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INVESTIGATING WHEAT YIELD AND CLIMATE PARAMETERS REGRESSION MODEL BASED ON AKAIKE INFORMATION CRITERIA

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Abstract

Wheat is a staple food of Pakistan and a central commodity of world food security. Wheat yield production is likely to be affected adversely (or positively at some places) in a changing climate scenario and ever-increasing demand due to burgeoning world population and may lead to a growing food security issue because of changing climate. This study investigated the co-variability of wheat yield production in Pakistan with the principal climate parameters, precipitation and temperature, through a linear regression method by adopting the Akaike Information Criteria (AIC)-based best model selection strategy, for given data over 51-year period. Employing the AIC technique on twenty different combinations of seasonal aggregates of rainfall, seasonal mean temperature, seasonal minimum and maximum temperatures, the investigation revealed that the model containing a combination of seasonal-minimum temperature and seasonal-mean temperature is the best model for wheat yield production followed by 7 equally adequate models with different combinations of climate parameters from the data. Hence, seasonal-averaged minimum and mean temperatures proved to be the best-fit regressors deduced by the AIC-based criterion.

Key words: AIC, Precipitation, Regression, Temperature, Wheat yield.

Introduction

The crops yield across any region are affected by the climate prevailing over that area particularly temperature and precipitation leaving their pronounced effect on yield and production. It is now well documented that agriculture yields are markedly influenced by climatic variables like precipitation, temperature, humidity and sunshine radiations, in addition to some other factors and therefore agriculture production, commodity prices and economic growth are affected by climate (Spash, 2007a, 2007b; Kirby *et al*., 2016). Pakistan witnessed less crop yields in rain-dependent areas during deficient-rain years than half of those in areas with river-fed irrigation (Anon., 2001). Wheat crop was seriously affected in 1972-73 and 1973-74 by adverse weather (CIMMYT, 1989). There was a drastic reduction in wheat yields in the years 1987 and 1994 owing primarily to a lessened winter rainfall (Aslam *et al*., 2004). On the other hand, the heat stress resulted by uncharacteristically high temperatures caused an early maturity of wheat grains which ultimately reduced wheat yields by 13 percent in Pakistan in the year 2010 (Rasul *et al*., 2011). Pakistan faced water shortages and drought conditions for the last several years due to lesser rains and high temperatures which has resulted in a diminished wheat production both in irrigated and rain-fed areas, with around 60% yield gap, although there are some other limiting factors like non-availability of inputs like seed, inefficient fertilizer use and weed infestation (Anon., 2013). Similarly, due to shrinking winter and lengthening of summer season, gram's crop in the Thal region (Punjab province) is noticed to have been adversely affected (Anon., 2007). The objective of this study is to explore about a robust correlation between wheat yield productivity and climatic variables, temperature and precipitation by using multiple regression model based on the Akaike Information Criteria (*AIC*), a technique of best regression model selection for Pakistan.

Intergovernmental Panel on Climate Change 5th Assessment Report (Anon., 2014) demonstrates that climate change (principally characterized by a change in temperature and precipitation) is projected to undermine food security with wheat, rice and maize production, in tropical and temperate regions, is most likely to have negative impact for local temperature increases of 2°C or more above the 20th century levels, though individual locations are likely to benefit. The report further projects (*with high confidence*) that the global food security would be at large risk due to global temperature's potential increase of about 4°C or more above late 20th century levels, combined with increasing food demand.

A study on climate change effects on major crops of Pakistan demonstrated that maximum temperature adversely affects the wheat production, minimum temperature positively affects all the crops and rainfall effect is negative except for wheat. Crop production would suffer loss due to climate change and hence not only the agricultural sector itself could suffer recession but impact would also be agriculture-related industries and other sectors such as manufacturing and services. The change in crop production will have a multiplier effect (Khan *et al*., 2020).

The temperature and precipitation variability strongly impacts the yields of wheat and barley crops in Iran as the highest yields of crops were noticed to be associated with peak precipitation years and low yields were experienced during a less-than-average rainfall (Bannayan *et al*., 2011). Wheat yields and other winter crops in northwest India experienced stagnation or decrease owing to rising temperatures (Chander *et al*., 2008). Another study established that the maximum and minimum temperatures have significant effect on *Kharif* rice yield in India, while *Rabi* rice yield are adversely affected by maximum temperature and rainfall (Farook & Kannan, 2015). For the Kwara State Nigeria, it is indicated that the maize and rice yields are hugely impacted by climate (Akpenpuun, 2013).

For the USA, UK and Western European States, it is revealed that increase of temperature affects wheat yield in terms of yield losses because of moisture stress resulted by evapotranspiration owing to higher temperature (Warrick, 1998). Wheat yield was found pointedly reduced in Hubei and Hunan provinces for each degree increase in growing season minimum temperature, while it showed a marked increase in Tianjin province China (Tao *et al*., 2008). These studies clearly indicate that the wheat crop yield, among other crops, is directly or indirectly affected by the climate parameters, temperature and precipitation.

The given scenario thus necessitates to explore whether a correlation exists between wheat yield productivity and climate parameters in Pakistan; how robust it is and which of the parameter (temperature, precipitation or any other) has more pronounced impact. Many agronomists did the regression analysis to predict or estimate the mean value of certain crop-yield based on climate factors (Janjua *et al*., 2010; Ahmed *et al*., 2011; Kazmi & Rasul, 2012; Khattak & Shabbir, 2012; Tariq *et al.*, 2014; Baig & Amjad, 2014). With regression analysis, a mean or average value of one variable based on fixed values of other variables can be predicted (Gujarati & Porter, 2008). The dependent variable being statistical, random or stochastic and the explanatory one with fixed values behave asymmetrically (Gujarati & Porter, 2008). The agronomists thus have used the regression analysis to foresee the mean value of a certain crop-yield based on climate factors. For Potohar region of Pakistan, such a regression model suggested that favorable temperature conditions contribute a great deal in developing higher number of wheat grains in a spike which results in proper size and weight of grain provided water is supplied optimally (Kazmi & Rasul, 2012). A similar study on correlation and regression analysis of wheat yield in Pakistan and climatic variables established that there exists a significant relationship between wheat yield and climate variables and that the variance in wheat production can be explained by temperature, humidity, wind and precipitation (Khattak & Shabbir, 2012). The use of Simple, Stepwise and Multiple regression models and linear production function-LPF indicated that wheat production is negatively affected by increase in maximum temperature during January and November while it has a positive correlation with minimum temperature during November and March in irrigated areas of Punjab-Pakistan (Tariq *et al*., 2014). On the other hand, production of wheat in the rain-fed regions is significantly impacted by minimum temperature during February and November whereas rainfall in the month of March shows a negative correlation. The investigation showed that there is a direct relationship of wheat yield with solar radiation and a combined effect of solar radiation and temperature while an inverse relationship with temperature alone (Ahmed *et al*., 2011). The vector auto regression (VAR) method was used to indicate that the major crops of Pakistan predominantly depend on temperature and availability of water while precipitation has negative impact (Baig & Amjad, 2014). The VAR model was also used for assessing climate change impact on wheat production in Pakistan to conclude that the wheat production has not been under any negative impact of climate change at present, however future CO_2, precipitation and temperature changes would have a positive impact on wheat production in Pakistan (Janjua *et al*., 2014).

With this backdrop, this study attempted to model a correlation between wheat yield productivity and temperature and precipitation using multiple regression model based on the Akaike Information Criteria (*AIC*), a technique of best-fit regression model selection. Using AIC-based selection of best model from amongst number of models is perhaps first attempt as far as Pakistan is concerned. *AIC* is the criteria to select a best-fit model from amongst those which too otherwise apparently seem the good one.

Study area: Pakistan, with a geographical stretch between 24 °N to 37.5 °N and 61 °E to 76.5 °E, is amongst few countries with a diverse climate. Its south possesses hot and arid climate feature; sub-mountainous northern parts show a moderate and humid climate and extreme north has very cold weather characteristics. Southern areas very commonly observe the summer temperature of 50°C, while northern parts experience winter temperature as low as -20°C to -22°C (PMD, 1961-90). The annual precipitation distribution on spatial scale also exhibits a large variation from south to north, 40 mm in south to about 1800 mm in the north (PMD, 1981-2010; Sarfaraz *et. al*., 2015) with eastern parts of the country experiencing more summer (monsoon) rains and western ones dominated by winter season (December-March, DJFM) rainfall caused by weather systems travelling from the west (Khan, 1993).

Being an agrarian country Pakistan economy centrally depends on agriculture which contributes 21 percent to the national GDP, provides 44 percent of the country's total labour force. Agriculture directly or indirectly provides livelihood to about 62 percent of the country's rural population and hence is a second largest sector. Pakistan encompasses two principal crop seasons 'Kharif' (or summer) and 'Rabi' (or winter). The Kharif spans over June – October, while Rabi starts in October and ends in April-May. Rice, sugarcane, cotton, maize, mong, mash, bajra and jowar are Kharif crops collectively produced on 61% of the total crop area, while wheat, gram, lentil (masoor), tobacco, rapeseed, barley and mustard are Rabi crops. The major crops, wheat, rice and cotton contribute 33.1 percent to the value added in overall agriculture and 7.1 percent to GDP (Anon., 2013).

Wheat has a central position in country's agricultural policies with sharing a value addition of 9.9 percent to agriculture and 2.0 percent to GDP owing to be a primary and essential food of Pakistan. As a Rabi season dominant crop, it accounts for 69 per cent of the total cropped area which, otherwise, excluding fallow areas is grown on 80% of the actual cropped area during the Rabi season (Byerlee *et al*., 1986). The district-wise spatial distribution of wheat production across Pakistan is given in Fig. 1. Favorable weather conditions characterized by temperature, precipitation, humidity and winds are critically important for agriculture growth with wheat and other Rabi crops are affected by winter months' (DJFM) climate. The studies mentioned above and others used various regression models like vector auto regression model (VAR), least square method, LSM, linear and multiple regression methods and least absolute shrinkage and selection operator, LASSO to investigate the climate-wheat yield productivity relationship.

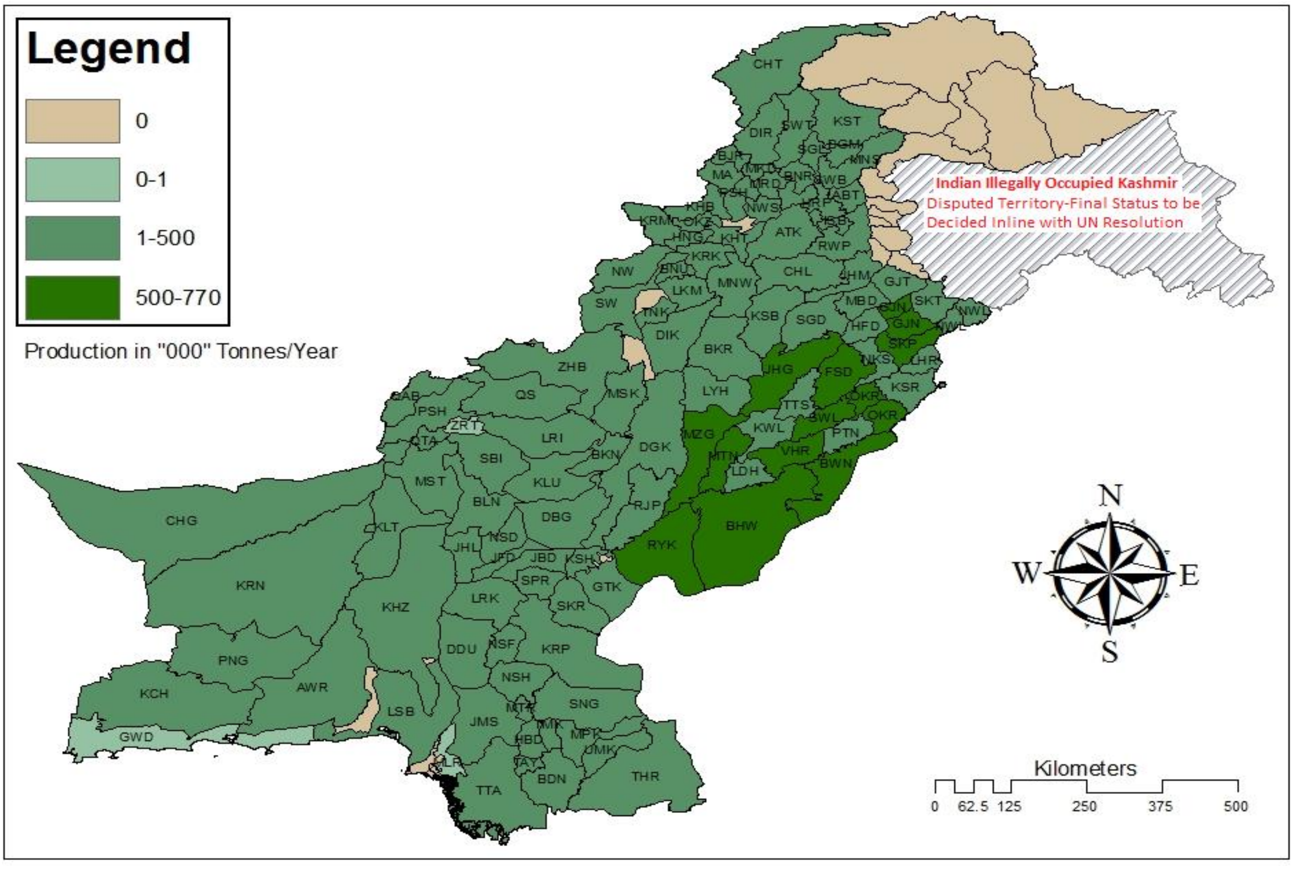

Fig. 1. District-wise wheat production across Pakistan (data source: PBS, 2011). No data from Kashmir.

Akaike information criteria (AIC)-based best model selection: Models are generally termed as approximations to unknown reality or truth; to quote George Box (1987) "all models are wrong but some are useful" (Burnham & Anderson, 2011). In present study, wheat production in Pakistan is modeled with climatic parameters of temperature and precipitation of winter season by using the *AIC* technique to pick up the best model identified from the given data. Selection of model is important as in under-fitted model, one cannot be sure of true variability in outcome variables while an over-fitted model may compromise generality and hence *AIC* is a way to keep balance between these risks (Snipes & Taylor, 2014). The *AIC* was developed as a mean to compare different models on a given outcome. It is principally used in biological, environmental, marine and watershed sciences along with wide usage in pharmacological and marketing fields (Andrew & Currim, 2003). A proper association between K-L (Kullback-Liebler) information and maximum likelihood, which combined estimation and model selection to lead to optimization, was presented by Akaike (Akaike, 1973, 1974). The K-L (Kullback & Liebler, 1951) information is a measure between a conceptual reality and approximating model, upon which Akaike relied to derive *AIC* (Burnham & Anderson, 2011). The Akaike's procedures in essence are information-theoretic as they are based on the K-L information (Akaike, 1983b, 1992, 1994). Given a set of candidate models, *AIC* is then computed for each of the model and the one with a minimal *AIC* score is regarded as the best model for given empirical data. This is deliberated as a simple, persuasive idea, built on strong notional grounds of entropy, K-L information and likelihood theory (Burnham & Anderson, 2011). Model selection based on AIC is equivalent to certain cross-validation methods (Stone, 1974, 1977). The least absolute shrinkage and selection operator, LASSO, and AIC techniques were used to select the best model for milk predictands in cow milk with climate predictors for Iran (Milani *et al*., 2016). The detailed methodology adopted follows in section 2.

Materials and Methods

Climate data, monthly averaged precipitation and temperature for 51-years' period, 1961-2015, were obtained from Pakistan Meteorological Department (PMD). These are quality-controlled data, as PMD regularly publishes these in their Climatic Normals and archives. The wheat-yield production data in tonnes/hectare for the same period were obtained from the Bureau of Statistics, Pakistan.

Four seasonal temperature indices (T_{min}, seasonal-mean minimum temperature, T_{max}, seasonal-mean maximum temperature, T_{mean}, seasonal-mean temperature and $T_{DJFMA,}$ temperature) were worked out by taking averages over four months (December to March, DJFM) and five months (December to April, DJFMA). The seasonal rainfall indices (R_1 and R_2) were realized by summing up the monthly total rainfall amounts of DJFM and DJFMA respectively. Hence, 6 climate indices for the season - December to March/April - are considered for this study as wheat is generally sown in November and harvested in May (April in some southern areas) according to the Ministry of Agriculture and Food Research crop calendar. The methodology adopted is that the given data of six climate indices are combined into 20 different predictors (Table 1). Keeping wheat -yield as predictand, the multiple linear regression is carried out to assess how much each of the predictor explains the wheat yield.

Employing the Statistical Package for Social Scientists (SPSS 21, 2012), the multiple linear regression of wheat yearly (the predictand) production is performed with each of 20 indices (the predictors). The methodology of building models with 20 different combinations of temperature and precipitation indices is shown in Table 1. The results of regression analysis in terms of residual sum of squares (RSS), P-value, the coefficient of determination (R^2) and significant (p-value) values are given in Table 2. To ascertain the best model and scale or rank the rest, the Akaike Information Criteria, *AIC*, is applied. The AIC equates various contending models (or working theories) all at once ascertaining how convinced is the model's approximation to the desired truth. This is the method which quantifies the model selection uncertainty and corollary can be based on a combination of models in the events where no single model comes out as the best model (Matthew & Moussalli, 2010). The AIC value for each model is calculated using the following equation;

AIC=n*ln(RSS/n)+2*K …………………………… (1)

where 'n' is the total number of observation (sample size), K is the degree of freedom or number of parameters, and RSS is the residual sum of squares. Then using refinement technique for corrected estimate for small data samples (Hurvich & Tsai, 1989; Burnham & Anderson, 2002) the AIC-corrected, AICc, is calculated using equation 2;

AICc=AIC+(2*K(K+1))/ n-K-1 …………………… (2)

And finally calculated the shortest distance to the 'truth' (Δi) for each model by

Δi =AICi – minAICc ……………………………… (3)

Δi is the strength of evidence whose minimum value gives the best model (Burnham & Anderson, 2001).

Results

A 51-year time-series plot of annual wheat yield progression (in '000' tonnes) and wheat crop area ('000' hectares) across Pakistan is shown in Fig. 2 that depicts continuous rise in wheat yield production but steadiness in crop area.

To assess the wheat-yield regression with principal climate parameters (seasonal temperature and precipitation) the multiple linear regression of annual wheat-production with 6 different climate indices (with their 20 different combinations) was carried out using the statistical software, SPSS 21. The regression analysis' statistics; residual sum of squares (RSS), Pearson Correlation, R^2, Durbin-Watson statistic, F-value and P-value for proposed 20 models are shown in Table 2. The 14 models with significance value (p<0.001, last column Table 2), R^2 in range of 0.36 to 0.73 and Pearson Correlation of 0.6 to 0.8 should apparently be adequately significant models; but, based upon the AIC technique, the case is not so and only 8 models (from the 20) fulfil the best-fit model criteria . These 8 best-fit models with values of minimum Δi and AICc are shown in colored fonts in Table 3. The model M_6 (**T_{mean}+T_{min}**) with minimum AIC score (and Δi = 0) hence emerges as the best model (Rank 1). The values of R^2, F, Durbin-Watson statistic and Pearson Correlation for the best-fit model, M_6, are **0.72**, 61.044, **1.322** and **0.78** respectively which means that over 72 percent variance in wheat yield production is elucidated by the combined sum of seasonal-mean temperature and seasonal-mean minimum temperature. The other fitting models (with Δi < 10) are M_9 and M_{13} both ranked 2nd and M_{15}, M_{14}, M_7, M_2 and M_{12} rank 3rd, 4th, 5th , 6th and 7th respectively with rest falling way far to fulfill the best-fit criteria.

Table 1. Model notation, predictand, predictors & model description. β_0 is the slope and ϵ is constant.

Model notation	Predictand	Predictor(s)	Model description
M_1	Wheat yield=	R_1	$\beta_0 + R_1 +\epsilon$
M_2	Wheat yield=	T_{mean}	$\beta_0 + T_{mean} +\epsilon$
M_3	Wheat yield=	T_{max}	$\beta_0 + T_{max} +\epsilon$
M_4	Wheat yield=	T_{min}	$\beta_0 + T_{min} +\epsilon$
M_5	Wheat yield=	T_{DGFMA}	$\beta_0 +T_{DGFMA} + \epsilon$
M_6	Wheat yield=	$T_{min} +T_{mean}$	$\beta_0 + T_{min} +T_{mean} + \epsilon$
M_7	Wheat yield=	$T_{max} +T_{mean}$	$\beta_0 + T_{max} +T_{mean} + \epsilon$
M_8	Wheat yield=	$T_{min} + T_{max}$	$\beta_0 + T_{min} +T_{max} + \epsilon$
M_9	Wheat yield=	$T_{min} + T_{max} + T_{mean}$	$\beta_0 + T_{min} +T_{max} +T_{mean} + \epsilon$
M_{10}	Wheat yield=	$R_1 + T_{min}$	$\beta_0+R_1 +T_{min} + \epsilon$
M_{11}	Wheat yield=	$R_1 + T_{max}$	$\beta_0 +R_1 + T_{max} + \epsilon$
M_{12}	Wheat yield=	$R_1 + T_{mean}$	$\beta_0 +R_1 + T_{mean} + \epsilon$
M_{13}	Wheat yield=	$R_1 + T_{mean} +T_{min}$	$\beta_0+R_1 + T_{mean} +T_{min} + \epsilon$
M_{14}	Wheat yield=	$R_1 + T_{mean} +T_{max}$	$\beta_0+R_1 + T_{mean} +T_{max} + \epsilon$
M_{15}	Wheat yield=	$R_1 + T_{mean} +T_{max} + T_{min}$	$\beta_0+R_1 + T_{mean} +T_{max} + T_{min} + \epsilon$
M_{16}	Wheat yield=	R_2	$\beta_0 + R_2 +\epsilon$
M_{17}	Wheat yield=	$R_2 + T_{mean}$	$\beta_0 + R_2 + T_{mean} + \epsilon$
M_{18}	Wheat yield=	$R_2 + T_{max}$	$\beta_0 + R_2 + T_{max} + \epsilon$
M_{19}	Wheat yield=	$R_2 + T_{min}$	$\beta_0 + R_2 + T_{min} + \epsilon$
M_{20}	Wheat yield=	$R_2 + T_{DJFMA}$	$\beta_0 +R_2 + T_{DJFMA} + \epsilon$

Table 2. Wheat yield production and climate parameters' regression statistics.

Dependent variable (Predictand)	Climate parameter/ predictor	Residual sum of squares (RSS)	Pearson correlation	R^2	F-value	Durbin-watson	P-value (Sig.)
Wheat-yield	R_1	1995818067	0.058	0.003	0.168	0.039	0.684
	T_{mean}	765678104.3	0.058	0.618	79.160	1.520	<0.001
	T_{max}	1968483459	0.131	0.017	0.850	0.098	0.361
	T_{min}	1998909528	0.043	0.002	0.092	0.045	0.764
	T_{DJFMA}	1288668226	0.597	0.357	27.148	0.632	<0.001
	T_{min} +T_{mean}	**565161259.3**	**0.786/0.043/**	**0.718**	**61.044**	**1.322**	**<0.001**
	T_{max} +T_{mean}	733375747.1	0.786/.043/	0.634	41.537	1.468	<0.001
	T_{min} + T_{max}	1967285504	0.786/.058	0.018	0.431	0.105	0.652
	T_{min} + T_{max} + T_{mean}	564342997.8	0.131/.043/ 0.131	0.718	39.929	1.346	<0.001
	R_1+ T_{min}	1994187694	0.043/0.058	0.004	0.102	0.040	0.903
	R_1 + T_{max}	1918522864	0.131/.058	0.042	1.052	0.106	0.357
	R_1 + T_{mean}	655330930.7	0.786/.043/	0.673	49.342	1.571	<0.001
	R_1 + T_{mean} +T_{min}	561249833.0	0.786/0.131/0.058	0.720	40.235	1.431	<0.001
	R_1 + T_{mean} +T_{max}	540078346.0	0.786/0.131/0.043/.058	0.730	31.143	1.438	<0.001
	R_1 + T_{mean} +T_{max} + T_{min}	545319515.0	0.786/0.131/0.043/.037	0.728	30.733	1.380	<0.001
	R_2	1077522142	0.597/.037	0.462	20.606	.695	<0.001
	R_2 + T_{mean}	1077522142	0.597/.037	0.462	20.606	.695	<0.001
	R_2+ T_{max}	1243605981	0.597/.131	0.379	14.648	.492	<0.001
	R_2+ T_{min}	1283379679	0.597/.043	0.359	13.451	.669	<0.001
	R_2+T_{DJFMA}	1077522142	0.597/.037	0.462	20.606	.695	<0.001

The value (p<0.001) is significant, while others are non-significant

Table 3. Models, Climate Indices, df- the degree of freedom (no of variables), AIC values, AICc, AIC-corrected values and Δi (minimum distance to the "truth")

Model	Climate index, Predictor(s)	Degree of freedom – df (no of variables)	AIC	AICc	Δi	Model ranking
M_1	R_1	1	537.8	535.9	22	
M_2	T_{mean}	1	521.6	519.7	5.8	6
M_3	T_{max}	1	535.6	533.8	19.9	
M_4	T_{min}	1	535.5	533.9	20	
M_5	T_{DJFMA}	1	543.1	541.2	27.3	
M_6	**T_{min}+T_{mean}**	**2**	**516.5**	**513.3**	**0**	**1**
M_7	T_{max}+T_{mean}	2	521.6	518.9	5	5
M_8	T_{min}+T_{max}	2	537.5	534.9	21	
M_9	T_{mean}+T_{max}+T_{min}	3	518.5	515.3	1.4	2
M_{10}	R_1+T_{min}	2	537.6	535.0	21.1	
M_{11}	R_1+T_{max}	2	537.6	535.0	21.1	
M_{12}	R_1+T_{mean}	2	523.5	520.9	7	7
M_{13}	R_1+T_{mean}+T_{min}	3	518.5	515.3	1.4	2
M_{14}	R_1+T_{mean}+T_{max}	3	518.5	515.3	3.8	4
M_{15}	R_1+T_{mean}+T_{max} +T_{min}	4	520.9	517.7	2.8	3

It is evident from Table 3 that the 8 fitting models fulfill the general criteria of lowest values of AIC, AICc and minimum value of Δi, which is 0 for best-fit model and less than 10 for other fitting models.

Discussion

A multiple linear regression of wheat yield production with the seasonal-mean temperature, seasonal-mean maximum, seasonal-mean minimum temperatures and seasonal rainfalls established that based on *AIC* method (AIC, 1973), there are 8 different regression models from the 20 initially proposed (Table 3). M_6 with minimum AIC score (Δi = 0) is the best-fit model for given data which comprises the winter (DJFM) - season mean temperature and seasonal- mean minimum temperature (**T_{mean} + T_{min}**). The results show 7 more models (M_9, M_{13}, M_{15}, M_{14}, M_7, M_2 and M_{12}) with *AIC* score less than 10 (Δi= 1.4 to 7) adequately good enough to be considered. The models with values Δi < 2 are to be considered as good as the best-fit model (Matthew & Moussalli, 2010;

Snipes & Taylor, 2014) and the models with $\Delta i = 6$ ought not be disregarded (Richards, 2005). With this standpoint, the models M_9 and M_{13} ($\Delta i = 1.4$ for both) are as good as the model M_6, while the models M_{15}, M_{14}, M_7 and M_2 all having $\Delta i < 6$ can too be regarded appropriate models and the model M_{12} with $\Delta i=7$ may also be taken into account. The ranking of credible models is done from the best (with $\Delta i = 0$) downwards to the one with $\Delta i=7.5$, by adopting the approach of a ‘robust set’ or ‘rational set’ of models with realistically best approximation, which produces a 95pc confidence set of models (Burnham & Anderson, 2002). Hence in this study the model $\mathbf{M_6}$ emerging as the best-fit model followed by models M_9 and M_{13} both ranked 2nd and M_{15}, M_{14}, M_7, M_2 and M_{12} ranking 3rd, 4th, 5th , 6th and 7th respectively (Burnham & Anderson, 2002; Matthew & Moussalli, 2010) are equally good enough models for the given set of data.

It is evident that the seasonal-mean temperature, T_{mean} is found common in all 8 models and rightly so because it is the season-averaged temperature which helps ripening the wheat grains. To ascertain the trends of climate indices, the Mann-Kendall (Mann, 1945; Kendall, 1975; Gilbert, 1987) trend test was applied which showed that seasonal mean temperature, T_{mean} has a statistically significant (at p=0.015) increasing trend while other climatic indices do not show any significant trend. Many studies established linkage of ongoing global temperature increase with crops’ yields including wheat. The potential increase in seasonal-mean temperature in future would therefore affect wheat yield in different parts of Pakistan differently with potentially adverse effect in plains of the country, and vice versa in mountainous areas (Hussain & Mudassar, 2007). Thus rising mean temperature consequently can reduce the wheat yield production which in turn jeopardize the national food security. On the other hand, seasonal rainfall (R_1), contributing in 3 models, may also affect the wheat yield production as the studies on climate change demonstrate that the rainfall would generally be erratic and uneven.

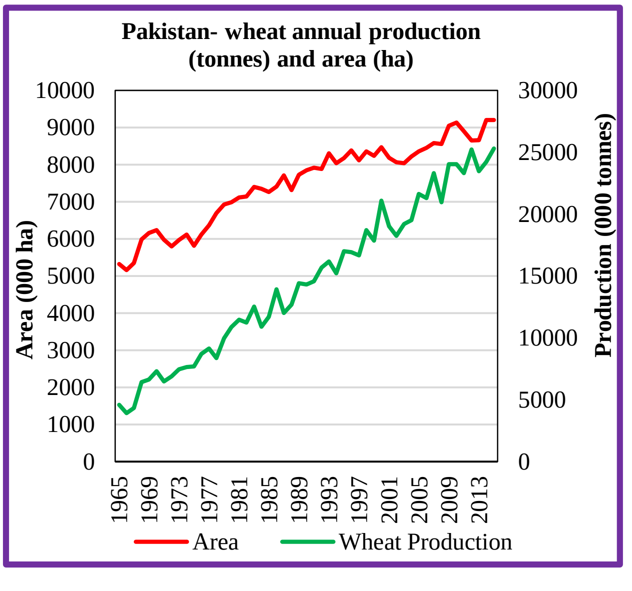

Fig. 2. Pakistan yearly wheat production (‘000’ tonnes) with crop area (‘000’ ha) for 1965-2015 (Data source: PBS).

Conclusion

This study addressed the linear regression modeling of wheat yield with climate parameters, temperature and rainfall and found that best approximated model emerged (M_6) is the one that comprises seasonal-mean temperature and seasonal-mean minimum temperature with 7 other models (ranked 2nd to 6th) scoring minimal AICc and Δi values ($\Delta i = 1.4$ to 7) fall very close to the best-fit model (Burnham & Anderson, 2002; Matthew & Moussalli, 2010; Snipes & Taylor, 2014) and can be regarded as equally good enough. The results of the study indicate that the seasonal-mean, seasonal-mean maximum (daytime) and seasonal-mean minimum (nighttime) temperatures come forth as the major contributing regressors (see models M_7, M_9, M_{12}, M_{13}, M_{14} and M_{15} Table 3) with wheat yield production.. The seasonal-mean temperature exhibiting a marked rising trend coupled with rising daytime as well as nighttime temperatures (though not statistically significant) at most of the places in Pakistan would potentially be a significant threat for future wheat crop which may have serious consequences for national food security. Apart from temperatures, the winter season rainfall when combined with temperature indices also emerges out as a contributing regressor to wheat production in some of fitting models (M_{12}, M_{13}, M_{14} and M_{15}). Many studies including the IPCC AR5 reveal that owing to climate change, the rainfall more likely to be erratic/ uneven and temperatures very likely to rise in future which definitely may pose a serious problem to future agriculture. To cope with adverse and negative effects, a better strategy of efficient utilization of water resources, climate-resilient cultivars, better soil management, innovation in agriculture technology and adaptation to changing climate at farm-levels needs to be exercised. Further plan is to work regression modeling of wheat yield production and other crops with solar radiation, wind (speed and direction), rainfall (summer and annual) and humidity parameters so as to make a possible contribution towards better agriculture and national food security in Pakistan.

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