Empirical Models for the Estimation of Diurnal Temperature

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ABSTRACT

Air temperature is an essential climatological component which controls and influences various earth surface processes. Accurate estimation of air temperature is essential in various sectors such as industries, agriculture, and energy. Air temperature is also one key factor in predicting other meteorological variables such as stream flow, evapotranspiration, and solar radiation.

We performed fitting for diurnal temperature data using polynomial fit. Measured diurnal temperature data gotten from land surface temperature data from NRCRI for 2014-2019 were analyzed. The curve fitting method found suitable to be applied to the filtered diurnal temperature data is the polynomial fit. The polynomial data fitting method was used for data smoothing and was tested by using different degrees of polynomial curve fittings. The error measurement was calculated using the root mean square error (RMSE) and by determining the R^2 value. The error measurement of RMSE and R^2 shows that the errors between the polynomial degrees are of 95% confidential interval. The polynomial fittings were carried out by using Matlab. From the numerical results, the fitting model gave better results without any wiggle at both end points of the graph and the value of RMSE is 0.4725and R^2 value is 0.9879. Polynomial fitting 10th degree has given better R^2 (0.9879) and RMSE is 0.4725.

(Keywords: curve fitting, polynomial fit, air temperature, diurnal temperature data, Matlab)

INTRODUCTION

Global warming has recently drawn scientists' attention since it is correlated with the rise in air temperature. Increasing air temperature leads to changes in climatic conditions, such as sea-level rise, growth of extreme events and global warming, ultimately negatively impacting humans' lives. Air temperature (Ta) is one of the main inputs in several models in hydrology, climate, meteorology, etc. Air temperature is the state variable of the atmosphere which affects atmospheric, land surface and sea surface processes. Extreme changes in air temperature may cause damage to plants and animals (Zhang, *et al.,* 2020). Accurate estimation of air temperature is essential in various sectors such as industries, agriculture, and energy. Air temperature is also one key factor in predicting other meteorological variables such as stream flow, evapotranspiration, and solar radiation. The temporal patterns of air temperature is complicated because it is swayed by a broad range of variable parameters like wind-speed, time, sky conditions, solar zenith angle, soil moisture, location, emissivity and thermal inertia. Some of these parameters cannot be measured by remote sensing.

The stressful effect of climate on death rate (mortality) has been proved which means that the farther the temperature from the human comfort zone, the further the stress, resulting in increased death rate (Marmor, 1975; Ramlow, *et al.,* 1990). A significant relationship has been determined between temperature and death rate for some world cities. Deaths that are directly related to the temperature such as increased body temperature can be the result of cardio-respiratory diseases or poor functioning of the vessels that transfer nutrients and blood to the body (Kalkstein 1991; Martens 1998).

Since climate has a significant effect on human's social and individual life, climatic weather forecast is performed based on current and predicted values of atmospheric parameters (Teshnehlab and Monshi, 2003). The role of maximum temperature is quite clear in increasing the evaporation and transpiration, reduction of surface and underground water, the spread of various diseases, forest fires, the process of melting glaciers, and drought and water shortages in other areas (Hosseini, 2009).

Significant changes in global temperatures or global warming are considered as the most important aspects of climate change in the present century. If estimating and predicting methods have enough accuracy, they can be used in planning and management (Karamooz, *et al*., 2006). High temperature can also cause many disasters in road transportation. Direct impact on the vehicle through evaporation of gasoline and water (Keay and Simonda, 2005) and driver fatigue (Eriksoon and Lindqvist, 2003) are among these cases. Several models have been put in place to accurately predict temperature changes over a wide range.

In meteorology, the term "Diurnal" often refers to the change of temperature from the daytime high to the nighttime low. Diurnal can also said to be any pattern that reoccurs after every 24 hours as a result of Earth rotation on its axis. Diurnal temperature variation is the difference between a high air temperature and a low temperature that occurs during the same day. Several diurnal temperature cycle (DTC) meteorological models generate diurnal data of climatic variables from their mean daily values using the analogy between their cycles during the day and trigonometric functions (Jury and Horton, 2003; Saito and Šimůnek, 2009). According to Ephrath, *et al*. (1996), Diurnal changes in variables are needed to be calculated from daily values available using meteorological models. Stisen, *et al*. (2007), used TVX based DTC modeling to acquire diurnal variation of air temperature.

The importance of accurate forecast of air temperature in water resources management, land–atmosphere interaction and agriculture cannot be overemphasized. It is somewhat difficult to accurately predict air temperature due to its non-linear and chaotic nature. Studies have shown that neural network models can be employed as promising tools to forecast air temperature. ANN-based approaches have been widely used to predict air temperature due to their fast-computing speed and ability to deal with complex problems (Tran, *et al.,* 2021). It is found that the ANN methods are mainly viable for short-term air temperature forecasting.

Different types of ANNs have been utilized to forecast air temperature such as multi-layer perceptron (MLP), recurrent neural network (RNN), long short-term memory (LSTM), convolutional neural network (CNN), and many others (Cifuentes, *et al.,* 2020). Each of these ANN has its unique structure for temperature pattern and forecast. Due to the chaotic and complex nature of air temperature data, accurate air temperature forecasting has remained a major challenge for many decades (Tran, *et al*., 2021). According to researchers, one of the effective methods that has numerous uses in the science of climate are artificial neural networks (Abbot, *et al.,* 2012). Its power and high-speed in simulating processes that are not properly understood or comparing them with other methods is time-consuming and difficult is the main reason for its acceptance and growing use.

Generally, it can be said that artificial neural networks are a high-capability robust model that can be viewed positively on climate and hydrological issues. Uniquely, this network can extract the law, the data including the noisy data (Dehghani and Ahmadi, 2008). Jain (2003) predicted the temperature of South Georgia for the next one to twelve hours using the artificial neural network. Khosravi, *et al*., (2010) considered the use of artificial neural networks in the field of atmospheric sciences and calculating climatological parameters. They used variables such as relative humidity, average wind speed, average hours of sunshine, and the difference between the average minimum temperature and the average maximum temperature as Perception multilayer neural network input.

Accurate prediction of air temperature has remained a major challenge especially when the forecast time horizon increases for many decades due to the chaotic and complex nature of air temperature data. To this knowledge, several empirical models are being put in place which will aid accurate measurements of diurnal temperature data over the last few decades. This study aims to use Empirical Models to estimate diurnal temperatures by Estimating the air temperature (Ta) DTC parameters, identifying new research problems arising for future researchers, and providing a review of different empirical Models relating to Diurnal temperature.

MATERIALS AND METHODS

Umudike is a semi-urban settlement in Ikwuano Local Government Area (LGA) of Abia State, located at the Southeastern part of Nigeria with two seasonal periods (dry and rainy seasons). Rainy season spans from March and ends in November while dry season continues to mid-March of the following year.

The surface temperature data used in this work was gotten from National Root Crops Research Institute (NRCRI), diurnal temperature was computed from the surface temperature data.

The polynomial data fitting or regression model can be described by the following elaborations. For the given observation data$(x_i, y_i), i = 1,2,3, \dots, N$; the regression model (or fitting) is defined as:

$$y_i = f(x_i) + \varepsilon_i, i = 1,2,3, \dots, N. \quad (1)$$

Where $f$is a regression (or fitting) function and ε_i are zero-mean independent random error with a common variance r^2. For polynomial fitting, let $f(x) = a_0 + a_1 x + a_2 x^2 + \cdots + a_n x^n$where n is a positive integer and the degree of the polynomial. Now, say $N > n + 1$ then we may fit the data by using least square approach. Let the error of fitting model is given as:

$$e_i = y_i - f(x_i) = y_i - \{a_0 + a_1 x_i + a_2 {x_i}^2 + \cdots + a_n {x_i}^n\} \quad (2)$$

Taking sum square of the error given in Eq. (2) lead to:

$$S = \sum_{i=0}^{N} {e_i}^2 = \sum_{i=0}^{N} [y_i - \{a_0 + a_1 x_i + a_2 {x_i}^2 + \cdots + a_n {x_i}^n\}]^2 \quad (3)$$

The least square fitting is obtained if the sum of error in Eq. (3) is minimized. Hence,

$$\frac{\partial s}{\partial a_i} = 0, i = 0,1, \dots, n \quad (4)$$

From Eq. (4), the following system of linear equations can be obtained:

$$BA = C \quad (5)$$

Where,

$$B = \begin{bmatrix} N & \sum x_i & \sum {x_i}^2 & \dots & \sum {x_i}^n \\ \sum x_i & \sum {x_i}^2 & \sum {x_i}^3 & \dots & \sum {x_i}^{n+1} \\ \sum {x_i}^2 & \sum {x_i}^3 & \sum {x_i}^4 & \dots & \sum {x_i}^{n+2} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \sum {x_i}^n & \sum {x_i}^{n+1} & \sum {x_i}^{n+2} & \dots & \sum {x_i}^{2n} \end{bmatrix},$$

$$A = \begin{Bmatrix} a_0 \\ a_1 \\ a_2 \\ \vdots \\ a_n \end{Bmatrix}$$

And

$$C = \begin{Bmatrix} \sum y_i \\ \sum x_i y_i \\ \sum {x_i}^2 y_i \\ \vdots \\ \sum {x_i}^n y_i \end{Bmatrix}$$

Equation (5) can be solved by using Cholesky's method or Gaussian elimination (with pivoting if needed). If $n = 2$, the least square fitting in Eq. (1) is called quadratic regression method (or quadratic fitting) given by:

$$y = a_0 + a_1 x + a_2 x^2 \quad (6)$$

The system of linear in Eq. (6) becomes:

$$\begin{bmatrix} N & \sum x_i & \sum {x_i}^2 \\ \sum x_i & \sum {x_i}^2 & \sum {x_i}^3 \\ \sum {x_i}^2 & \sum {x_i}^3 & \sum {x_i}^4 \end{bmatrix} . \begin{Bmatrix} a_0 \\ a_1 \\ a_2 \end{Bmatrix} = \begin{bmatrix} \sum x_i \\ \sum x_i y_i \\ \sum {x_i}^2 y_i \end{bmatrix} . \quad (7)$$

Matlab routine is used in computing the coefficient of the polynomial of degree *n–1* to fit *n* number of the diurnal temperature T_D and *t* data provided.

ERROR MEASUREMENT

There exists many statistical goodness fit measurements. For instance, RMSE, R^2 value, Adjusted R2 value, Mean Biased (MB), Mean Square Error (MSE) and Sum Square Error (SSE) etc. In this study we adopt the same error measurement as discussed in Karim and Singh i.e., RMSE and R^2 value. RMSE can be calculated by using the following formula:

$$RMSE = \sqrt{\sum_{j=1}^{M} (y_j - \hat{y}_j)^2} \qquad (8)$$

Where y_j is an original data and $\hat{y}_j$ is fitting data.

RESULTS AND DISCUSSION

We applied polynomial fitting (regression) starting with the 2nd degree until 10th degree. All the polynomial coefficients are calculated based on 95% confidence interval. Table 2 summarized all the polynomial fitting results. Figures 5(a) until 5(i) show the polynomial fitting for diurnal temperature data.

DATA FITTING MODEL FRAMEWORK

This section gives framework for Diurnal Temperature data fitting.

Figure 1 shows the basic block diagram which describes the flow of polynomial data fitting methods.

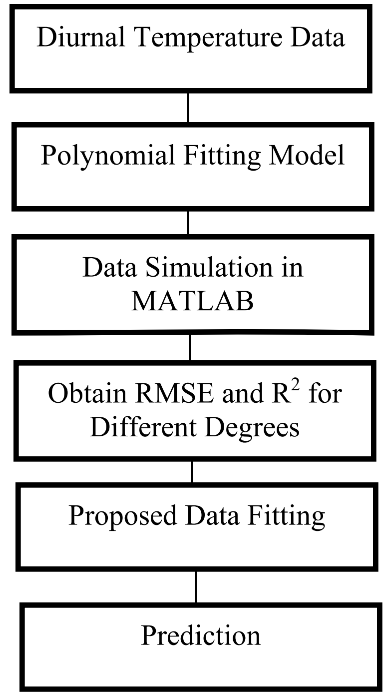

Figure 1: Data Fitting.

Table 1: RMSE Value and R^2 for Polynomial Fitting.

Data Fitting	Statistical Goodness Fit	
Degree (n)	RMSE	R^2
2	0.7486	2.1556
3	0.8036	1.9054
4	0.9046	1.3279
5	0.9601	0.8591
6	0.9601	0.8584
7	0.9762	0.6636
8	0.9778	0.6405
9	0.9839	0.5462
10	0.9879	0.4725

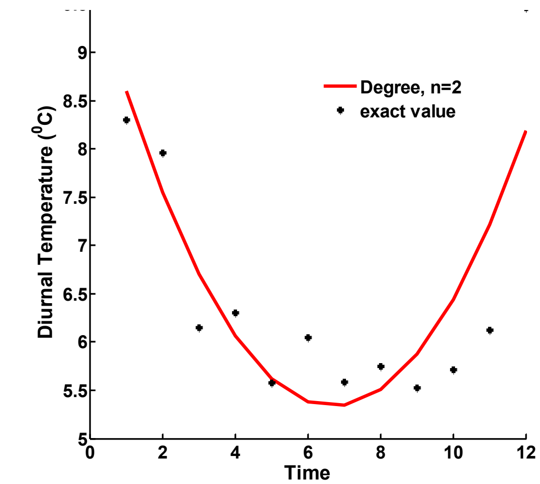

Figure 2(a).

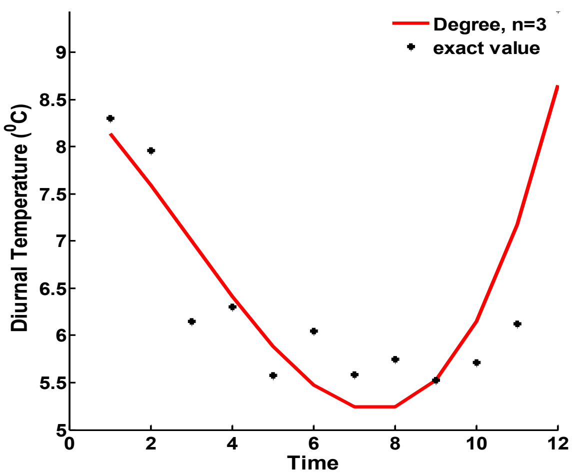

Figure 2(b).

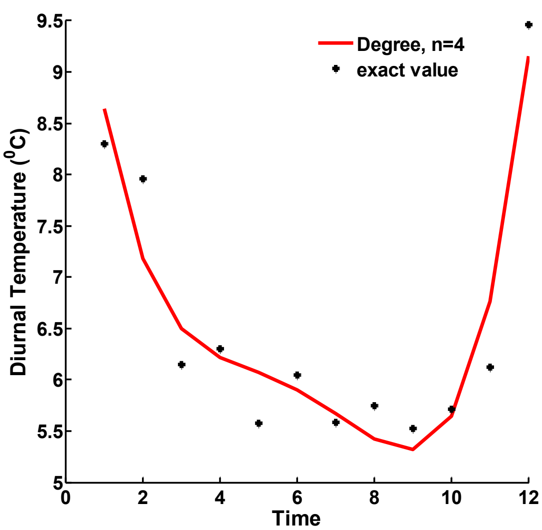

Figure 2(c).

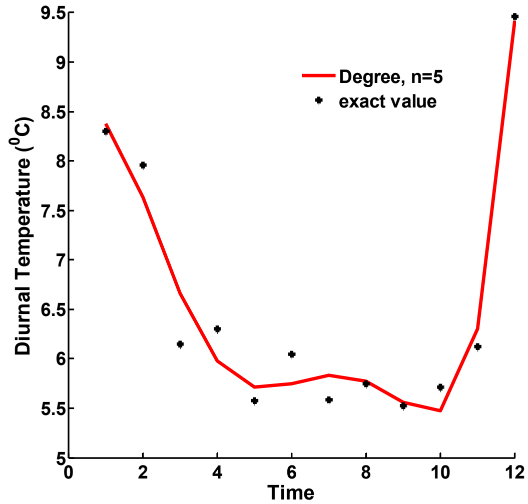

Figure 2(d).

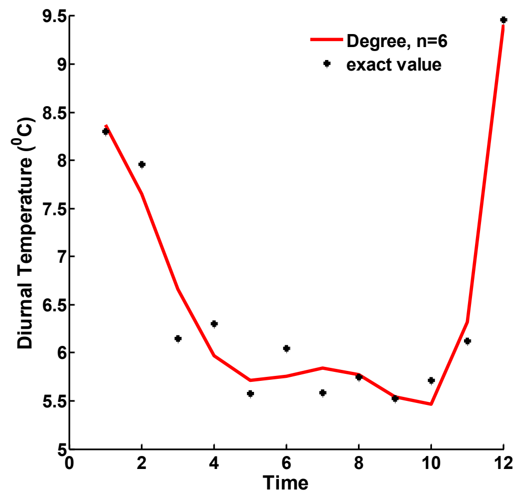

Figure 2(e).

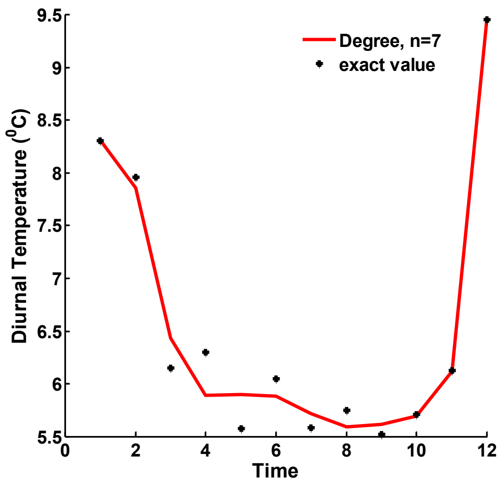

Figure 2(f).

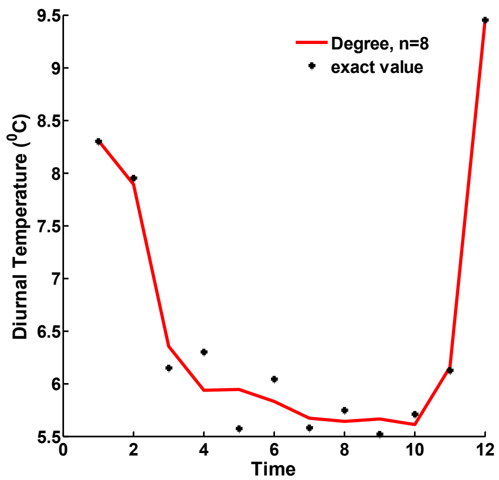

Figure 2(g).

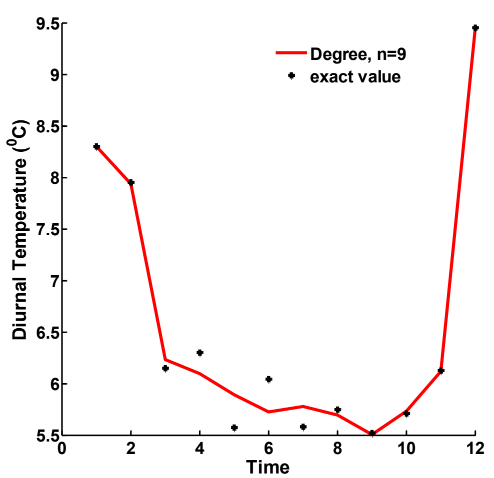

Figure 2(h).

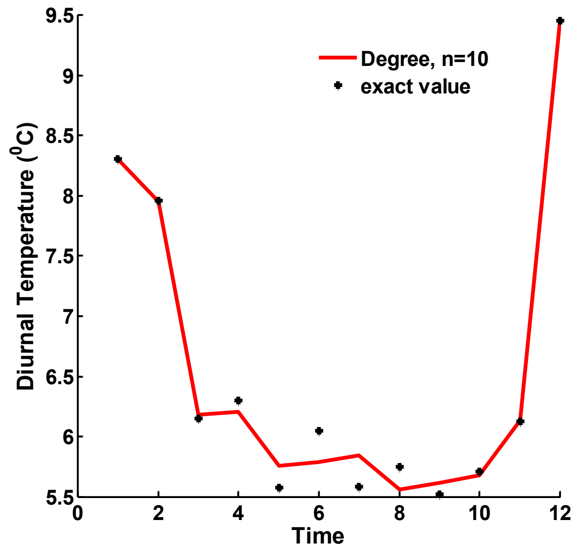

Figure 2(i).

Figure 2: Various polynomial fitting (a) n=2 (b) n=3(c) n=4 (d) n=5 (e) n=6 (f) n=7 (g) n=8 (h) n=9 (i) n=10

From Figures 2(a) to 2(i), it can clearly be seen that once the degree of the polynomial is increasing, the fitting graphs will start to wiggle. The polynomials of degree 7^{th}, 8^{th}, 9^{th}, and 10^{th} seem to give better results as compared with the other degrees. For polynomial fitting with degree are quadratic, cubic, and quartic, the value of RMSE and R^2 can be obtained in Table 1.

From the table, Polynomial fitting with 10^{th}degree gives better R^2 (0.4725) and RMSE is 0.9879. The error measurement of RMSE and R^2 shows that the errors between the polynomial degrees are of 95% confidential interval.

DIURNAL TEMPERATURE PREDICTION

In this section, the forecasting model for Diurnal Temperature data is proposed. Based on the results, the quadratic polynomial fitting is suitable to fitting the Diurnal Temperature in NRCRI, Umudike. Thus, it is proposed that two fitting models be used to predict the amount of diurnal temperature received in NRCRI for over the years.

Several fitting methods were tested to the diurnal temperature data obtained in NRCRI, Abia State. From the numerical results as well as graphical displays, quadratic polynomial fitting with one term is suitable for the purpose. This study has improved the results obtained in Karim and Singh. Furthermore, a fitting method for diurnal temperature data collected for every month in NRCRI is underway. For future study the new weighted fitting method based on model given in Eq. (6), respectively, is proposed.

CONCLUSION

To conclude, the diurnal temperature data fitting by using the polynomial fit method has been discussed in detail. We proposed models to estimate the monthly diurnal temperature of Umudike from LST data and temporal variables using polynomial fit model. The model has been obtained empirically and validated using National Root Crops Research Institute (NRCRI) between 2014-2019. This study shows that the data with no "good quality" usually underestimate Ta and are not reliable. Therefore, a thorough filtering process was carried out to retain only the "good quality" data although this filtering drastically reduced the available LST data (at less than 5% of studied data).

After the data has been smoothed, the model for diurnal temperature can be used to predict or forecast the received amount of diurnal temperature in Umudike. One of the applications of the polynomial fit model can be used to determine the best approximation of the relationship between the dependent and independent variable. The curve fit that returned the highest correlation factor was the polynomial fit. From the numerical results, the fitting model has given better results without any wiggle at both end points of the graph and the value of RMSE is 0.4725and R^2 value is 0.9879. Polynomial fitting 10^{th}degree has given better R^2 (0.9879) and RMSE is0.4725. It is thus concluded that the LST data are useful for estimating long term trends in Ta.

Future research will focus on extending the years of study and on analyzing more stations with Ta and LST data. In addition, improving the quality of the LST data in this type of environment is essential, using new versions of MODIS-LST or other sensors. On the other hand, other space-time variables could be added to the models obtained here which would allow their validity to be studied in other areas that are not covered.

REFERENCES

1. Abbot, J. and J. Marohasy. 2012. "Application of Artificial Neural Networks to Rainfall Forecasting in Queensland, Australia". *Adv. Atmos. Sci.* 29: 717–730.

2. Cifuentes, J., G. Marulanda, A. Bello, and J. Reneses. 2020. "Air Temperature Forecasting using Machine Learning Techniques: A Review". *Energies*. 13: 4215

3. Dehghani, A.A. and R. Ahmadi. 2003. "Estimated Discharge of Drainage Areas without Statistical using Neural Network". *The First International Conference on Water Crisis*. Zabol University, 22–20 March 2008.

4. Ephrath, J.E., J. Goudriaan, and A. Marani. 1996. "Modelling Diurnal Patterns of Air Temperatures, Radiation, Wind Speed and Relative Humidity by Equations for Daily Characteristics". *Agric Syst*. 51: 377–393.

5. Eriksoon, M. and S. Lindqvist. 2001. "Regional Influence on Road Slipperiness during Winter Precipitation Events". *Physical Geography*. Department of Earth Science, box 460, se 405.

6. Hosseini, S.A. 2009. "Estimation and Analysis of Maximum Temperatures in Ardabil City using Artificial Neural Networks Theory Model". Master's thesis. University of Mohaghegh: Ardabili, Iran.

7. Jain, A. 2003. "Predicting Air Temperature for Frost Warning using Artificial Neural Network". A Thesis Submitted to the Graduate Faculty of The University of Georgia in Partial Fulfillment of the Requirements for the Degree Master of Science: Athens, GA. 92 p.

8. Jury, W.A. and R. Horton. 2003. *Soil Physics, sixth ed.* Wiley: New York, NY.

9. Kothandaraman, V. 2007. "Air-Water Temperature Relationship in the Illinois River". JAWRA. 8(1): 38–45.

10. Kalkstein, L.S. 1991. "A New Approach to Evaluate the Impact of Climate on Human Mortality". *Environ. Health Perspect*. 96: 145–150.

11. Karamooz, M., F. Ramezani, and S. Razavi. 2006. "Long Term Forecast of Rainfall Using Meteorological Signals: Application of Neural Networks". The Seventh International Congress on Civil Engineering. Tarbiat Modarres University, Tehran, Iran.

12. Keay, K. and I. Simonda. 2005. "The Association of Rainfall and other Weather Variables with Road

Traffic Volume in Melbourne, Australia". *Accid. Anal. Prev*. 37: 109–127.

13. Khosravi, M., M. Azhdari Moghaddam, H. Nazari Pure, and S. Razmjoee. 2010. "Predict of Shiraz Maximum Temperature using an Artificial Neural Network". The Fourth Congress of the Islamic World Geographers. 1–14.

14. Marmor, M. 1975. "Heat Wave Mortality in New York City, 1949 to 1970". *Arch. Environ. Health*. 30: 130–136.

15. Martens, W.J.M. 1998. "Climate Change, Thermal Stress and Mortality Changes". *Soc. Sci. Med*. 46(3): 331–344.

16. Muhammet, B. 2012. "The Analysis of Precipitation and Temperature in Afyonkarahisar (Turkey) in Respect of Box-Jenkins Technique". *J. Academic Social Sci. Studies*, 5(8): 196-212.

17. Ramlow, J.M. and L.H. Kuller. 1990. "Effects of the Summer Heat Wave of 1988 on Daily Mortality in Allegheny County, PA". *Public Health Reports*. 105, 283–289.

18. Saito, H. and J. Šimůnek. 2009. "Effects of Meteorological Models on the Solution of the Surface Energy Balance and Soil Temperature variations in Bare Soils". *Hydrology*. 373(3–4): 545–561.

19. Sharma, N., P. Sharma, D. Irwin, and P. Shenoy. 2011. "Predicting Solar Generation from Weather Forecasts using Machine Learning". *Proceedings of the 2011 IEEE International Conference on Smart Grid Communications*. Brussels, Belgium. 17–20 October; pp. 528–533.

20. Stisen, S., I. Sandholt, A. Nørgaard, R. Fensholt, and L. Eklundh. 2007. "Estimation of Diurnal Air Temperature using MSG SEVIRI Data in West Africa". *Remote Sens. Environ*., 110: 262–274.

21. Teshnehlab, M. and M. Monshi. 2003. "Climate Prediction of Meteorological Parameters using Neural Fuzzy Networks based on the Training of Tali Section Parameters". Third Climate Change Conference, Isfahan, Meteorological Organization, Isfahan University.

22. Tran, T.T.K., S.M. Bateni, S.J. Ki, and H. Vosoughifar. 2021. "A Review of Neural Networks for Air Temperature Forecasting". *Water*. 13: 1294. https://doi.org/10.3390/w13091294

23. Zhang, Z., Y. Dong, and Y. Yuan. 2020. "Temperature Forecasting via Convolutional Recurrent Neural Networks Based on Time-Series Data". *Complexity*.

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