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Original Article

Forest yield prediction under different climate change scenarios using data intelligent models in Pakistan

Previsão de produção florestal em diferentes cenários de mudanças climáticas usando modelos inteligentes de dados no Paquistão

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Abstract

This study aimed to develop and evaluate data driven models for prediction of forest yield under different climate change scenarios in the Gallies forest division of district Abbottabad, Pakistan. The Random Forest (RF) and Kernel Ridge Regression (KRR) models were developed and evaluated using yield data of two species (Blue pine and Silver fir) as an objective variable and climate data (temperature, humidity, rainfall and wind speed) as predictive variables. Prediction accuracy of both the models were assessed by means of root mean squared error (*RMSE*), mean absolute error (MAE), correlation coefficient (*r*), relative root mean squared error (*RRMSE*), Legates-McCabe's (*LM*), Willmott's index (*WI*) and Nash-Sutcliffe (NS_E) metrics. Overall, the RF model outperformed the KRR model due to its higher accuracy in forecasting of forest yield. The study strongly recommends that RF model should be applied in other regions of the country for prediction of forest growth and yield, which may help in the management and future planning of forest productivity in Pakistan.

Keywords: climate change, forest yield, RF and KRR models, prediction, Gallies forest, Abbottabad.

Resumo

Este estudo teve como objetivo desenvolver e avaliar modelos baseados em dados para previsão da produção florestal em diferentes cenários de mudanças climáticas na divisão florestal Gallies do distrito de Abbottabad, Paquistão. Os modelos Random Forest (RF) e Kernel Ridge Regression (KRR) foram desenvolvidos e avaliados usando dados de produção de duas espécies (pinheiro-azul e abeto-prateado) como uma variável objetiva e dados climáticos (temperatura, umidade, precipitação e velocidade do vento) como preditivos variáveis. A precisão da previsão de ambos os modelos foi avaliada por meio de erro quadrático médio (RMSE), erro absoluto médio (MAE), coeficiente de correlação (r), erro quadrático médio relativo (RRMSE), Legates-McCabe's (LM), índice de Willmott (WI) e métricas Nash-Sutcliffe (NSE). No geral, o modelo RF superou o modelo KRR devido à sua maior precisão na previsão do rendimento florestal. O estudo recomenda fortemente que o modelo RF seja aplicado em outras regiões do país para previsão do crescimento e produtividade florestal, o que pode ajudar no manejo e planejamento futuro da produtividade florestal no Paquistão.

Palavras-chave: mudanças climáticas, produção florestal, modelos RF e KRR, predição, floresta das Galinhas, Abbottabad

1. Introduction

Recently, climate change is the biggest dilemma all over the world. Many researchers stated that atmospheric greenhouse gases emissions are the main source for changing global climatic conditions (Ashraf et al., 2015; Hussain et al., 2014, 2017, 2018). The drift in global warming has been proved by the observation of climate,

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since 1900 the average temperature has been raised by 0.8% globally (Lindner et al., 2010), and since 1880 the 12 warmest years were observed in between 1990 and 2005 (Ciais et al., 2005). Forests are very sensitive to changing climate, because rapid environmental variation does not allow trees to adapt due to their lengthy life span. There are numerous factors associated with climate change that are influencing forest ecosystem and which can act in combination or independently (Lindner et al., 2010). For instance, photosynthesis rates are increased by the rising concentration of carbon dioxide (CO_2) in environment (Ainsworth and Long, 2005). The rate of tree growth may not rise correspondingly with increase in photosynthesis because of other limiting factors such as nutrients availability (Luo et al., 2004). Climate change posed significant threat for forests throughout the world (Fischlin et al., 2009). Forest productivity is directly affected from increase in temperature due to carbon dioxide concentration, changes in humidity, variations in timing and amount of rainfall, and altered storm and drought frequencies (Hyvonen et al., 2007). Similarly, pest attacks, variation in fire frequencies and distribution of tree species due to climate change would also affect the forest productivity (Medlyn et al., 2011). Variation in global temperature might cause huge redistribution and shift of forests in the boreal region (Zhou et al., 2005). In response to the expected change in climate, several tree species data intelligent models have been developed in the previous twenty years (Ashraf et al., 2013, 2015).

Forest managers are facing challenges in the implementation of sustainable forest management due to possible consequences of growing atmospheric temperature and carbon dioxide concentration on the productivity and growth of forest. For the estimation of total tree height, volume, and diameter at breast height (DBH), empirical statistical models of yield and growth have been used conventionally (Zhou et al., 2005). Due to absence of past data, inappropriately these models have been failed in simulation of the effects of climate change on forest stands and the growth dynamics of some regions' forests. As, these models do not consider climate variables such as precipitation, temperature, and variation in carbon dioxide concentration, because these models only simulate forests yield and growth totally based on historic measurement (Peng, 2000). Forest growth models could be utilized as an effective management tool, because growth models developed for management need simple and easily available data (Johnsen et al., 2001). Growth and yield models are very convenient tools for managing large forests (Aghimien et al., 2016). Forest growth and yield models deliver quantitative evidence about continuous state of change in forest stand. These models are effective in future prediction of forest growth and yield, updating forest inventories, and making forest-harvesting plans (Weiskittel et al., 2011). With the help of information provided by management-oriented growth and yield models, efficient forest management plans can be made (Pretzsch, 2009). Therefore, data intelligent models have been successfully applied globally to predict future forest yield using historical data. However, there is no study conducted for the prediction of forest yield using data intelligent models in Pakistan. Therefore, in the present study machine-learning models have been developed to predict forest yield to provide baseline information's to forest managers in Pakistan. Thus, the objective of this study was to found out the future yield of two high-value principal tree species (blue pine and silver fir) under different climate change scenarios in the moist temperate forest of Gallies, Abbottabad, Pakistan.

2. Material and Method

2.1. Theoretical overview

2.1.1. Random forest

The Random Forests (RF) algorithm was projected by Leo Breiman for the first time in 1999 and can be widely utilized for regression and classification functions (Breiman, 2001). This algorithm could be significant for the selection of different variables, interaction recognition, clustering and so on. The RF is a classification tool comprising of many tree classifiers, which uses two commanding machine-learning techniques, such as random selection of functions and bagging (Jiang et al., 2007). When bagging, training data comprising of bootstrap samples are used for the training of each tree, and then predictions are made by maximum tree votes. RF is a further development of bagging. When growing a tree, RF randomly selects a subset of features to split at each node rather than using all functions. To evaluate the predictive power of the RF model, it performs cross-validation in corresponding with the training step, by utilizing the so-called out-of-bag (OOB) samples. Specifically, each tree is grown during training with a specific sample of bootstrap. Since the bootstrapping exchanges samples from the training dataset, some of the sample's sequences are skipped, while others in the sample are repeated. The skipped sequences create the OOB samples. On average, each tree is grown utilizing about of the training sequences, leaving as OOB. As, OOB sequences are not used in the building of tree but can be utilized to estimate the prediction performance (Svetnik et al., 2003). The algorithm of random forest is described below:

Draw bootstrap samples from the original data.

For every sample of bootstrap make an unpruned regression tree. At each node, sample of the predictors randomly instead of taking the best split among all predictors and select the best split from among those variables. (Bagging could be considered as the superior case of random forests attained when, the quantity of predictors).

An estimate of the error rate can be obtained, based on the training data, such as following:

a) At each bootstrap repetition, the data cannot be predicted in the bootstrap sample (called as out-of-bag, or OOB data) using the tree grown with the bootstrap sample;
b) The OOB predictions are aggregated (each data point would be OOB around 36% of the times on the average,

so aggregate these predictions). Now calculate the rate of error, and name it the error rate of OOB (Bylander, 2002).

The key benefits of the advanced RF application are that it has been evidenced as the most accurate and strong algorithms in the prediction of many datasets (Caruana et al., 2008). It can handle regression issues with multiple inputs and examine their relative importance. Also, the performance of RF is not very complex to its hyper parameters in the algorithm (Qi et al., 2018; Kuhn and Johnson, 2013). In most real-world applications, the RF algorithm is fast enough, but performance can be significant and further methods are preferred (Donges, 2018). Figure 1 represents the schematic view of the RF model.

2.1.2. Kernel ridge regression

Kernel ridge regression (KRR) is a very simple but powerful machine learning model used for nonparametric regression, which is calculated by solving a linear system (Avron et al., 2017). KRR is obtained by coupling the kernel trick with the ridge regression and is sometime termed as the linear least square regression with regularization of Tikhonov (Chu et al., 2011). Assume that we have a training data $\left((x_1,y_1),\ldots,(x_N,y_N)\right)$, where N represent the total number of training samples. X is a features matrix, $x_1,x_2,\ldots,x_N]$, of size $N \times d$ and $Y = [1,2,\ldots,m]$ is a $N \times 1$ vector of class labels.

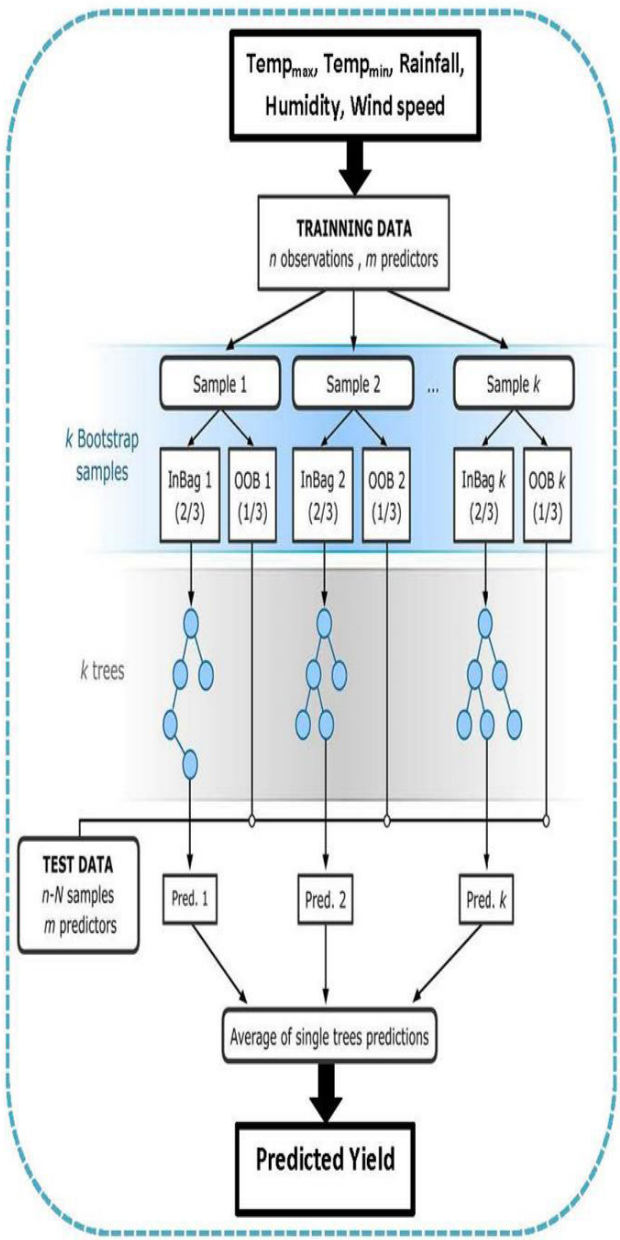

Figure 1. High-resolution flow chart of the Random Forest (RF) model.

KRR depends on ridge regression and ordinary least square (OLS) (Saunders et al., 1998; Rakesh and Suganthan, 2017). The purpose of OLS is to minimize the square loss:

$$\min_{\beta} \ \| Y - X\beta \|^2 \tag{1}$$

where $\|\|$ represents the L_2 norm. A λ called ridge or shrinkage parameter is added in above Equation 1 to control the commutation among the variance and bias of the estimates, which generates the following equation:

$$\min_{\beta} \ \| Y - X\beta \|^2 + \lambda \ \| \beta \|^2 \tag{2}$$

Solution for the Equation 2 is $\beta = \left(X^T X + \lambda I \right)^{-1} X^T Y$ where, *I* denote the identity matrix. The forecasted label of a new unlabeled *x* is represented by $\beta^T x$.

KRR uses the kernel trick which outspreads the linear regression into nonlinear and high dimensional or even into an infinite dimensional space. The data x_i is replaced by the feature vectors: $x_i \to \Phi = \Phi(x_i)$ in *X* which is brought by the kernel where $K_{ij} = k\left(x_i, x_j\right) = \Phi\left(x_i\right)\Phi\left(x_j\right)$. Hence, the forecasted class label of new example *x* can be given as Equation 3:

$$Y^T \left(K + \lambda I \right)^{-1} k \tag{3}$$

here $k = \left(k_1, \ldots, k_N\right)^T, k_n = x_n \cdot x$ and $n = 1, \ldots, N$.

With KRR one can easily utilize the most commonly used functions, like polynomial or Gaussian or linear, without evaluating the feature vectors $\Phi(x)$. Figure 2 represents the schematic view of the KRR model.

3. Data and Methods

3.1. Data collection

In this study, the acquired data includes environmental variables such as monthly rainfall, wind speed at 5am and pm, wind direction at 5am and pm, minimum and maximum temperature and humidity at 5am and pm, for the years 1963 to 2016 were collected from Pakistan Meteorological Department (PMD), Islamabad as can be seen in Table 1. While the yield data of two tree species (Silver fir and Chir pine) for selected region of study were obtained for the period of 1963 to 2016 from Pakistan Forest Institute Peshawar (PFI), Forest Working Circle Peshawar (FWC) and Forest Department, Khyber Pakhtunkhwa. Climate variables such as temperature, humidity, precipitation, rainfall and wind speed effect forest ecosystem composition and function as well as play a pivotal role in forest growth (Lindner et al., 2010). Forest growth and productivity are affected directly or indirectly through changes in climate variables (Gibbs et al., 2007). Increase in temperature disturbs the length of forest growing season and alter its geographical distribution due to which the habitat of forest species is likely to move from lower altitude to higher altitude (Backlund et al., 2008). Climate change is probable to raise in some regions the risk of drought and in others the risk of high rainfall and flooding. Warming temperature changes the time of snow melting, which disturbs the availability of water (Karl et al., 2009).

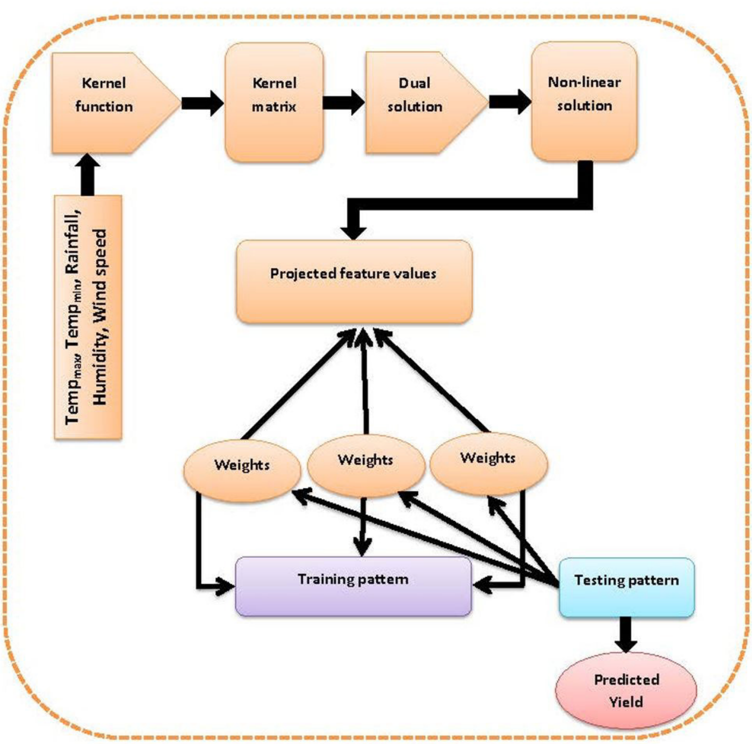

Figure 2. Schematic view of Kernel Ridge Regression (KRR) model.

3.2. Study area

Present study was designed in the Gallies forest division of district Abbottabad (Figure 3). The forest division Gallies are in District Abbottabad Khyber Pakhtunkhwa Province, Pakistan. The total area of Gallies are 147753.72 hectares, mostly consist of moist temperate forest (Ali, 2018). Northern latitudes of the Gallies are approximately 33°–55 and 34°-20, while eastern longitudes are 73°-20 and 63°-30. The total length of the forests present in the Gallies are about 39 km, extended from north to south. Main populated areas of the study area are Nathia Galli, Bagnotar, Donga Galli, Biran Galli and Bara Galli. The study

Table 1. Descriptive statistics of study site for Blue pine and Silver fir species.

Site	Geographic characteristics			Forest yield statistics						
	Longitude (°E)	Latitude (°N)	Elevation (m)	Species	Mean	Std.	Min	Max	Skew	Kurt.
Abbottabad	73.00	34.00	1256	Blue pine	135102.7	81319.7	7766.0	226226.0	-0.9	-1.1
				Silver fir	44262.2	32113.4	1747.0	108981.0	-0.1	-1.3

Climatological statistics (1962–2016)

	Mean	Std.	Min	Max	Skew.	Kurt.
Rainfall	99.9	35.4	3.1	146.6	-1.8	2.9
Min. temperature	29.0	133.5	8.2	992.0	7.3	53.9
Max. temperature	23.1	0.9	21.5	25.2	0.1	-0.7
Humidity at 5 am	71.3	4.8	61.0	79.8	-0.3	-0.5
Humidity at 5pm	49.7	3.3	43.6	57.2	0.3	-0.1
Wind speed at 5am	0.5	0.6	0.0	2.3	2.2	4.2
Wind speed at 5pm	1.6	0.8	0.6	4.2	1.8	4.2

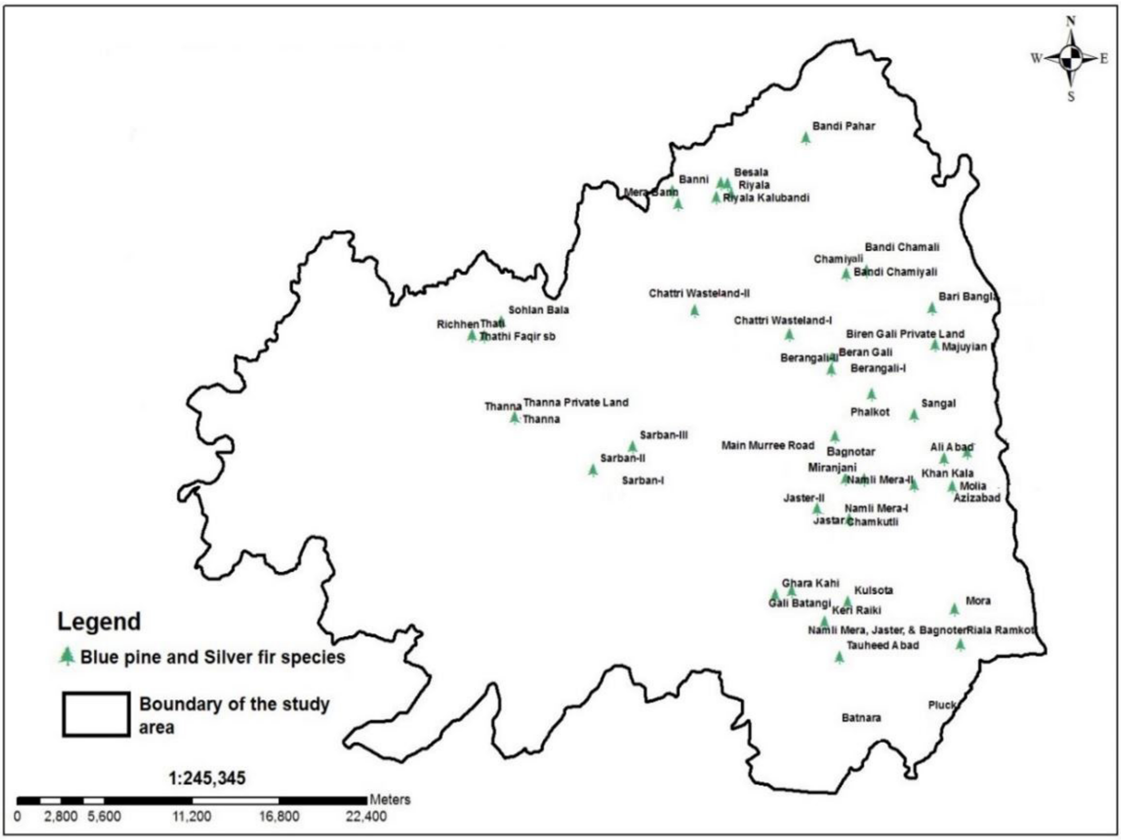

Figure 3. Location map of the study area.

area is surrounded by Abbottabad on its west, Haripur on the south, and Murree on the south east, while, Kunhar and Jhelum Rivers are located on its north and east respectively (Kayani et al., 2014).

The total population of the study area are 880666 with major tribes inhibiting are Awan, Gujjars, Jadoons and Rajput. The population mainly rely on agriculture and livestock rearing, having literacy rate of 30%. Climatic conditions vary from sub-tropical in the lower areas to moist temperate in upper regions of the study area. Gallies receive heavy snowfall in winter while summer season is pleasant and average rainfall ranges from 1200 mm to 1700 mm annually. Geological structure is composed of Triassic, Jurassic and Cretaceous rocks (Kayani et al., 2014). Gallies are categorized into three major forest types that are; Dry Sub-tropical Broad-Leaved Forest, Sub-tropical Pine Forest and Moist Temperate Forest. Major social hurdles of the area are poor literacy rate, bad infrastructure and poverty. Whereas, conversion of land, biodiversity loss and land sliding are the biophysical problems.

3.3. Model performance evaluation criteria

Performance of the RF and KRR models for the prediction of forest yield was evaluated from the independent validation data set by relating predicted values with observed values. The American Civil Engineering Society (Ali et al., 2018) recommends two categories of model assessment techniques, including statistics (or by comparing the simulated and observed data visually) and standardized performance metrics. For examining the dissimilarities among the factors maximum, minimum, mean, variance, skewness, kurtosis and standard deviation, statistical metrics are used however, standardized metrics are utilized to check the expected results against the observed data.

Following are the mathematical formulations (Prasad et al., 2017; Dawson et al., 2007; Legates and McCabe Junior, 1999).

• Correlation coefficient (r) is expressed as Equation 4:

$$r=\left(\frac{\sum_{i=1}^{N}\left(FY_{OBS,i}-\overline{FY}_{OBS,i}\right)\left(FY_{PRE,i}-\overline{FY}_{PRE,i}\right)}{\sqrt{\sum_{i=1}^{N}\left(FY_{OBS,i}-\overline{FY}_{OBS,i}\right)^{2}}\sqrt{\left(FY_{PRE,i}-\overline{FY}_{PRE,i}\right)^{2}}}\right) \quad (4)$$

• Willmott's index (WI) is expressed as Equation 5:

$$WI=1-\left[\frac{\sum_{i=1}^{N}\left(FY_{PRE,i}-FY_{OBS,i}\right)^{2}}{\sum_{i=1}^{N}\left(\left|FY_{PRE,i}-\overline{FY}_{OBS,i}\right|+\left|FY_{OBS,i}-\overline{FY}_{OBS,i}\right|\right)^{2}}\right],0\le WI\le 1 \quad (5)$$

• Nash-Sutcliffe coefficient (NS_E) is expressed as Equation 6:

$$NS_E=1-\left[\frac{\sum_{i=1}^{N}\left(FY_{OBS,i}-FY_{PRE,i}\right)^{2}}{\sum_{i=1}^{N}\left(\overline{FY}_{OBS,i}-\overline{FY}_{PRE,i}\right)^{2}}\right] \quad (6)$$

• Root mean square error ($RMSE$) is expressed as Equation 7:

$$RMSE=\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(FY_{PRE,i}-FY_{OBS,i}\right)^{2}} \quad (7)$$

• Mean absolute error (MAE) is expressed as Equation 8:

$$MAE=\frac{1}{N}\sum_{i=1}^{N}\left|\left(FY_{FOR,i}-FY_{OBS,i}\right)\right| \quad (8)$$

• Legates-McCabe's (LM) is expressed as Equation 9:

$$LM=1-\left[\frac{\sum_{i=1}^{N}\left|FY_{PRE,i}-FY_{OBS,i}\right|}{\sum_{i=1}^{N}\left|FY_{OBS,i}-\overline{FY}_{OBS,i}\right|}\right] \quad (9)$$

Where FY_{OBS} and FY_{PRE} are the observed and predicted i^{th} values of forest yield (FY), $\overline{FY}_{OBS}$ and $\overline{FY}_{PRE}$ are the observed and predicted means FY in the set of cross-validations (test) and N represent the reference point number in the test set. The performance metrics regarding physical reasoning, it can be deduced that the coefficient of correlation, confined by (0,1) where 0 = relatively poor to 1,0 = perfect model, labels the variance proportion in observed forest yield that is explained by the KRR and RF models (Deo and Şahin, 2017; Mohammadi et al., 2015). However, the r equation is based on the consideration of the linear relationship between FY_{OBS} and FY_{PRE} and is therefore imperfect in its ability to deliver a strong notation as it standardizes observed and predicted means and variances. Though, the $RMSE$ and MAE can provide better predictive information whereby $RMSE$ is used to measure the goodness-of-fit relevant to higher values while the MAE is not focused on large events or small scale but evaluates all deviations from the observed values equal in method and independent of the sign. It is important to note that although $RMSE$ can evaluate the model with a higher skill level than the correlation coefficient, this measure is calculated from the squared variances. Therefore, the performance evaluation is predetermined in favor of higher magnitude events, which in maximum cases have the large error and are unresponsive to lower magnitude sequences (Dawson et al., 2007). Hence, due to occasional large errors, the $RMSE$ may be more sensitive than other performance measures because the squaring process can lead to very large errors leading to disproportionate weighting (Legates and McCabe Junior, 1999). To solve this problem, the Willmott's index (WI) was calculated by seeing the proportion of the mean squared error instead of the square of the differences, which offers an advantage over the values of r, $RMSE$ and MAE. Considering the geographical variation between the current study sites, which may produce differences in the distribution of forest yield data, the relative root means square error ($RRMSE$) has also been calculated (Mohammadi et al., 2015; Prasad et al., 2017) to evaluate and compare the model over different geographical locations. According to (Ertekin and Yaldiz, 2000), the degree of accuracy of a model is excellent if $RRMSE < 10\%$, good if $10\% < RRMSE < 20\%$, fair if $20\% < RRMSE < 30\%$, and bad if $RRMSE > 30\%$. Nash-Sutcliffe efficiency (NS_E) is another standardized metric that determines the relative magnitude of the residual variance of the predicted data relative to measured variance. Legates-McCabes (LM) is the most innovative and commanding metric than WI and NS_E, which uses the comparison fit to evaluate WI and NS_E. LM can be robust enough to evaluate outcomes by addressing r weaknesses and using WI and NS_E baselines, as well as a $RMSE$ and MAE rating (Legates and McCabe Junior, 1999).

3.4. Model development

The RF and KRR models were developed in MATLAB R2016b programming environment (The Math Works Inc. USA). All the simulations were obtained on 2.93 GHz dual-core PC with Pentium 4 operating system. The models are developed in the following steps:

Data partitioning

The data are partitioned straightly 70% and 30% prior into training and testing subsets, respectively. Antecedent time lagged inputs (*i.e.*, rainfall, wind speed, wind direction, minimum and maximum temperature and humidity) at (t – 1) are used to develop the models to predict yearly forest yields.

Normalization process

The data are normalized between [0, 1] using Equation 10 (Hsu et al., 2003).

$$\Lambda_{NORM} = \frac{(\Lambda - \Lambda_{MIN})}{(\Lambda_{MAX} - \Lambda_{MIN})} \quad (10)$$

In Equation 10, Λ represents the input/output, Λ_{MIN} = the minimum value, Λ_{MAX} = the maximum value of the data and Λ_{NORM} = the corresponding normalized numeric value.

3.5. RF model

In the final phase of the modelling, the RF model is then applied to predict a year ahead forest yield by incorporating the environmental based input variables. After incorporating the input variables at (t – 1) lags into the RF model, different types of parameters were tuned that include the number of trees and number of predictors to train the model. The RF model is validated/tested independently. The performance of RF is benchmarked with KRR model. Different types of kernals (such as linear, gaussian, polynomial) are used to get the optimum KRR model.

4. Results and Discussion

4.1. Results

4.1.1. Box plots

In the present study boxplots of the Random Forest vs Kernel ridge regression models were designed to find out prediction error (PE) for the yield of blue pine and silver fir in the testing period of 1996 to 2016 as shown in Figure 4. Green box shows random forest model, blue box represents kernel ridge regression model, while the red colored + sign in both boxes show the outliers which signify the extreme magnitudes of the simulation error in the testing period. PE is the difference between the simulated values and observed values. If the difference between these values is more the model gives poor prediction, and when the difference is less the prediction will be better and model will be considered as best. Similarly, when the box size is bigger the model will perform poor, and when box is smaller the model will be good. These boxplots are showing that

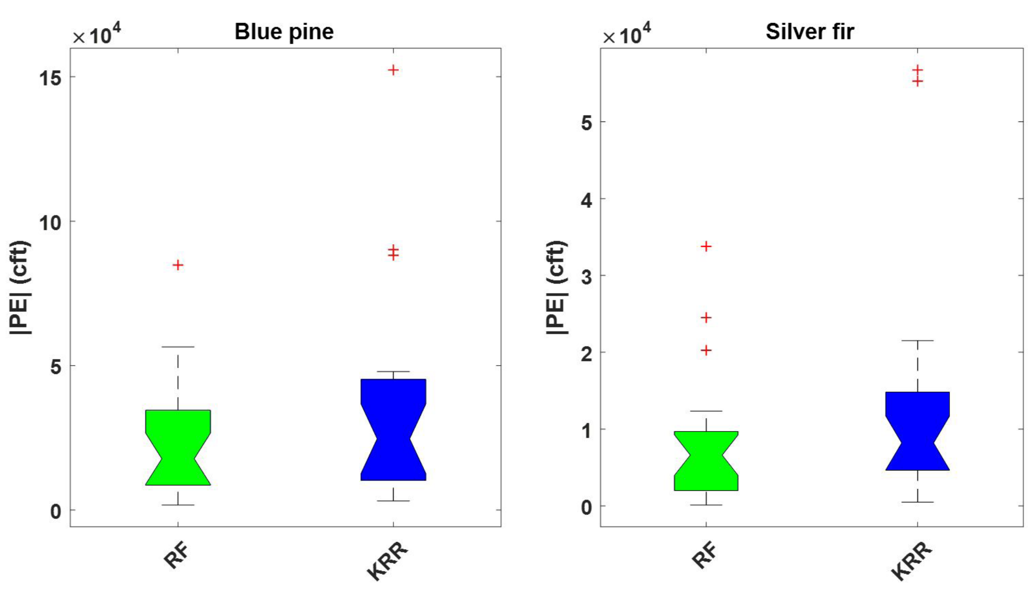

Figure 4. Box-plots of the Predicted error |PE| (cft) in testing period (1996-2016) for the RF and KRR models between the predicted and observed yields of Blue pine and Silver fir species.

the box is smaller, and PE is less in random forest model for blue pine specie in response to the kernel ridge regression model whose box is bigger and PE is also more. Similarly, for silver fir specie the random forest model again showed less PE and smaller box than the KRR model. Therefore, by observing (Figure 4), RF model performed better than the KRR model for both species.

4.1.2. Polar plots

In the present study polar plots were designed which demonstrate the Predicted error (PE) in Cubic feet (cft) for the RF and KRR models between the predicted and observed yields of blue pine and silver fir species in the testing period (1996-2016), as shown in (Figure 5). The green dots display the PE of RF model and the blue dots are showing the PE of KRR model which can be seen in (Figure 5). The model which has less predicted error will be considered as a better model. The results revealed that PE for the years 1997, 1998, 1999, 2000, 2001, 2004, 2005, 2007, 2008, 2009, 2011, 2013, 2014 and 2015 were significantly low for the RF model between the predicted and observed yields of blue pine. While, KRR model showed same results for blue pine in the years of 1996, 2002, 2003, 2006, 2010, 2012, and 2016. Similarly, PE was less in 1997, 1999, 2000, 2001, 2002, 2004, 2005, 2007, 2008, 2009, 2011, 2013, 2014, 2015, and 2016 in RF model in response to KRR model which revealed less magnitude of predicted error in 1996, 1998, 2003, 2006, 2010, and 2012 between predicted and observed yields silver fir. When both RF and KRR models were compared based on these results shown in (Figure 5), the RF model performed better presenting less magnitude of error than the KRR model.

4.1.3. Empirical cumulative distribution function (ECDF)

In Figure 6, prediction performance of RF and KRR models were tested by plotting ECDF of the absolute PE between observed and predicted yields of blue pine and silver fir species in testing period (1996-2016). In the following Figure 6, the green line represents RF model, red line shows KRR model, Y-axis is ECDF ranging from 0 to 1, and X-axis is the PE, which ranges from 0 to 2 for blue pine and 0 to 6 for silver fir. The model having minimum error at ECDF 1 will be considered as best model. The results revealed that RF model bears 0.7 PE while, for KRR model the PE is 1.5 between the predicted and observed yields of blue pine. Similarly, for silver fir the PE's were 3.4 and 5.6 for RF and KRR models respectively. Therefore, the (Figure 6) clearly showed that RF model was more precise than the KRR model in prediction for the yield of both blue pine and silver fir species.

4.1.4. Taylor diagram

Taylor diagram was made as shown in (Figure 7), which quantified the similarities between the predicted and observed yields of blue pine and silver fir species in terms of their standard deviation and correlation for RF and KRR models. The Taylor diagram was made for the testing period of 20 years (1996-2016) which provided a more

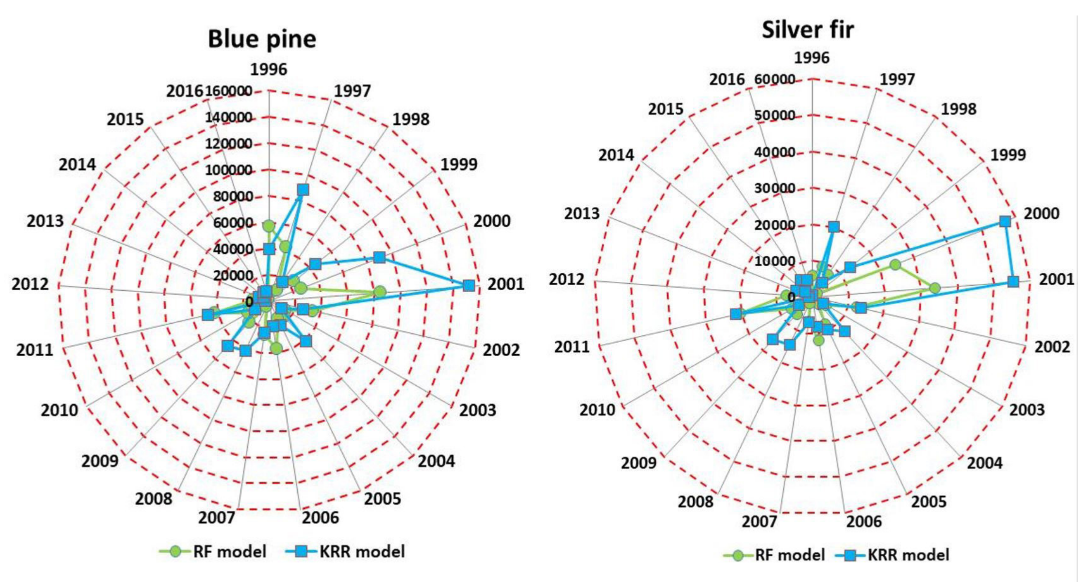

Figure 5. Polar plots show the Predicted error |PE| (cft) in testing period (1996-2016) for the RF and KRR models between the predicted and observed yields of Blue pine and Silver fir species.

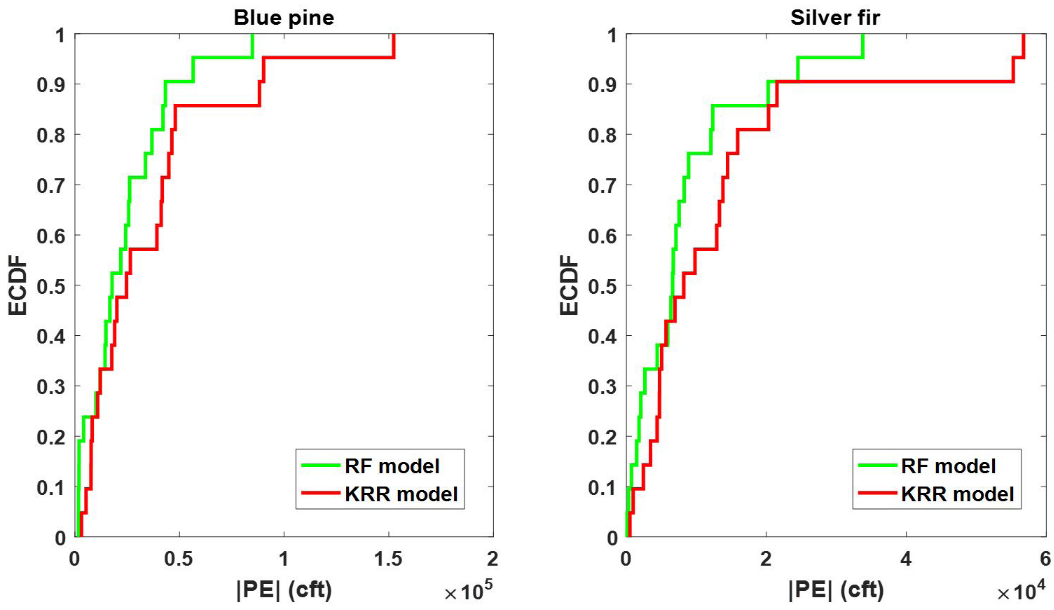

Figure 6. Empirical cumulative distribution function (ECDF) of the Predicted error |PE| (cft) in testing period for the RF and KRR models between the predicted and observed yields of Blue pine and Silver fir species.

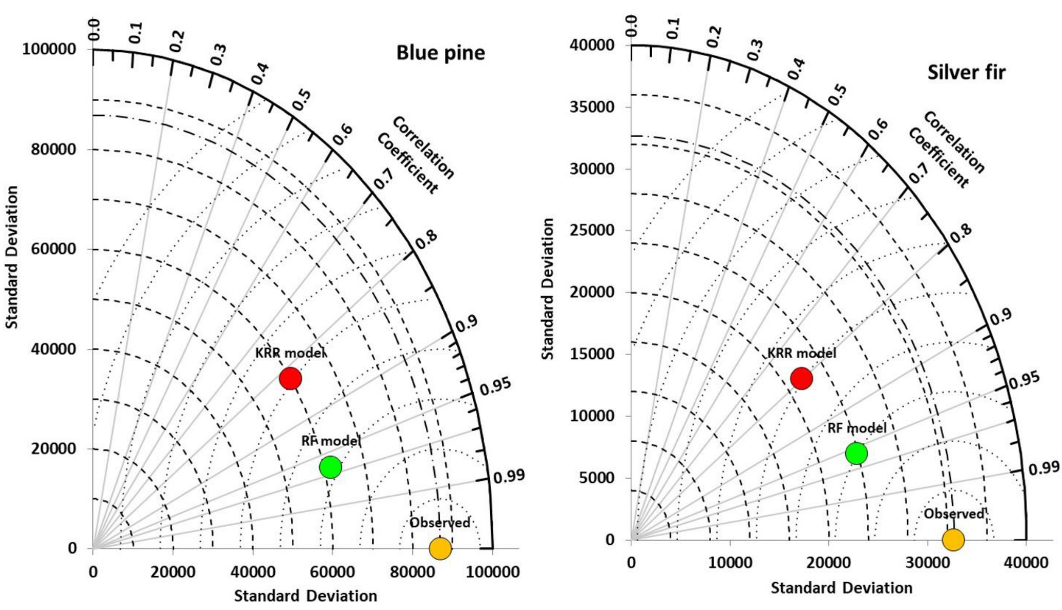

Figure 7. Taylor diagram showing the correlation coefficient between the predicted and observed yields (Blue pine and Silver fir) (cft) and standard deviation for the RF and KRR models.

accurate and conclusive statement about the statistical results of how well the predicted yield matched with the observed yield in term of their correlation. Correlation of observed yield is 100% or 1 that can be seen in the following figure. In Figure 7, the red dot shows predicted yield of KRR model, green dot represents RF model, and observed yield is shown by the yellow dot. The model having minimum distance between the correlation of simulated yield and observed yield will be evaluated as better model. The results showed that the correlation coefficient for predicted yield of blue pine for RF model was 0.97 and 0.8 for KRR model. Similarly, for silver fir the correlation of RF model was 0.95 followed by KRR model which was 0.8. RF model was closer to the observed yield in both species as their correlation was 0.97 and 0.95 respectively, compared to KRR model having correlation of 0.8 and 0.8. So, RF model again performed better than the KRR model in terms of their correlation.

4.1.5. Willmott's index (Wi), Nash-Sutcliffe (Ns_e) and Legates-Mccabe's (Lm) agreement

In the present project, the accuracy of RF and KRR model in testing period for both species (blue pine and silver fir) were evaluated based on *WI*, NS_E and *LM* shown in Table 2. The model having higher value in terms of *WI*, NS_E and *LM* is considered more accurate than the other model. Current results revealed that for blue pine and silver fir the proposed RF model attained the highest values of *WI* = 0.854 and 0.845, NS_E = 0.866 and 0.864 and *LM* = 0.693 and 0.704 respectively followed by KRR model having values of *WI* = 0.713 and 0.682, NS_E = 0.646 and 0.602, and *LM* = 0.529 and 0.521 respectively. The result showed that RF model was more accurate in prediction in response to the KRR model, and blue pine attained higher accuracy based on higher values of WI, NS_E and LM agreement followed by silver fir.

4.1.6. Root mean square error (Rmse), Mean absolute error (MAE) and coefficient of determination (r)

The accuracy of the developed RF model was evaluated in comparison with KRR model in terms of *RMSE*, *MAE* and *r* for the prediction of blue pine and silver fir species as revealed in Table 3. The RF model applied for the simulation of blue pine acquired higher values of *RMSE* = 31042.6 *cft*, *MAE* = 23461.6 *cft* and *r* = 0.964, followed by KRR model where *RMSE* = 11761.1 *cft*, *MAE* = 8277.0 *cft* and *r* = 0.80. Similarly, when applied for silver fir prediction, RF model again yielded higher values of *RMSE* = 50443.5 *cft*, *MAE* = 35960.7 *cft* and *r* = 0.957, followed by KRR model having *RMSE* = 20117.3 *cft*, *MAE* = 13382.4 *cft* and *r* = 0.799. Based on higher values of *RMSE, MAE* and *r*, it is evident that RF model outperformed KRR model in the yield prediction of both blue pine and silver fir.

5. Discussion

Deforestation rate in Pakistan is considered second highest in the world. World Conservation Union (IUCN) has investigated that abrupt increase in population growth would leads to 3% increase in wood use in Pakistan annually. Hence it is predicted that if Pakistan continues the same rate of deforestation, there forests will be vanished within coming ten or fifteen years (Ali and Benjaminsen, 2004). Pakistan forest cover is 4.2 million hectares which is about 4.8% of the overall land area of the country (Zaman and Ahmad, 2012). Due to rapid increase in population, forest cover is also decreasing, because the local people depend on forest resources i.e., house construction, ecotourism, wooden furniture manufacture, fuelwood, and medicinal plants extraction. From 1996 to 2000 about 2.35 million m^3 round wood was extracted for industrial use in Pakistan (Hussain et al., 2017). According to global climate risk index 2019, Pakistan is the 7th most vulnerable country to climate change due to global warming (Eckstein et al., 2019).

Data intelligent models are an important tool in decision making for agriculture, hydrology, forest and wildlife to resolve issues caused due to global warming (Ali et al., 2018). Rapid changes in the climatic conditions are modifying tree growing environments by altering the site conditions. It is expected that the forest resources will be more influenced by climate change than the other natural resources (Ashraf et al., 2015). Forest resources such as timber, fuelwood, medicinal plants, and wood production are limited in Pakistan and there is a prior need to manage those resources for the future (Zaman and Ahmad, 2012). For the better management of forest, we need advance and reliable predictive growth and yield model. In the present study two models such as RF and KRR model were developed for two tree species (Blue pine and silver fir) in Gallies forest division, Abbottabad to predict forest yield by using historical forest yield data and environmental variables from 1966 to 2016, as input predictors as can be seen in Appendix A. RF model was compared with KRR model in the current study, the RF model showed better results based on higher values of RMSE, MAE and R. Due to the better performance of RF model it can be applied on other forest types of Pakistan to predict and manage forest yield as this department has been neglected so far.

Table 2. Performance of **RF** *vs.* KRR models in testing period using Willmott's index (*WI*), Nash-Sutcliffe (NS_E) and Legates-McCabe's (*LM*) agreement.

Species	RF model			KRR model		
	WI	NS_E	***LM***	***WI***	NS_E	***LM***
Blue pine	0.854	0.866	0.693	0.713	0.646	0.529
Silver fir	0.845	0.864	0.704	0.682	0.602	0.521

Table 3. Testing performance of **RF** *vs.* KRR models measured by root mean square error (*RMSE*), mean absolute error (*MAE*), coefficient of determination (*r*).

Species	RF model			KRR model		
	RMSE (cft)	***MAE (cft)***	***r***	***RMSE (cft)***	***MAE (cft)***	***r***
Blue pine	31042.6	23461.6	0.964	11761.1	8277.0	0.80
Silver fir	50443.5	35960.7	0.957	20117.3	13382.4	0.799

In the present study yield of only two species were predicted, we can use the proposed model for the prediction of multiple forest species. Data regarding soil condition can be added to predict the forest yield as it influences the productivity of forest. Further data about uncontrolled grazing can be added in the follow-up work which is an important variable for yield prediction as it is an issue for sustainable forest management. Other variables such as solar radiation, light intensity, drought and geology of the site which directly affect the forest yield can also be coupled with meteorological data in the follow-up work to achieve better results regarding forest yield prediction. RF model and KRR model have not been used in forest yield prediction globally so far but some other models were used such as artificial neural network (ANN) and regression-based models were used by (Ashraf et al., 2013) for the development of volume increment model and individual tree based basal area (BA) (Ashraf et al., 2012), developed an individual-tree-based model (JABOWA-3) for the prediction of forest growth and yield.

In terms of model optimization for forest yield prediction, we can achieve better prediction by hybridizing different models rather than using single models. Therefore, the proposed model could be optimized with ensemble method (Ali et al., 2018; Lei and Wan, 2012; Yun et al., 2008) to attain more precise results. Another optimization method like the ANFIS algorithms can be used for forest yield prediction which is more precise and powerful (Yaseen et al., 2018). Moreover, some other more advanced models such as Optimization of Particle Swarm (Chen et al., 2005; Zhisheng, 2010), Ensemble methods (Dietterich, 2002), chaos theory, Genetic algorithms (Davis, 1991) and Firefly algorithms (Yang, 2010) can be coupled with recently explored copulas (Nguyen-Huy et al., 2018; Nelsen, 2003) which possibly will produce decent results because of their optimization capability. Least square support vector machine (Yuan et al., 2017) based copula (LSSVM-copula) and autoregressive fractionally integrated moving average-based copula (ARFIMA-copula) models can be utilized for the prediction of forest yield. Yield of different forest types in Pakistan can also be predicted by Extreme learning machine developed by Huang et al. (2006) and Support vector machine studied by (Cortes and Vapnik, 1995). While the obstacle of model uncertainty is avoided by the standard statistical approaches which causes over-fitting and makes the decisions riskier, Bayesian model averaging (BMA) techniques (Raftery et al., 2005) can model uncertainty for more precise predictions. Hence, BMA techniques can be utilized to model uncertainty in forest yield that is resulted from different factors like extreme weather conditions, missing climate data and the more likely climate change influence. To enhance the scope of this study multi-resolution tools like frequency resolution could be utilized. Similarly, maximum overlap discrete wavelet transformation (Prasad et al., 2017; Khalighi et al., 2011), empirical mode decomposition EMD (Rilling et al., 2003; Al-Musaylh et al., 2018), and singular value decomposition (De Lathauwer et al., 1994), are superior models and can be utilized for the prediction of forest yield. Feature selection techniques (Salcedo-Sanz et al., 2018; Guyon and Elisseeff, 2003) is another way of model optimization for the simulation of forest yield with more precision and accuracy.

6. Conclusions and Recommendations

This study aimed to develop data driven models for the prediction of forest yield under climate change in the Gallies forests, Pakistan. In the present work RF and KRR models were developed using yield data of two species (Blue pine and Silver fir) as an objective variable and climate data (temperature, humidity, rainfall and wind speed) as predictive variables. Both models were compared based on their prediction accuracy, and it was found that the RF model outperformed the KRR model. The performance of RF model in comparison with KRR model was evaluated for blue pine and silver fir species by using the most advanced normalized metrics of Willmott's index (*WI*), Nash-Sutcliffe (NS_E), Legates-McCabe's (*LM*) agreement, relative root mean square error (*RRMSE*) and coefficient of determination (*r*). Current results revealed that for blue pine and silver fir the proposed RF model attained the maximum values of *WI* = 0.854 and 0.845, NS_E = 0.866 and 0.864 and *LM* = 0.693 and 0.704 respectively followed by KRR model having values of *WI* = 0.713 and 0.682, NS_E = 0.646 and 0.602, and *LM* = 0.529 and 0.521 respectively. Moreover, RF model yielded relative percentage error of 50.3% for blue pine and 52.0% for silver fir while KRR yielded 81.7% for blue pine and 88.9% for silver fir. Whereas, RF model yielded the coefficient of determination (*r*) values of 0.964 for blue pine and 0.957 for silver fir in comparison with the KRR model having values of 0.80 for blue pine and 0.799 for silver fir in the Gallies forest division. This was the ever first study on forest yield prediction under climate change scenarios in Pakistan and it will contribute to the climate change adaptation activities based on sustainable forest management in Pakistan. This study will provide insight for future management and mitigation of climate change to save or protect the perilous effects of climate change on our forest yield and overall health and vigor. The proposed model can be applied to other forest types in other region of Pakistan as it can help forest department and forest managers in the management of forest and to address chronic effects of changing climate in a better way. Thus, it is highly recommended that RF model can be utilized for the prediction of forest yield in the future.

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Appendix A. Environmental and forest yield variables Information's for Gallies Forest Division, Pakistan.

Table 1A. Environmental and forest yield variables in the Gallies forest division of Abbottabad, Pakistan.

Year	Rainfall	min temp	max temp	humidity at 5am	humidity at 5pm	Wind speed at 5am	Wind speed at 5pm	Yield of Blue pine (Cft)	Yield of Silver fir (Cft)
1963	95.85833333	13.08333333	23.93333333	63.33333333	47.66666667	0.489692982	1.609868421	189779	35697
1964	102.425	12.44166667	23.19166667	64.08333333	47	0.489692982	1.609868421	179295	47212
1965	103.7666667	12.31666667	22.7	64.5	48.58333333	0.489692982	1.609868421	149709	56398
1966	121.5916667	12.50833333	23.44166667	63	47.66666667	0.489692982	1.609868421	157929	70476
1967	123.3833333	12.15	23.10833333	65	50.41666667	0.489692982	1.609868421	180610	47937
1968	105.7333333	12.2	22.99166667	66	48.83333333	0.489692982	1.609868421	208825	8537
1969	94.05	13.075	23.75833333	61	45	0.489692982	1.609868421	207907	18456
1970	96.56666667	13.3	24.025	62.16666667	43.58333333	0.489692982	1.609868421	190237	41527
1971	102.5166667	13.20833333	23.85833333	61.83333333	43.75	0.489692982	1.609868421	190191	39118
1972	107.7416667	11.71666667	22.55	66.33333333	45.5	0.489692982	1.609868421	174459	53809
1973	125.5	11.53333333	22.25833333	71.83333333	52.91666667	2.241666667	3.791666667	182191	45041
1974	96.69166667	10.81666667	22.45	68.08333333	46.66666667	2.258333333	4.166666667	181577	55669
1975	124.4	10.59166667	21.80833333	68.33333333	46.41666667	2.283333333	4.091666667	183270	44461
1976	131.6833333	10.425	21.86666667	70.83333333	49.75	1.991666667	2.775	199856	20508
1977	133.2166667	10.95833333	22.35833333	73.58333333	51.25	1.708333333	2.358333333	150883	79156
1978	134.5666667	10.80833333	22.3	71.5	54.16666667	1.625	2.233333333	161670	76123
1979	100.825	10.50833333	22.325	72.83333333	52.66666667	0.691666667	2.725	159791	77655
1980	111.3833333	10.65	22.61666667	72	53.33333333	0.483333333	2.05	148012	76888
1981	118.7666667	10.16666667	22.525	73.83333333	50.58333333	0.216666667	1.608333333	158100	74135
1982	118.5666667	9.991666667	21.475	75.83333333	53.91666667	0.175	1.425	168875	79361
1983	113.3416667	9.825	21.50833333	74.75	52.91666667	0.283333333	1.35	188121	66957
1984	115.2916667	10.325	22.53333333	70.25	48.08333333	0.191666667	1.233333333	146026	108981
1985	103.2666667	10.95	23.25833333	69.66666667	47.33333333	0.333333333	1.366666667	182683	72254
1986	133.5583333	10.05	21.80833333	75.16666667	52	0.3	1.158333333	182047	75044
1987	118.2416667	10.39166667	23.3	72.16666667	48.41666667	0.416666667	1.375	215631	40471
1988	107.8416667	11.31666667	23.59166667	67.91666667	46.75	0.341666667	2.05	226226	29029

Table 1A. Continued...

Year	Rainfall	min temp	max temp	humidity at 5am	humidity at 5pm	Wind speed at 5am	Wind speed at 5pm	Yield of Blue pine (Cft)	Yield of Silver fir (Cft)
1989	101.8583333	10.45	22.4	67.5	44.25	0.341666667	1.55	196879	58658
1990	141.9	11.525	22.91666667	73.08333333	52.33333333	0.325	1.058333333	205779	50288
1991	124.9583333	10	22.35	73.66666667	53.08333333	0.191666667	0.825	179081	76633
1992	146.6166667	9.941666667	22.05833333	74.58333333	55.66666667	0.125	1.025	163330	90865
1993	91.54166667	9.733333333	23.19166667	68.66666667	48.25	0.25	0.975	169879	89971
1994	133.3333333	9.058333333	22.1	77	57.16666667	0.141666667	0.775	202342	51273
1995	102.8666667	8.233333333	22.23333333	75.91666667	57	0.258333333	1.025	217604	48021
1996	117.425	10.575	22.53333333	72.91666667	51.5	0.208333333	0.858333333	205930	50447
1997	130.2916667	10.41666667	21.50833333	76.41666667	56.66666667	0.041666667	0.558333333	198549	59707
1998	106.7833333	11.2	23.66666667	71.08333333	51.08333333	0.008333333	0.608333333	177930	75031
1999	92	11.78333333	23.96666667	71.08333333	49	0.041666667	0.616666667	193511	70078
2000	95.18333333	10.84166667	24.10833333	73.91666667	48.16666667	0.058333333	1.183333333	189073	95949
2001	78.33333333	10.19166667	24.65833333	72.58333333	45.16666667	0.175	1	207833	77931
2002	86.46666667	11.14166667	24.44166667	73.25	45.25	0.133333333	2.3	8721	2687
2003	126.1166667	10.76666667	23.36666667	78	50.33333333	0.133333333	1.6	7956	3267
2004	97.60833333	11.24166667	24.33333333	76.16666667	48.5	0.125	1.583333333	7766	4335
2005	97.05	10.18333333	22.85	78.16666667	50.41666667	0.05	1.516666667	8433	1951
2006	112.225	11.15833333	23.575	79.75	51.75	0.083333333	1.425	8478	1747
2007	99.50833333	10.525	24.06666667	76.41666667	50	0.108333333	1.416666667	8522	3028
2008	117.3083333	10.5	23.60833333	79.58333333	51.83333333	0.091666667	1.35	7937	3844
2009	85.525	10.025	24.125	76.75	47.83333333	0.108333333	1.25	7973	2547
2010	97.86666667	10.25	24.78333333	78.66666667	49.91666667	0.066666667	0.916666667	8130	4127
2011	50.59	992	23.99	69.75431034	49.07758621	0.489692982	1.609868421	8187	3824
2012	3.320404153	9.592259918	23.21532783	69.75431034	49.07758621	0.489692982	1.609868421	8346	3560
2013	4.191148233	10.21493367	23.78962856	69.75431034	49.07758621	0.489692982	1.609868421	8355	2376
2014	3.630638121	10.01655082	23.28994006	69.75431034	49.07758621	0.489692982	1.609868421	8597	2068
2015	4.247571994	10.10961742	23.32796683	69.75431034	49.07758621	0.489692982	1.609868421	8087	3476
2016	3.066825794	10.96794124	25.1757221	69.75431034	49.07758621	0.489692982	1.609868421	8440	3002

Table 2A. Data t-1.

95.8583	13.0833	23.9333	63.33333333	47.66666667	0.489692982	1.609868421	179295
102.425	12.4417	23.1917	64.08333333	47	0.489692982	1.609868421	149709
103.767	12.3167	22.7	64.5	48.58333333	0.489692982	1.609868421	157929
121.592	12.5083	23.4417	63	47.66666667	0.489692982	1.609868421	180610
123.383	12.15	23.1083	65	50.41666667	0.489692982	1.609868421	208825
105.733	12.2	22.9917	66	48.83333333	0.489692982	1.609868421	207907
94.05	13.075	23.7583	61	45	0.489692982	1.609868421	190237
96.5667	13.3	24.025	62.16666667	43.58333333	0.489692982	1.609868421	190191
102.517	13.2083	23.8583	61.83333333	43.75	0.489692982	1.609868421	174459
107.742	11.7167	22.55	66.33333333	45.5	0.489692982	1.609868421	182191
125.5	11.5333	22.2583	71.83333333	52.91666667	2.241666667	3.791666667	181577
96.6917	10.8167	22.45	68.08333333	46.66666667	2.258333333	4.166666667	183270
124.4	10.5917	21.8083	68.33333333	46.41666667	2.283333333	4.091666667	199856
131.683	10.425	21.8667	70.83333333	49.75	1.991666667	2.775	150883
133.217	10.9583	22.3583	73.58333333	51.25	1.708333333	2.358333333	161670
134.567	10.8083	22.3	71.5	54.16666667	1.625	2.233333333	159791
100.825	10.5083	22.325	72.83333333	52.66666667	0.691666667	2.725	148012
111.383	10.65	22.6167	72	53.33333333	0.483333333	2.05	158100
118.767	10.1667	22.525	73.83333333	50.58333333	0.216666667	1.608333333	168875
118.567	9.99167	21.475	75.83333333	53.91666667	0.175	1.425	188121
113.342	9.825	21.5083	74.75	52.91666667	0.283333333	1.35	146026
115.292	10.325	22.5333	70.25	48.08333333	0.191666667	1.233333333	182683
103.267	10.95	23.2583	69.66666667	47.33333333	0.333333333	1.366666667	182047
133.558	10.05	21.8083	75.16666667	52	0.3	1.158333333	215631
118.242	10.3917	23.3	72.16666667	48.41666667	0.416666667	1.375	226226
107.842	11.3167	23.5917	67.91666667	46.75	0.341666667	2.05	196879
101.858	10.45	22.4	67.5	44.25	0.341666667	1.55	205779
141.9	11.525	22.9167	73.08333333	52.33333333	0.325	1.058333333	179081

Table 2A. Continued...

124.958	10	22.35	73.66666667	53.08333333	0.191666667	0.825	163330
146.617	9.94167	22.0583	74.58333333	55.66666667	0.125	1.025	169879
91.5417	9.73333	23.1917	68.66666667	48.25	0.25	0.975	202342
133.333	9.05833	22.1	77	57.16666667	0.141666667	0.775	217604
102.867	8.23333	22.2333	75.91666667	57	0.258333333	1.025	205930
117.425	10.575	22.5333	72.91666667	51.5	0.208333333	0.858333333	198549
130.292	10.4167	21.5083	76.41666667	56.66666667	0.041666667	0.558333333	177930
106.783	11.2	23.6667	71.08333333	51.08333333	0.008333333	0.608333333	193511
92	11.7833	23.9667	71.08333333	49	0.041666667	0.616666667	189073
95.1833	10.8417	24.1083	73.91666667	48.16666667	0.058333333	1.183333333	207833
78.3333	10.1917	24.6583	72.58333333	45.16666667	0.175	1	8721
86.4667	11.1417	24.4417	73.25	45.25	0.133333333	2.3	7956
126.117	10.7667	23.3667	78	50.33333333	0.133333333	1.6	7766
97.6083	11.2417	24.3333	76.16666667	48.5	0.125	1.583333333	8433
97.05	10.1833	22.85	78.16666667	50.41666667	0.05	1.516666667	8478
112.225	11.1583	23.575	79.75	51.75	0.083333333	1.425	8522
99.5083	10.525	24.0667	76.41666667	50	0.108333333	1.416666667	7937
117.308	10.5	23.6083	79.58333333	51.83333333	0.091666667	1.35	7973
85.525	10.025	24.125	76.75	47.83333333	0.108333333	1.25	8130
97.8667	10.25	24.7833	78.66666667	49.91666667	0.066666667	0.916666667	8187
50.59	992	23.99	69.75431034	49.07758621	0.489692982	1.609868421	8346
3.3204	9.59226	23.2153	69.75431034	49.07758621	0.489692982	1.609868421	8355
4.19115	10.2149	23.7896	69.75431034	49.07758621	0.489692982	1.609868421	8597
3.63064	10.0166	23.2899	69.75431034	49.07758621	0.489692982	1.609868421	8087
4.24757	10.1096	23.328	69.75431034	49.07758621	0.489692982	1.609868421	8440

Table 3A. Normal Data t-1.

0.64578	**0.00493**	**0.74307**	**0.12444**	**0.30061**	**0.21159**	**0.29142**	**0.78517**
0.69161	0.00428	0.51889	0.16444	0.25153	0.21159	0.29142	0.64974
0.70097	0.00415	0.37028	0.18667	0.3681	0.21159	0.29142	0.68737
0.82536	0.00435	0.59446	0.10667	0.30061	0.21159	0.29142	0.79119
0.83787	0.00398	0.4937	0.21333	0.50307	0.21159	0.29142	0.92035
0.71469	0.00403	0.45844	0.26667	0.3865	0.21159	0.29142	0.91614
0.63316	0.00492	0.69018	0	0.10429	0.21159	0.29142	0.83526
0.65072	0.00515	0.77078	0.06222	0	0.21159	0.29142	0.83505
0.69225	0.00506	0.7204	0.04444	0.01227	0.21159	0.29142	0.76304
0.72871	0.00354	0.32494	0.28444	0.1411	0.21159	0.29142	0.79843
0.85264	0.00335	0.23678	0.57778	0.68712	0.98168	0.89607	0.79562
0.6516	0.00263	0.29471	0.37778	0.22699	0.98901	1	0.80337
0.84496	0.0024	0.10076	0.39111	0.20859	1	0.97921	0.87929
0.89579	0.00223	0.11839	0.52444	0.45399	0.87179	0.61432	0.65512
0.90649	0.00277	0.267	0.67111	0.56442	0.74725	0.49885	0.7045
0.91591	0.00262	0.24937	0.56	0.77914	0.71062	0.4642	0.69589
0.68044	0.00231	0.25693	0.63111	0.66871	0.30037	0.60046	0.64198
0.75412	0.00246	0.34509	0.58667	0.71779	0.20879	0.41339	0.68815
0.80565	0.00197	0.31738	0.68444	0.51534	0.09158	0.29099	0.73748
0.80425	0.00179	0	0.79111	0.76074	0.07326	0.24018	0.82557
0.76779	0.00162	0.01008	0.73333	0.68712	0.12088	0.2194	0.63288
0.7814	0.00213	0.3199	0.49333	0.33129	0.08059	0.18707	0.80068
0.69748	0.00276	0.53904	0.46222	0.27607	0.14286	0.22402	0.79777
0.90887	0.00185	0.10076	0.75556	0.61963	0.12821	0.16628	0.9515
0.80198	0.00219	0.55164	0.59556	0.35583	0.17949	0.22633	1
0.72941	0.00313	0.6398	0.36889	0.23313	0.14652	0.41339	0.86566
0.68765	0.00225	0.2796	0.34667	0.04908	0.14652	0.27483	0.9064
0.96708	0.00335	0.43577	0.64444	0.64417	0.13919	0.13857	0.78419

Table 3A. Continued...

0.84886	0.0018	0.26448	0.67556	0.69939	0.08059	0.0739	0.71209
1	0.00174	0.17632	0.72444	0.88957	0.05128	0.12933	0.74207
0.61566	0.00152	0.51889	0.40889	0.34356	0.10623	0.11547	0.89067
0.9073	0.00084	0.18892	0.85333	1	0.05861	0.06005	0.96053
0.69469	0	0.22922	0.79556	0.98773	0.10989	0.12933	0.9071
0.79628	0.00238	0.3199	0.63556	0.58282	0.08791	0.08314	0.87331
0.88608	0.00222	0.01008	0.82222	0.96319	0.01465	0	0.77893
0.72202	0.00302	0.66247	0.53778	0.55215	0	0.01386	0.85025
0.61885	0.00361	0.75315	0.53778	0.39877	0.01465	0.01617	0.82993
0.64107	0.00265	0.79597	0.68889	0.33742	0.02198	0.17321	0.91581
0.52348	0.00199	0.96222	0.61778	0.11656	0.07326	0.1224	0.00437
0.58024	0.00296	0.89673	0.65333	0.1227	0.05495	0.48268	0.00087
0.85694	0.00258	0.57179	0.90667	0.49693	0.05495	0.28868	0
0.65799	0.00306	0.86398	0.80889	0.36196	0.05128	0.28406	0.00305
0.6541	0.00198	0.41562	0.91556	0.50307	0.01832	0.26559	0.00326
0.76	0.00297	0.63476	1	0.60123	0.03297	0.24018	0.00346
0.67125	0.00233	0.78338	0.82222	0.47239	0.04396	0.23788	0.00078
0.79547	0.0023	0.64484	0.99111	0.60736	0.03663	0.2194	0.00095
0.57367	0.00182	0.80101	0.84	0.31288	0.04396	0.19169	0.00167
0.6598	0.00205	1	0.94222	0.46626	0.02564	0.09931	0.00193
0.32987	1	0.7602	0.4669	0.40448	0.21159	0.29142	0.00265
0	0.00138	0.52604	0.4669	0.40448	0.21159	0.29142	0.0027
0.00608	0.00201	0.69964	0.4669	0.40448	0.21159	0.29142	0.0038
0.00216	0.00181	0.5486	0.4669	0.40448	0.21159	0.29142	0.00147
0.00647	0.00191	0.56009	0.4669	0.40448	0.21159	0.29142	0.00309