Pakistan.

Khanum, R., Mumtaz, A.S. and Kumar, S., 2013. Predicting impacts of climate change on medicinal asclepiads of Pakistan using MaxEnt modeling. Acta Oecologica, 49, pp.23-31.

Kogo, B.K., Kumar, L., Koech, R. and Kariyawasam, C.S., 2019. Modelling climate suitability for rainfed Maize cultivation in Kenya using a Maximum Entropy (MaxEnt) approach. Agronomy, 9(11), p.727.

Kramer-Schadt, S., Niedballa, J., Pilgrim, J.D., Schröder, B., Lindenborn, J., Reinfelder, V., Stillfried, M., Heckmann, I., Scharf, A.K., Augeri, D.M. and Cheyne, S.M., 2013. The importance of correcting for sampling bias in MaxEnt species distribution models. Diversity and Distributions, 19(11), pp.1366-1379.

MNFSR, 2017. *National Food Security Policy (Draft).* Islamabad.

Nabout, J.C., Caetano, J.M., Ferreira, R.B., Teixeira, I.R. and Alves, S.D.F., 2012. Using correlative, mechanistic and hybrid niche models to predict the productivity and impact of global climate change on maize crop in Brazil. Natureza & Conservacao, 10, pp.177-183.

Nelder, J.A. and Verrall, R.J., 1997. Credibility theory and generalized linear models. ASTIN Bulletin: The Journal of the IAA, 27(1), pp.71-82.

Pakistan Bureau of Statistics, 2011. Agricultural Statistics of Pakistan. Lahore.

Pakistan Bureau of Statistics, 2017. *Agricultural Statistics of Pakistan.* Lahore.

Pakistan Bureau of Statistics, 2018. *Agricultural Statistics of Pakistan.* Lahore.

Pakistan Bureau of Statistics 2015. Compendium on Environment Statistics of Pakistan.

PARC, 2015. Wheat in Pakistan; A status paper. Pakistan Agricultural Research Council, Islamabad.

Parry, M.L., C. Rosenzweig, A. Iglesias, G. Fischer and M.T.J. Livermore, 2004. Effects of climate change on global food production under SRES emissions and socio-economic scenarios. Global Environmental Change, 14: 53-67.

Pearson, R.G., 2007. Species' distribution modeling for conservation educators and practitioners. *Synthesis. American Museum of Natural History*, *50*, pp.54-89.

Peavey, L., 2010. Predicting pelagic habitat with presence-only data using maximum entropy for Olive Ridley Sea Turtles in the eastern tropical Pacific. Master Thesis. Nicholas School of the Environment, Duke University.

Peterson, A.T., Stockwell, D.R. and Kluza, D.A., 2002. Distributional prediction based on ecological niche modeling of primary occurrence data. Predicting species occurrences: issues of scale and accuracy, pp.617-623.

Phillips, S.J., Anderson, R.P. and Schapire, R.E., 2006. Maximum entropy modeling of species geographic distributions. *Ecological modelling*, *190*(3-4), pp.231-259.

Planning Commission. 2017. *Annual Plan 2017-18.*

Ray, D., Behera, M.D. and Jacob, J., 2018. Evaluating ecological niche models: a comparison between MaxEnt and GARP for predicting distribution of Hevea brasiliensis in India. Proceedings of the National Academy of Sciences, India Section B: Biological Sciences, 88(4), pp.1337-1343.

Reddy, M.T., Begum, H., Sunil, N., Pandravada, S.R., Sivaraj, N. and Kumar, S., 2015. Mapping the climate suitability using MaxEnt modeling approach for Ceylon spinach (Basella alba L.) cultivation in India. Journal of Agricultural Sciences–Sri Lanka, 10(2).

Rehman, A., Jingdong, L., Shahzad, B., Chandio, A.A., Hussain, I., Nabi, G. and Iqbal, M.S., 2015. Economic perspectives of major field crops of Pakistan: An empirical study. Pacific Science Review B: Humanities and Social Sciences, 1(3), pp.145-158.

Root, T.L., Price, J.T., Hall, K.R., Schneider, S.H., Rosenzweig, C. and Pounds, J.A., 2003. Fingerprints of global warming on wild animals and plants. Nature, 421(6918), p.57.

Rosenzweig, M.L., 1995. Species diversity in space and time. Cambridge University Press.

Stocker, T. ed., 2014. Climate change 2013: the physical science basis: Working Group I contribution to the Fifth assessment report of the Intergovernmental Panel on Climate Change. Cambridge University Press.

Taylor, K.E., Stouffer, R.J. and Meehl, G.A., 2012. An overview of CMIP5 and the experiment design. Bulletin of the American Meteorological Society, 93(4), pp.485-498.

Van Vuuren, D.P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., Hurtt, G.C., Kram, T., Krey, V., Lamarque, J.F. and Masui, T., 2011. The representative concentration pathways: an overview. Climatic change, 109(1-2), p.5.

van Vuuren, D.P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., Hurtt, G.C., Kram, T., Krey, V., Lamarque, J., Masui, T., Meinshausen, M., Nakicenovic, N., Smith, S.J., & Rose, S.K. 2011. The representative concentration pathways: an overview. Climatic Change, 109, 5-31

Wang, X., Ji, Y., Zhou, G., Wang, S. and Yao, X., 2019. Climate Suitability and Vulnerability of Winter Wheat Planting in Gansu under the Background of Global Warming. Journal of Geoscience and Environment Protection, 7(4), pp.239-250.

Warren, R., N. Arnell, R. Nicholls, P. Levy and J. Price, 2006. Understanding the regional impacts of climate change. Research report prepared for the Stern Review, Tyndall Centre Working Paper 90, Tyndall Centre, Norwich.

World Bank, 2017. Pakistan Development Update. Growth: A Shared Responsibility .

Wu, Z., Zhang, H., Krause, C.M. and Cobb, N.S., 2010. Climate change and human activities: a case study in Xinjiang, China. Climatic Change, 99(3-4), pp.457-472.

Yang, X., Tian, Z., Sun, L., Chen, B., Tubiello, F.N. and Xu, Y., 2017. The impacts of increased heat stress events on wheat yield under climate change in China. Climatic Change, 140(3-4), pp.605-620.

Yue, Y., Zhang, P. and Shang, Y., 2019. The potential global distribution and dynamics of wheat under multiple climate change scenarios. Science of The Total Environment.