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ORIGINAL PAPER

Prediction of heat waves over Pakistan using support vector machine algorithm in the context of climate change

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Abstract

Many efficient forecasting models have been found to fail or show low skill due to the changes in the predictor–predictand relationship with the changes in global climate. An attempt has been taken to develop a climate change resilient heatwave prediction model using machine learning (ML) algorithms known as Support Vector Machines (SVM), random forest and artificial neural network. The National Centres for Environmental Prediction/National Centre for Atmospheric Research reanalysis data of ocean-atmospheric variables were used as the predictors of ML models for forecasting the number of heatwave days (HWDs) in the summer of Pakistan. An SVM based recursive feature elimination method was used to select the skilful predictors. The ML models were developed by considering a moving window of 29 years with a time step of 5 years to incorporate the changes in the relation of HWDs with its predictors due to climate change. The result showed changes in the relationship of HWDs with all the ocean-atmospheric variables considered in this study as probable predictors, which indicates the necessity of forward-rolling approach proposed in this study for the development of climate change resilient forecasting model. The relative performance of ML showed the higher capability of SVM to predict HWDs with an %NRMSE of 36, R^2 of 0.87, md score of 0.76 and an rSD of 0.88 during the validation period. The result revealed the potential of SVM model to be used for reliable forecasting of heatwaves in the context of climate change.

Keywords Heatwaves · Forecasting · Climate change · Machine learning algorithm · Robust prediction model

1 Introduction

Heatwaves have gained wide attention in recent years due to their extensive impact on the human health, ecosystem, agriculture and economy (Gao et al. 2018). The heatwaves are becoming more severe, longer and recurrent with the increase of global temperature (Meyer et al. 2014). Climate models projected a continuous increase in the intensity and frequency of the heat waves over the present century (Khan et al. 2019b, 2020b; Russo et al. 2014). Besides, a longer period of heatwaves with potentially fatal temperature conditions has been projected across the globe (Mora et al. 2017). Excessive exposure to heatwave can have an adverse effect on the environment, human health, crop, and livestock (Shahid 2010). Preparedness is considered as one of the most important measures to cope with heatwaves. Early warning of heatwaves is the most effective way of making the community prepared about possible heatwaves. A large number of forecasting models have been developed and implemented for the prediction of different meteorological phenomena. However, the prediction of a meteorological phenomenon is always a challenging task (Khan et al. 2019d), especially during recent years due to the changing climate.

Climate change has caused some of the highly skilled climate forecasting models to show low skill in recent years due to the changes in their prediction capability (Gao et al. 2018). Even some of the most skilled prediction

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models have been found to fail to detect the forthcoming events in recent years (Rajeevan et al. 2007; Wang et al. 2015). Predicting any climate variable can be challenging even with some of the most skilled machine learning (ML) methods (Ali et al. 2018, 2020). Wang et al. (2015) argued that skills of some of the identified predictability sources decrease due the climate change such as the statistical models developed for the prediction of Indian summer monsoon rainfall (ISMR) have shown negative skill in some recent years. For example, many ISMR models failed to predict extreme events in 1994, 2002, 2004 and 2009. Apart from the statistical models, the dynamical models have also shown low skill in predicting the heatwave over China in recent years (Gao et al. 2018). Prediction models have shown that short term skill in the prediction is comparatively higher, while lower skills are mostly observed in the prediction of the long-term long-range phenomena (MacLeod 2018), which may be due to the changing climate. However, the failure of such models was found more prominent during the last few decades (Wang et al. 2015). Sophisticated General circulation models such as Beijing Climate Centre Climate System Model (BCC-CSM) have also shown a lower skill to predict the meridional pattern of summer precipitation over East Asia-Northwest Pacific (EA-NWP) and it's East Asia-Pacific (EAP) teleconnection which are due to the changing pattern in the large-scale atmospheric variables (Gong et al. 2017).

Historically researchers have revealed that the low skill in forecasting models or failure is mostly during the El Nino years which causes a change in the pattern of predictors (Krishna Kumar et al. 2006). However, recent failures are much associated with the climate change which has caused most of the models to fail due to their less capability to capture the new sources of predictability which have emerged due to the recent climate change. The predictability sources tend to change their strength for prediction and the location which eventually cause a low model performance (Wang et al. 2015). Therefore, prediction models should consider climate change and incorporate the climate change impacts on prediction capability for reliable forecasting of heatwaves in the context of climate change. Such system can serve as the key element for the mitigation and adaptions to the heatwave and protection of life and environment to ensure sustainable development (Al-Mukhtar and Qasim 2019; Gao et al. 2018; Khan et al. 2019d; Singh et al. 2018).

Predicting heat waves has been one of the major challenges for the climatologist due to their complex non-linear interaction with the large scale atmospheric variables (Khan et al. 2019d). The prediction of the heat waves can be carried out broadly using two approaches i.e. statistical and dynamical (Nissan et al. 2017). The statistical approach of forecasting is conducted by using the empirical models developed by relating the large-scale ocean-atmospheric variable with heatwaves. On the other hand, dynamical models depend on the physical interactions of ocean, atmosphere, and land for the development of the prediction model, which makes the development of the model computationally intensive. Therefore, statistical models are broadly used for the development of the heatwave prediction model (Gao et al. 2018; Khan et al. 2019d; Nissan et al. 2017; Stedman 2004). The capability of conventional statistical methods often found limited to solve intricate non-linear prediction problems (Prasad et al. 2019). Considering the ability of ML algorithms in apprehending multidimensional complex processes, various types of ML models have been employed in recent years for robust prediction of different natural phenomena (Ali and Prasad 2019; Khan et al. 2020a).

The main objective of this study is to develop a climate change resilient robust heatwave prediction model to predict heatwave days (HWD) during summer over Pakistan. The novelty of the study is the development of ML-based forward rolling forecasting models where a moving window is employed to consider the changes in heatwave predictors due to climate change in order to provide a climate change resilient robust forecasting of seasonal HWDs. The changes in the relationship of HWDs with different ocean-atmospheric variables over time were evaluated to show how changes in predictable sources of heatwaves over Pakistan. A recursive feature elimination method was used for the selection of predictors of HWDs and three widely used ML algorithms, support vector machine (SVM), random forest (RF) and artificial neural network (ANN) were used for the development of the prediction model, considering their capability to simulate highly non-linear phenomena. Pakistan has experienced some of the deadliest heat waves in recent years, which resulted in thousands of deaths (Khan et al. 2019c). The damages from the heat waves may increase in the coming decades not only in Pakistan (Khan et al. 2018, 2020b) but also in the neighbouring regions due to high vulnerability to natural disasters (Cheema 2015). As the heatwaves are increasing and projected to become more common in forthcoming years, there is a need for the development of a robust model for forecasting heatwaves as a potential mitigation measure to climate change.

2 Study area and data

Pakistan located in South Asia was chosen as the study area due to its high vulnerability to increasing heatwaves (Iqbal et al. 2019; Khan et al. 2020c). The study area is shown in Fig. 1. The climate of Pakistan is arid and a semi-arid, which experiences cold winter in December–February and

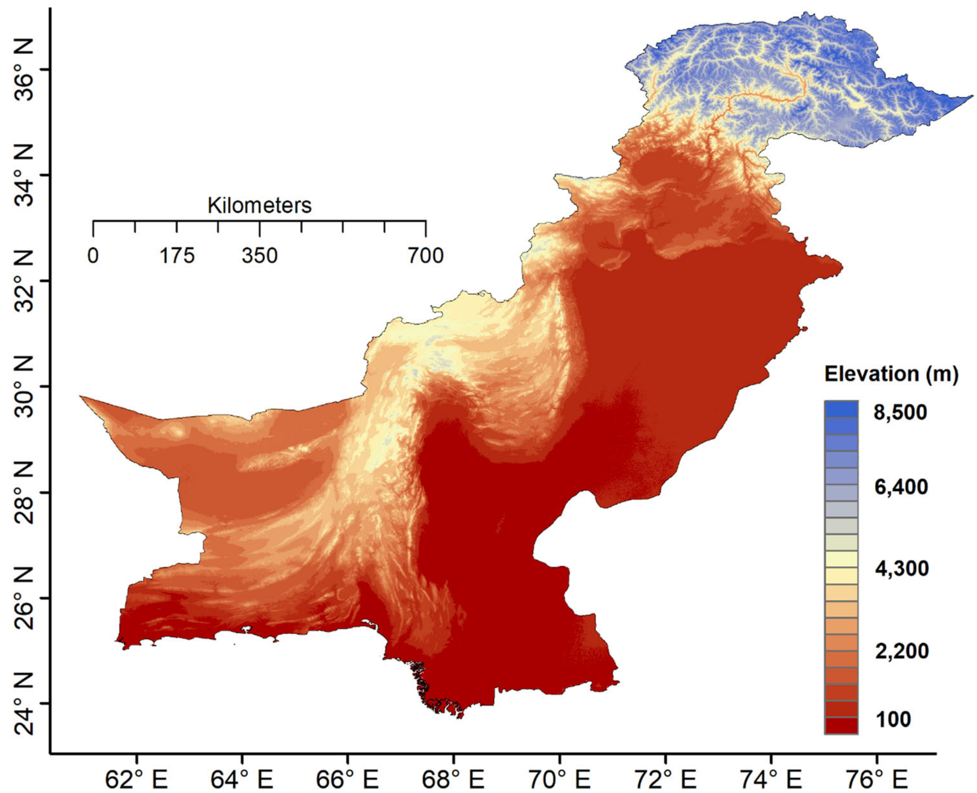


Fig. 1 The map of Pakistan. The topography of the country is shown using the color ramp

hot summer during May–August (Ahmed et al. 2020; Khan et al. 2019a; Nasim et al. 2018). The temperature variation over Pakistan is very high. It experiences high temperature in the south and sub-zero temperatures in the northern region (Iqbal et al. 2019). The heatwaves are mostly experienced during May, June, and July (MJJ). During these months some of the highest recorded temperature has been reported, which usually exceed more than 50 °C, causing damage to the human health, ecosystem and agriculture loss (Khan et al. 2019c, 2019d).

2.1 Heat wave data

Pakistan occupies a land of 796,095 km^2 with varying topography. However, the climate of the country is monitored using only 96 meteorological stations. This constraint makes it very hard to analyse the spatial characteristics of the climate in the country (Iqbal et al. 2019). To overcome such issue, gridded dataset are used to monitor different climatic characteristics. Such gridded datasets have been found very effective of climate analysis in the data-scarce region (Ahmed et al. 2019). This study uses Princeton Global Forcing (PGF) dataset (1948–2016) with a relatively higher resolution (0.25° × 0.25°). The dataset is developed using gauge data and NCEP/NCAR reanalysis data (Sheffield et al. 2006). The PGF data has been widely used in a different climatic study over the globe and different regions of Asia. It has also been validated and studied over Pakistan in heatwave related studies (Aadhar and Mishra 2017; Khan et al. 2018, 2019c, 2020a,2020b; Sheffield et al. 2012; Zhu et al. 2017). Therefore, the daily maximum temperature of PGF was used for the estimation of HWDs during MJJ over Pakistan for the development of prediction models.

2.2 Reanalysis dataset

The NCEP/NCAR reanalysis data of various atmospheric parameters were used as predictors for the prediction of HWDs. The NCEP/NCAR reanalysis provides datasets of various atmospheric variables at 17 different pressure level which is continuously updated since 1948 with a resolution of 2.5° × 2.5° (Kalnay et al. 1996). The NCEP dataset has been utilized for the developed of prediction models (Al-Mukhtar and Qasim 2019; Folberth et al. 2019; Khan et al. 2019d, 2020a; Maini et al. 2003). The predictor of a climatic phenomenon depends on the season, predictand and climatic condition of the region of interest (Folberth et al. 2019). Therefore, the NCEP variables were selected based on their physical relation with heatwaves in Pakistan. Previous studies based on synoptic analysis of heatwave phenomena revealed Geopotential Height (HGT), Relative Humidity (RH), Air Temperature (AT), U Wind (UW), V Wind (VW) and Sea Level Pressure (SLP) as the major drivers of heatwaves in Pakistan and nearby region (Gao et al. 2018; Khan et al. 2019d). The synoptic climate during the recent heatwaves in Pakistan revealed that the direction and velocity of wind and RH are the major factors of heatwaves (Khan et al. 2019d, 2020a). The wind circulation of Pakistan depends on SLP in the Bay of Bengal and difference in HGT, while the RH depends on AT. Therefore, those six NCEP reanalysis variables were considered in the present study for the development of seasonal HWDs prediction model. The climate domain consisted of 357 grid points at 4 different pressure levels for the extraction of probable predictors. Table 1 shows the description of the atmospheric variable used for the selection of the predictor.

3 Methods

The model was developed for the prediction of HWDs during summer months (May–July) at beginning of the summer season (April). The intention was that the proposed seasonal forecasting model could be used to provide early information on the possible occurrence of heatwaves in Pakistan. The procedure used for the prediction of HWDs is elaborated using a flowchart in Fig. 2. The steps followed at outlined below.

1. The HWDs over Pakistan during the summer months (MJJ) were calculated for each year for the period 1948–2016 using the PGF daily maximum temperature dataset to generate a time series of seasonal HWDs in Pakistan.
2. The monthly data of atmospheric variables identified in the previous studies as heatwave defining factors for Pakistan were collected for the period 1948–2016 from NCEP/NCAR reanalysis dataset. The data of the variables for different pressure levels for the pre-summer months, February–April (FMA) were used to select the predictors.
3. Considering a climate domain covered by 357 NCEP grid points, the reanalysis data of the selected variables for all the grid points of the climate domain was used to generate the principal components (PCs) of each variable of each pressure level for each month of FMA using the principal component analysis (PCA).
4. A non-linear machine learning method known as SVM-RFE was used where the time series of HWDs during MJJ was used as the predictand and the PCs representing the large variance of each variable (estimated in step 3) as predictors to select the most skilful PCs as the final set of predictors.
5. Three widely used machine learning methods namely SVM, RF and ANN were used for the development of models for the prediction of HWDs over Pakistan during MJJ using the final set of predictors selected by the SVM-RFE. The performance of the models was compared to select the best model.
6. Considering that global warming alters the predictor–predictand relationship over time, the best ML algorithm was used to develop a prediction model for every 29 years data and the prediction of HWDs was carried out with a moving window of five years. The updated model in every five-year able to adapt climate change impacts on the predictor–predictand relationship and provide a climate change resilient robust forecasting model.

The methodology adopted in this study is detailed in following subsections.

3.1 Climate domain selection

The data of prediction variables were extracted from 357 NCEP/NCAR grid points (Fig. 3). Accurate prediction of HWDs requires selection of an adequately sized climate domain. The climate domain should neither be large enough that may result in the selection of false predictors or increased computation time and cost, nor it should be small enough to capture the climatic effect. The extent of the climate domain is usually decided based on the influence of synoptic on the selected region (Sachindra et al. 2018b). The climate domain extending from 0° to 55° N and 35° to 95° E was selected as the circulations over this domain have high influence on the climate of Pakistan (Khan et al. 2019d, 2020a).

3.2 Selection of the predictors

Probable predictors from the previous studies were identified from the NCEP/NCAR reanalysis dataset. The selection of the predictors depends on the predictand variable in consideration, season and the region (Folberth et al. 2019; Sachindra and Kanae 2019). The reanalysis data of the selected variables (Table 1) for all the grid points of the climate domain was used to generate the PCs

Table 1 NCEP/NCAR large scale atmospheric variables used as the predictors in this study

Atmospheric variables	Symbol	Pressure level (hpa)
Geopotential height	HGT	925, 850, 700, 500
Relative humidity	RH	925, 850, 700, 500
Air temperature	AT	925, 850, 700, 500
U wind	UW	925, 850, 700, 500
V wind	VW	925, 850, 700, 500
Sea level pressure	SLP	Surface

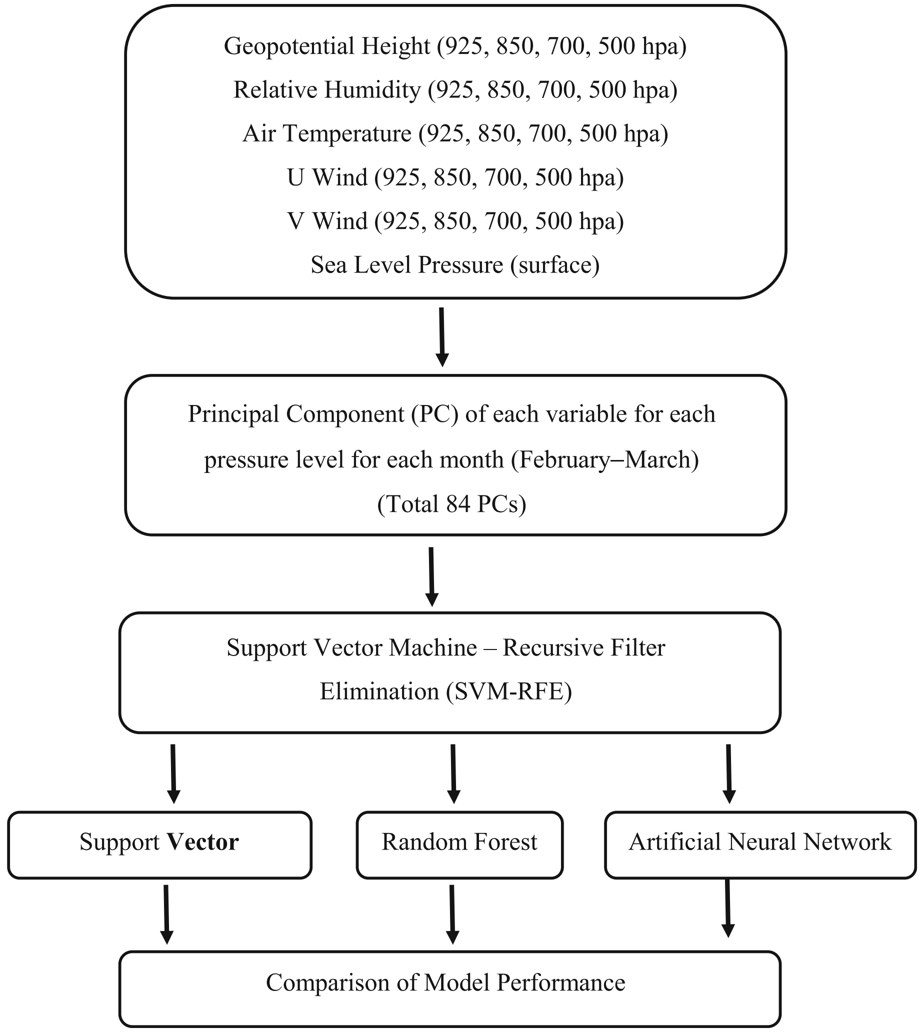


Fig. 2 The procedure used for the prediction of HWDs using machine learning algorithms

of each variable of each pressure level for each month of FMA. The PCs representing the large variance of each variable were used in SVM-RFE to eliminate the PCs with lower skills. Finally, the selected PCs by SVM-RFE were used as predictors for the development of the ML models. The RFE algorithm removes the predictor with less information and redundant information/predictors, in the process selecting the optimum number of predictors. Details of the SVM-RFE can be found in Wang et al. (2015).

3.3 Definition heat waves

In any heatwave related study, the first step usually involves defining the heatwave. Heatwaves are usually defined with a certain threshold of temperature or percentile for a given period in days (Robinson 2001; Wang et al. 2017; You et al. 2017). A common perception is that the heatwave is a drastic phenomenon above a certain temperature for a given period. This study used the definition provided by Khan et al. (2019c) which a heatwave event is considered as the daily maximum temperature above the 95th percentile of the maximum temperature of the base year (1971–2000) for at least 5 consecutive days over Pakistan. The seasonal variation over the country is very high due to significant spatial and temporal variation of the climate. Thus, a percentage-based heatwave definition appropriately represents the stress and heat waves experienced over the country (Khan et al. 2019c, 2020b).

3.4 Prediction of heatwave days

Models were developed for forecasting HWDs over Pakistan using ML methods. The description of the ML algorithms used in the present study is given below.

3.4.1 Support vector machines (SVM)

SVM is one of the most skilled ML algorithms (Cortes and Vapnik 1995) which has been widely used for the development of prediction models. SVM can be used in

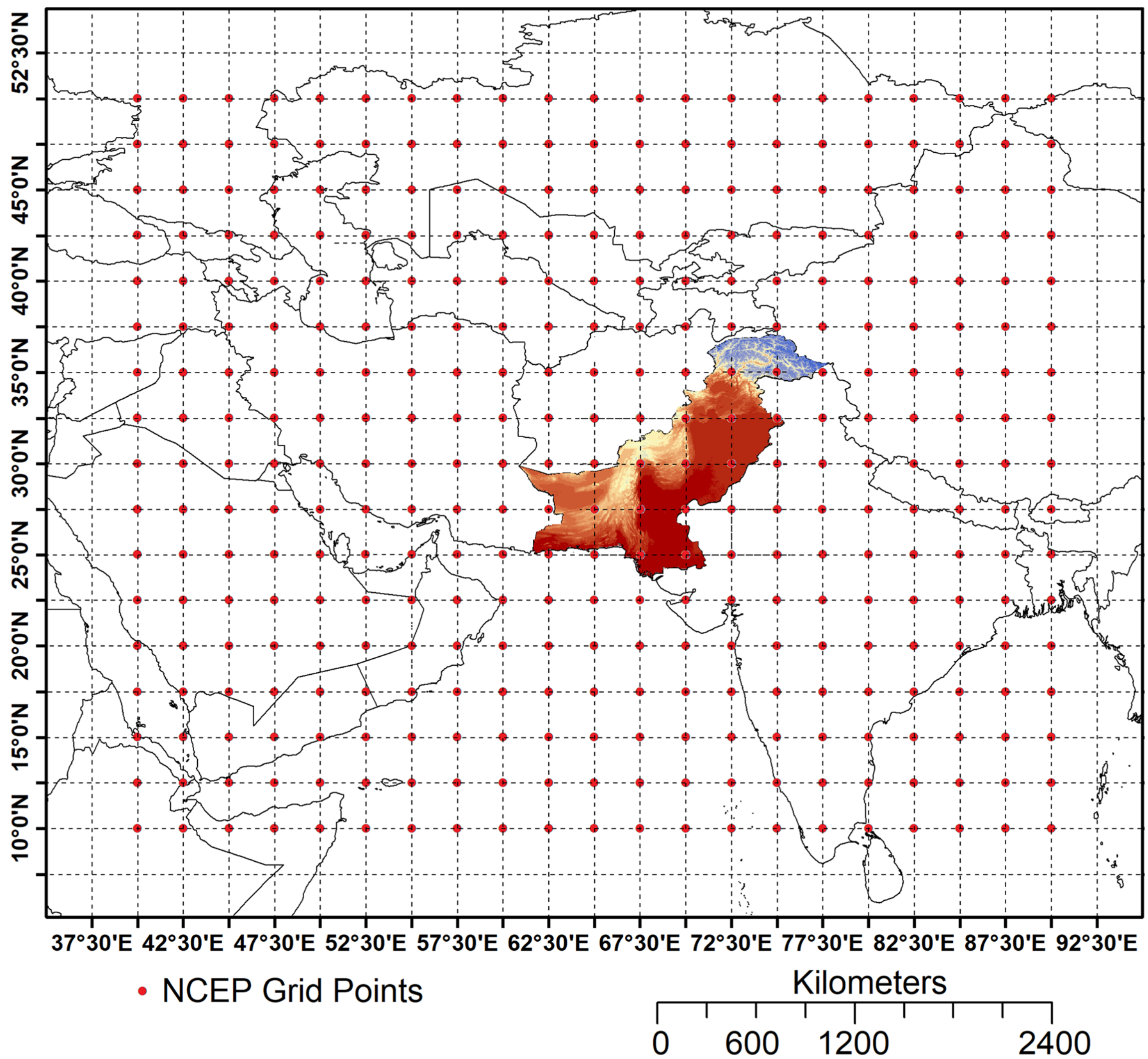


Fig. 3 Selected climate domain in the present study. The NCEP/NCAR grid points are shown using red dots with 2.5° × 2.5° spatial resolution

developing both regression and classification models (Vapnik 2013; Vapnik and Vapnik 1998). In SVM, the non-linear problem is mapped into higher dimensional space to make it a linear problem to be solved using SVM kernel functions (e.g. polynomial, radial, sigmoid, and linear). Therefore, a kernel function should be selected appropriately in order to develop SVM based prediction models. Polynomial and radial kernels are widely used for the development of the SVM based prediction models (Ganguli and Reddy 2014; Tripathi et al. 2006). However, it has been found that the polynomial kernel showed better result with SVM (Khan et al. 2020a; Sachindra et al. 2018a). The polynomial kernel can be defined as Eq. (1),

$$K(x_i, x_j) = (x_i . x_j + c)^d \tag{1}$$

where $\mathbf{x_i}$ and $\mathbf{x_j}$ are the predictor and predictand data respectively, d is the degree of the polynomial, and c is a constant that allows a trade-off between the influence of the higher and lower order terms. The "svm" function of R version 3.6.2 was used for the development of SVM model in this study.

3.4.2 Random forest (RF)

The RF is an ensembled ML algorithm where a large number of regression trees are generated to make a collective decision for prediction (Breiman 2001). Different tree in RF produces different outcomes. Two techniques namely boosting, and bagging can be used in RF for making a final decision based on the outcomes of each tree. In boosting, more importance is provided for the trees which can identify inaccurate prediction and the final prediction is made based on weighted voting (Cutler et al. 2007). In bagging, regression trees are developed using a bootstrap sample and the prediction is made based on majority voting. Details of RF can be found in Breiman

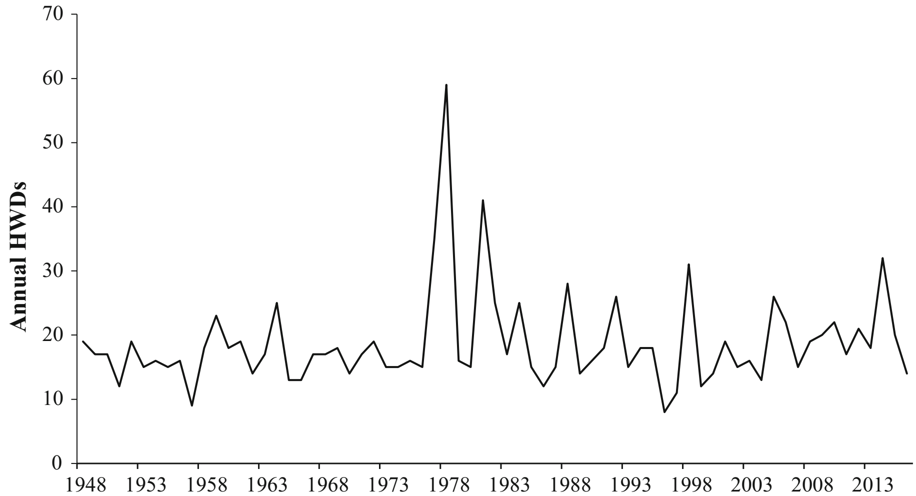


Fig. 4 Time series of annual HWDs over Pakistan

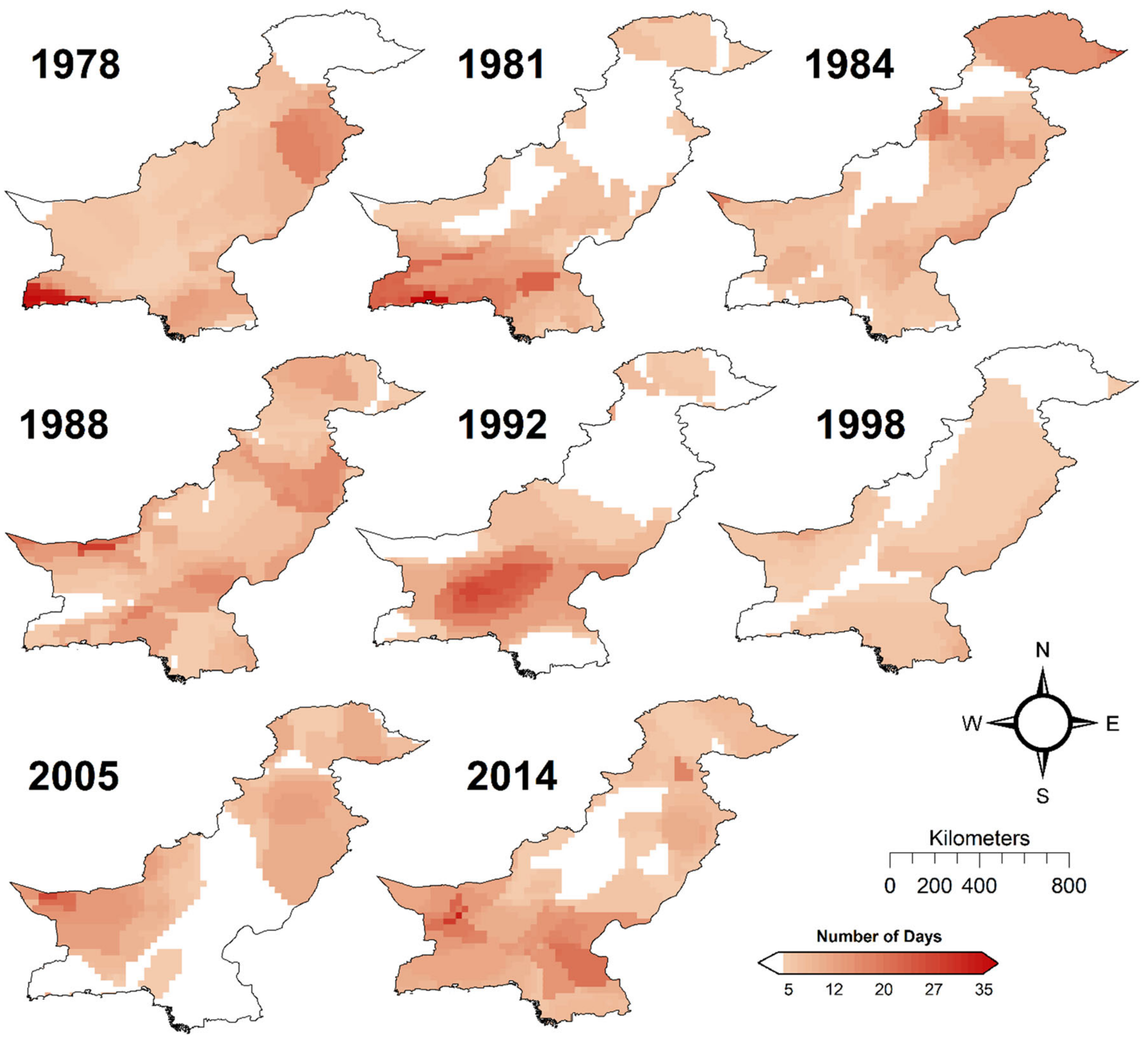


Fig. 5 Spatial distribution of HWD over Pakistan

(2001). In this study, the "randomForest" package of R version 3.6.2 was used for RF model development.

3.4.3 Artificial neural network (ANN)

The ANN algorithm is conceptualized following the procedures used by the brain to make a decision (Kumar et al. 2002). The basic structure of ANN comprised of a number of layers where the layers are composed of neurons. A conventional ANN has three layers, one used to get inputs, one for processing the input and the last layer is for delivering output (Modaresi et al. 2018). However, the number of hidden layers can be more, which depends according to the complexity of the problem. Usually, a trial and error approach is used to develop the topology of ANN, particularly the number of the hidden layer. ANN gets the inputs through the input layer, manipulates the inputs in the hidden layer and passed the outcome to the output layer. ANN assigned different weights to different inputs to make a prediction. The prediction error is used to finetune the weights to improve the prediction in each iteration (Kumar et al. 2002). In this study, the ANN model was developed using "brnn" function of R version 3.6.2.

Fig. 7 The spatial pattern of the correlation of the atmospheric temperature at 925 hPa pressure level with the maximum temperature of Pakistan ▶

3.5 Development of models

A forward rolling approach was used to develop the robust forecasting model through the incorporation of the climate change effect. In this approach, the model was developed for every 29 years and the prediction of the next year heat waves was carried out. The model was updated in every five-year to adapt to the changes in the predictor–predictor relationship due to climate change. It is expected that the model would be resilient to climate change effect as it is taking the changes in predictors into account during prediction (Wang et al. 2015). The performance of M-models depends on their hyperparameter values. A k-fold cross-validation method (Kuhn 2008) was used for the setting of hyperparameters of the ML models used in this study. In this approach, calibration data is arbitrarily divided into k groups and then the data of (k − 1) groups are merged for training the model and the data in the rest one group is used for validation. The process is repeated for k times with new group of data as validation set in each time. This allows

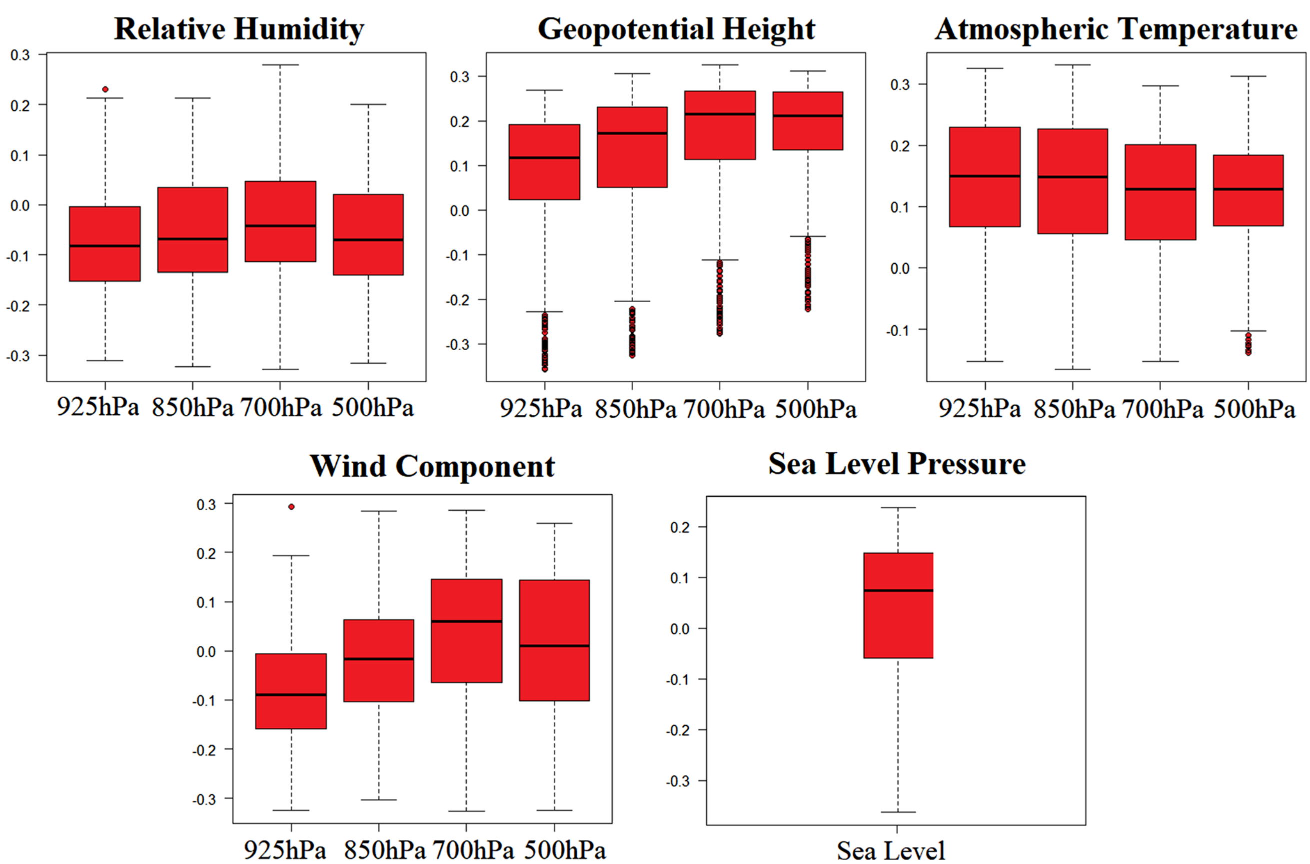
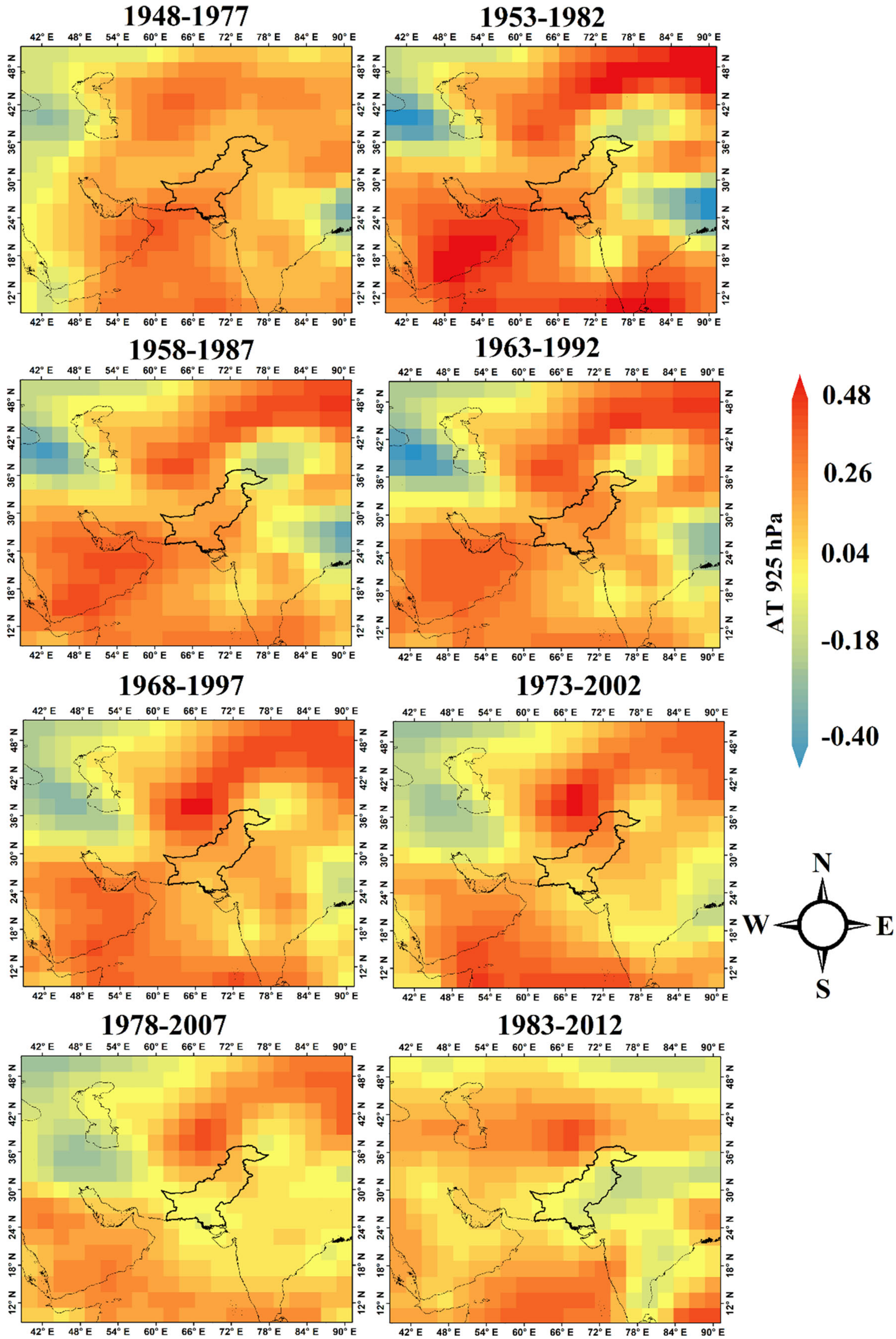


Fig. 6 Correlation of the selected atmospheric variable and the HWDs over Pakistan


1948-1977
1953-1982
1958-1987
1963-1992
1968-1997
1973-2002
1978-2007
1983-2012
42° E 48° E 54° E 60° E 66° E 72° E 78° E 84° E 90° E
12° N 18° N 24° N 30° N 36° N 42° N 48° N
AT 925 hPa
0.48
0.26
0.04
-0.18
-0.40
N
W
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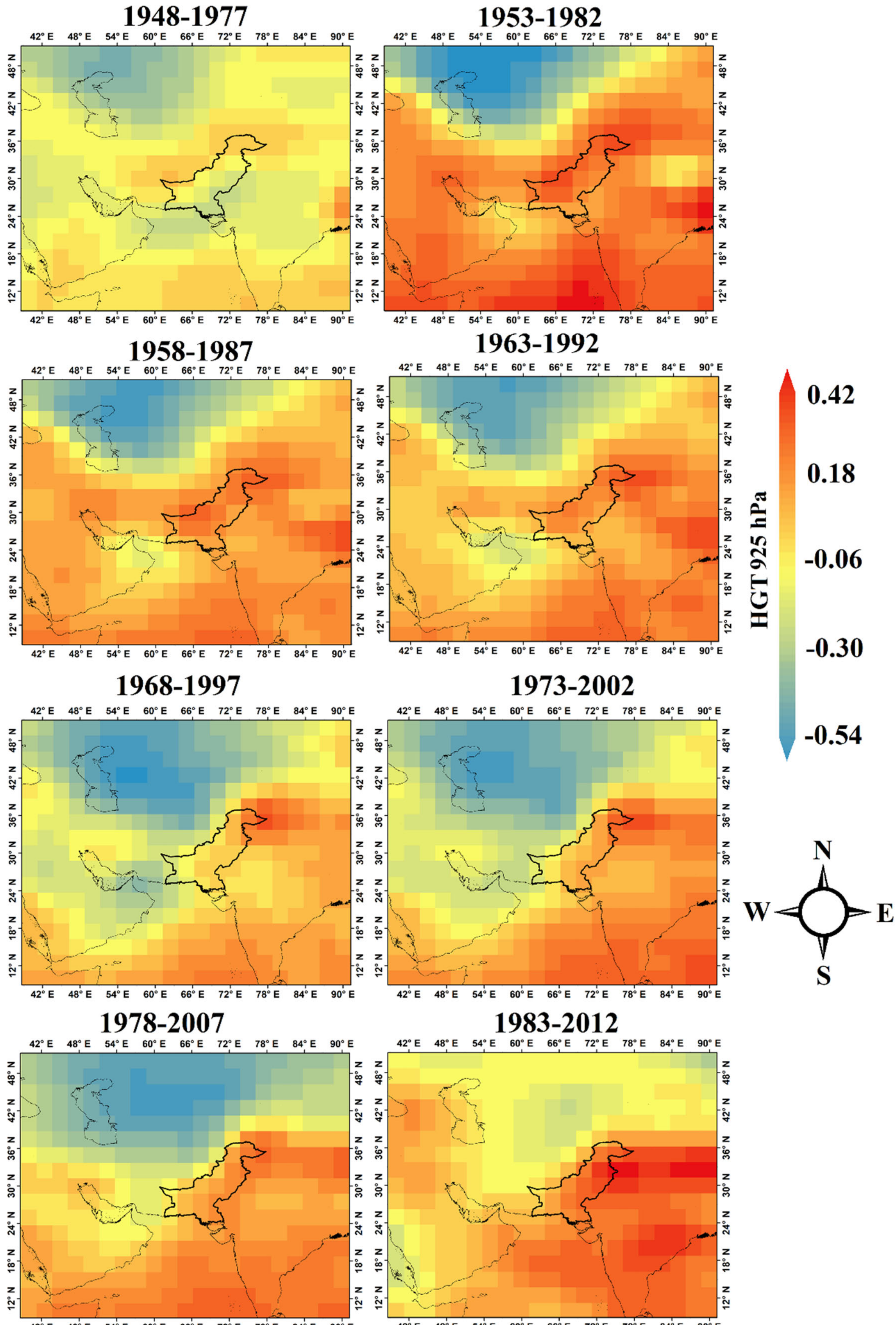


Fig. 8 The spatial pattern of the correlation of the geopotential height at 925 hPa pressure level with the maximum temperature of Pakistan

calibration of the models for the whole dataset. The average of the hyperparameter values at each iteration are the optimum values of hyperparameters for the simulation of complete dataset. In this study, the value of k was decided through a trial and error approach. Best performance of the models was noticed was k was considered 3. Three hyperparameters of SVM namely, regularization parameter, degree of the polynomial kernel function and kernel coefficient, one for RF which is the number of trees, and three for ANN namely, number of hidden layers, size of neurons in hidden layer and bias were optimized in this study. In a forward rolling approach, the models were calibrated for a different 29-year period. The optimum parameter values for each period was used for the prediction of HWDs for the next five years.

3.6 Performance assessment

Statistical performance matrices were used to assess the skill of the prediction models. Four different matrices were used in this study i.e. Coefficient of determination (R^2) (Nagelkerke 1991), normalized root mean squared error (NRMSE) (Fienup 1997), Percentage of bias (Pbias) (Yapo et al. 1996) and modified index of agreement (*md*) (Willmott 1981) represented as Eqs. (2), (3), (4) and (5) respectively.

$$\boldsymbol{R}^2 = \frac{\sum_{i=1}^{N} (\boldsymbol{O}_i - \bar{\boldsymbol{O}}).(\boldsymbol{S}_i - \bar{\boldsymbol{S}})}{\sum_{i=1}^{N} \left(|\boldsymbol{S}_i - \bar{\boldsymbol{S}}|\right)^2 \sum_{i=1}^{N} \left(|\boldsymbol{O}_i - \boldsymbol{O}|\right)^2} \quad (2)$$

$$\boldsymbol{NRMSE} = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N} (\boldsymbol{S}_i - \boldsymbol{O}_i)^2}}{\boldsymbol{sd}(\boldsymbol{O}_i)_{\boldsymbol{normalized}}} \quad (3)$$

$$\boldsymbol{PBIAS} = 100.\frac{\sum_{i=1}^{N} (\boldsymbol{S}_i - \boldsymbol{O}_i)}{\sum_{i=1}^{N} (\boldsymbol{O}_i)} \quad (4)$$

$$md = 1 - \frac{\sum_{i=1}^{N} (O_i - S_i)^j}{\sum_{i=1}^{N} \left(|S_i - \bar{O}| + |O_i - \bar{O}|\right)^j} \quad (5)$$

where N is the number of samples. $\boldsymbol{O}_i$ and $\bar{\boldsymbol{O}}$, are the ith observation and the average of observations, respectively. $\boldsymbol{S}_i$ and $\bar{\boldsymbol{S}}$ are the ith simulated value and the average of simulated values, respectively.

4 Results

4.1 Calculation of heat wave days

The yearly heatwave days (HWDs) calculated based on heatwave definition of (Khan et al. 2019c) is shown in Fig. 4. Figure 5 shows the spatial distribution of the HWDs over Pakistan during different severe heatwave years. While an increase in trend was noticed, the increase was insignificant. The highest HWDs was noticed in 1978 with 59 HWDs. Overall, relatively more HWDs are observed in recent years. Spatial distribution of HWDs showed more heatwaves in the southern regions of Pakistan.

4.2 Selection of the predictors

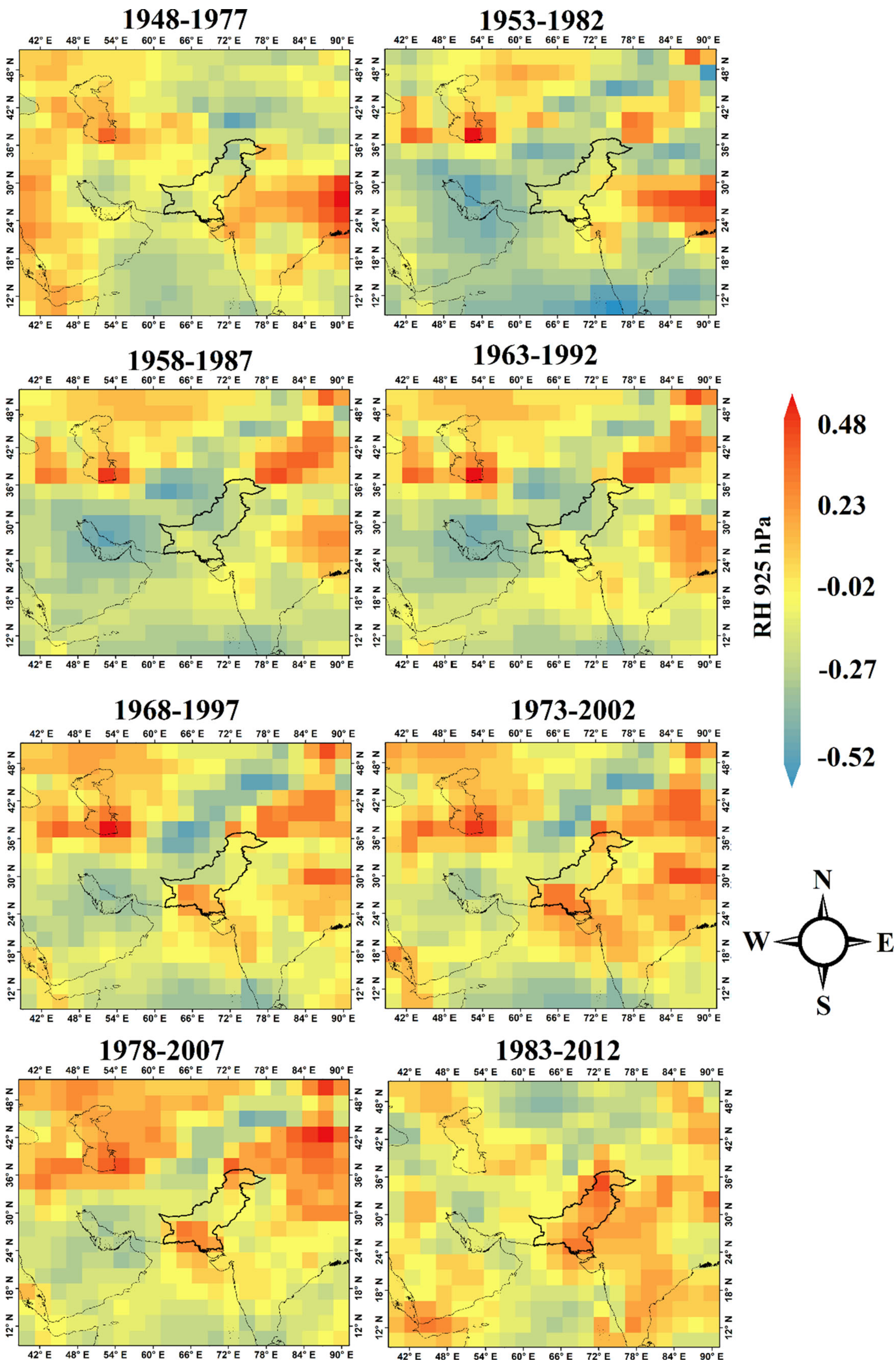
Figure 6 shows the boxplot of correlation between the NCEP predictors and HWDs. Higher positive correlations were observed for HGT, AT and SLP while negative correlations were seen for RH and wind components.

4.3 Selection of the predictors

The changes in the relation between the NCEP predictors and the maximum temperature are shown in Figs. 7, 8, 9, 10, 11 and 12. The spatial correlation for different years between 1948 and 2012 are shown in the figure to illustrate the changes in the relationship between each NCEP predictors and the maximum temperature. Non-consideration of these changes is the major cause of low skill of forecasting models (Wang et al. 2015) as climate change causes a spatial shift in predictability sources.

The *AT* showed correlations with the maximum temperature of Pakistan between − 0.40 and 0.48 is shown in Fig. 7. A strong positive correlation was developed during 1948–1977 which remained until 1978–2007. Afterwards, it was observed to weaken over the years and a moderate positive correlation was found during 1983–2012. For the HGT a higher relationship was seen to evolve from moderate correlation in the starting periods of the analysis (1948–1977) (Fig. 8). However, the negative correlation with HGT was observed in the upper regions of the climate domain which was found to diminish over time. Unlike the other variables, the *RH* was not found to change significantly over time (Fig. 9).

The major driving factors for heat waves in Pakistan is the wind vectors. The correlation of wind vectors with the maximum temperature of Pakistan is shown in Figs. 10 and 11. A positive correlation of wind vectors over the Caspian Sea and the Indian ocean during 1948–77 and 1973–2002 were observed, while the correlation was found negative for the u-wind. The correlation was found to decrease during 1978–2007 and vanish completely during 1983–2012. A much similar pattern was noticed for the v-wind. A positive correlation of maximum temperature of Pakistan with the v-wind was found over central Asia and the Indian Ocean during 1948–77. The correlation was found to become weak during 1983–2012. A weaker correlation during 1948–1977 was found to become negative in the upper region of the climate domain while a positive correlation was found to evolve over the Indian Peninsula.


1948-1977
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1978-2007
1983-2012
42° E 48° E 54° E 60° E 66° E 72° E 78° E 84° E 90° E
12° N 18° N 24° N 30° N 36° N 42° N 48° N
RH 925 hPa
0.48
0.23
-0.02
-0.27
-0.52
N
W
E
S

◀ **Fig. 9** The spatial pattern of the correlation of the relative humidity at 925 hPa pressure level with the maximum temperature of Pakistan

A more dominated negative correlation was seen over the climate domain with the SLP during 1948–1953, which changed to a more dominated positive correlation in the later decades. It gradually became more positively correlated over the Indian peninsula in the south-east and negatively correlated in the northern regions.

4.4 Prediction of heat wave days over pakistan

The performance of the models was evaluated using a time series plot and performance metrics to understand their prediction skill. The time series and the performance metrics of the three ML models are presented in Fig. 13 and Table 2 respectively. The results obtained during different 5-year validation periods were aggregated to prepare the time series. The results showed the ability of all the ML models in replicating the variability of HWDs. All the models were able to reconstruct the anomaly pattern of HWDs which indicates their ability to forecast the possible changes (increase or decrease) in HWDs. Comparison of the relative performance of the models revealed a higher performance of SVM than the other models in terms of all statistical indices. The R^2 of SVM was 0.89 compared to 0.84 for RF and 0.73 for ANN. A high R^2 in SVM prediction indicates the ability of the model to predict the changes in HWDs reliably. The NRMSE% of SVM was found only 32.6% compared to 152% for RF and 53.5% ANN. The rSD which is used to assess the similarity in the variability of two data series revealed a near-perfect value (0.98) for SVM. The md of SVM was also found much higher (0.81) compared to RF (0.52) and ANN (0.65). The time series plot of simulated HWDs by different models revealed the ability of SVM to predict the observed HWDs more reliably for the entire validation period compared to RF and ANN. The results indicated a high potential of the SVM model to be employed for forecasting HWDs in Pakistan.

5 Discussion

Heatwaves are generally defined as the days with temperature above a threshold (Khan et al. 2019c; Robinson 2001; You et al. 2017). Therefore, the number of HWDs in a season is generally used to define the heatwave condition of the season (Vitart and Robertson 2018). Seasonal forecasting models are generally used to forecast the possible occurrence of HWDs in the forthcoming season. In this study, models were developed to forecast the number of HWDs in Pakistan during summer (May to July) before the beginning of summer. Three ML models were used in this study for forecasting HWDs. These classical ML methods have been found highly efficient in solving various complex problems. The results revealed the ability of the ML models to predict the year-to-year variability of HWDs reasonably. A seasonal forecasting model is considered successful if it can predict the variability of heatwave days properly. It means the major aim of such models is to provide early information on whether heatwave will be more in the coming summer or less or severe. The results obtained using the classical ML methods revealed their ability to replicate the seasonal variability of HWD accurately.

The comparative assessment of the models revealed the ability of SVM to predict HWDs with high accuracy. The correlation between simulated and observed HWDs was 0.89 using SVM (Table 2). The rSD was 0.98 (the perfect rSD is 1) which means it was able to replicate the seasonal variability of HWD accurately. The study indicates the performance of the forecasting model depends on the ML algorithm used for the development of the model. Performance of ML models depends on the nature of the problem and the dataset used (Sachindra and Kanae 2019; Yaseen et al. 2018). Therefore, the selection of the appropriate ML algorithm is not straightforward. It is required to compare the performance of different ML algorithms to select the best one for the development of the forecasting model.

The performance of forecasting models significantly depends on the variables used as predictors (Khan et al. 2020a). The methods generally used for selection of input such as correlation coefficient are based on the linear relationship of predictors and predictand. Such predictors cannot guarantee good performance when used as inputs in non-linear models like ML models used in this study. A non-linear approach was used for the selection of inputs considering the nonlinear relationship between input and output (Galelli and Castelletti 2013). Better performance of all the ML models may be also due to the proper selection of inputs.

Studies have reported that the forecasting models have failed or showed low skill in recent year due to climate change. The changes in skills are mostly related to new predictability sources (Wang et al. 2015). The present study revealed a large change in association of ocean-atmospheric variables with HWDs of Pakistan. The results indicate that relation of HWDs with ocean-atmospheric variables would change under warming scenarios. Therefore, the skill of HWDs prediction models may reduce rapidly due to climate change. Updation of models is important to make it resilient to climate change. In this study, a forward rolling approach is used where the

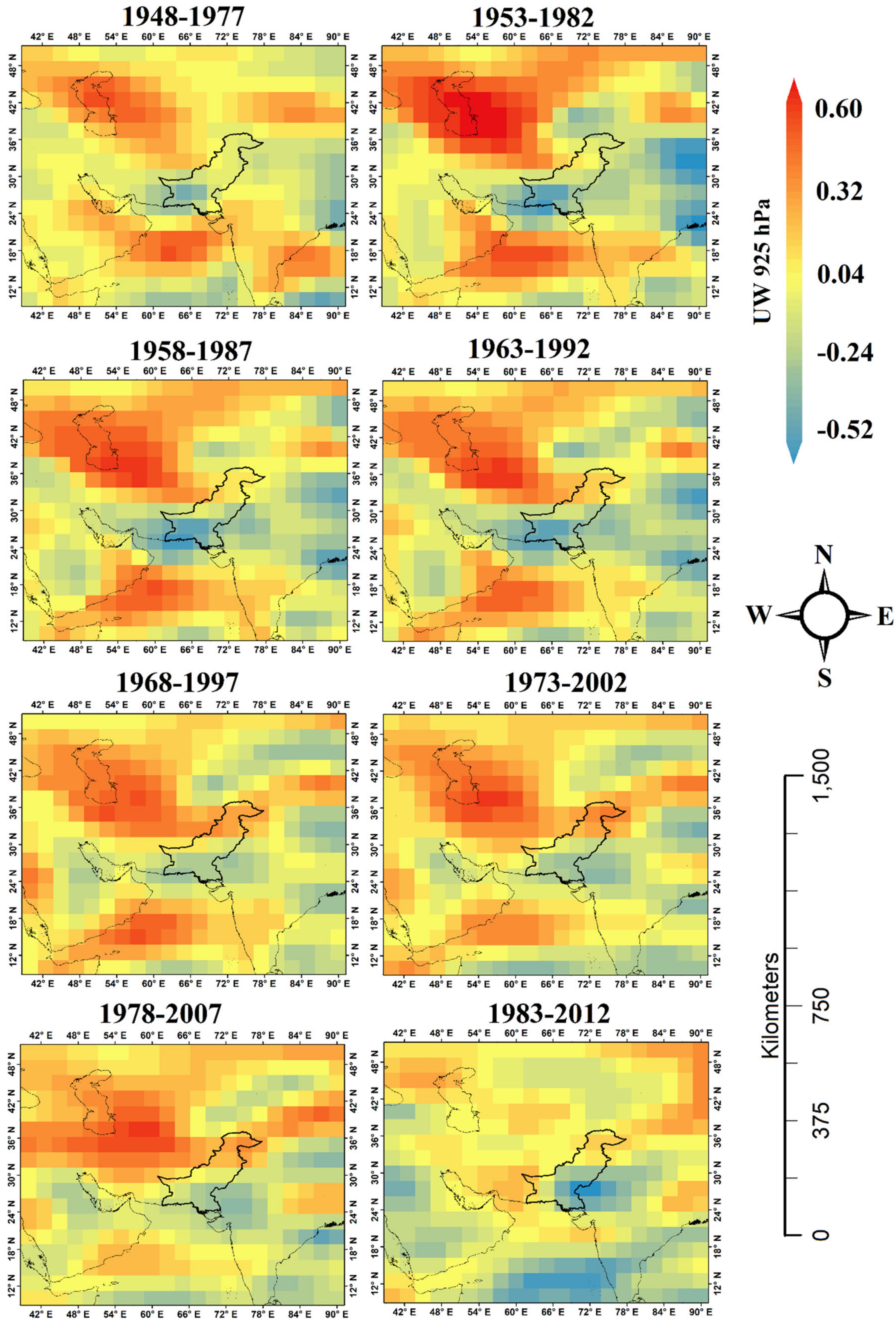


Fig. 10 The spatial pattern of the correlation of the u-wind at 925 hPa pressure level with the maximum temperature of Pakistan

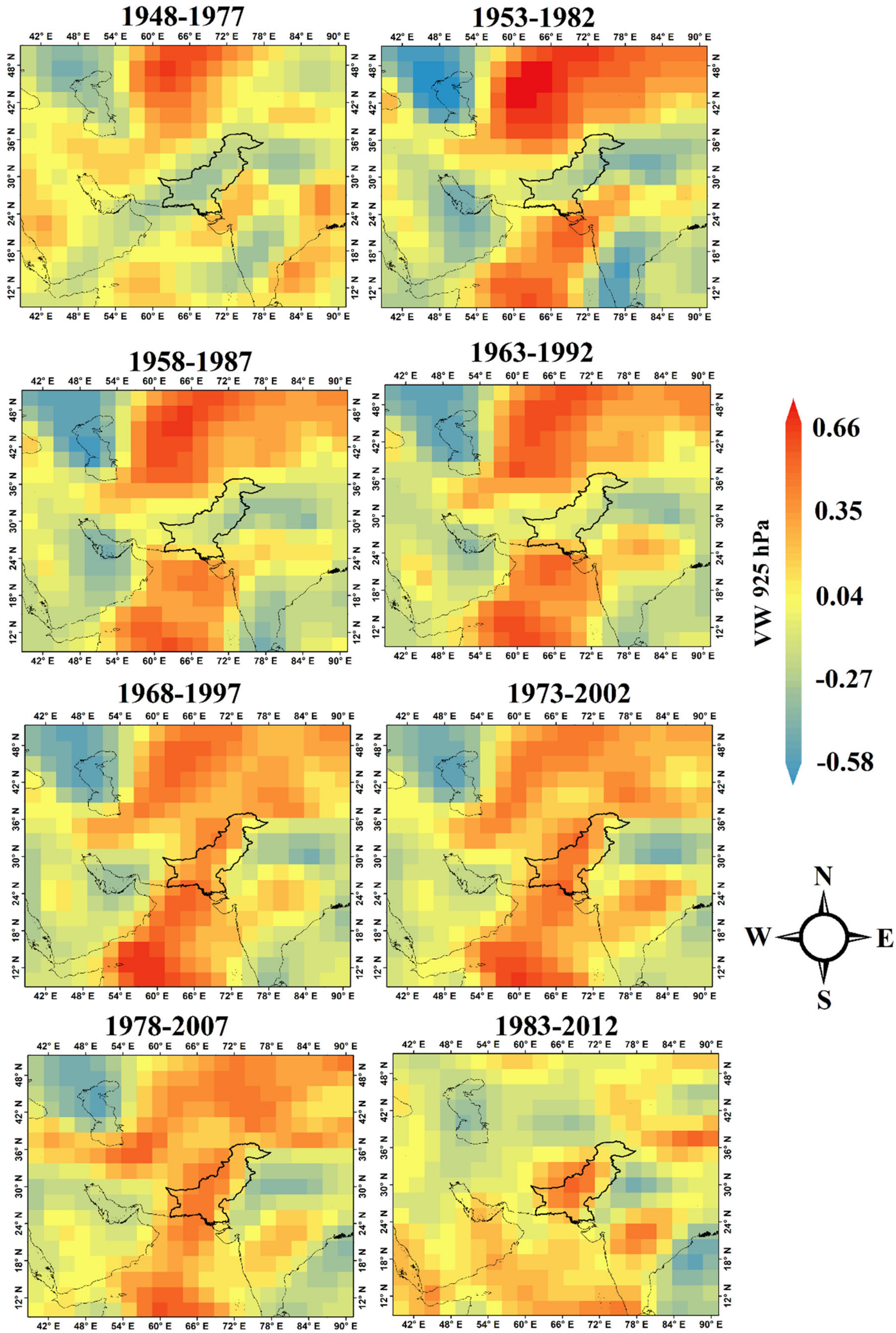
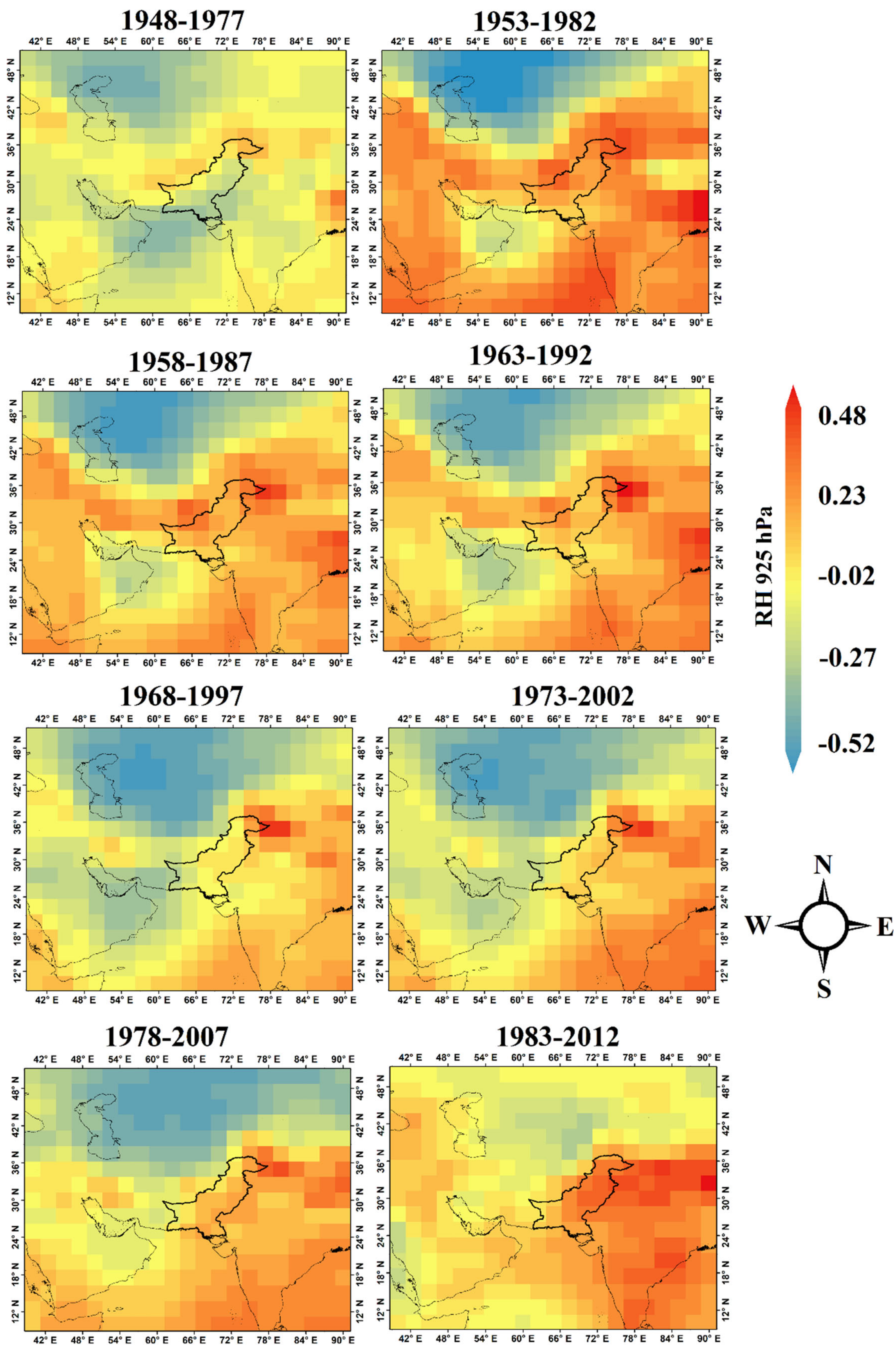


Fig. 11 The spatial pattern of the correlation of the v-wind at 925 hPa pressure level with the maximum temperature of Pakistan


1948-1977
1953-1982
1958-1987
1963-1992
1968-1997
1973-2002
1978-2007
1983-2012
42° E
48° E
54° E
60° E
66° E
72° E
78° E
84° E
90° E
12° N
18° N
24° N
30° N
36° N
42° N
48° N
RH 925 hPa
0.48
0.23
-0.02
-0.27
-0.52
N
W
E
S

◀ **Fig. 12** The spatial pattern of the correlation of the sea level pressure at 925 hPa pressure level with the maximum temperature of Pakistan

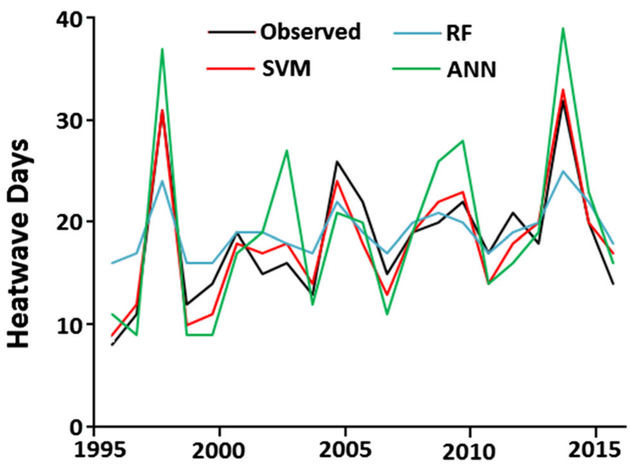


Fig. 13 Time series of the number of HWDs predicted by ML models

Table 2 The performance indices of the SVM, RF and ANN models in the prediction of HWDs

Indices	SVM	RF	ANN
R^2	0.89	0.84	0.73
NRMSE %	32.6	152.1	53.5
rSD	0.98	2.38	0.71
md	0.81	0.52	0.65

predictor–predictand relationship is updated based on changing relationships with the changes in different ocean and atmospheric variables. Therefore, the models are capable in providing robust forecasting under climate change scenarios.

6 Conclusion

A large change in association of ocean-atmospheric variables with HWDs of Pakistan with time was noticed. The changes were found more noticeable for the variables in the lower atmosphere (925 hPa), especially in the past few decades. These are due to the global warming-induced climate change. This caused the pattern of association of those variables with HWDs either changed or diminished as a whole. These patterns play a key role in the skill of forecasting model. As most of the variables show a temporal and a spatial change over the period, incorporating these changes in forecasting model, the failure or the low skill of the model can be avoided. Therefore, the forecasting models in this study were calibrated using a forward rolling approach to adapt to climate change. The forecasting model developed in this study showed good forecasting capability of HWDs over Pakistan in term of all statistical metrics used. The SVM-based forward rolling model showed higher skill in forecasting heatwaves. The SVM model can be used for reliable forecasting of heatwaves of Pakistan in the context of climate change. In future, the performance of other ML algorithms can be evaluated to assess their potential in forecasting heatwaves of Pakistan. Besides, uncertainty in prediction can be assessed for better decision making on probable occurrence of heatwaves.

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