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Assessment of Data-driven Models in Downscaling of the Daily Temperature in Birjand Synoptic Station

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ABSTRACT: In this study, seven models such as multivariate regression, Contemporaneous Autoregressive-Moving Average (CARMA), CARMA-ARCH (Autoregressive Conditional Heteroskedasticity), Support Vector Regression (SVR), Adaptive Neuro-Fuzzy Inference System (ANFIS), Support Vector Machine (SVM) and Genetic Programming (GP) were investigated to downscaling the maximum daily temperature of Birjand synoptic station using 26 predictor's parameters that resulting from the fifth Intergovernmental Panel on Climate Change (IPCC) report and compared. The max daily temperature values measured from 12/03/1961 until 20/12/2005. In all mentioned methods from 26 predictive parameters using the Pearson correlation test, 15 parameters were selected that have a high correlation with the max daily temperature values. The results of evaluating the accuracy and model indicated that from the same models such as GP, ANFIS and SVM, the GP model has the least amount of errors (about 4 °C) and in the regression models (multivariate regression and SVR), SVR have been lowest error rate (about 1 °C) and the highest accuracy in simulated max daily temperature values. The results of the investigation the error rate of the mentioned models indicated that after the SVR model, two CARMA and CARMA-ARCH stochastic models have high and acceptable accuracy about 97 percentages. In general, the results of the simulation the max daily temperature indicates the best accuracy of regression toward another methods. One of the reasons for the results of the SVR model is to optimize the parameters of the model using the ant colony algorithm for estimating the maximum temperature values of the Birjand synoptic station.

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1- Introduction

Following the steady growth of industries and factories and hence increasing the consumption of fossil fuels, it has increased greenhouse gases, especially CO_2 emissions, in recent decades. The increase in this greenhouse gas has been so high that its concentration reached 280 ppm in 1750 to 379 ppm in 2005 [1]. If the consumption of fossil fuels continues at current speeds and volumes, it's likely that the gas will spill over 600 ppm before the end of the 21st century [1]. Changes in greenhouse gas emissions in the climate of the planet are called climate change. The results of studies from the global climate change trend in the last century by the Intergovernmental Panel on Climate Change (IPCC) show that the phenomenon of climate change, as the world's temperature increased in most parts of the world, has been referred to in scientific societies is called as Global warming. According to a comprehensive study by the IPCC on a continental scale, the climate change phenomenon has not only affected global temperatures, but also changes in the characteristics of systems that balance the Earth's atmosphere with the existence of has brought. The most important tool for simulating the future status of climate parameters is the use of general circulation models of the atmosphere. One of the biggest problems with large-scale climatic models is the outputs of these models. The difference in precision of downscaling methods can lead to differences in simulation results that will result in an examination of the accuracy of downscaling methods. The downscaling of the process of climate information transfer is from a large-scale to micro-scale climatic model. There are two dynamic and statistical methods for showing the outputs of downscaling climatic models. At present, the efforts of many institutions and climatic communities in the development of dynamic downscaling techniques are intuitive to demonstrate local and regional climate change. The models can be used for dynamic downscaling are WEPP[1]

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1 Water Erosion Prediction Project

‹SDSM[1] ‹USCLIMATE[2] ‹ASD[3] ‹ PRECIS[4] ‹ LARS[5] ‹ RegCM3[6] and MM5. Dynamic downscaling is based on the numerical simulation of atmospheric physics and ocean processes in nature, which includes high-resolution regional climatological models. This method has a lot of uncertainty, hence the need for time and cost to eliminate uncertainty and its main limitation is to make calculations very complicated, and therefore the statistical method is recommended. Because it requires much less computation and is usually easier to perform. At present, one of the most prestigious tools for producing climate scenarios is the oceanic-atmospheric circulation model, which is based on the laws of physics by mathematical rules. Despite the significant increase in the general circulation patterns of the atmosphere, so far none of these models are capable of predicting meteorological stations at a small scale. To this end, statistical models, dynamic and proportional models for quantitative simulation and transformation have been developed from Global Climate Model (GCM) models that can convert the outputs of the numerical model to the station scale. To do this, comprehensive studies have been done on the planet. For example, Khan et al. (2006) investigated the uncertainty of three downscaling models SDSM, WG-LARS and ANN. The results showed that the SDSM and WG-LARS models performed better than the ANN model [2]. Steele et al. (2008) investigated the effect of climate change on the three basins in Ireland, using the general and small-scale public circulation model [3]. The results showed that during the period of 2010-2060 there will be an increase in winter precipitation and a decrease in summer precipitation. Akhtar et al. (2008) examined the impact of climate change in the Hindu Kush-Karakoram basin in the Himalayas for the period of 2070-2100, and their results showed an increase in temperature and precipitation in the studied basin [4]. Chu et al. (2010) evaluated a downscaling model of temperature, evapotranspiration, and precipitation in the Haihe River Basin in China. The results of this assessment showed that patterns of climate change variation can be simulated with acceptable accuracy [5]. Liu et al. (2011) evaluated two statistical downscaling patterns, which are the A Nonhomogeneous Hidden Markov Model (NHMM) and s Statistical downscaling Model (SDSM) model, on the daily precipitation data of Tarim Lake in China [6]. The comparison tools in this research were the remaining functions, correlation analysis, and density and probability distribution functions. In general, the results showed that both methods with some performance differences in the processing and validating the pattern have the necessary stability. Based on the results of this study, the performance of the NHMM method is slightly better than SDSM in the monthly rainfall simulation, so that the user will be able to simulate the rainfall for all months. However, both NHMM and SDSM patterns are less accurate due to the random components in the rainfall modeling pattern, which are less accurate in the annual precipitation sampling. Meenu et al. (2012) used a hydrological model for the hydrological modeling of the Tunga– Bhadra River region in India, and the SDSM downscaling method for exponential micromachining of minimum and maximum temperatures and daily rainfall in the research area [7]. The results of water balance showed the rainfall and runoff, and reduction of real evapotranspiration losses on the area. Rajabi and Shabanlou (2012) used the SDSM model to assess the climate change of the Kermanshah region in western Iran and its effect on climate indicators such as Johnson, Corner and Dumartron [8]. In this study, using the HadCM3 general atmospheric circulation pattern with considering the A2 and B2 emission scenarios the climate change were evaluated for the period of 2011-2039, 2040-2069, and 2077-2099. The results showed that the climate in the region will be dry in the 2077-2099 period, and this change will be for the A2 scenario. Cheema et al. (2013) evaluated the performance of SDSM downscaling method on the process of minimum temperature data of Pakistani stations in the period 1991-2010 [9]. According to the results of this research and according to the Mann Kendall test, the incremental minimum annual temperature is significant.

In addition, the analyses showed that there is a good agreement between the data of the sample temperature and the actual data, while the Pearson correlation coefficient for most regions was more than ninety percent. The researchers used a variety of statistical methods to examine the process. Their results showed a significant change in the climate in the northern provinces of Pakistan. Kazemi et al. (2014) used the SDSM method to output the daily temperature of the global ECHAM5 model [10]. Their results showed that downscaled data is more accurate than ECHAM5 model data. The correlation coefficient of the quantified data with the observed data is between 81 and 94%, while the correlation for global model data is between 73% and 87%. In this study, the percentage of bias (PBIAS), Nash-Sutcliff and Adjusted Index were used for evaluating precipitation data and temperature. The PBIAS index was the minimum temperature (-0.30%), the Nash-Sutcliff (0.80) and the corrected correction index (0.83) for maximum daily temperature at the Bangladesh Shelter Station. Among the five reengages stations, the downscaled precipitation showed a minimum (1.31%), Nash-Sutcliff (0.76), and a corrected index (0.79) for the maximum. Temperatures and precipitation data correlated with observed data to be matched. Campozano et al. (2016) compared different models of downscaling, such as SVM, ANN and SDSM, in the downscaling of the monthly precipitation of the Potte River Basin in southern Ecuador [11]. The results showed that the LS-SVM and ANN models have a higher accuracy than the SDSM downscaling model. For downscaling the rainfall and daily temperatures, various methods have been discussed in various studies. But what's important is that, given the nature of the daily temperature data, what model can fit these data well? Finally, the purpose of this study was to investigate the accuracy of various methods including artificial intelligence and stochastic methods to

1 Statistical Downscaling Model

2 United States Climate

3 Automated Statistical Downscaling

4 Providing Regional Climates for Impacts Studies

5 Long Ashton research station

6 Regional climate model

modeling and downscaling the daily temperature values in the Birjand synoptic station during the period of 1961-2005.

2- Materials and Methods

2- 1- A case study

South Khorasan Province in the east of the Iran with an area of 95385 square kilometers is located between the geographical latitudes of 32′ 57° to 50′ 61° eastern and the geographical latitudes of 31′ 30° to 15′ 45° north. The province is neighboring from the north to Khorasan Razavi province, from the east to Afghanistan, from the south with Sistan and Baluchistan province, from the southwest to Kerman province, and from the west with the provinces of Yazd, Isfahan and Semnan. This is indicative of the importance the strategic situation of the province is border and security. Figure 1 shows the location of South Khorasan province and Birjand city in relation to neighboring provinces, and Figure 2 shows the maximum value of the temperature during the statistical period of 1961-2005 that were used. This data is from the Iranian Meteorological Organization.

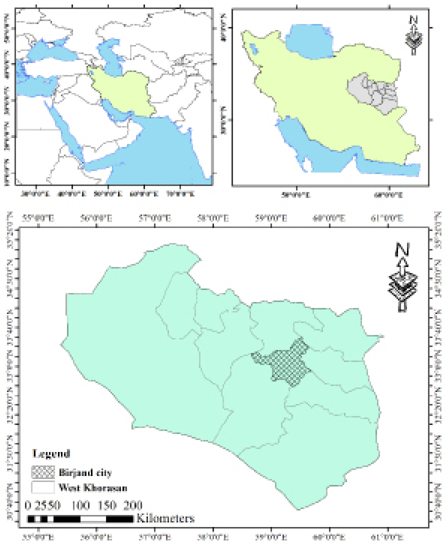

Figure 1. Location of Birjand city in Iran and south Khorasan

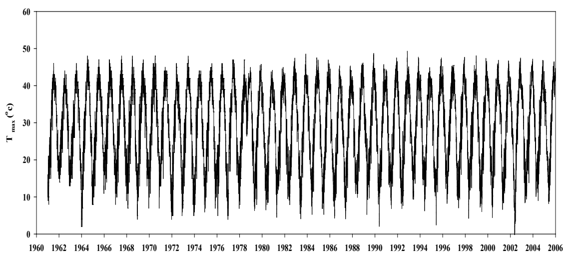

Figure 2. Changes in the maximum daily temperature values of the Birjand synoptic during the 1961-2005

2- 2- Trend evaluation

In this study, the trend of the time series of maximum daily temperature values of the studied station with non-parametric Man-Kendall test is investigated. This test has been widely used in hydrology, climatology and metrology studies [12, 13]. The necessary condition for using this test is the lack of autocorrelation in the data series, however, the data may have a significant correlation. Therefore, firstly, the correlation of data should be eliminated so that we can use the Kendall test [14]. For this purpose, in the present study, instead of the conventional Mann-Kendall test (MK1), another version including the Mann-Kendall test was used with complete removal of self-correlations [14-19]. In this study to downscaling the mentioned data, the ANFIS, GP, SVM, SVR, CARMA, CARMA-ARCH, and multivariate regression methods were used and compared.

2- 3- Adaptive Nero-Fuzzy Inference System (ANFIS)

An Adaptive Nero-Fuzzy Inference System method is a hybrid method in which the fuzzy sector establishes the relation between the input and output variables and the characteristics related to fuzzy membership functions are also determined by the neural network. In an ANFIS model, the structure of the model is first selected with parameters specific to the inputs, the degree of membership, and the rules and functions of the membership degree. Then, a part of the existing data is selected as an input-output that can be used to teach this system [20].

2- 4- Gene expression program

The method of Gene expression programming was proposed by Ferreira in 1999 [21]. This method is a combination of genetic programming and genetic algorithm, in which linear chromosomes with fixed lengths are similar to those used in the genetic algorithm and branch structures with different sizes and forms, similar to decomposition trees in genetic programming. Since in this method all branch structures of different sizes and shapes are encoded in fixed-length linear chromosomes, they have caused the phenotype and genotype to be separated in this method and the system can take advantage of all evolution is due to their existence.

2- 5- Support Vector Machine

The first application of this method to water issues by Dibak et al. was presented in 2001 with rainfall-runoff modeling. The support vector machine is an applied learning system is based on the theory of optimization, which is based on the principle of inductive minimization of structural error and leads to an overall optimal response. In the SVM regression model, a function associated with the dependent variable Y, which itself is a function of several independent variables x, is estimated. Similar to other regression issues, it is assumed that the relation between independent and dependent variables with algebraic function f (x), plus some disturbance (allowed error ε), is assumed to be Equation 1.

$$f(x) = W^T . \phi(x) + b \tag{1}$$

$$y = f(x) + noise \tag{2}$$

If W (vector of coefficients) and b (constant) are characteristic of the regression function and Φ is also a kernel function, then the purpose is to find a functional form f (x). This is accomplished by training the SVM model by a set of examples (instruction set).

2- 6- AR and ARMA Linear Models

Since the early 1960s, time series models have been widely used to predict the river flow. The main reason for the widespread use of these models is their ability to create a correlation between the flow rates of current flow with the previous time on one side and the simplicity of the structure of the model on the other. Thomas and Feiring (1962) used these models for the first time and in the 1970s developed these models in three stages [22]: (1) model recognition (2) parameter estimation; and (3) model evaluation was developed for hydrological and meteorological parameters [23].

2- 7- ARCH-Models

The first model that provides a systematic framework for volatility modeling is the ARCH model of Engle [24]. The basic idea of ARCH models is that (a) the mean corrected asset return at is serially uncorrelated, but dependent, and (b) the dependence of at can be described by a simple quadratic function of its lagged values. Specifically, an ARCH(m) model assumes that:

$$\varepsilon_t = \sigma_t z_t \ and \ \sigma_t^2 = a_0 + \sum_{i=1}^{m} b_i \varepsilon_{t-i}^2 \tag{3}$$

That σ_t^2 is conditional variance, ε_t is model remaining error with mean equal zero and variance equal one. $a_0 \geq 0, b_i \geq 0$ are models parameter, m is model rank and Z_t is a time series of desired parameter [24].

2- 8- Models validation

For evaluation of the performance of models, two correlation coefficient and root mean square error tests were used.

$$RMSE = \left[\frac{\sum_{i=1}^{n} (\hat{Q}_i - Q_i)^2}{N} \right]^{0.5} \tag{4}$$

$$R = \sqrt{1 - \frac{\sum_{i=1}^{n} (Q_i - \hat{Q}_i)^2}{\sum_{i=1}^{n} (Q_i - \overline{Q})^2}} \tag{5}$$

$$NSE = 1 - \frac{\sum_{i=1}^{n} (Q_i - \hat{Q}_i)^2}{\sum_{i=1}^{n} (Q_i - \overline{Q}_i)^2} \tag{6}$$

That Q_i ، and is a historical data, modeled data and means of studied data respectively and n is a $\overline{Q}$ and $\hat{Q}$ number of data [25]. For fitting and combining the ARMA models with ARCH models, first using the mentioned data to modeling the ARMA model and then combined the ARMA and ARCH models with calculated the conditional variance of remaining time series.

3- Results and Discussion

In this study, the modified Mann-Kendall test with removing of correlation effects has been used to study the trend of maximum temperature values at the synoptic station of Birjand. The results of the study of changes in the maximum daily and annual temperature values at the synoptic station of Birjand showed that the trend of this parameter is incremental but not significant. As indicated, in this research, for the downscaling of maximum daily temperature values of Birjand synoptic station using CanESM2 predictive data, the accuracy and efficiency of various models such as ANN, SVM, SVR, ANFIS, GP, CARMA, CARMA-ARCH and multivariate regression were compared. The model stands for the Canadian Earth System Model, and is the fourth generation of weather models developed by the Canadian Center for Modeling and Climate Analysis (CCCma) under the auspices of its environmental organization. Since one of the most important steps in modeling is choosing the right mix of input variables, therefore, the correlation between input and output variables should be calculated. Before examining and simulating the data, using the Pearson correlation method, the correlation between 26 predictive parameters of CanESM2 and daily values of the maximum temperature of the synoptic station of Birjand was estimated. The results showed that among the 26 predictive parameters of CanESM2, only 15 parameters have a good correlation with the daily data of the maximum station temperature of the selected station. The 15 parameters selected and their correlation coefficients are presented in Table 1. In fact, the parameters that were correlated with the observed observations at the synoptic station in Birjand were selected. After selecting the predictive parameters, using these 15 predictive parameters, the maximum daily temperature values of the synoptic station of Birjand during the statistical period of 1961-2005 were simulated using the mentioned data-driven models.

In using the models, about 80% of the maximum daily temperature data of the synoptic station of Birjand was considered as the input of the model and 20% of it was considered as the experimental input of the models. The results of the accuracy of data modeling were presented in Table 2.

The model of vector support machine in the training phase has an overestimation. This is also at the testing stage. The results of the evaluation of the error rate of the support vector machine model in estimating the maximum values of the temperature of the Birjand station showed that this model has a lower accuracy than the optimized method of support vector regression. The error rate of the support vector machine model in estimating the maximum temperature of the Birjand station is at 5.5 ° C and at 5.66 ° C in training and testing phase respectively. This error rate in the support vector machine technique is approximately 5 times of support vector regression method. The multivariate regression model is well simulated as the maximum and minimum points of the studied data. The results of studying the accuracy of this model in estimating the maximum temperature of Birjand station showed that the error rate of this model is equal to 4.096 degrees Celsius in the statistical period which is better than the results of the support vector machine model. Genetic programming model, like other models, has been able to estimate the maximum and minimum values of the studied data. The accuracy of the genetic programming model in estimating the maximum temperature of the Birjand station is acceptable in two stages of training and testing. The results of evaluation the error rate of the genetic programming model in estimating the maximum temperature of the Birjand station showed that the error rate of this model in the estimation of the values in the training stage is 4.08 degrees Celsius and in the testing stage is about 4.26 degrees Celsius, which is more than the support vector machine model and is more careful.

The ANFIS model also has a good ability to estimate of the maximum temperature of the Birjand station in two stages of training and testing. By estimating the mean squared error values in estimating the error values of the ANFIS model, it was found that the error rate of this model in the training stage is about 4.23 degrees Celsius and in the experimental stage is 6.36 degrees Celsius. In addition to regression and artificial intelligence techniques, the ARMA family has been used for statistical analysis of multivariate time series. These models, known for their CARMA model, have a high ability to modeling meteorological and hydrologic values. The results of studying and estimating the maximum values of Birjand station using ARMA family stochastic models showed that this model has a higher ability to estimate the maximum temperature of Birjand station. These results are well evident in both the training and the testing stage. The results of the evaluation of the error rate of the mentioned model in estimating the values indicated that

Table 1. Results of correlation between predictive values and daily temperature of Birjand Synoptic Station

Predictor variables	Description of predictor variables	Correlation	Predictor variables	Description of predictor variables	Correlation
MSLPGL	Mean seal level pressure	-0.61	p8-fgl	850hPa Wind speed	-0.09
p1_FGL	1000hPa Wind speed	-0.06	p8-ugl	850hPa Zonal wind component	-0.45
p1_Ugl	1000hPa Zonal wind component	-0.58	p8-vgl	850hPa Meridional wind component	-0.42
p1_Vgl	1000hPa Meridional wind component	-0.42	p8-zgl	850hPa Relative vorticity of wind	0.05
p1_zgl	1000hPa Relative vorticity of wind	0.046	p8-thgl	850hPa Wind direction	-0.28
p1thgl	1000hPaWind direction	-0.055	p8-zhgl	850hPa Divergence of true wind	-0.07
p1zhgl	1000hPa Divergence of true wind	-0.106	p500gl	500hPa Geopotential	0.69
p5-fgl	500hPa Wind speed	-0.075	p850gl	850hPa Geopotential	-0.41
p5-ugl	500hPa Zonal wind component	-0.63	prcpgl	Total precipitation	-0.51
p5-vgl	500hPa Meridional wind component	0.240	s500gl	500hPa Specific humidity	0.40
p5-zgl	500hPa Relative vorticity of wind	-0.28	s850gl	850hPa Specific humidity	0.49
5-thgl	500hPa Wind direction	-0.43	shumgl	1000hPa Specific humidity	0.42
5-zhgl	500hPa Divergence of true wind	0.53	tempgl	Air temperature at 2m	0.29

Table 2. Results of the accuracy of studied models in estimating daily mean temperature values

Model	RMSE (oC)	N-S	Correl	Step
SVR	1.184	0.998	0.994	Train
	0.984	0.992	0.996	Test
GP	4.085	0.853	0.931	Train
	4.262	0.969	0.923	Test
Regression	4.069	0.856	0.931	---
SVM	5.504	0.727	0.887	Train
	5.666	0.726	0.861	Test
ANFIS	4.239	0.842	0.928	Train
	6.398	0.649	0.914	Test
CARMA	2.508	0.945	0.973	Train
	2.417	0.951	0.976	Test
CARMA-ARCH	2.454	0.948	0.974	Train
	2.362	0.953	0.976	Test

this model had an error rate of 2.50 ° C at the training stage and an error rate equal to 2.41 ° C at the training stage. According to the obtained results, it can be concluded that after the optimized support vector regression model, this model provides better results in estimating maximum values of Birjand station. In this study, in addition to the mentioned models, the combination of time series multivariate models called CARMA model with non-linear models of ARCH family, modeling the maximum values of the temperature in the synoptic station of Birjand on the daily scale in statistical period 1961-2005 were evaluated. Modeling and estimating the maximum daily temperature values of Birjand synoptic station has been improved by combining linear and nonlinear models of conditional variance. The results of fitting the observational and computational data obtained from estimating the maximum values of the temperature at the Birjand synoptic station using the hybrid models showed that this model is well fitted with historical data and has been able to present the better results than the linear time series model. The results of estimating the error rate of the combined model in estimating the maximum temperature values of the Birjand synoptic station showed that the error rate of this model in estimating the values in the two stages of training and testing was respectively 2.45 and 2.36 degrees Celsius respectively.

However, the results suggest that the accuracy of the optimized support vector regression model is still higher than other models. The results of modeling and fitting of the data with the SVR model at the testing stage are presented in Figure 3.

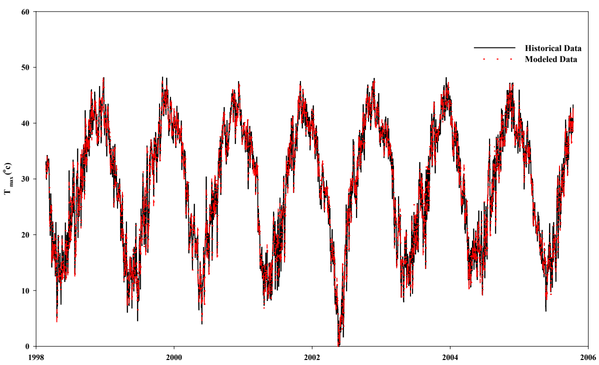

Figure 3. Estimates of the maximum daily values of the Birjand synoptic Station using the SVR model at the testing stage

It should be noted that in using vector support regression method, the ant colony algorithm was used to optimize the model parameters. A total of 100 iterations were used in run of the ant colony algorithm and ultimately, the c, ε and sigma values were optimally optimized. The results of evaluation the error of the support vector regression model in estimating the maximum temperature values of the Birjand station showed that the error rate of this model is in the training phase is 1.181 degrees Celsius and in the training phase is 0.984 degrees Celsius, which it is acceptable accuracy. One of the factors that improves the SVR model results compared to other models is to optimize its parameters. Among the regression models, the SVR model has the highest accuracy. Tripathi et al. [26] also confirmed the accuracy of the SVR regression method in the downscaling observation of climate data. Karamouz et al [27] and Khan et al. [2] also showed that the accuracy of artificial intelligence models in the downscaled the maximum daily values is weak.

4- Conclusion

In this study, the accuracy of seven different models in simulating the maximum daily temperature values of the Birjand station during the statistical period of 1961-2005 was investigated. In this regard, 26 predictive parameters of CanESM2 were used. The studied models in this study are support vector regression, genetic programming, multivariable regression, support vector machine, ANFIS, multivariate time series model and hybrid multi-variable time series model. After reviewing and correcting the mentioned data, among the 26 predicted parameters, 15 parameters were selected based on their correlation with maximum daily temperature values of Birjand synoptic station. Using these 15 parameters and maximum values of Birjand synoptic station, the mentioned data was estimated and modeled using available models. The results of the study of the accuracy of these models were studied in two stages of training and testing. The results of the models' effectiveness showed that other than the support model, other methods have high efficiency in estimating the maximum daily temperature values. The results of RMSE analysis showed that among the seven models examined, the support vector regression model has a higher accuracy than the other models. The results also showed that CARMA-ARCH model and CARMA model ranked second and third among the studied models. The fourth rank in terms of modeling accuracy is related to multivariable regression. Similarly, the fifth to seventh rankings are related to genetic programming, ANFIS, and support vector machines. It should be noted that for estimating the parameters of the SVR model, the optimization ant colony algorithm was used and the three parameters of the nonlinear SVR model were optimized.

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References

[1] S. Solomon, D. Qin, M. Manning, Z. Chen, M. Marquis, K. Averyt, M. Tignor, H.J.S.S. Miller, IPCC, 2007: Climate change 2007: The physical science basis. Contribution of Working Group I to the fourth assessment report of the Intergovernmental Panel on Climate Change, (2007).

[2] M.S. Khan, P. Coulibaly, Y. Dibike, Uncertainty analysis of statistical downscaling methods, Journal of Hydrology, 319(1-4) (2006) 357-382.

[3] S. Steele-Dunne, P. Lynch, R. McGrath, T. Semmler, S. Wang, J. Hanafin, P. Nolan, The impacts of

climate change on hydrology in Ireland, Journal of hydrology, 356(1-2) (2008) 28-45.

[4] M. Akhtar, N. Ahmad, M.J. Booij, The impact of climate change on the water resources of Hindukush–Karakorum–Himalaya region under different glacier coverage scenarios, Journal of hydrology, 355(1-4) (2008) 148-163.

[5] J. Chu, J. Xia, C.-Y. Xu, V. Singh, Statistical downscaling of daily mean temperature, pan evaporation and precipitation for climate change scenarios in Haihe River, China, Theoretical and Applied Climatology, 99(1-2) (2010) 149-161.

[6] Z. Liu, Z. Xu, S.P. Charles, G. Fu, L. Liu, Evaluation of two statistical downscaling models for daily precipitation over an arid basin in China, International Journal of Climatology, 31(13) (2011) 2006-2020.

[7] R. Meenu, S. Rehana, P. Mujumdar, Assessment of hydrologic impacts of climate change in Tunga–Bhadra river basin, India with HEC-HMS and SDSM, Hydrological Processes, 27(11) (2013) 1572-1589.

[8] A. Rajabi, S. Shabanlou, Climate index changes in future by using SDSM in Kermanshah, Iran, J. Environ. Res. Dev, 7(1) (2012).

[9] S.B. Cheema, G. Rasul, G. Ali, D.H. Kazmi, A comparison of minimum temperature trends with model projections, Pakistan Journal of Meteorology, 8(15) (2011).

[10] D.H. Kazmi, G. Rasul, J. Li, S.B. Cheema, Comparative study for ECHAM5 and SDSM in downscaling temperature for a geo-climatically diversified region, Pakistan, Applied Mathematics, 5(1) (2014) 137.

[11] L. Campozano, D. Tenelanda, E. Sanchez, E. Samaniego, J. Feyen, Comparison of statistical downscaling methods for monthly total precipitation: case study for the paute river basin in Southern Ecuador, Advances in Meteorology, 2016 (2016).

[12] F. Ahmadi, M. Nazeri Tahroudi, R. Mirabbasi, K. Khalili, D. Jhajharia, Spatiotemporal trend and abrupt change analysis of temperature in Iran, Meteorological Applications, 25(2) (2018) 314-321.

[13] R. Zamani, R. Mirabbasi, M. Nazeri, S.G. Meshram, F. Ahmadi, Spatio-temporal analysis of daily, seasonal and annual precipitation concentration in Jharkhand State, India, Stochastic Environmental Research and Risk Assessment, 32(4) (2018) 1085-1097.

[14] K. Khalili, M.N. Tahoudi, R. Mirabbasi, F. Ahmadi, Investigation of spatial and temporal variability of precipitation in Iran over the last half century, Stochastic environmental research and risk assessment, 30(4) (2016) 1205-1221.

[15] M. Kendall, Rank Correlation Measures [M], London: Charles Griffin, (1975).

[16] S. Kumar, V. Merwade, J. Kam, K. Thurner, Streamflow trends in Indiana: effects of long term persistence, precipitation and subsurface drains, Journal of Hydrology, 374(1-2) (2009) 171-183.

[17] H.B. Mann, Nonparametric tests against trend, Econometrica: Journal of the Econometric Society, (1945) 245-259.

[18] P.K. Sen, Estimates of the regression coefficient based on Kendall's tau, Journal of the American statistical association, 63(324) (1968) 1379-1389.

[19] H. Theil, A rank-invariant method of linear and polynomial regression analysis, in: Henri Theil's contributions to economics and econometrics, Springer, 1992, pp. 345-381.

[20] M. Karakus, B. Tutmez, Fuzzy and multiple regression modelling for evaluation of intact rock strength based on point load, Schmidt hammer and sonic velocity, Rock mechanics and rock engineering, 39(1) (2006) 45-57.

[21] C. Ferreira, Algorithm for solving gene expression programming: a new adaptive problems, Complex Systems, 13(2) (2001) 87-129.

[22] H.A. Thomas, Mathematical synthesis of streamflow sequences for the analysis of river basin by simulation, Design of water resources-systems, (1962) 459-493.

[23] J.D. Salas, Applied modeling of hydrologic time series, Water Resources Publication, 1980.

[24] R.F. Engle, Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation, Econometrica: Journal of the Econometric Society, (1982) 987-1007.

[25] J.E. Nash, J.V. Sutcliffe, River flow forecasting through conceptual models part I—A discussion of principles, Journal of hydrology, 10(3) (1970) 282-290.

[26] S. Tripathi, V. Srinivas, R.S. Nanjundiah, Downscaling of precipitation for climate change scenarios: a support vector machine approach, Journal of hydrology, 330(3-4) (2006) 621-640.

[27] M. Karamouz, M. FALAHI, S. Nazif, F.M. RAHIMI, Long lead rainfall prediction using statistical downscaling and artificial neural network modeling, (2009).

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