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Research Article

Assessing Changes in Climate Variability Observation and Simulation of Temperature and Relative Humidity: A Case of East London, South Africa

Israel Ropo Orimoloye, Sonwabo Perez Mazinyo, Werner Nel and Enoch Terlumun Iortyom

Department of Geography and Environmental Science, University of Fort Hare, Private Bag X1314, 5700 Alice, Eastern Cape Province, South Africa

Abstract

Background and Objectives: The contrariety between recent observed and simulated trends in a global climate warming has inspired a debate about conceivable events and indications for future climate fluctuation projections. Nonetheless, little has been said in this discussion in regards to observed and simulated trends of temperature and relative humidity as these two features contribute extensively to the warming earth. The present study aimed to evaluate and model seasonal fluctuation of observed air temperature and relative humidity in East London, Eastern Cape South Africa. **Materials and Methods:** The historical data of temperature and humidity were obtained from the South African Weather Service and analyzed through the ordinary least square regression model in Gretl statistical software. **Results:** The study investigated trends patterns in temperature, relative humidity and appraises the relationship between the observed and simulated temperature and relative humidity in the course of recent decades (1986–2016), the trend also predicted for the next 14 years (2017-2030). The observed, modeled and future trend patterns of temperature and relative humidity were produced using statistical analysis. In general, the simulated trends fall within the observed range of trends (95% confidence interval), with better consistency for the longer period. Seasonal trend patterns contrast for the seasons, with the autumn and summer exhibiting perpetual positive trends across the decades and spring and winter season exhibiting a coherent cooling pattern across the study years that has developed in the recent years and this is regenerated by the model for the year 2030. **Conclusion:** The present study recommended that local consistency between models and observations may be a key in knowing the changes in the climatic variability along with its adverse effects on human health, agriculture, ecological sustainability and socioeconomic status in the region.

Key words: Assessment, climate variability, temperature, humidity, future trend

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Corresponding Author: Israel Ropo Orimoloye, Department of Geography and Environmental Science, University of Fort Hare, Private Bag X1314, Alice, 5700, Eastern Cape Province, South Africa Tel: +27732244901

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Competing Interest: The authors have declared that no competing interest exists.

Data Availability: All relevant data are within the paper and its supporting information files.

INTRODUCTION

The illustration of the mean state and inconsistency of recent changing climate is indispensable for various purposes in local, regional and global change studies. These incorporate the observation and identification of environmental change and climate model assessment¹. Climatic features observation needs consistency and reliable datasets for accurate analysis and forecasting. Climatic datasets which describe variability in space, time², historically had deficient spatial scope and coverage and have been off coarse resolution. This is because the dataset's significant purpose which is monitoring prevailing climate and its historic view, environmental change detection does not necessarily require spatially consistent fields or higher resolution.

The disparity between recent observation and simulation trends in global atmospheric fluctuation has incited a discussion about possible causes and suggestions for future climate change projections^{3,4}. Nonetheless, little has been said in this debate in regards to observed and modeled trend pattern in temperature and relative humidity as these two variables contributed significantly to a warming earth^{5,6}. For temperature extremes, there is a logical model concession to the general spatial trend before the end of the 21st century and generally, the simulated trend has been noted to be steady with observed pattern⁷. Notwithstanding, high variation is superimposed on the signal, which represents, for example, a challenge to a model assessment of local changes in the observational period. Moreover, changing climate happens sporadically and has a significantly higher year-to-year variability than mean climate⁸. In this manner, internal variation is the dominant vulnerability responsible for the increase of heat extremes at local to regional scale even by the mid 21st century. It is generally recognized that a single transient simulation of a known climate model ought not to be relied upon to support the time progression of the observations, because of the absence of consistency of internal fluctuation at multidecadal timescales^{9,10}.

The amount of water present in the air is one of the most deciding contributors to the real greenhouse influence and the volume of water vapor in the air is presumed to increase under situations of greenhouse induced gas warming, prompting a significant input on the anthropogenic climate and environmental change^{8,10}. Hypothetical and modeling investigations forecast that relative humidity will continue generally consistent at the universal scale as the climate warms, prompting an expansion in specific humidity¹¹⁻¹³. While significant increments in surface relative humidity have been distinguished in a few regions^{14,15}, it has not been indicated

whether these progressions are because of natural or human impacts on climate. In the same manner, air temperature and relative humidity regulate or modify dissipation and transpiration procedures which have explicit associations with both the hydrological cycle and surface energy budget. Human comfort and well-being are impacted by temperature and relative humidity fluctuations, especially in summer and autumn. The continuous increase in relative humidity and temperature may lead to extreme heat which usually results in higher mortality and morbidity dominantly in the elderly, infants and people with existing heart disease and respiratory illness. Considerable excess mortality has been seen amid various recent extreme heat^{16,17}, including disastrous weather events¹⁸. The climatic elements adding to enhanced morbidity and mortality mostly identify with an association of extreme temperature, with high relative humidity¹⁹ and frequently to an extended period (a few days) of the extreme weather event. The present study aimed to evaluate and model seasonal fluctuation of observed air temperature and relative humidity in East London, Eastern Cape South Africa. The choice of this city was done because of the recent development and urbanization trends which might modify urban climate in the area. Furthermore, due to the recent frequent forecast by the South African Weather Service about extreme heat and abnormal weather occurrence in the coastal areas of the country including the study area which represents different climates and coastal cities in the region. The Fig. 1 shows the map of the study area.

MATERIALS AND METHODS

The series to be considered for the analysis are historical series of air temperature and relative humidity of the city of East London, Eastern Cape, South Africa for three decades between 1986 and 2016 spanning 30 years. East London is a city on the Southeast shore of South Africa. A city in Buffalo city metropolitan region, Eastern Cape Province of South Africa, with the Latitude 32°59'0"S and Longitude 27°52'0"E and area of about 168.86 km² (65.20 sq mi). East London has a humid subtropical atmosphere with warm temperatures. In any case, it has no genuine dry season, with a dry climate in winter and the wettest conditions in the spring and pre-winter. Between December and January, shorter and lesser dry period is experienced. East London has a record breaking minimum temperature of 3°C (37.4°F) and maximum temperature records of 42°C (107.6°F). The warmest temperatures are recorded in the spring months as opposed to summer measured in other nearby urban areas.

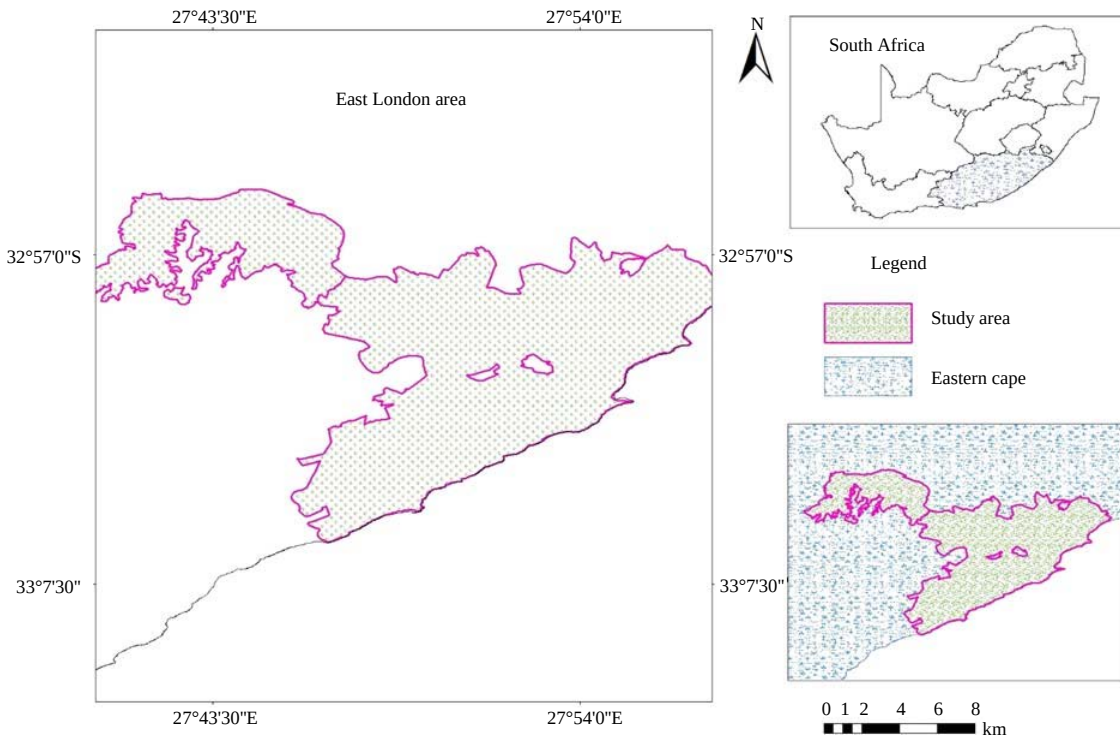


Fig. 1: East London area in Buffalo city metropolitan municipality, South Africa

Data and methods: To define and examining different trends of temperature and relative humidity, monthly maximum temperature (Tmax) and average monthly relative humidity obtained from the South African Weather Service (SAWS) during 1986-2016 was used. Before discharging the dataset, the SAWS performed thorough quality control techniques, including remedying suspect/wrong readings and amending in homogeneities possibly brought on by possible abnormalities taking the data and by instrumentation defect. Having been used in many pieces of literature, it was considered one of the best climate features datasets in South Africa. This study focused on monthly and seasonal trend during the study period.

Gretl regression model analysis: To confirm the trend pattern of temperature and relative humidity, ordinary least squares regression model analysis for the two variables was carried out. The first phase was estimated utilizing the statistics from ordinary least squares models using the observed temperature (X_1) and relative humidity (X_2) where the relative humidity is dependent variables. For the second phase is the least squares regression against time, in order to regress trend against time, time variables were required and this was done by adding time trend in Gretl, in the same manner periodic dummies

were also employed and each dummy represents each month of the year in the model (for example $dm_1 = 1$, if month = 1, 0, therefore, $dm_1 = 1$ if January, 0 otherwise, $dm_2 = 1$ if February, 0 otherwise etc.). Furthermore, to account for monthly variation (Fig. 2, 3) have to exclude one of the dummies, in the present analysis, the dummy of January was excluded. Likewise, ordinary least square (OLS) regression was utilized to show and examine the estimation of a dependent variable in view of its direct relationship to at least one independent factor as an indicator. OLS has been utilized as a part of the different studies to model comparable variables, for example, the global temperature and ground temperature²⁰⁻²². The present study utilized the equation of the model as showed in Eq. (1) and (2):

$$y = \Phi_0 + \Phi_1 X_1 + \Phi_2 X_2 + \epsilon \quad (1)$$

Where Φ describes the parameters in the model that show how the changes in each of the independent factors x impact the reliant variable y and ϵ is an error term which addresses unexplained variation in the subject variable. Given a sequence of random population data and subsequent to assessing the parameters, the resulting linear regression model was given in Eq. 1:

$$y_i = \Phi_0 + \Phi_1 X_{1i} + \Phi_2 X_{2i} + e_i \quad (2)$$

The subscript i indexes are specific observation. The term i is the residual. It is the distinction between the observed and model anticipated estimations of the dependent variable (Fig. 4, 5). The model exactness

is assessed by the sample forecast coefficient of determination, the last 5 years were removed (2011-2016) from the observed temperature and relative humidity data (it depend on the choice of the study) and these years were forecasted in order to validate the model (Fig. 4, 5).

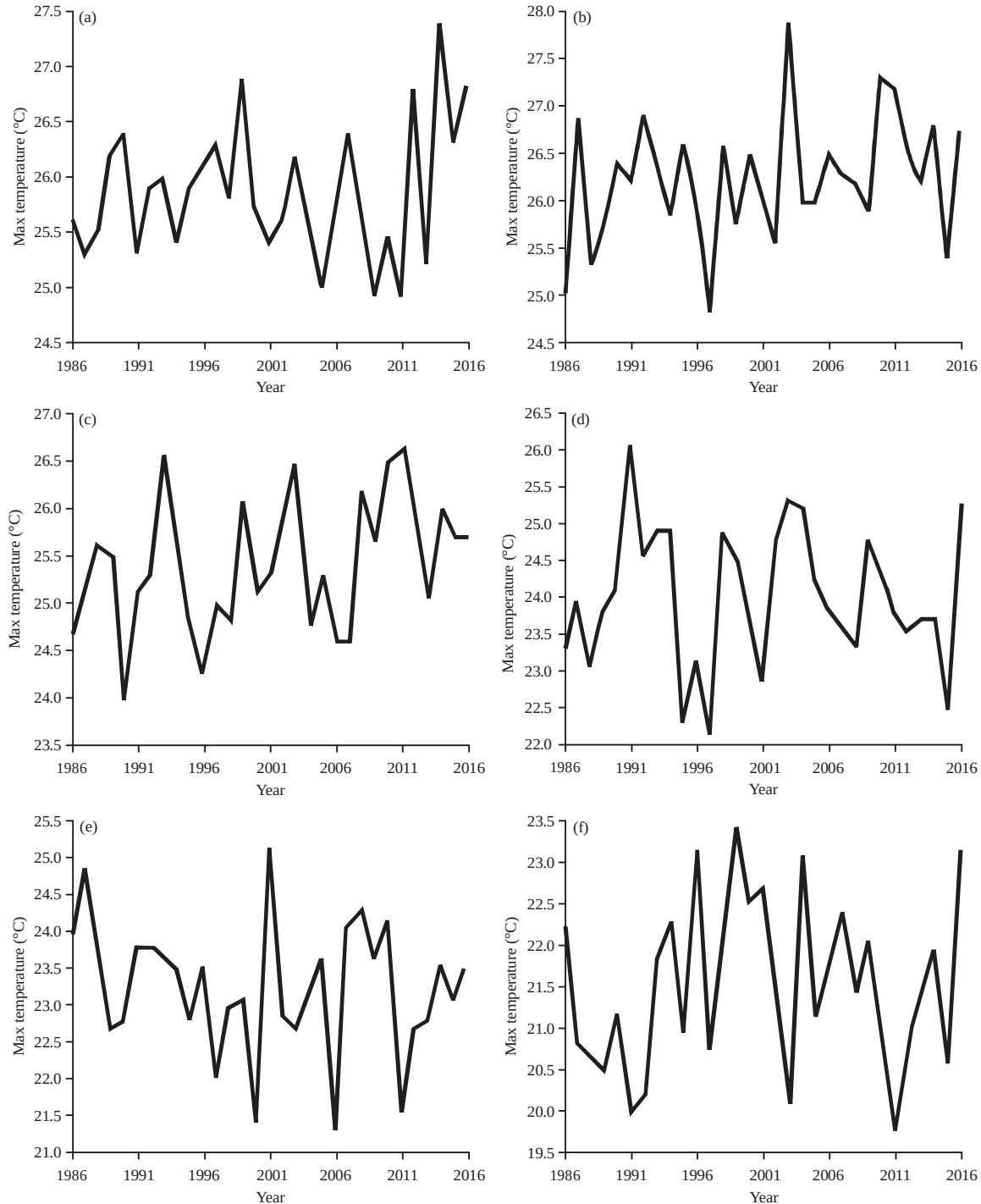


Fig. 2(a-l): Continue

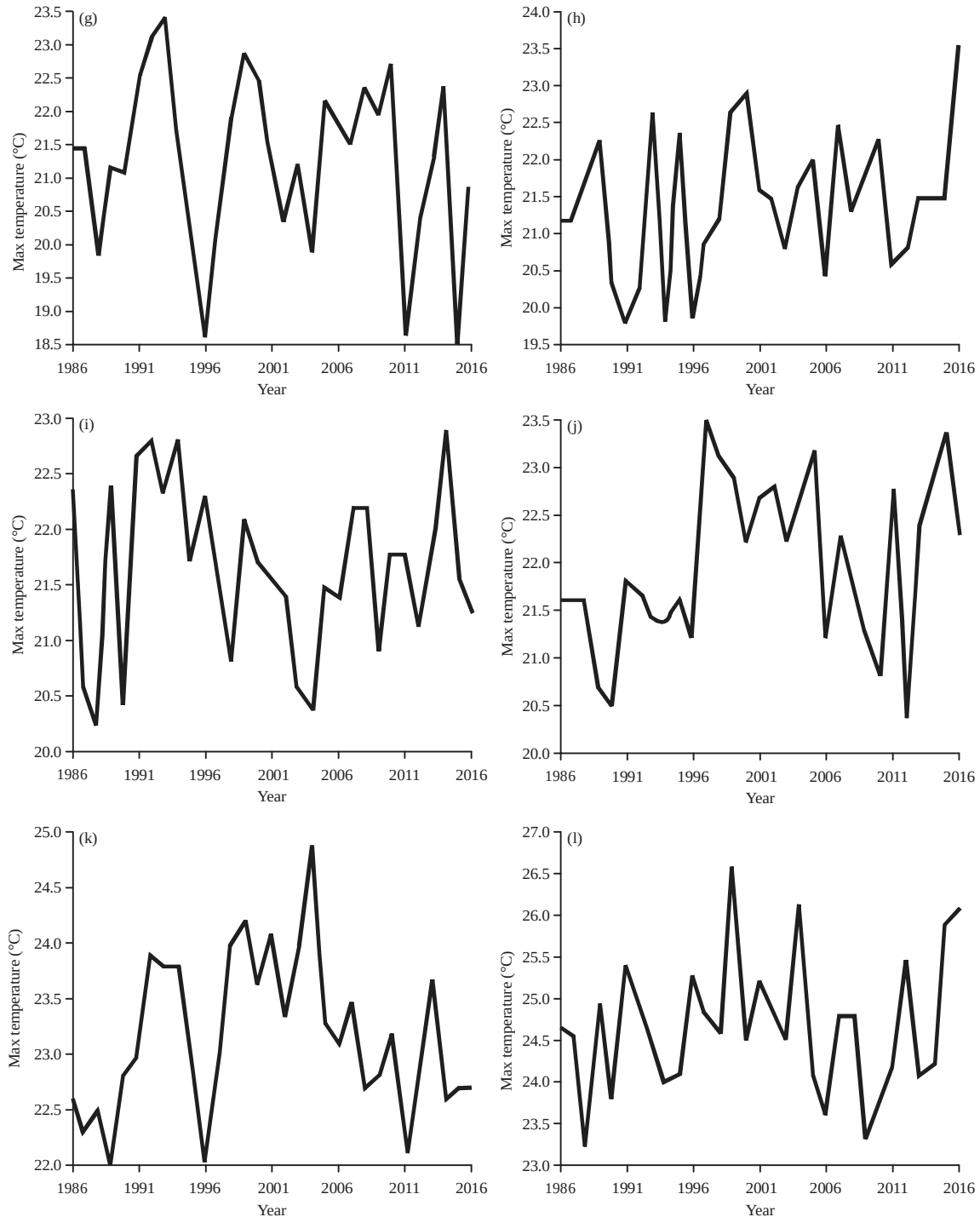


Fig. 2(a-l): Time series of monthly trend of observed maximum temperature, °C (1986-2016)

a: January, b: February, c: March, d: April, e: May, f: June, g: July, h: August, i: September, j: October, k: November, l: December

RESULTS AND DISCUSSION

Chow test: To complete the Chow test and check whether there was a statistically significant distinction in the trend for the autumn and summer period contrasted with the

spring and winter period, the study correlated a multiple linear regression analysis to all the 372 (total number of months for the study period where each season has 93 months across the study period as shown in Fig. 3, 6) data for each variable grouped. The regression model used was presented in Eq. (2).

Seasonal OLS regression models: Seasonal regression models were processed after the completion of the Chow test. OLS regression analysis for each variable for the period of study employing the Gretl statistical analysis model was considered. The theoretical model equation applied here is the same as in the Chow test (Eq. 2). The Table 1

demonstrated the quality of the connection between the model and the dependent variable.

The data in Table 1 revealed the seasonal regression model deviated from the actual value or observed by less than 0.1% (mean percentage error) for both temperature and relative humidity which make this modeled valid and suitable

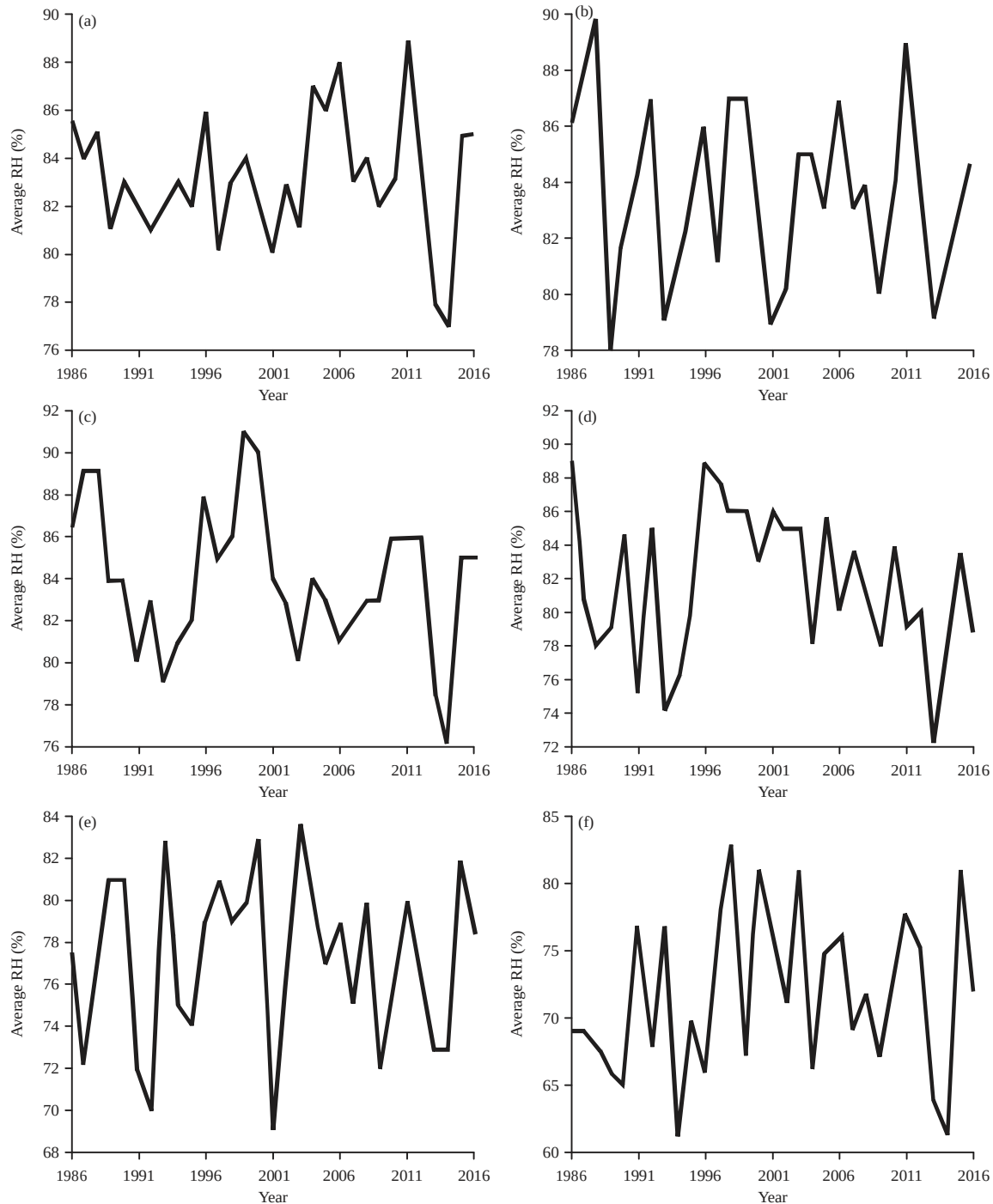


Fig. 3(a-l): Continue

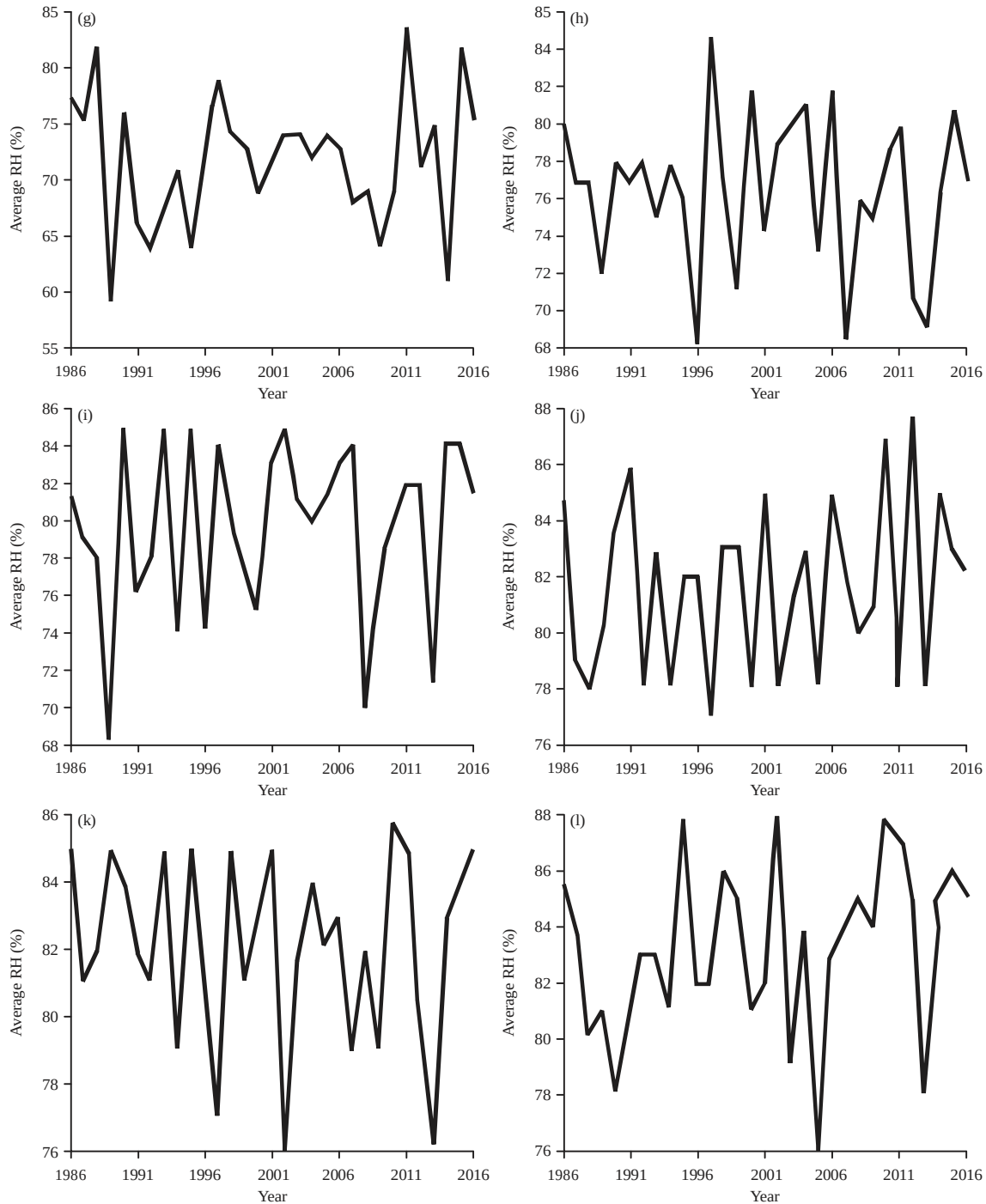


Fig. 3(a-l): Time series of monthly trend of observed average relative humidity, % (1986-2016)

a: January, b: February, c: March, d: April, e: May, f: June, g: July, h: August, i: September, j: October, k: November, l: December

for the future prediction. Overall, 5 years validation model are on the average of about 3.2 and 4.8% for temperature and relative humidity, respectively away from the actual observation, therefore, this indication connotes that the model was suitable and efficient.

Prediction of maximum temperature and relative humidity between 2017 and 2030: With significant accentuation put on trends pattern of temperature and relative humidity, whether and how these meteorological features vary with season have received little attention in the existing studies. The Fig. 4-7 show accumulated monthly and seasonal occurrences during

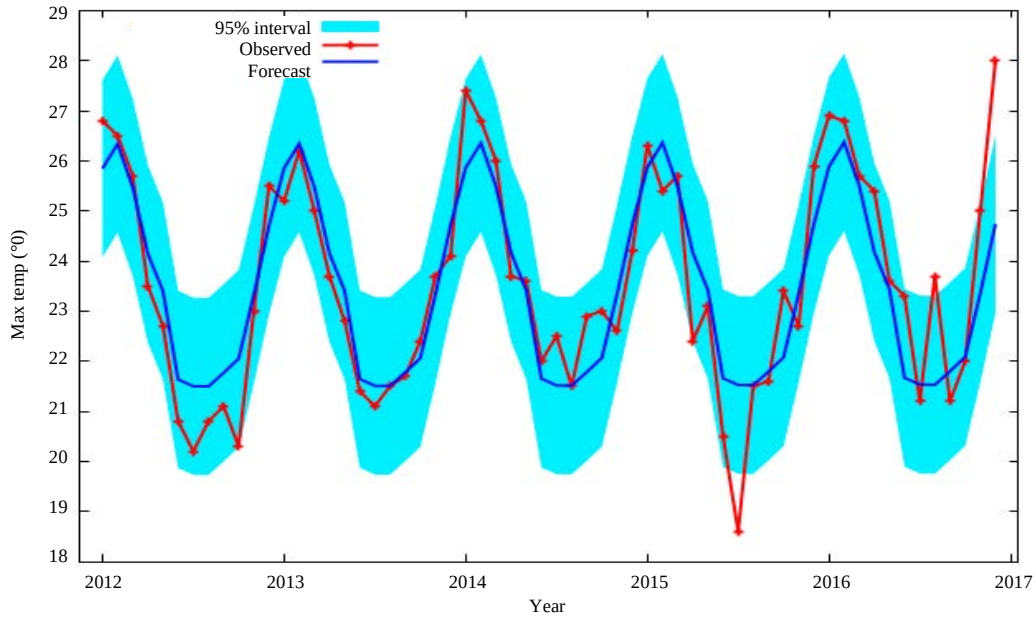


Fig. 4: Model validation with monthly maximum temperature °C (2012-2016)

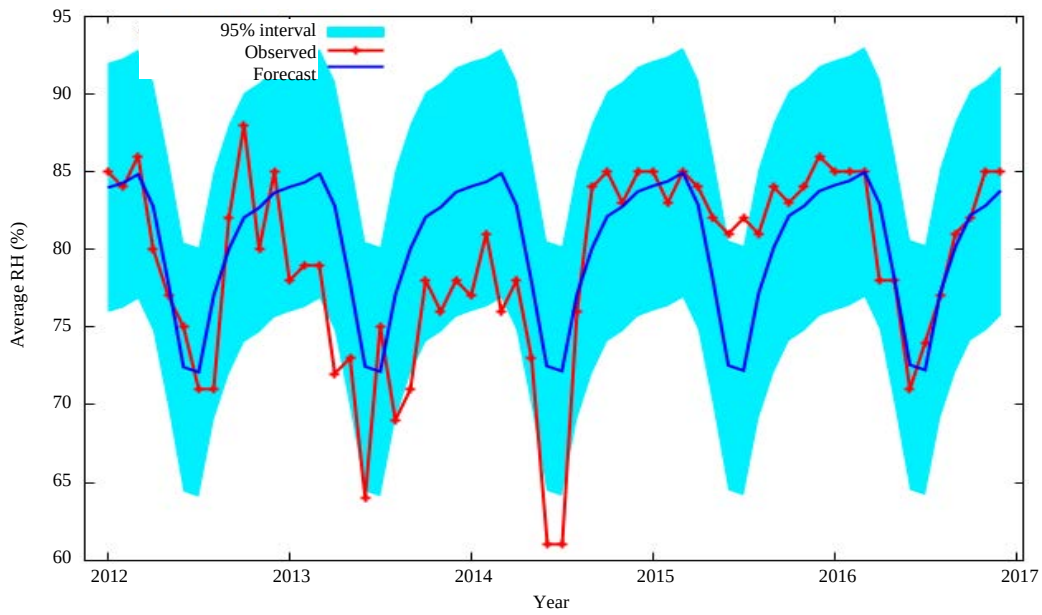


Fig. 5: Model validation with monthly average relative humidity % (2012-2016)

Table 1: Results of the model validation and chow test for the complete 2012-2016 time series

Model/Var.	R ²	Adjusted R ²	Standard error of the estimate	Mean error (%)	Mean abs. error (%)	Chow test F p
Max. Temp	0.802211	0.794273	0.878141	-0.067367	3.2297	<0.0000 0.0233
RH	0.548899	0.531493	3.988048	-2.0643	4.8657	<0.0000 0.9624

1986-2016. In general, compared to independent time trend and periodic dummies, compound events were less frequently

observed. Interestingly, the occurrence of different trend pattern exhibited obvious monthly and seasonal preferences.

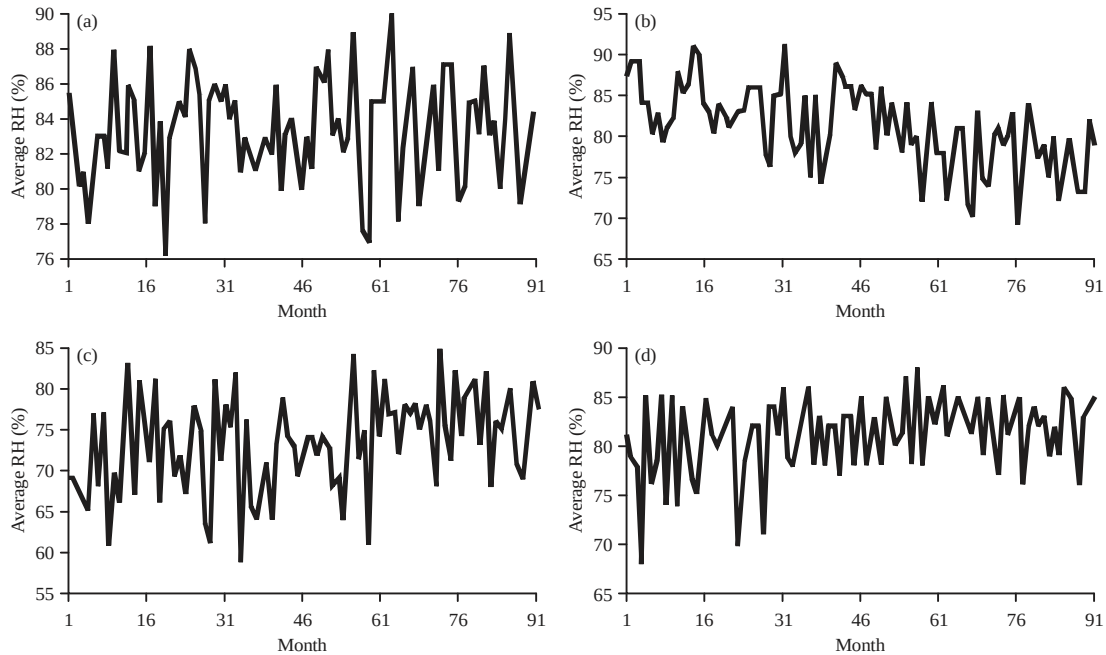


Fig. 6(a-d): Time series of seasonal trend of observed relative humidity, % (1986-2016)

(a) Summer (December, January, February), (b) Autumn (March, April, May), (c) Winter (June, July, August) and (d) Spring (September, October, November)

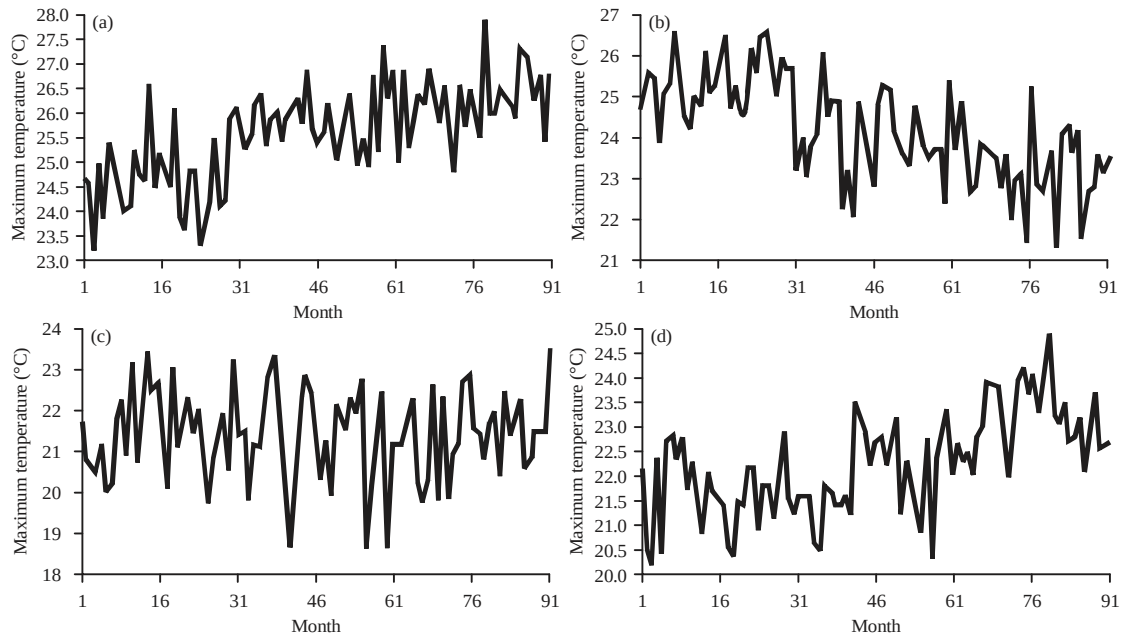


Fig. 7(a-d): Time series of seasonal trend of observed maximum temperature, °C (1986-2016)

(a) Summer (December, January, February), (b) Autumn (March, April, May), (c) Winter (June, July, August) and (d) Spring (September, October, November)

Most changes of temperature appeared in autumn and summer and relative humidity in spring and winter.

Furthermore, in autumn and summer period where RH fluctuated between 65 and 90%, respectively. However, in spring season where RH was between 70 and 95% during the study period and in winter it was between 60 and 85%. This

revealed that spring received the highest relative humidity and winter received the lowest maximum during the period. This coastal city also suffered from a steady increase in temperature during the past three decades which might be due to warm South Easterly trade wind from the Indian Ocean²³⁻²⁵. This region is economically developed and densely

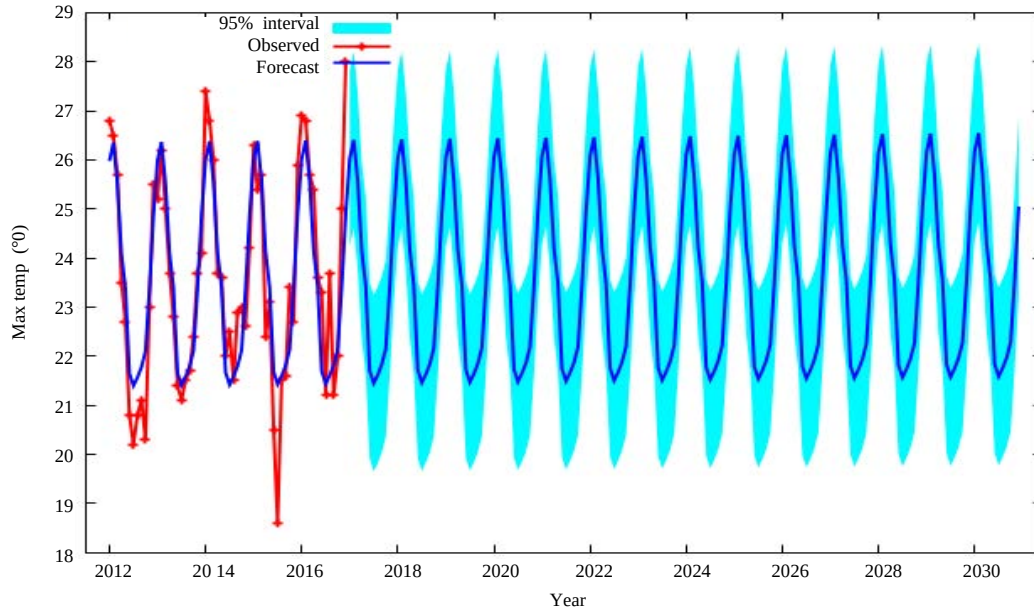


Fig. 8: Maximum temperature prediction (2017-2030)

Table 2: Seasonal coefficients and statistics for the multiple regression analysis of the time series for temperature and relative humidity (1986-2016)

Model	Season	Variable	Coefficient	Typical dev.	Statistic t-value	Value of p
Observation 1	DJF_Summer	Temp.	0.0151083	0.00196563	7.686	<0.0001
		RH	0.497697	0.634207	0.7848	0.4347
Observation 2	MAM_Spring	Temp.	0.0141914	0.00129708	10.94	<0.0001
		RH	-2.72893	0.393882	-6.928	<0.00001
Observation 3	JJA_Winter	Temp.	0.00341834	0.00183565	1.862	0.0659
		RH	1.37600	0.376922	3.651	0.0004
Observation 4	SON_Autumn	Temp.	0.00880867	0.00204291	4.312	<0.0001
		RH	1.54777	0.520306	2.975	0.0038

populated, so recurrent changes in climatic trends could result in great environmental upshot and economic losses, owing to high exposure to weather extremes. In contrast, the majority of these increases concentrated in the autumn and summer months throughout the study period for temperature, particularly in the past one and half decades. Accompanying increased relative humidity can exacerbate impacts of extreme heat^{12,26,27}. While in one hand, during extreme temperature periods, the mortality may increase exponentially with relative humidity once exceeding 80% with 28°C^{17,28}, on the other hand, during severe droughts, extremes with low relative humidity (lower than 40%) may aggravate damages to agriculture^{29,30}. In order to measure and project the future trend of temperature and relative humidity during the period, Gretl regression model was used. Consequently, it was essentially determined by local prevailing climate conditions, i.e., humid climate in the coastal area of the country and moist and warm South Easterly trade winds which may contribute to the changes in trend pattern of temperature and relative humidity in the study³¹.

Furthermore, future trend of relative humidity and temperature were predicted using OLS regression models and it was revealed that these two climatic variables will experience slight increases between 2017 and 2030 as presented in Fig. 8 and 9. The model shows that the predicted trend pattern fell within the 95% confidence interval and the adjusted R^2 was 79 and 53% for temperature and relative humidity, respectively (Table 1) which indicated how well the regression model predicts responses for new observations and the adjusted R^2 is usually lesser than R^2 for the model to be accurate. Data in Table 2 shows the seasonal coefficients and significant statistics for the regression analysis of the time series for temperature and relative humidity between 1986 and 2016. The larger the absolute value of the t-value and the greater the level of significance, from Table 2, summer and spring months have the highest t-value for temperature and relative humidity, respectively. While the spring and winter months have the least value for temperature and relative humidity, respectively which connotes how significance is the seasonal statistics for the regression analysis for temperature and relative humidity.

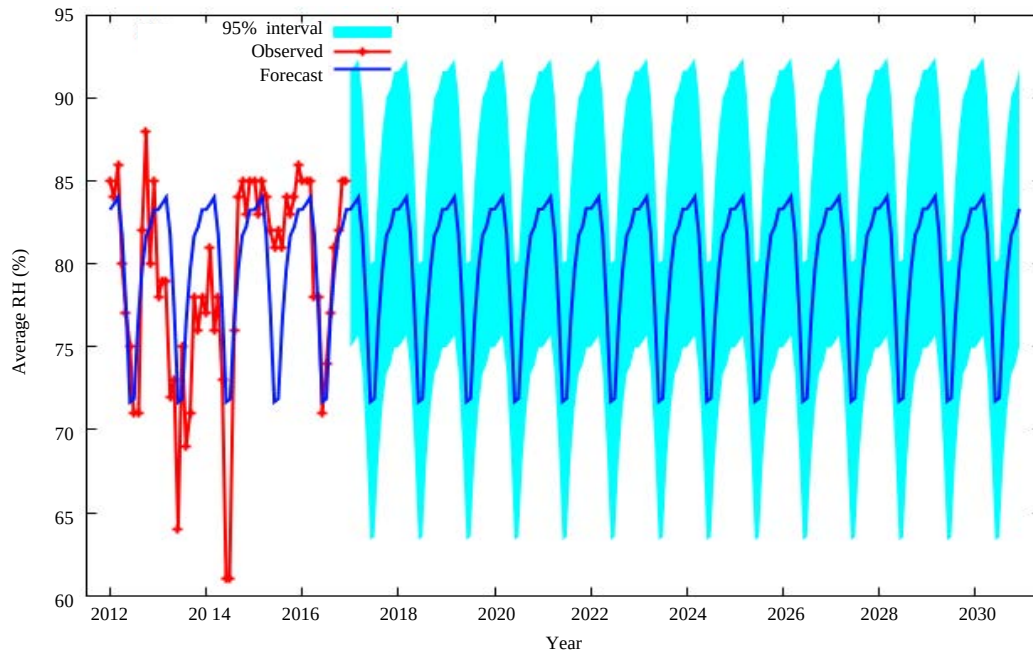


Fig. 9: Average relative humidity prediction (2017-2030)

The p-value was found to be below alpha value (0.05) in almost all the seasons which implies that the result is significant³².

CONCLUSION

Using meteorological observations from 1986-2016 datasets of temperature and relative humidity of East London in South Africa, this study has presented monthly and seasonal trend pattern time series of the climatologies of humidity and temperature variables. Computations were done using monthly observations in Gretl statistical analysis. This study shows that spring received the highest relative humidity and winter received the lowest maximum during the period. Air temperature has increased more steadily compared to relative humidity, with stronger trends in summer and autumn, relative humidity has strong trends spring and winter as presented in this study. Downward trends were observed for both temperature and humidity, with stronger trends in spring. This seaside city also experienced steady increment in temperature during the previous three decades which may be due to warm South Easterly winds from the Indian Ocean. Furthermore, this study presents the future trend pattern (2017-2030) of relative humidity and temperature for East London. This study has examined the trend pattern of temperature and relative humidity and presented its future trend. Further suggested that local coherence amongst models and observations might be a key

in identifying the alterations in the climatic variability along with its conflicting consequences on human health, agriculture, natural environment and economic condition in the region.

SIGNIFICANT STATEMENTS

This study investigates the trend pattern of temperature and relative humidity for the 1986-2016 and further modeled the future trend of both parameters in the study area. This study discovers that local consistency between models and observations which add to existing knowledge and this is crucial in knowing the shifts in the climatic change, variability and its conflicting effects on the environment, human health, agriculture, ecological sustainability and socioeconomic status in the region.

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