

Spatio-temporal variations of land surface temperature and precipitation due to climate change in the Jhelum river basin, India

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सार – इस शोध पत्र में भारत के झेलम बेसिन में प्रस्तावित अवधि (2011-2100) के लिए वर्षा और तापमान की स्थानिक-कालिक विविधताओं की जांच की गई है। कृत्रिम न्यूरल नेटवर्क (ANN) और वेवलेट कृत्रिम न्यूरल नेटवर्क (WANN) मॉडल जैसे सांख्यिकीय डाउनस्केलिंग तकनीकों का उपयोग करके RCP 8.5 परिदृश्य के तहत वर्षा और तापमान परिवर्तों का अनुमान लगाया जाता है। सबसे पहले, सभी अध्ययन स्टेशनों के लिए ANN और WANN मॉडलों का उपयोग करके अनुमानित पूर्वानुमानों के द्वारा पूर्वानुमान दिया गया। प्रदर्शन के आधार पर, WANN मॉडल को वर्षा और तापमान की डाउनस्केलिंग के लिए एक कुशल मॉडल के रूप में चुना जाता है। कैन ESM2 मॉडल के RCP 8.5 से संबंधित भविष्य के पूर्वानुमान आंकड़ों को WANN मॉडल का उपयोग करके भविष्य की अवधि (2011-2100) के लिए मासिक तापमान और वर्षण में डाउनस्केलिंग किया गया। भविष्य के अनुमानों की जांच में पता चला है कि औसत वार्षिक वर्षा में 17-25% की औसत वृद्धि और 21^{वीं} सदी के अंत तक सभी चयनित स्टेशनों में मासिक औसत वर्षा में 20-25% औसत वृद्धि होगी। 21^{वीं} सदी के अंत तक सभी अध्ययन स्टेशनों के लिए मासिक औसत तापमान में भी 2-3 °C की वृद्धि होगी। बेसिन के अधिकांश हिस्सों में सभी चार ऋतुओं के लिए अनुमानित अवधि का ऋतुनिष्ठ तापमान बढ़ता हुआ देखा गया है।

ABSTRACT. The present study investigated the spatio-temporal variations of precipitation and temperature for the projected period (2011-2100) in the Jhelum basin, India. The precipitation and temperature variables are projected under RCP 8.5 scenario using statistical down scaling techniques such as Artificial Neural Network (ANN) and Wavelet Artificial Neural Network (WANN) models. Firstly, the screened predictors were downscaled to predictand using ANN and WANN models for all the study stations. On the basis of the performance criteria, the WANN model is selected as an efficient model for downscaling of precipitation and temperature. The future screened predictor data pertaining to RCP 8.5 of CanESM2 model were downscaled to monthly temperature and precipitation for future periods (2011-2100) using WANN models. The investigation of the future projections revealed an average increase of 17-25% in the mean annual precipitation and 20-25% average increase in the monthly mean precipitation for all the selected stations towards the end of 21st century. The monthly mean temperature also showed an increase of 2-3 °C for all the study stations towards the end of 21st century. The mean seasonal temperature of the projected period is found to be increasing for all the four seasons in most parts of the basin.

Key words – Statistical downscaling, Precipitation, Temperature, Spatio-temporal changes.

1. Introduction

Global circulation models (GCMs) have been widely used for predicting changes in future climate on both regional as well as continental levels. To examine accurately the hydrological as well as environmental impacts of climate change, high resolution scales are required. Although GCMs are able to reproduce reliable atmospheric data; owing to their low resolution, they lack in capability to resolve sub-grid scale land surface processes. Due to this mismatch in resolution between global and regional scales GCMs projections cannot be used directly in catchment scale applications (Farzan *et al.*, 2013; Piras *et al.*, 2016; Reshmidevi *et al.*, 2017).

To use this GCM output directly in any hydrological process downscaling is generally followed. The most commonly used downscaling techniques are statistical and dynamical downscaling techniques. In dynamic downscaling technique a regional climate model of high resolution is nested within coarse grids of GCM (Jones *et al.*, 1993). However, statistical downscaling model (SDSM) has been widely used since last two decades throughout the world (Kannan & Ghosh, 2013; Mahmood & Babel, 2014; Mandal *et al.*, 2016; Chithra & Thampi, 2017). The statistical downscaling technique which creates statistical relationships between coarse scale variables and local scale variables, is much simpler than dynamic downscaling (Mehrotra *et al.*, 2013; Osman &

Abdellatif, 2016). Among the statistical downscaling techniques, regression-based approaches have been widely used for climate downscaling, owing to their simplicity in application. The most commonly used regression-based approaches are Multi Linear Regression (MLR) (Nourani & Farboudfam, 2019; Osman & Abdellatif, 2016), Support Vector Machines (SVM) (Mandal *et al.*, 2016; Sachindra *et al.*, 2018; Sehgal *et al.*, 2016; Tripathi *et al.*, 2006), Artificial Neural Networks (ANN) (La & Pan, 2016; Nourani & Farboudfam, 2019; Sehgal *et al.*, 2016), Multi-Resolution Volterra (MRV) and Multi-scale Wavelet Entropy (MWE) (Sehgal *et al.*, 2016) and Adaptive Neuro-Fuzzy Inference System (ANFIS) (Zare & Koch, 2018). Despite the popularity, some of these techniques like SVM, MRV and ANFIS suffer the major drawback where the relationship between input, output and the model process generally remains unidentified. The potential of ANNs to capture non-linear relationships between predictors and predictand and the capability of simulating time-varying and nonlinear characteristics of atmospheric variables at different scales has gained wide recognition and led to several successful downscaling applications of ANNs. Osman & Abdellatif (2016) employed ANN, Generalized Linear Model (GLM) and Multiple Linear Regressions (MLR) for downscaling large scale atmospheric variables to monthly mean rainfall in north-western England. They concluded that ANN model showed more adaptability than MLR and GLM models by acquiring better overall performance. Sachindra *et al.* (2018) used ANN, SVM, Genetic Programming (GP) and Relevance Vector Machine (RVM) for downscaling precipitation. Based on the investigation of their results, it was found that ANN outperforms the other three models in downscaling high extremes of precipitation in Victoria Australia. Nourani *et al.* (2018) employed Least Square Support Vector Machine (LSSVM) and ANN for downscaling rainfall with nonlinear predictor screening approach. They applied ensemble technique to the model outputs and successfully projected the future rainfall upto the end of 21st century in North West Iran. The ANN approach is based on the interconnected structure of brain cells and is faster highly adaptive and robust in noisy and complex environment as compared to the other nonlinear regression models. They have black box properties, hence does not require prior knowledge of the process. Despite these promising results, some other studies reveal inefficiency and drawbacks of ANNs over the other regression models (Sehgal *et al.*, 2016; Wang & Ding, 2003).

The consistency and efficiency of downscaling models depends upon the quantity and quality of applied data. The crucial step which precedes the model development for efficient downscaling is input preparation. The general approaches employed for input

selection in statistical downscaling models are correlation analysis (Hadi *et al.*, 2016; Mahmood & Babel, 2014) and principal component analysis (Kannan & Ghosh, 2013; Maier & Dandy, 2000). However, these techniques do not take into account the underlying distribution and highly heterogeneous nature of the atmospheric variables. The seasonal variation in the climate data significantly affects the modelling processes and hence affects the prediction ability of the model in practical applications (Nourani & Farboudfam, 2019). Wavelet analysis has been extensively used in the fields of time series analysis and provides detailed information about the data by analyzing both frequency and time domains (Mukesh *et al.*, 2010; Wang & Ding, 2003; Zare & Koch, 2018). Wavelet transform is applied to the data set to obtain information that is not readily available in the original data set. Wavelet based models have been extensively used in the recent past for a diverse set of problems. Tiwari & Chatterjee (2011) used ANN, wavelet based ANN, bootstrap based ANN and wavelet bootstrap based ANN for daily discharge forecasting in Mahanadi river basin. They found that wavelet based models (WANN and WBANN) showed better results as compared to ANN and BANN. Wang & Ding (2003) applied ANN and WANN models for the prediction of hydrology. The investigation of the results revealed that WANN shows increase in the forecasting accuracy. Sehgal *et al.* (2016) compared the downscaling results of wavelet based multi-resolution Volterra model with ANN and MLR. The results showed that wavelet-based multi-resolution Volterra model significantly outperformed the other models.

Several studies could be found in the technical literature regarding the use of SDSM techniques for downscaling temperature and precipitation in the Jhelum basin (Ashiq *et al.*, 2010; Mahmood & Babel, 2013; Mahmood *et al.*, 2015; Rashid *et al.*, 2016). However, most of these studies were restricted to the part of the Jhelum basin in Pakistan. A few studies (Akhter & Ahmad, 2017) were carried out in the Jhelum basin, India. In their study, ANN and MLR modelling approaches were used to downscale monthly temperature and precipitation upto 21st century. However, their research study was carried out without any consideration to spatial and temporal distributions. In the study of (Mahmood & Babel, 2014), SDSM was used to project future changes in temperature extremes in the Jhelum basin India and Pakistan. Mahmood *et al.* (2015), presented spatial-temporal changes of temperature and precipitation in the Jhelum basin India and Pakistan upto 21st century. However, the spatial analysis presented for future scenarios was provided for only three decades: 2020s, 2050s and 2080s without any consideration for seasonal variations. The obvious research gap in the previous

technical literature is the detailed spatial seasonal analysis of future climate in the Jhelum basin. This will take into account the seasonal variations in temperature and precipitation and narrow down the focus of concerned competent authorities to specific area of the basin in a particular season. This also helps the policy makers to suggest proper mitigation measures for proper basin management. In this study, statistical downscaling models were developed using ANN and WANN approaches to downscale the monthly climate of Jhelum basin, India upto 21st century. We have adopted a robust methodology for screening of predictors, by coupling correlation approach with the wavelet decomposed components of potential predictors to select the dominant predictors. The study extends its contribution to the available literature by presenting mean spatial seasonal analysis as well as mean monthly and mean annual temporal analysis of temperature and precipitation for four periods: 1980-2010, 2011-2040, 2041-2070 and 2071- 2100 under RCP 8.5 scenario in the Jhelum basin, India. This integrated analysis paves the way for researchers who wish to investigate the impact climate change on water resources in the Jhelum basin, India.

2. Study area and data analysis

2.1. Study area

The whole Jhelum basin is located in India and Pakistan, it stretches between 33°-35° N and 73°-76° E. The total catchment area of the basin is 33,342 km². The Jhelum River is one of largest tributaries of Indus river and the Indus basin is one of the largest basins in the world (Ashiq *et al.*, 2010; Mahmood & Babel, 2013). The Jhelum basin has a drainage area of 17622 km² upto Indian boarder, with an average elevation of 708 to 5353 m above mean sea level. The Indian part of the basin is bounded by the Pir-Panjal from east and great Himalayan mountain ranges from west (Akhter & Ahmad, 2017; Himayoun *et al.*, 2019; Mahmood *et al.*, 2015). Fig. 1 shows the digital elevation of the Jhelum basin, India along with the location of Jhelum River. The basin has four meteorological stations (Gulmarg, Srinagar, Quazigund and Pahalgam) and three runoff gauging stations (Sangam, Baramulla and Rammunshibagh). The climate of the basin consist of moist winters and mild temperature in summers Himayoun & Roshni, 2020. The maximum rise in temperature occurs in the month of July. The basin receives most of the precipitation (about 40%) during spring season in the form of rainfall, followed by winters in the form of snowfall. The reason for the pre monsoon precipitation is the western disturbance which first hits the Pir Panjal (Dar *et al.*, 2019; Romshoo *et al.*, 2018).

2.2. Data analysis

The regional climate is governed by the circulation pattern of large scale climate variables. These climate variables are selected as predictors for downscaling. Predictors should be readily available and strongly correlated with the predictand. Keeping in view these condition, geopotential height, surface temperature, specific humidity, relative humidity, meridional wind, zonal wind and omega at five pressure levels (1000 hPa, 700 hPa, 500 hPa, 300 hPa and 100 hPa) were selected as predictors. Statistical downscaling models develop statistical relationship between predictor and the predictand. Here we use observed precipitation and temperature data as predictand and large scale reanalysis data as predictor. Predictor data has been extracted from National Centers for Environmental Prediction/National Centers for Atmospheric Research (NCEP/NCAR) reanalysis dataset at spatial resolution of 2.5° × 2.5° and at temporal resolution of one month. Monthly observed mean precipitation and temperature data for Qazigund, Srinagar, Pahalgam and Gulmarg was obtained from Indian meteorological department (IMD) Pune for a period from January 1979 to Dec 2010. The detail statistics of the data as well as information about the stations is presented in Table 1 and Figs. 2(a&b).

In this study the output of CanESM2 GCM model developed by Canadian Centre for Climate Modelling and Analysis at spatial resolution of 2.8° × 2.8° has been used for downscaling precipitation and temperature for future emission scenario RCP8.5. CanESM2 is developed by the Canadian Centre for Climate Modeling and Analysis and is an earth system model of second generation from the Coupled Model Inter-comparison Project (CMIP5). Datasets from both NCEP/NCAR and GCM were interpolated to the gauging site (station location) using bilinear interpolation.

3. Theory of models used

3.1. Artificial Neural Networks (ANNs)

Artificial Neural Networks (ANNs) are information processing systems that are inspired by the function of biological neural networks like human brain. They are composed of processing units called neurons which are interconnected by weighted synaptic connections (Maier & Dandy, 2000). Each neuron has five components: input, output, activation function, summation function and weight. ANNs have ability to model complex relationships between data of predictors and predictand. Being essentially nonlinear regression models, they can solve highly complex problems like downscaling of temperature and precipitation. The multilayer artificial neural networks consists of an arrangement of an input

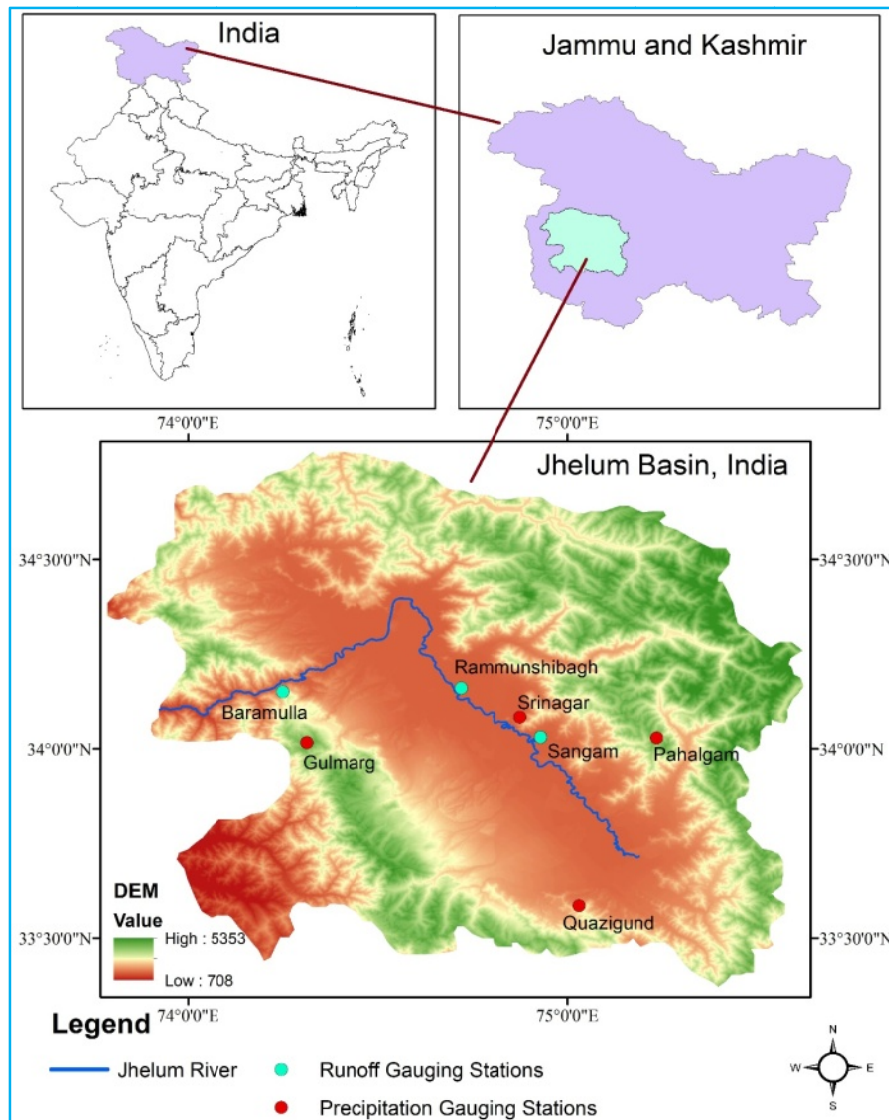
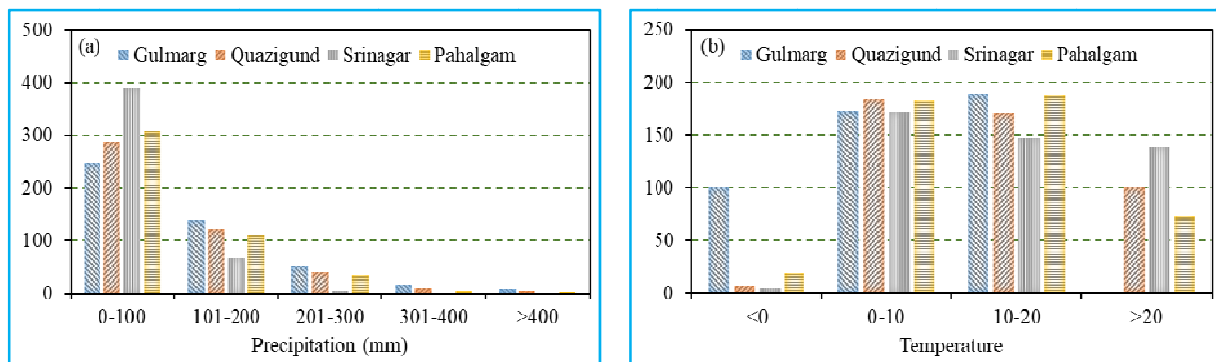


Fig. 1. Digital elevation model of the Jhelum basin, India, along with the location of Jhelum River



Figs. 2(a&b). (a) Histogram of the observed precipitation from 1979-2010 from all the study stations and (b) histogram of the observed temperature from 1979-2010 from all the study stations

TABLE 1
Location and data statistics of meteorological stations in the Jhelum basin, India

IMD stations	Period of record	Latitude	Longitude	Maximum	Minimum	Mean	St. dev.
Precipitation (mm)							
Gulmarg	1979-2010	34.15	74.15	693.4	0	117.62	102.46
Quazigund	1979-2010	33.63	75.15	625.4	0	99.14	85.3
Srinagar	1979-2010	34.09	74.79	365	0	57.78	49.48
Pahalgam	1979-2010	34.01	75.19	421.43	0	90.25	71.67
Temperature (°C)							
Gulmarg	1979-2010	34.15	74.15	18.8	-7.5	7.09	7.14
Quazigund	1979-2010	33.63	75.15	23.8	-3.45	12.63	7.19
Srinagar	1979-2010	34.09	74.79	25.9	-3.05	13.8	7.57
Pahalgam	1979-2010	34.01	75.19	42.01	-4.01	11.31	7.34

layer, one or more hidden layers of nodes and an at least one output layer (Nourani *et al.*, 2018; Sachindra *et al.*, 2018; Sehgal *et al.*, 2016; Zare & Koch, 2018). The input layer receives and processes the signal and passes it to the output layer through neurons present in each layer.

3.2. Wavelet transform (WT)

Wavelet is a special kind of waveform which oscillates and decays within a short period of time. It decomposes a given function into different components at different resolution levels. Its shape can be chosen to match the outline of time series signal. The mother wavelet called wavelet function $\psi(t)$ has finite energy and is mathematically defined (Tiwari & Chatterjee, 2011) as follows:

$$\int_{-\infty}^{+\infty} \Psi(t) dt = 0 \quad (1)$$

where, $\psi(t)$ is mother wavelet.

The continuous wavelet transform (CWT) is obtained by rolling together a signal with an infinite number of functions, generated by translating and scaling a mother wavelet function. However discrete wavelet transform (DWT) is a sampled version of CWT. Discrete wavelet transform decomposes time series data into non-sinusoidal components which provide adequate information both for synthesis and analysis of the original time series data. The decomposition generally develops a tree called Mallat's wavelet decomposition tree (Mallat, 1989). The input signal passes through two

filters : low pass and high pass filter. We get a decomposed signal of Approximation (A1) and Detail (D1). The signal A1 is further decomposed by passing through these two filters and the process repeats until the required amount of approximations and details are obtained.

3.3. Evaluation criteria

The comparison between the observed and model simulated values is one of the simplest form of model calibration and validation. A number of performance indices are available to evaluate the model performance. The most commonly used are Correlation coefficient (R), Coefficient of determination (R^2), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE)

(i) Correlation coefficient (R)

$$R = \frac{\sum_{i=1}^n (O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^n (O_i - \bar{O})^2} \sqrt{\sum_{i=1}^n (P_i - \bar{P})^2}} \quad (2)$$

(ii) Coefficient of Determination (R^2)

$$R^2 = \left[\frac{\sum_{i=1}^n (O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^n (O_i - \bar{O})^2} \sqrt{\sum_{i=1}^n (P_i - \bar{P})^2}} \right]^2 \quad (3)$$

(iii) Root mean square error (RMSE)

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (O_i - P_i)^2} \quad (4)$$

(iv) Mean absolute error (MAE)

$$MAE = \frac{1}{n} \sum_{i=1}^n |O_i - P_i| \quad (5)$$

where, n , O_i , P_i , $\bar{O}$ and $\bar{P}$ are the sample number, observed values, calculated values, mean of the observed values and mean of calculated values respectively. The RMSE value shows the discrepancy between the observed and predicted values. Its value increases as the difference between the observed and predicted value increases. Mean absolute error (MAE) provides information about the prediction ability of the model and evaluates all deviations from observed values irrespective of the sign. Higher value of R and R^2 up to one is an indication of higher efficiency.

4. Methodology

4.1. Screening of predictors

The selection of significant input variables is the foremost task for developing a model. In this study, we have used two approaches for the screening of predictors. The first approach is used for the selection of dominant predictors for the ANN model. In this approach, dominant predictors were selected on the basis of simple correlation analysis. The predictors which pass the screening procedure were selected as inputs for the development of ANN model. The second approach consists of applying correlation analysis on the wavelet decomposed components of the predictors. This approach is used for the selection of dominant predictors for the WANN model. This approach takes into account the temporal features as well as seasonal attributes and the underlying distribution and highly heterogeneous nature of the atmospheric variables.

4.2. Downscaling models

The predictors previously screened are subjected to standardization prior to downscaling. These standardized dominant predictors are used to train ANN and WANN models for downscaling. Standardization reduces the systematic bias from NCEP/NCAR and GCM predictors. This procedure is carried out by subtracting the mean from data and dividing by the standard deviation. This procedure removes the units of the predictor variables and scales down the variables to a single uniform scale (Kannan & Ghosh, 2013; Mandal *et al.*, 2016; Mehrotra *et al.*, 2013; Nourani *et al.*, 2018; Tripathi *et al.*, 2006).

4.3. Future climate

In this step monthly precipitation and monthly temperature is downscaled for four stations for three

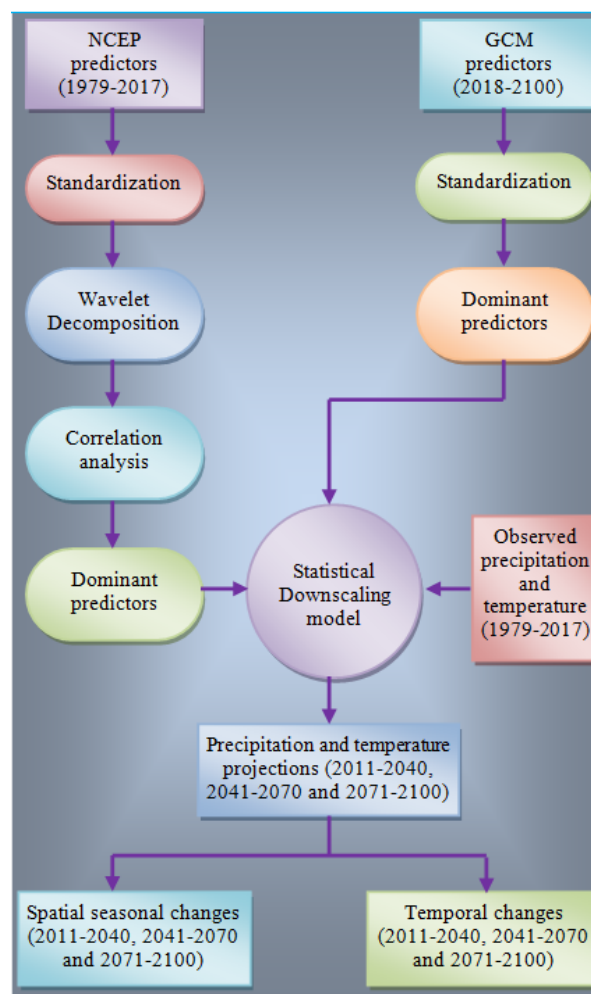


Fig. 3. Flow chart of the methodology used in WANN model

periods: 2011-2040, 2041-2070 and 2071-2100 under RCP8.5 emission scenario using WANN model. RCP scenarios demonstrates distinct greenhouse gas concentration pathways adopted by the IPCC in fifth Assessment Report. The RCP 8.5 scenario was selected for this study, since it corresponds to the pathway with the highest greenhouse gas concentrations and emissions. The methodology adopted for this research study is demonstrated in Fig. 3.

5. Results and discussion

5.1. Model evaluation

The proposed screening approaches for the selection of dominant predictors were applied to NCEP predictors. For each model, 7 atmospheric variables (at 5 pressure levels) were selected for the selection of dominant predictors. Those predictors showing correlation

TABLE 2

Dominant predictors for both temperature and precipitation

Stations	Potential Predictors
Precipitation	
Gulmarg	Vwind700, Rhum500, Omega500 and Omega300
Quazigund	Vwind500, Omega700, Omega500 and Omega300
Srinagar	Rhum500, Omega700, Omega,500 and Omega300
Pahalgam	Vwind700, Omega700, Omega500 and Omega300
Temperature	
Gulmarg	Geopht300, Geopht500, Shum1000 and Shum700
Quazigund	Geopht300, Geopht300, Shum1000 and Shum700
Srinagar	Geopht1000, Geopht500, Shum1000 and Shum700
Pahalgam	Geopht300, Geopht500, Shum1000 and Shum700

coefficient greater than 0.5 were selected as input for the ANN model. The potential predictors selected for the ANN model for the four stations for both precipitation and temperature are presented in Table 2. For WANN model the predictors are first decomposed using Discrete Wavelet Transform (DWT). The main issue regarding the use of DWT is the proper selection of decomposition level and Daubechies mother wavelet. In this research study, the structure has been selected on the basis of past studies (Nourani *et al.*, 2018; Nourani & Farboudfam, 2019; Zare & Koch, 2018). The Daubechies mother wavelet with two vanishing moments db2, at level three decomposition was used to decompose time series predictor data into details and approximations sub-series. The decomposition level is selected on the basis of length of data and is given by the equation as follows (Tiwari & Chatterjee, 2011):

$$L = \text{intlog}_{10} N \quad (6)$$

where, L is the decomposition level and N is length of data.

The ANN and WANN downscaling approaches were applied to downscale the standardized potential predictors to predictand for the four study stations. Prior to the downscaling, the data length of observed precipitation, observed temperature and the dominant predictors were divided into calibration and validation periods. The first 70 per cent (1979-2000) of the baseline data was used for calibration and the remaining 30 per cent (2001-2010) of the baseline data was used for the calibration of the models. The multilayer Feed Forward Neural Network (FFNN) algorithm with tangent sigmoid (Tansig) activation function was used in both the downscaling

models. The epoch number and the number of hidden neurons were selected by trial and error method. The structure with 450 epoch number and 12 hidden neuron was selected as the optimal network architecture based on the least generalization error (Nourani & Farboudfam, 2019).

The validation of both the ANN and WANN models in temperature and precipitation downscaling is summarized in Table 3. The model performance is evaluated for the four stations on the basis of selected evaluation criteria. The model which displays minimum NRMSE, minimum NMAE, maximum R and R^2 was chosen as the efficient downscaling model. Therefore, it was concluded from the Table 3, that WANN modelling approaches outperform the ANN approaches for all the four study stations, in both the temperature and the precipitation downscaling. In addition to this, the model performance was also evaluated from the Taylor diagrams and the random walk test. Figs. 4&5 show the Taylor diagrams for all the study stations. It gives an idea about the resemblance of model results to that of observed data (Taylor, 2001). The similarity between the observed and the model simulated is quantified in terms of their RMSE, standard deviations and correlation. The models are compared by observing its position on the plot. It is observed that WANN models show overall better performance for all the stations by displaying its position at minimum RMSE and maximum correlation coefficient. Figs. 6(a&b) shows the random walk test for (a) precipitation and (b) temperature downscaling results of the ANN and the WANN models for the four selected study stations. It is based on the sign test and is independent of distributional assumptions about the simulation errors (DelSole & Tippet, 2015). The model results are compared at every step, the path moves up by one step if WANN performs better otherwise it moves down by one step. The 95% confidence interval represents that both the modelling approaches are equally skillful. The path followed by the WANN modelling results is out of the confidence interval, continuously moving in upward direction. This indicates that WANN modeling approach is more skillful than ANN approach for all the study stations.

5.2. Future projections of temperature and precipitation

The standardized predictor data pertaining to RCP 8.5 of CanESM2 model were downscaled to monthly precipitation and monthly mean temperature for three future periods : 2011-2040, 2041-2070 and 2071- 2100, using WANN modeling approach. These three periods were selected as they represent the beginning, the mid and the end of the 21st century.

TABLE 3

Performance indices for precipitation and temperature downscaled by ANN and WANN models during the validation period

Models	Indices	Gulmarg	Quazigund	Srinagar	Pahalgam
Precipitation					
ANN	NRMSE	1	0.66	0	0.26
	NMAE	1	0.6	0	0.2
	R	0.71	0.69	0.67	0.72
	R ²	0.51	0.48	0.45	0.52
WANN	NRMSE	1	0.67	0	0.12
	NMAE	1	0.61	0	0.09
	R	0.82	0.79	0.76	0.84
	R ²	0.68	0.63	0.58	0.71
Temperature					
ANN	NRMSE	1	0.1	0	0.38
	NMAE	1	0.03	0	0.13
	R	0.65	0.72	0.74	0.68
	R ²	0.43	0.52	0.55	0.47
WANN	NRMSE	0.14	1	0.48	0
	NMAE	0.12	1	0.43	0
	R	0.96	0.91	0.78	0.95
	R ²	0.93	0.83	0.61	0.91

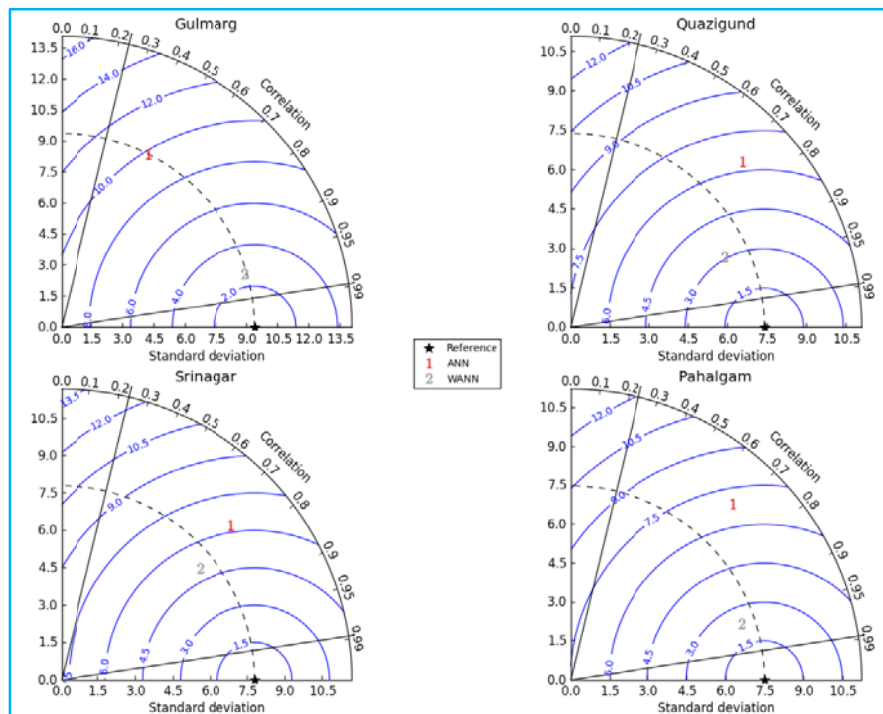


Fig. 4. Model comparison by Taylor diagram for downscaled precipitation

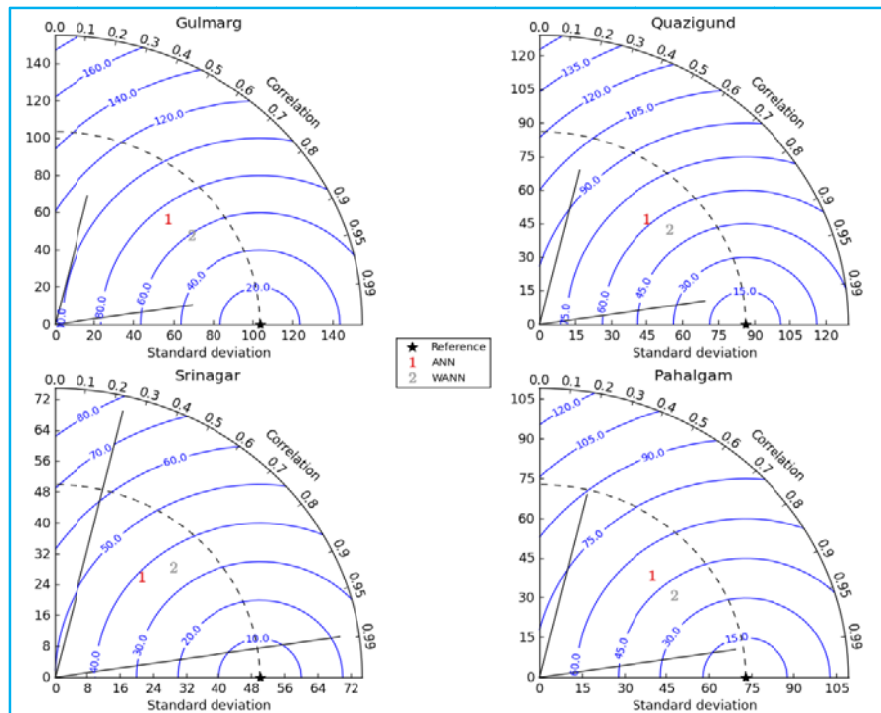
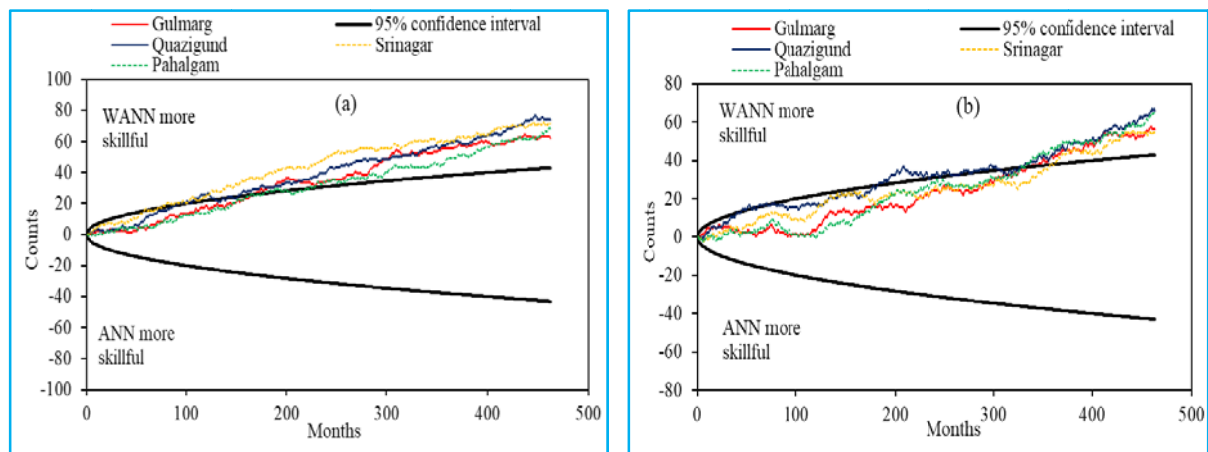


Fig. 5. Model comparison by Taylor diagram for downscaled temperature



Figs. 6(a&b). (a) Model comparison by random walk test for downscaled precipitation and (b) model comparison by random walk test for downscaled temperature

5.2.1. Temporal analysis

Fig. 7 shows the mean annual changes in precipitation for the study stations for the three future periods: 2011-2040, 2041-2070 and 2071-2100 under RCP 8.5 scenario. The mean annual precipitation is showing an increasing tendency for all the study stations. According to the simulation results (Fig. 7) an average increase of 200-300 mm (17-25%) in the mean annual precipitation is observed in the mid and the end of 21st century. Quazigund and

Srinagar stations are the most affected yielding 30-40% increase in the beginning and end of the 21st century respectively. Mahmood & Babel (2013) also reported this increasing trend in the mean annual precipitation. However, the study was conducted for only two future decades: 2050s and 2080s under A2 and B2 scenarios.

Figs. 8(a&b) shows the changes in mean monthly temperature and mean monthly precipitation for all the study stations in the future periods: 2011-2040, 2041-2070

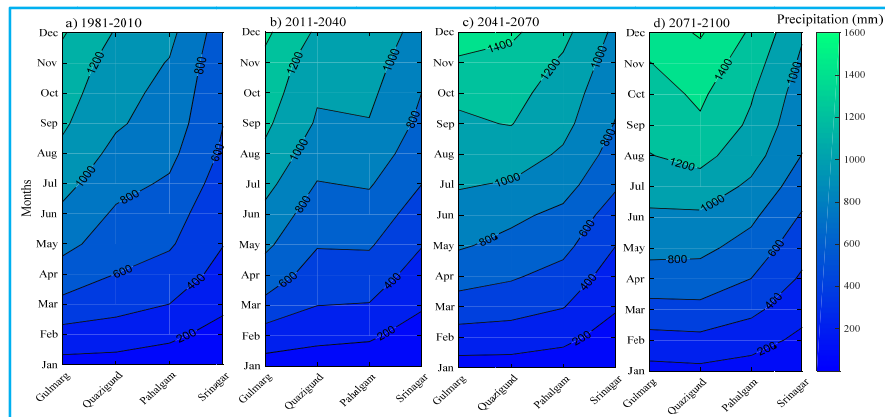
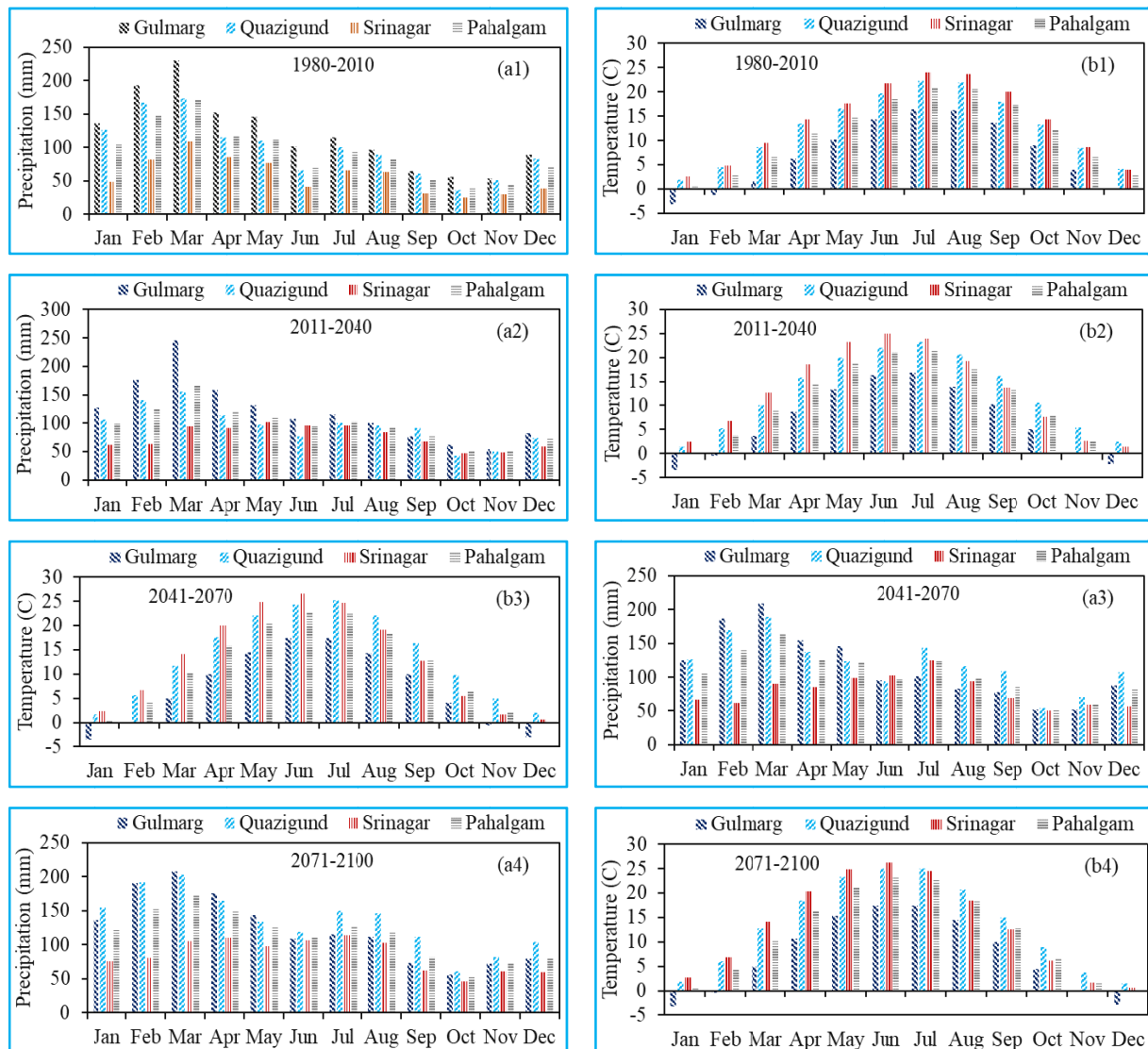


Fig. 7. The base line and future downscaled precipitation by WANN model for all the selected stations



Figs. 8(a&b). (a) The base line and future downscaled precipitation by WANN model and (b) the base line and future downscaled temperature by WANN model

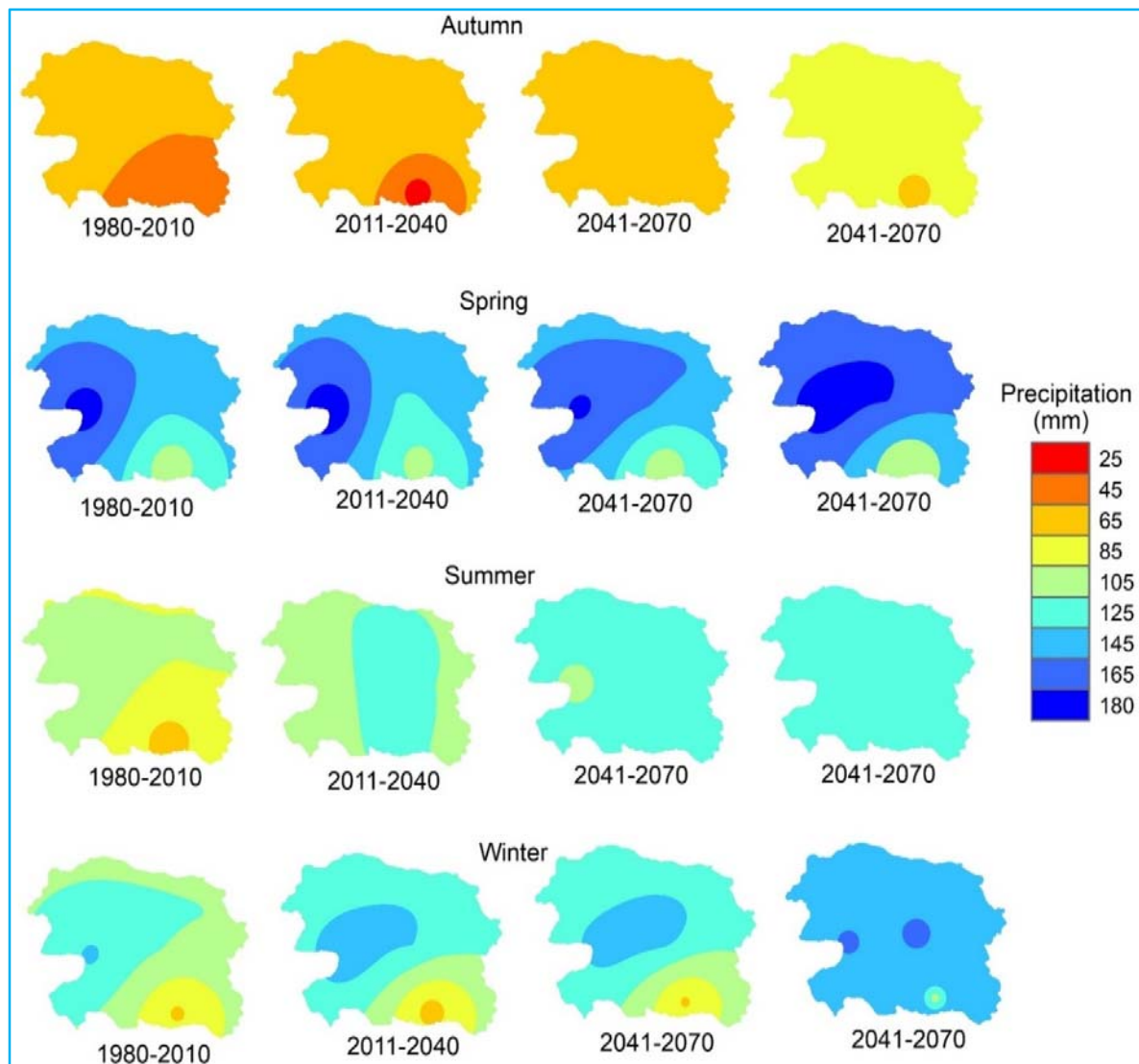


Fig. 9. Spatial distribution of mean seasonal precipitation for base line and for projected time periods in Jhelum river basin

and 2071-2100. The monthly mean precipitation is showing an increase tendency in most of months for all the study stations. The monthly mean temperature also projected an increasing tendency in all months except November and December for all the study stations. However, there is an increase in overall temperature over the basin. An increase of 40-50% in the months of July and August and an overall average increase of 20-25% in monthly mean precipitation is observed in the basin near the end of 21st century. In the months of May, April and June an increase of 3-4 °C is projected and in the months of November and December an increase of 2-3 °C in the monthly mean temperature is projected for all the stations near the end of 21st century. However, the overall monthly mean temperature is projected to increase by 2-3 °C over

the basin near end of the 21st century. The results of this study are in agreement with (Akhter & Ahmad, 2017; Mahmood & Babel, 2013), who also reported an overall increase in temperature as well as precipitation in future over the Jhelum basin.

5.2.2. Spatial analysis

The spatial changes in the mean seasonal temperature and mean seasonal precipitation were also analyzed for the future periods: 2011-2040, 2041-2070 and 2071-2100 with respect to baseline period (1980-2010) under RCP 8.5 scenario using Kriging interpolation method. Kriging is an advanced spatial analyst geoprocessing tool of ArcGIS. Fig. 9 shows the spatial

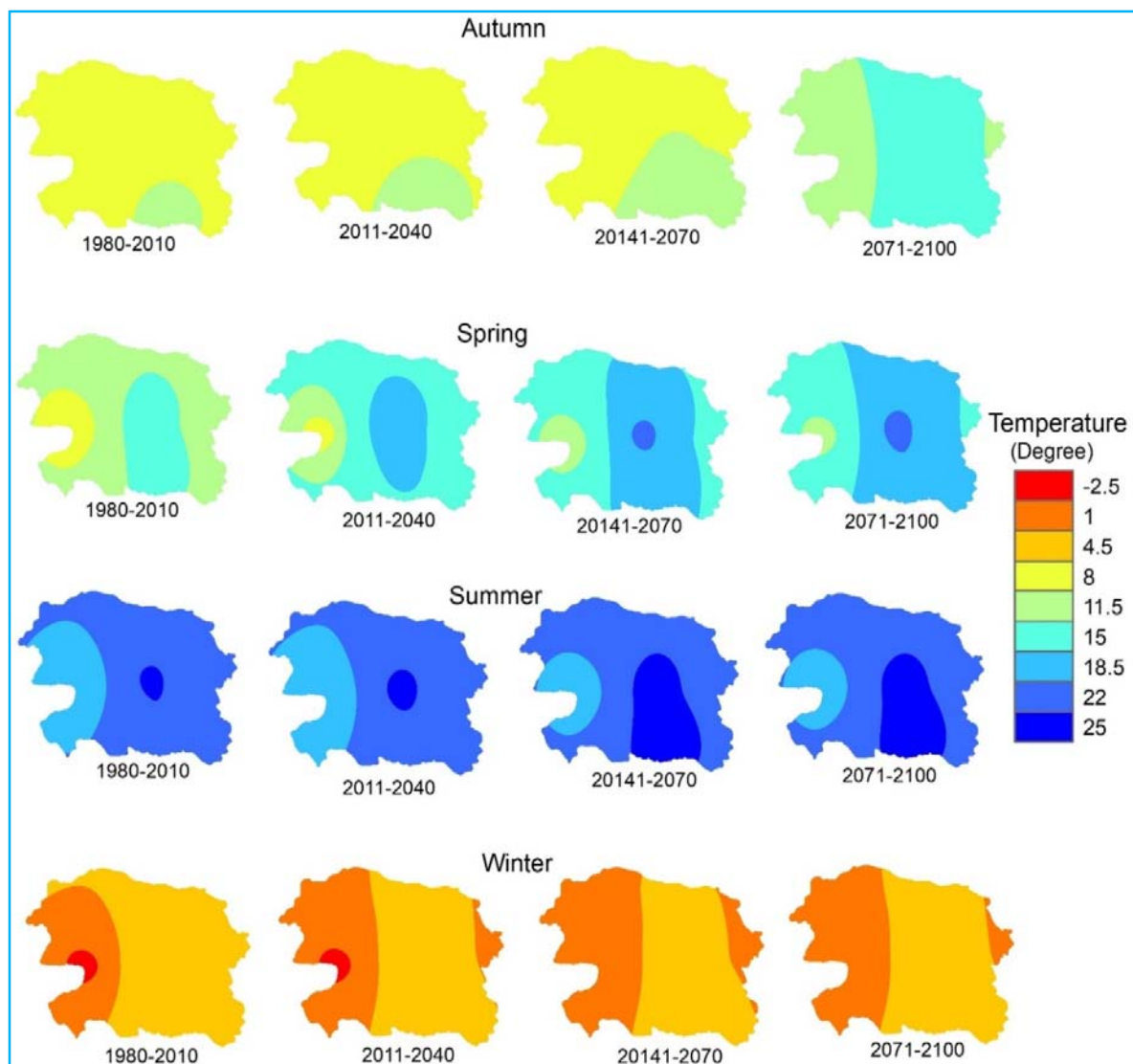


Fig. 10. Spatial distribution of mean seasonal temperature for base line and for projected time periods in Jhelum river basin

distribution of the mean seasonal precipitation in the four seasons for the selected future periods. The mean seasonal precipitation is projected to be increasing for all the seasons in most parts of the basin. In autumn, summer and spring seasons, the whole basin is predicted to be affected with the significant increase in precipitation near the end of the 21st century. However, east part of the basin is projected to be most affected by spring precipitation near the end of 21st century.

Fig. 10 presents the spatial changes in the mean seasonal temperature in the four seasons for the selected future periods. The mean seasonal temperature is predicted to be increasing for all the seasons in most parts of the basin. In autumn and spring seasons, the whole

basin is found to be affected with the significant increase in temperature near the mid and end of the 21st century. During the summer season, the south east part is projected to be affected near the end of 21st century. However, during winter season only a small part on the east side of the basin is predicted to be affected by the end of the 21st century. Ashiq *et al.*, (2010) also reported that most part of the Jhelum basin observes an overall increase in precipitation during winter and spring seasons under future A2 and B2 scenarios. In the study of (Mahmood *et al.*, 2015) most part of the Jhelum basin showed an increase in future projected temperature and precipitation under A2 and B2 scenarios. However some patches display a slight decrease in overall temperature and precipitation.

6. Conclusions

In this research study, statistical downscaling models were developed using ANN and WANN modelling approaches to downscale the future projections of temperature and precipitation over the Jhelum basin, India under RCP 8.5 emission scenario. The potential predictors were screened by two approaches: correlation and correlation coupled with the wavelet decomposed components of potential predictors. The screened predictors were downscaled to predictand using ANN and WANN models for all the study stations. The WANN model is selected as an efficient model based on performance. The future screened predictor data pertaining to RCP 8.5 of CanESM2 model were downscaled to monthly temperature and precipitation for three future periods: 2011-2040, 2041-2070 and 2071-2100, using WANN modeling approach. The analysis of the temporal changes revealed an average increase of 17-25% in the mean annual precipitation in the mid and the end of 21st century. Quazigund and Srinagar stations are the most affected yielding 30-40% increase in the beginning and end of the 21st century respectively. The monthly mean precipitation projected an average increase of 20-25% for all the study stations near the end of 21st century. The monthly mean temperature also showed an increase of 2-3 °C for all the study stations towards the end of 21st century.

Kriging interpolation method was used to investigate the spatial variations in future projected temperature in the study area. The spatial distribution of precipitation showed that mean seasonal precipitation is projected to be increasing for all the seasons in most parts of the basin. In the spring season east part of the basin is predicted to be most affected near the end of 21st century. However in autumn, summer and spring seasons, the whole basin is predicted to be affected with the significant increase in precipitation near the mid and end of the 21st century. However, east part of the basin is projected to be most affected by spring precipitation near the end of 21st century. The mean seasonal temperature is projected to be increasing for all the seasons in most parts of the basin. In autumn and spring seasons, the whole basin is predicted to be affected with the significant increase in temperature near towards the 21st century. During the summer season, the south east part is projected to be affected near the end of 21st century. However, during winter season only a small part on the east side of the basin is predicted to be affected by the end of the 21st century. Therefore, from the spatial temporal analysis of the future projections, it is concluded that the temperature increases and the precipitation becomes more intensified in the whole Jhelum basin, India near the end of the 21st century under RCP 8.5 scenario.

Disclaimer

The contents and views expressed in this research paper are the views of the authors and do not necessarily reflect the views of the organizations they belong to.

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