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STUDY THE IMPACT OF CLIMATE CHANGE ON MAXIMUM AND MINIMUM TEMPERATURE OVER ALEXANDRIA, EGYPT USING STATISTICAL DOWNSCALING MODEL (SDSM)

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ABSTRACT

The purpose of this study is therefore, to apply a statistical downscaling method and assess its strength in reproducing current climate for Alexandria maximum and minimum temperature at north coast of Egypt.Statistical downscaling model (SDSM) is used to describe the linkage between climate simulations given by a global circulation model, GCM, (CanESM2) and the local temperature data. Data for maximum and minimum daily−temperature records for Alexandria station in Egypt were considered duringthe period of 30 years (1980−2009). Analysis results have demonstrated that the minimum and maximum temperatures tend to increase during the first 30 years (1980−2009). The significant NCEP reanalysis data such have been used to develop the SDSMs for the linkage between the GCM outputs and the local temperatures. They have been then applied to construct the different RCP scenarios of the maximum and minimum temperatures until year 2100. Results have indicated that RCP 4.5 is the best one with increasing in both Tmax and Tmin based on baseline period (1980-2009) except in spring season the most periods are under estimation in all scenarios. Maximum temperature of RCP 4.5 stabilization scenario will increase by 0.88° C in the 2011-2040, 1.62° C in 2041-2070 and 1.98° C by the end of the century. Also RCP 4.5 minimum temperature scenario will increase by 1.52°C in the 2011-2040, 2.34°C in 2041-2070 and 2.75°C by the end of the century.

Key wards: Climate change, Statistical down scaling, RCP scenarios, Maximum and minimum temperature.

1 INTRODUCTION

Weather is the state of the atmosphere at a given time whilst climate is the average weather over a period of time (Thorpe, 2005). Even though the annual periodicity in weather patterns, the Earth's climate has changed many times during the planet's history, with events ranging from ice ages to long periods of warmth (Yehun, 2009).

Human activities, primarily the burning of fossil fuels and changes in land cover and use, are nowadaysbelieved to be increasing the atmospheric concentrations of greenhouse gases. This changes energy balances and tends to warm the atmosphere which will result in climate change IPCC reports indicate that mean annual global surface temperature has increased by about 0.3 - 0.6 o C since the late 19th century and it is expected to further increase by 1–3.5°C over the next 100 years (IPCC , 2007).

The scenarios of Climate change consider initial source of information for estimating plausible future climate are developed from Global Climate Models (GCMs). General circulation models or global climate models (GCMs), which are advanced mathematical models used to simulate the present climate and project future climate with forcing by greenhouse gases and aerosols, are the primary tool for capturing global climate system behaviour (Christensen et al., 2007).The climate change information needed for impact and adaptation studies is at a much finer spatial scale than that provided by most climate models (whether global or regional) . For regional climate-change impact studies, GCMs are problematic due to their lack of detailed regional information (IPCC 2007).

Consequently, large-scale GCM scenarios should not be used directly for impact studies (Schubert and Sellers,1997), to bridge the gap between the coarse spatial resolution of climate model output and the need for weather information at a higher resolution, downscaling methods have been developed. Downscaling is a process of transforming this coarse information to a finer spatial resolution.

There are two main approaches for downscaling: dynamical (DD) and statistical(SD) (Christensen et al., 2007; Fowler et al., 2007). The SD method establishes statistical relationships between large-scale climate information and local/regional variables (Hewitson and Crane 1996; Wilby et al. 2004), whereas DD employs regional climate models (RCMs) for limited regions withboundary conditions from GCM simulations. Both downscaling methods have strengths and limitations. Wilby et al. (2002) summarize some characteristics of SD and DD. Both SD and DD are dependent on GCM boundary forcing, domain size and location.Fowler et al. (2007) reviewed downscaling techniques and concluded that dynamical downscaling methods provide little advantage over statistical techniques, at least for present day climates. Given the advantages of being computationally inexpensive, able to access finer scales than dynamical methods and relatively easily applied to different GCMs, parameters and regions (Cubasch et al.,1996; Timbal et al., 2003; Wilby et al., 2004; Wood et al., 2004). SD methods use Empirical statistical methods derive relationships between large-scale atmospheric variables (predictors) and observed local weather variables (predictands). These relationships are then applied to equivalent predictors from climate model data (B´ardossy and Plate,1992; von Storch et al., 1993; Wilby et al., 1998a,b; Zorita and von Storch, 1999; Beckmann and Buishand, 2002, Karl et al., 1990; Busuioc et al., 2001; Christensen et al., 2007). These relationships are applied to downscale future climate scenarios using GCM output predictors. SD methods can be classified basically into three types (Wilby et al., 2004)regression models (transfer functions), weather generators and weatherclassification. In general, SD methods which combine these techniques are often most effective (Christensen et al., 2007).The statistical down-scaling model (SDSM) incorporates both deterministic transfer functions and stochastic components (Wilby and Wigley, 1997; Wilby et al., 2002). SDSM has been widely applied in SD studies for both climate variables and air quality variables (Diaz-Nieto and Wilby, 2005; Dibike and Coulibaly, 2005; Khan et al., 2006; Wetterhall et al., 2006; Gachon and Dibike, 2007; Prudhomme and Davies, 2009; Wise, 2009), and has been recommended by the Canadian Climate Impacts and Scenarios (CCIS) project. (http://www.cics.uvic.ca).

Comparisons between the SDSM and other downscaling methods have shown that the SDSM performed well in reproducing observed climate variability (Dibike and Coulibaly, 2005; Diaz-Nieto and Wilby, 2005; Khan et al., 2006; Wetterhall et al., 2006; Gachon and Dibike, 2007; Prudhomme and Davies, 2009). For example, Khan et al. (2006) compared three downscaling methods, SDSM, Long Ashton Research Station Weather Generator (LARS-WG) model and an artificial neural network (ANN) for downscaling daily precipitation and maximum and minimum temperatures in a watershed of Canada and found SDSM performed the best. Similar results were also reported by Dibike and Coulibaly (2005). Although both SDSM and LARS-WG were able to reproduce mean daily precipitation reasonable well, SDSM performed better in simulating variability of precipitation, and better than the perturbation method in the Thames Valley, UK (Diaz-Nieto and Wilby, 2005). Wetterhall et al. (2006) evaluated four SD methods for daily precipitation in three catchments located in southern, eastern and central China and northern Europe, and showed that SDSM performed best.

Chaleeraktrakoon and Punlun (2010) are studied and analysed the variability of observed temperature data for the Chi and Mun river basins and described the linkage between climate simulations given by a global circulation model, GCM, (HadCM3) and the local temperature data, based on an accepted statistical downscaling model (SDSM). Results have indicated that the range of the future minimum and maximum temperatures is wider than that of the current ones.

Cheema et al. (2011) investigated of the recent trend of global warming for Pakistan to test the reliability of future data generation by a statistical downscaling model "SDSM". The evaluation has been performed for the period 1991-2010. There was a significant increase in temperature on the annual basis but the monthly change is not significant according to the Mann-Kendall test. The result showed a good accordance of the projected temperature with real time data. Different statistical techniques were applied to investigate the trend and significant change in minimum temperature. The strong correlation suggested that SDSM can be used with reasonable level of confidence to obtain future projections of night time temperature for the country.

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Ayalew et al. (2012) assess and quantify the magnitude of future changes of climate parameters using Statistical Downscaling Mode (SDSM) in Amhara Regional State in Ethiopia. Both maximum and minimum temperatures showed an increasing trend; and the increase in mean maximum and minimum temperature ranges from 1.55°C - 6.07°C and from 0.11°C - 2.81°C, respectively in the 2080s compared to the base period considered (1979- 2008).

General circulation models (GCMs), which are widely used to simulate future climate scenarios, do not provide reliable hours of daily series rainfall and temperature for hydrological modeling (Hassan et al. 2014). The statistical downscaling models are used to generate the possible future values of local meteorological variables such as rainfall and temperature in the selected stations in Peninsular of Malaysia. SDSM yields a better performance compared to LARS-WG, except SDSM is slightly underestimated for the wet and dry spell lengths. Although both models do not provide identical results, the time series generated by both methods indicate a general increasing trend in the mean daily temperature values.

Babel and Turyatunga (2015), using Statistical Downscaling Model (SDSM) v4.2 to downscale low-resolution future climate data obtained from general circulation model HadCM3 for two SRES scenarios, A2 and B2. In the western Uganda agro-ecological zone, the annual average temperature is expected to increase by between 0.69–2.46 and 0.66–1.78 °C under the A2 and B2 SRES scenarios, respectively, in the three future periods of 2020s, 2050s, and 2080s relative to the base period (1961–1990). Monthly average temperatures are expected to increase for most of the months but will slightly decrease for the month of November under both scenarios. The area of study is among Mediterranean region where mean annual temperatures are likely to increase more than the global mean, with the largest warming in summer and annual precipitation as well as the annual number of precipitation days very likely to decrease (Christensenet al. 2007, Alcamo, et al. 2007).

The aim of this study is using statistical downscaling method to study maximum and minimum temperature for Alexandria station at north coast of Egypt using SDSM model during the period from 1980-2009. As well as using RCPs scenarios to assess the impact of future climate change on maximum and minimum temperature for this station during future climatic period 2011-2040, 2041-2070 and 2071-2100.

2 DATA AND METHODOLOGY

This study was performed for Alexandria City, which is located in north Egypt (29.57°N, 31.12°W and -1.78 m below sea level).Alexandria is a semi-desert, characterized by only two seasons; hot dry summer from May to October and moderate mild winter from November to April with very little rainfall. The difference between the seasons is a variation in daytime temperature and changes in prevailing wind. Average annual temperature ranges between minimum of 14°C in winter and maximum of 30°C in summer(El-Shafieet al.2011)

2.1 Data used

Three different types of data will be used in this study as follows:

- Observed (historical) maximum and minimum temperature climatic data were available over the 30 year period from 1980 until 2009 at Alexandria station. This historical, data were obtained from the National Climatic Data Center (NCDC)☹http://www7.ncdc.noaa.gov/CDO/)
- Large-scale predictor at a scale of 2.5° long.×2.5° lat. variables representing the current climate condition (1980-2009)are obtained from the National Center for Environmental Prediction and national center of atmospheric research (NCEP/NCAR). These lists of large-scale predictor variables that will be used in the downscaling process are presented in Table (1).The candidate predictor set contained 26 normalized daily predictors (describing atmospheric circulation, thickness and moisture content at the surface, geopotential heights at 850 and 500 hPa).

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Table 1.List of (NCEP/NCAR) and RCP futures predictors.

No.	Daily predictor variable description	Code
1	Mean sea level pressure	mslp
2	Mean temperature at 2m	temp
3	Near surface specific humidity	shum
4	Near surface relative humidity	rhum
5	500 hPageopotential height	p500
6	850 hPageopotential height	p850
7	Relative humidity at 500 hPa	r500
8	Relative humidity at 850 hPa	r850
9	Airflow strength	**_f
10	Zonal velocity component	**_u
11	Meridional velocity component	**_v
12	Vorticity	**_z
13	Wind direction	**th
14	Divergence	**zh
** represents variable values derived from pressure fields near the surface at 500 hPa or 850 hPa heights (i.e., P_, P5 Or P8) respectively		

As with the Environment Canada predictor suite, all variables (except wind direction and precipitation) are expressed as z-scores using the mean and standard deviation of the baseline period 1961-1990. The results can be directly downloaded from the internet using the site: http://www.cics.uvic.ca/scenarios/sdsm/select.cgi.

- Future climate scenarios data are obtained as output from the second generation Canadian Earth System Model (CanESM2) developed by Canadian Centre for Climate Modeling and Analysis (CCCma) of Environment Canada. The grid cell size is uniform along the longitude with horizontal resolution of 2.8° and nearly uniform along the latitude of roughly 2.8°.The CanESM2 outputs were downloaded for three different climate scenarios via, Representative Concentration Pathway (RCP) 2.6, RCP 4.5 and RCP 8.5, which were used in this study. Both the CanESM2 output and NCEP/NCAR reanalysis project data have provided the same set of 26 predictor variables (Table 1) which were downloaded from Canadian Climate Data and Scenarios website (http://ccds-dscc.ec.gc.ca/).

2.2 Methodology

The Statistical DownScaling Model (SDSM) is considered decision support tool for assessing local climate change impacts using a robust statistical downscaling technique. Statistical DownScaling Model facilitates the rapid development of multiple, low–cost, single–site scenarios of daily surface. Statistical downscaling requires developing quantitative relationships between large-scale atmospheric variables/ GCM outputs (predictors) and local scale observed variables (predictands) (Wilby et al., 2004). Mathematically, this relationship can be written as (Dibike and Coulibaly 2005):

$Y = f(X)$

Where,

Y = Predictand, X = Predictor and f = Transfer function which has to be determined empirically from historical observations.

The Statistical Downscaling Model (SDSM) 5.2 was used in this study to downscale and project the future climate data. This model was downloaded from the website:

(http://co-public.lboro.ac.uk/cocwd/SDSM/).

SDSM is a downscaling tool developed by Wilby et al. (2002) for assessing the impacts of local climate change using statistical downscaling technique and is a hybrid of the stochastic weather generator and regression-based methods (Liu et al., 2011). The SDSM software reduces the task of statistically downscaling dailyweather series into following discrete steps: quality control and data

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transformation;screening of predictor variables;model calibration;weather generation (using observed predictors);statistical analyses;graphing model output and scenario generation (using climate model predictors).

3 RESULTS

3.1 Observed analysis

Thesequence of daily maximum and minimum temperature data of Alexandria station in the north coast of Egypt was collected. The periodof the available temperature records is 30years (1980−2009).The daily temperature data havebeen statistically investigated for theirtemporal variations based on annual time intervals to avoid theirinherent seasonality effect on the analyses.Figures1 and 4 present the trend of annualmaximum and minimum temperaturedata of Alexandria station. The figures show that theminimumand maximum temperaturesare increasing for the whole 30−yearperiod. However, the trend of maximum temperature decreased from1980 to 1994(Figure 2) and increased from 1995 to 2009 (Figure 3).

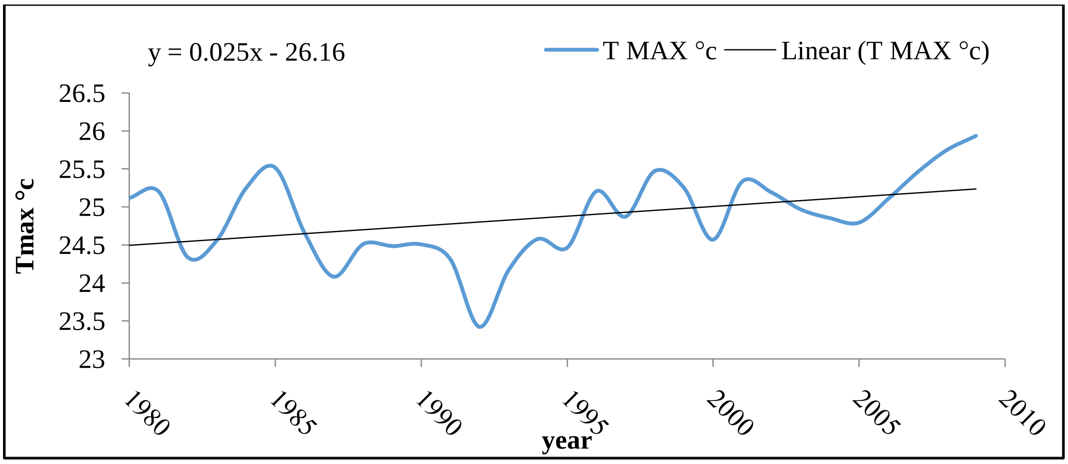

Fig 1:Maximum daily temperatures of Alexandria station (1980-2009).

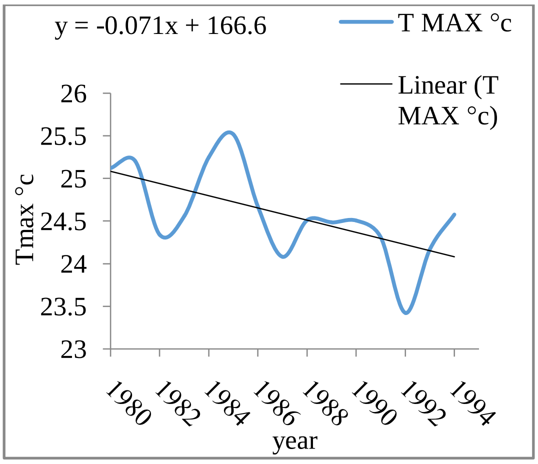

Fig 2: Maximum daily temperatures of Alexandria station (1980-1994).

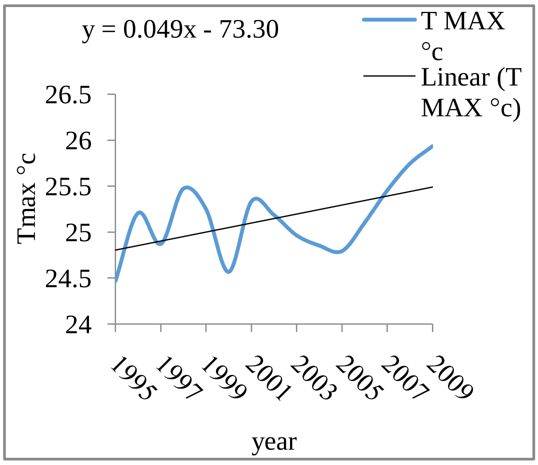

Fig 3: Maximum daily temperatures of Alexandria station (1995-2009).

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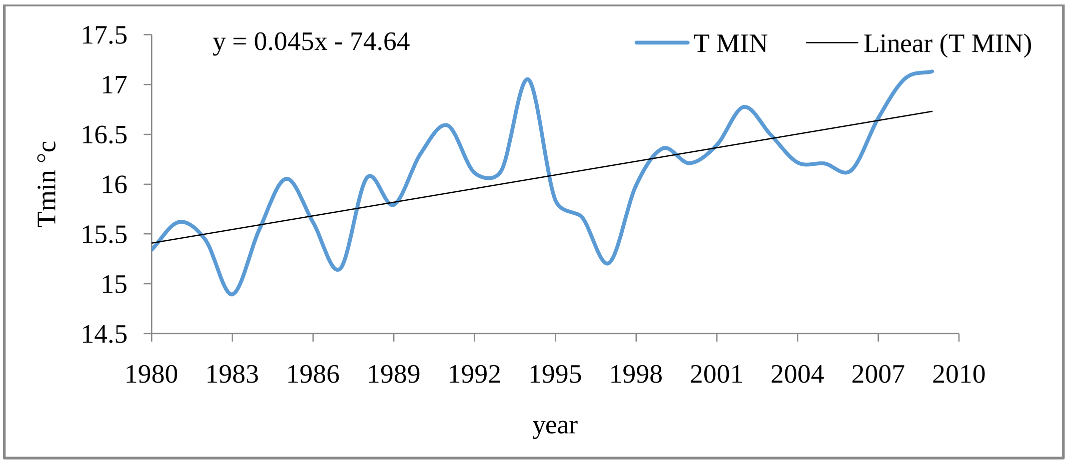

Fig 4: Minimum daily temperatures of Alexandria station (1980-2009).

3.2 Downscaling Daily maximum and minimum Temperature Time Series

3.2.1 *Predictors selecting*

From the 30 years of observed data representing the current climate, the first 20 years (1980–1999) are considered for calibrating the downscaling models while the remaining 10 years of data (2000–2009) are used to validate those models. The different parameters of model are adjusted during calibration to get the best statistical agreement between observed and simulated meteorological variables. For the cases of Tmax and Tmin, mean and variances of these variables corresponding to each month were considered as performance criteria. Selecting the most relevantpredictor variables (set of inputs) is the first and important taskin the downscaling process. In SDSM, screening of predictor variables is conducted through linear correlation analysis and scatter plots (between the predictors and predictand variables) and by investigating the percentage of variance explained by each predictand–predictor pair. Another important consideration is the annual cycle of the variables. Appropriate predictors are chosen by considering whether the identified variables and relationships are physically sensible for the particular experiment and study site (Dibike and Coulibaly 2007). Identification of the best predictors is presented below: All 26 atmospheric variables in the grid boxes (completely covering the entire study area) were selected as potential predictors. Subsequently, the most sensitive predictors for each predictand were identified through the screening. The list of selected predictor variables, their correlation coefficient and significance level for all the climatic variables and stations are given in Table 2. The results showed that different predictands are affected by different atmospheric predictors. The daily maximum temperature is more sensitive to surface Meridional wind component, mean temperature at 2 m and 500 hPageopotential height. While, daily minimum temperature is more sensitive to surface divergence lag data by one day, Surface specific humidity and Mean temperature at 2 m lag data by one day.

Table2. Large-scale climate predictors selected for computing surface meteorological variables.

Predictand	Predictors	Partial r	P value
Tmax	surface Meridional wind component (p__v)	0.353	0.000
	500 hPageopotential height (p500)	0.323	0.000
	Mean temperature at 2 m (temp)	0.726	0.000
Tmin	surface divergence lag the data by one day (p_zhlag)	0.291	0.000
	Surface specific humidity (shum)	0.441	0.000
	Mean temperature at 2 m lag the data by one day (templag)	0.667	0.000

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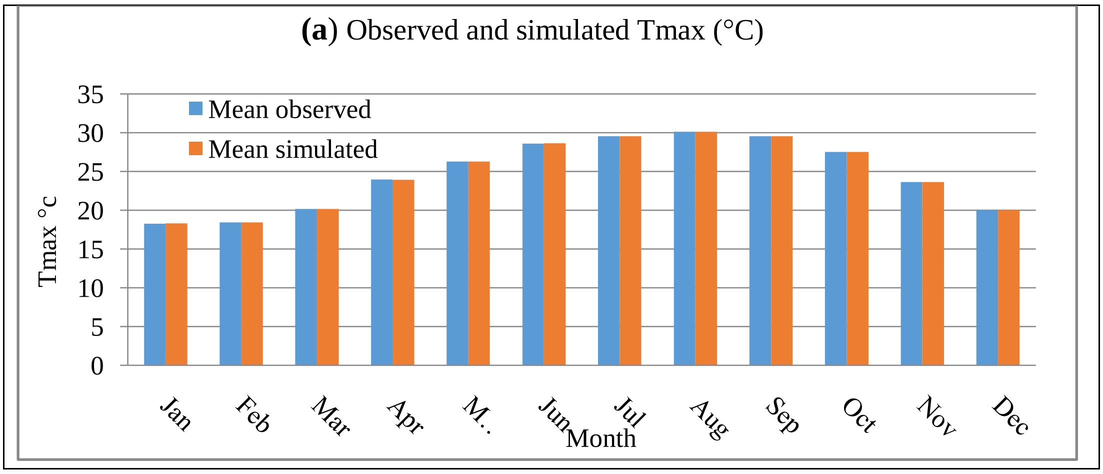
3.2.2 Calibration and validation

The model consists of 12 monthly regression equations for tow downscaling experiments. The model was calibrated and validated using observations (1980–1999) and (2000–2009), respectively. The predictor variables were from the NCEP/NCAR reanalysis data. The predictands were from the observed surface variables. Figure 5 and table 4 show the performance in the calibrated period (1980–1999). Figure 5 shows comparison of the downscaled and observed maximum and minimum temperature during the calibrated period for Alexandria station. As shown in the graphs, the model shows satisfactory agreement based on the mean simulated and observed, mean absolute error between the simulated and observed values and variance of observed and simulated of mean maximum and minimum temperature values.

Table 3: Performance of SDSM during the calibration periods (1980-1999)

Predictand	Month	SE	R2	**Predictand**	Month	SE	R2
T MAX	January	1.669	0.417	T MIN	January	1.985	0.43
	February	1.921	0.547		February	1.949	0.388
	March	1.83	0.641		March	1.998	0.405
	April	2.505	0.694		April	1.959	0.478
	May	2.346	0.657		May	1.713	0.496
	June	1.88	0.576		June	1.529	0.483
	July	1.338	0.366		July	1.287	0.363
	August	1.049	0.25		August	1.441	0.309
	September	1.25	0.538		September	1.831	0.366
	October	1.43	0.601		October	1.982	0.432
	November	1.617	0.617		November	1.928	0.571
	December	1.791	0.495		December	2.123	0.407

R2: Coefficient of determination; SE: Standard Error.



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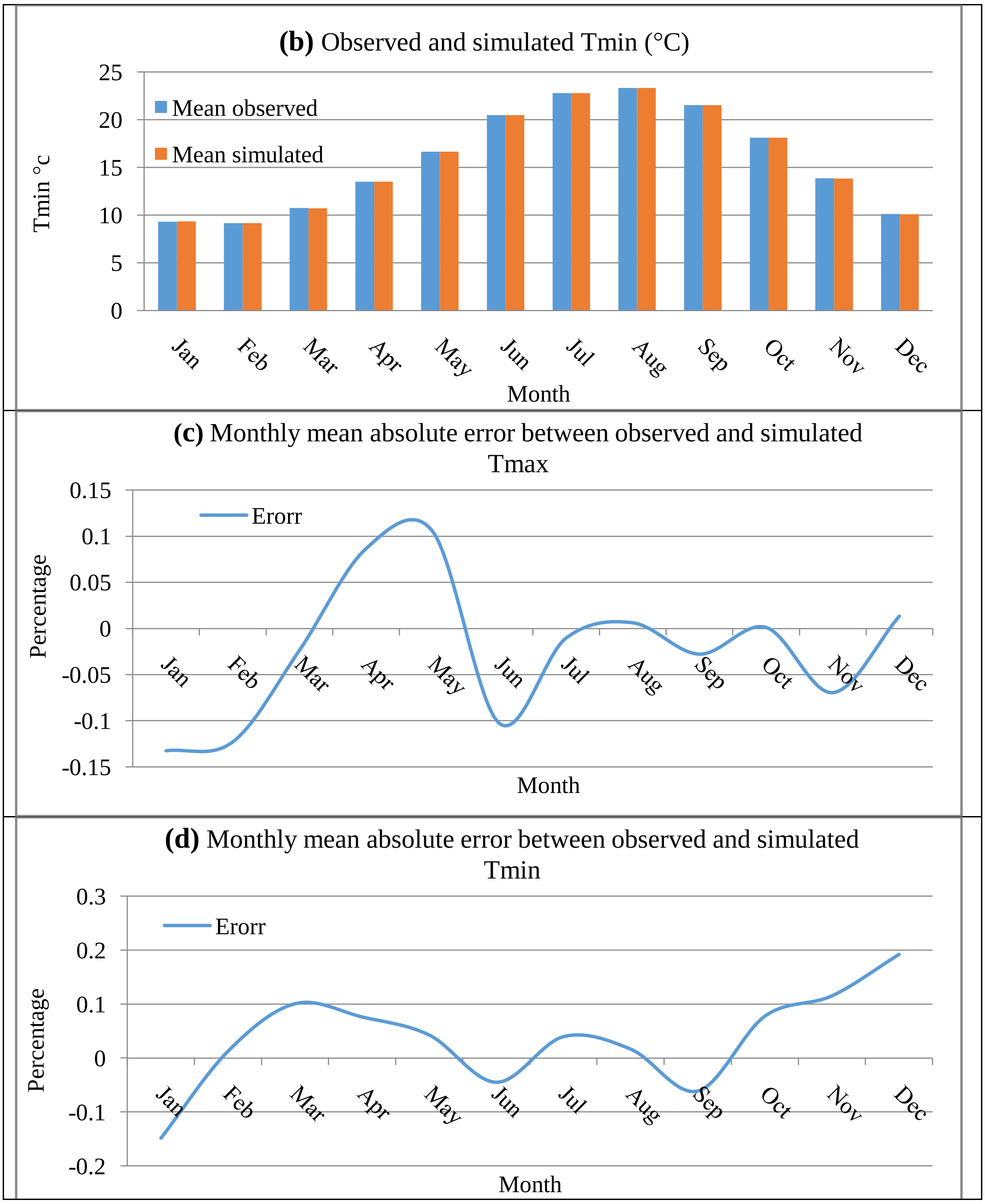

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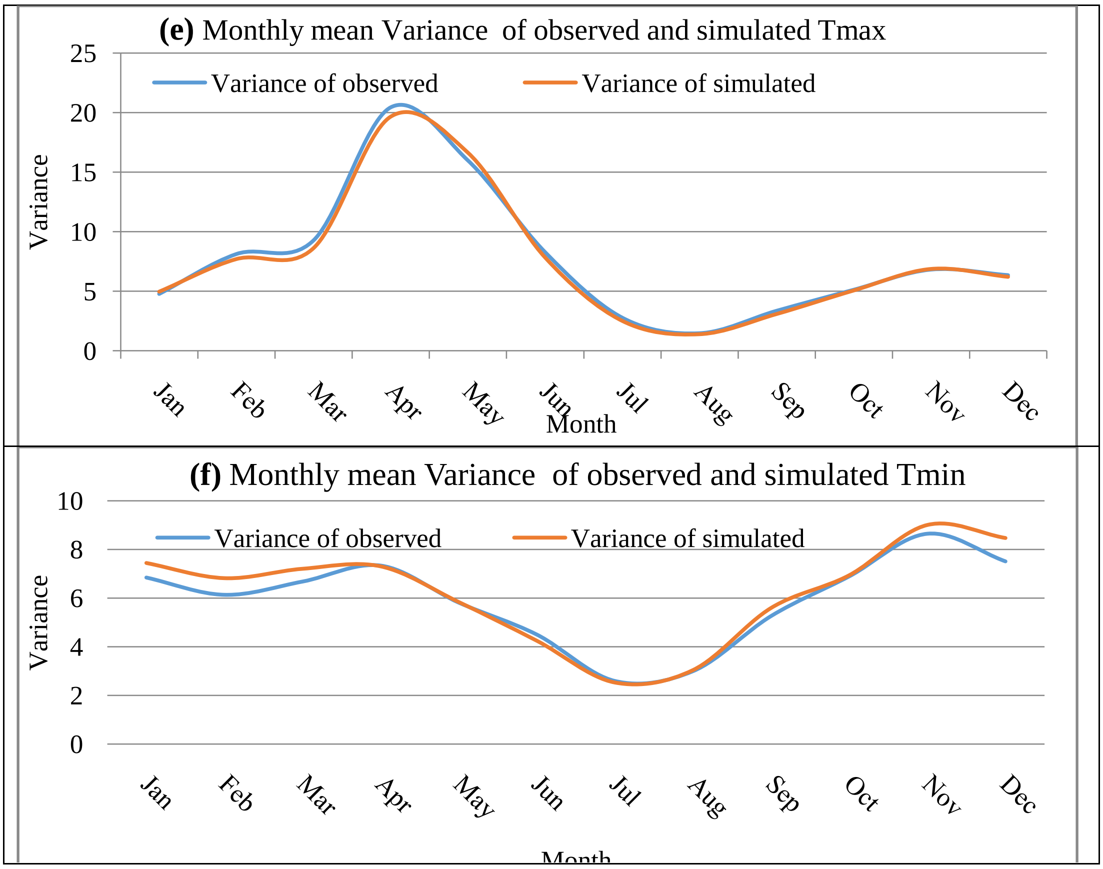
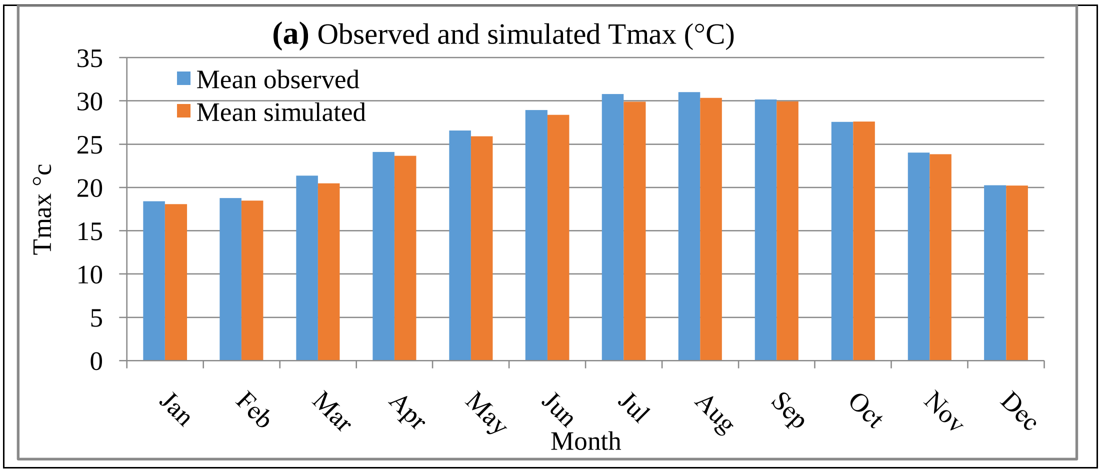


Fig 5:Observed and simulated SDSM-based downscaling for Tmax and Tmin during calibration period (1980-1999)

The statistical parameters established during the calibration process that explain the statistical agreement between observed and simulated data are then used for model validation. The 10 years data (2000-2009) were used to validate the performance of the model. For temperature (Tmax and Tmin), the mean, meanabsolute error and variance corresponding to each month are used to evaluate the performance of the model. The results (Figure 6) indicate a reasonable agreement between the simulated and observed values at Alexandria station with maximum error about -5.5% and 4.5% for Tmin and Tmax respectively.



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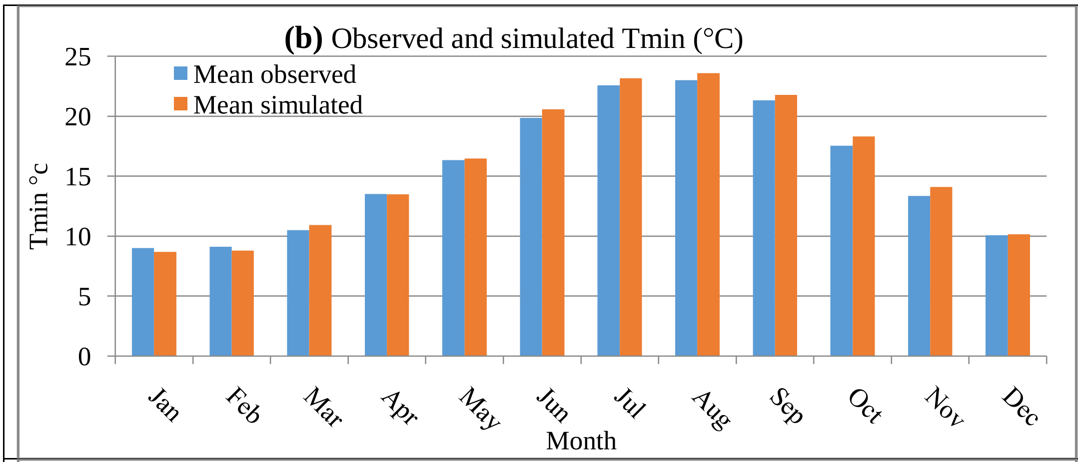

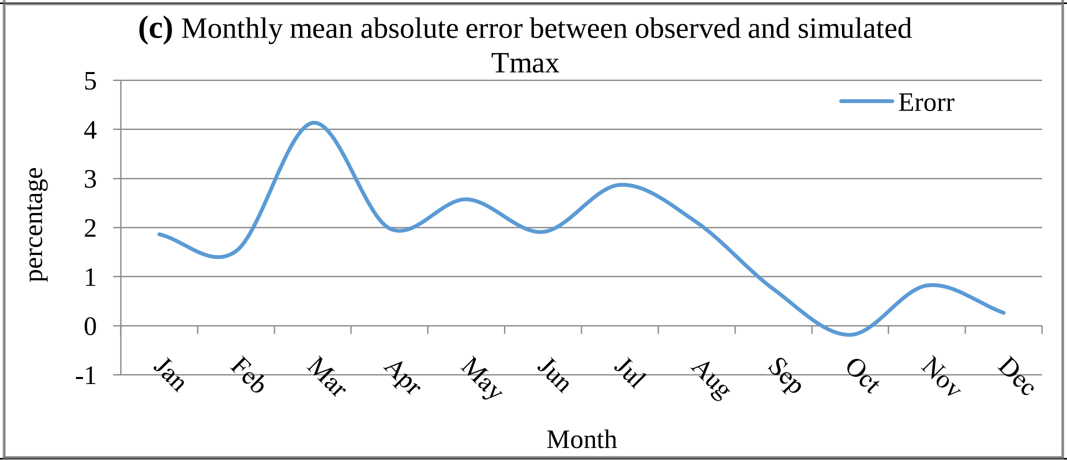

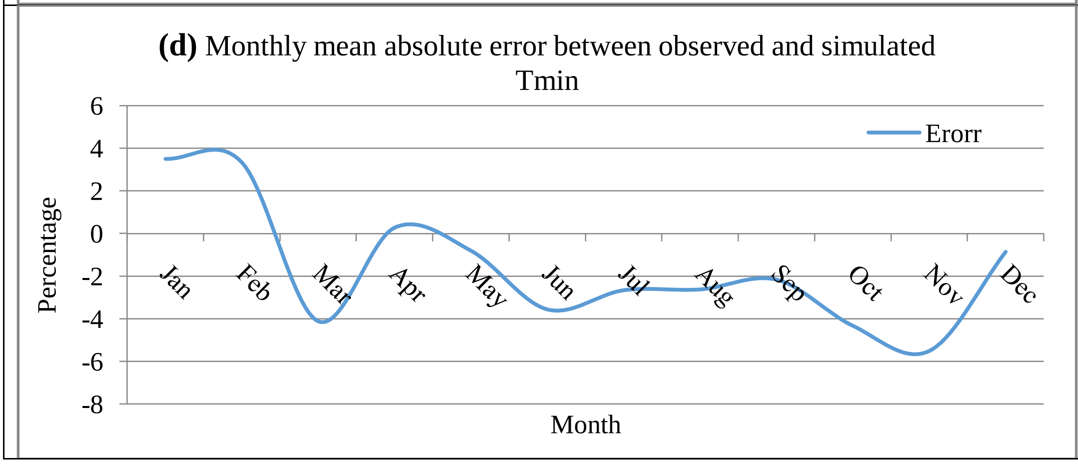

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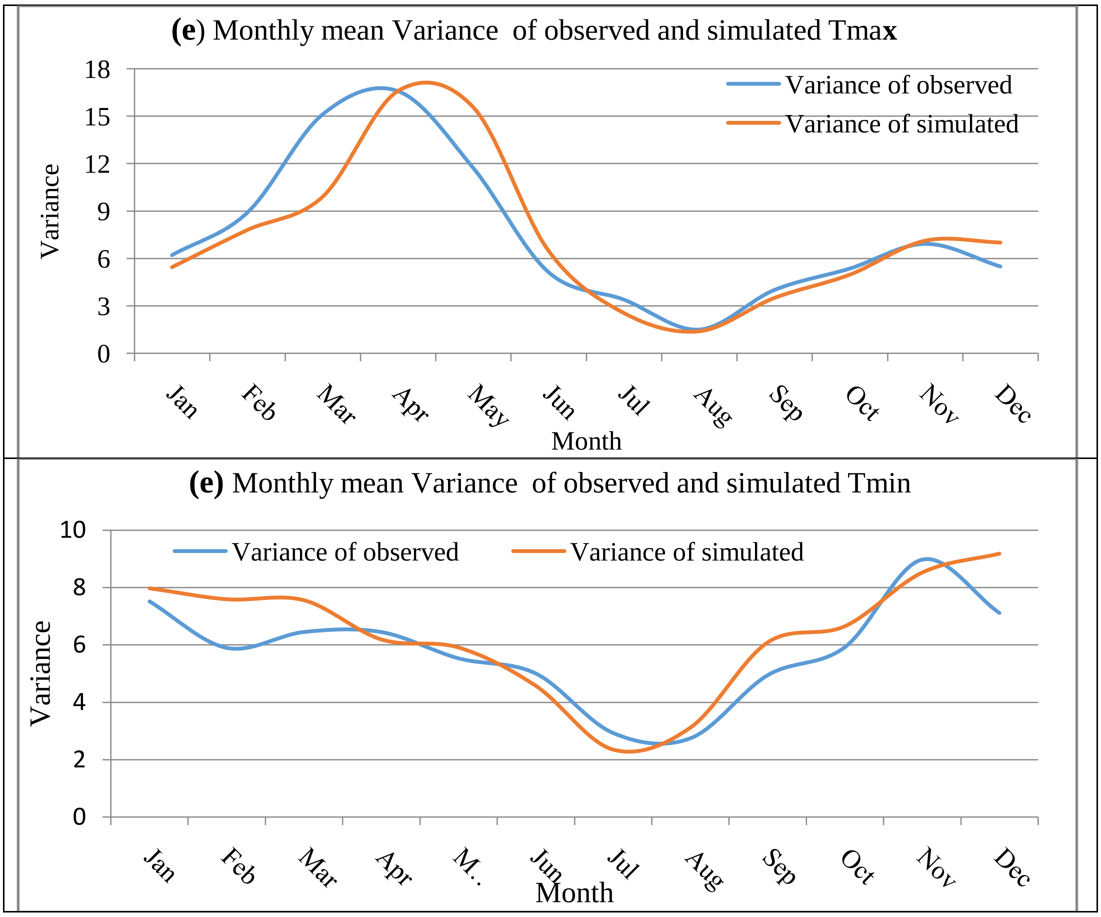


Fig6: Validation results SDSM-based downscaling for Tmax and Tmin(2000-2009).

The performance of the SDSM model was evaluated based on different statistical methods such as correlation coefficient (R), coefficient of determination (R2), root mean square error (RMSE), Nash-Sutcliffe efficiency (NSE) and RMSE-observations standard deviation ratio (RSR) value. The results obtained from these evaluation criteria revealed that the SDSM performed well for downscaling maximum and minimum temperature. The lower RMSE and RSR value and higher NSE, R and R2 value clearly demonstrated the better efficiency of SDSM in simulating the daily temperature data (Table 4). The values of all statistical parametersas shown Table 4 for both temperature variables showing better efficiency of SDSM in generating the daily temperature data.

Table 4.Statistical evaluation of SDSM performance for validation period (2000-2009).

ALEXANDRIA	R	R2	Nash-Sutcliffe Efficiency	RMSE	RSR
Tmax	0.94	0.87	0.89	1.74	0.33
Tmin	0.98	0.92	0.89	1.93	0.33

3.3 Generation of Climate Scenario

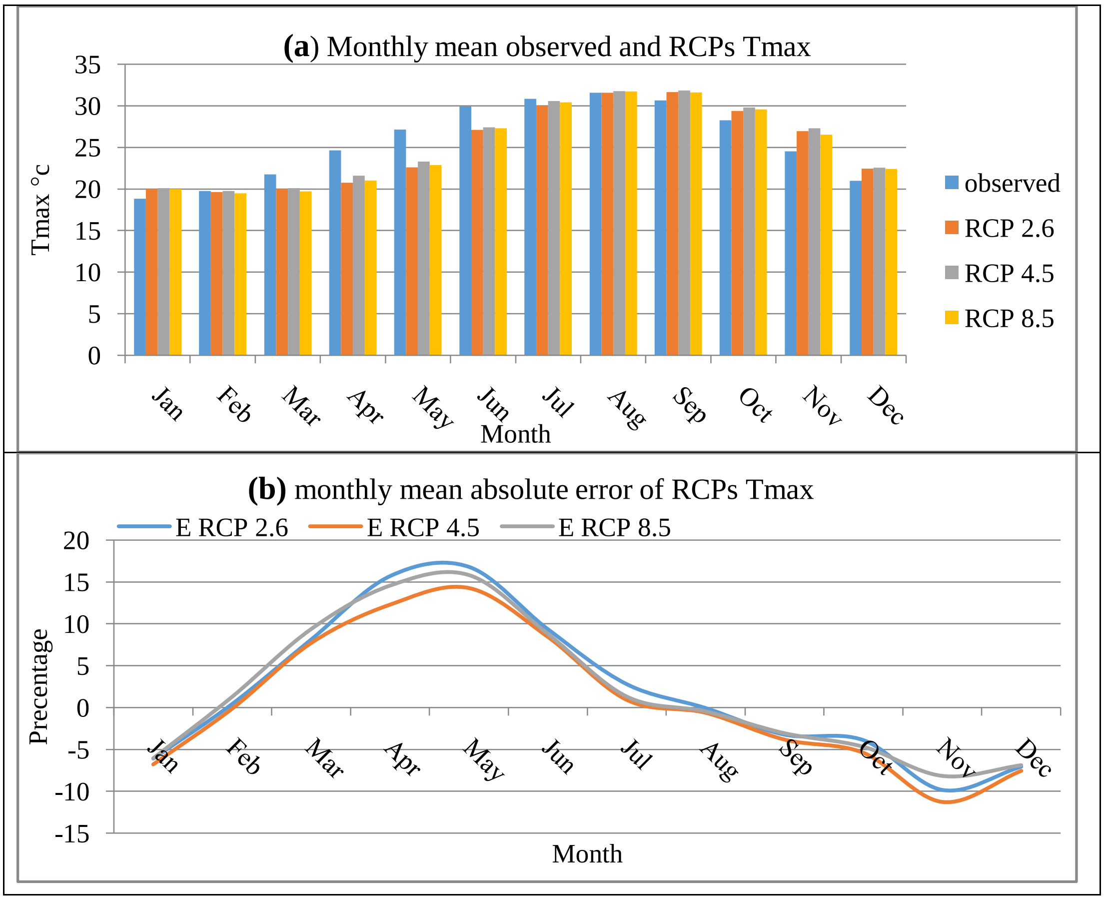
In this study, a future climate scenario is generated for maximum and minimum temperature at Alexandria station. The analysis of future climatic variables was done by classifying the future data into three time windows viz., 2011-2040, 2041-2070 and 2071-2100 respectively. The baseline period was considered as the duration from 1980-2009 to perform the behavior of the future climate variables. Once the downscaling models have been calibrated and validated, the next step is to use these models to downscale the future climate change scenario simulated by the GCM. In this case, instead of the NCEP/NCAR reanalysis data used as input to each of the downscaling models earlier, the large-scale predictor variables are taken from CanESM2 simulation output.

To determine the best suitable RCP scenario from the selected model (CanESM2) over the selected station, statistical analysis methods were used to give the goodness of fit measurements between the measured and projected data for all selected predictand variables (maximum and minimum temperatures) (Sayad et al. 2015). These statistical analysis methods such as Willmott index of agreement (d), Coefficient of Determination (R2), Root mean square error per observation (RMSE/obs) andMean bias error per observation (MBE/obs) can be shown in table 5.

Table 5. Goodness of fit between observed and projected maximum and minimum temperature of period (2006-2014).

ALEXANDRIA	T MAX				T MIN			
	d	R2	RMSE/obs	MBE/obs	d	R2	RMSE/obs	MBE/obs
RCP2.6	0.84	0.49	0.15	-0.02	0.93	0.75	0.18	0.02
RCP4.5	0.84	0.51	0.15	-0.01	0.93	0.77	0.17	0.04
RCP8.5	0.84	0.52	0.15	-0.02	0.92	0.71	0.19	0.02

The results in the above table revealed that, the highest closeness between measured and projected scenarios was found for RCP4.5. The visual comparison between monthly means of observed and simulated data output from RCPs during period (2006-2014) is shown in Figure 7. All RCPs outputs are above normal from July to February, while the months from March to June are below normal for Tmax and Tmin with large difference in Tmax.



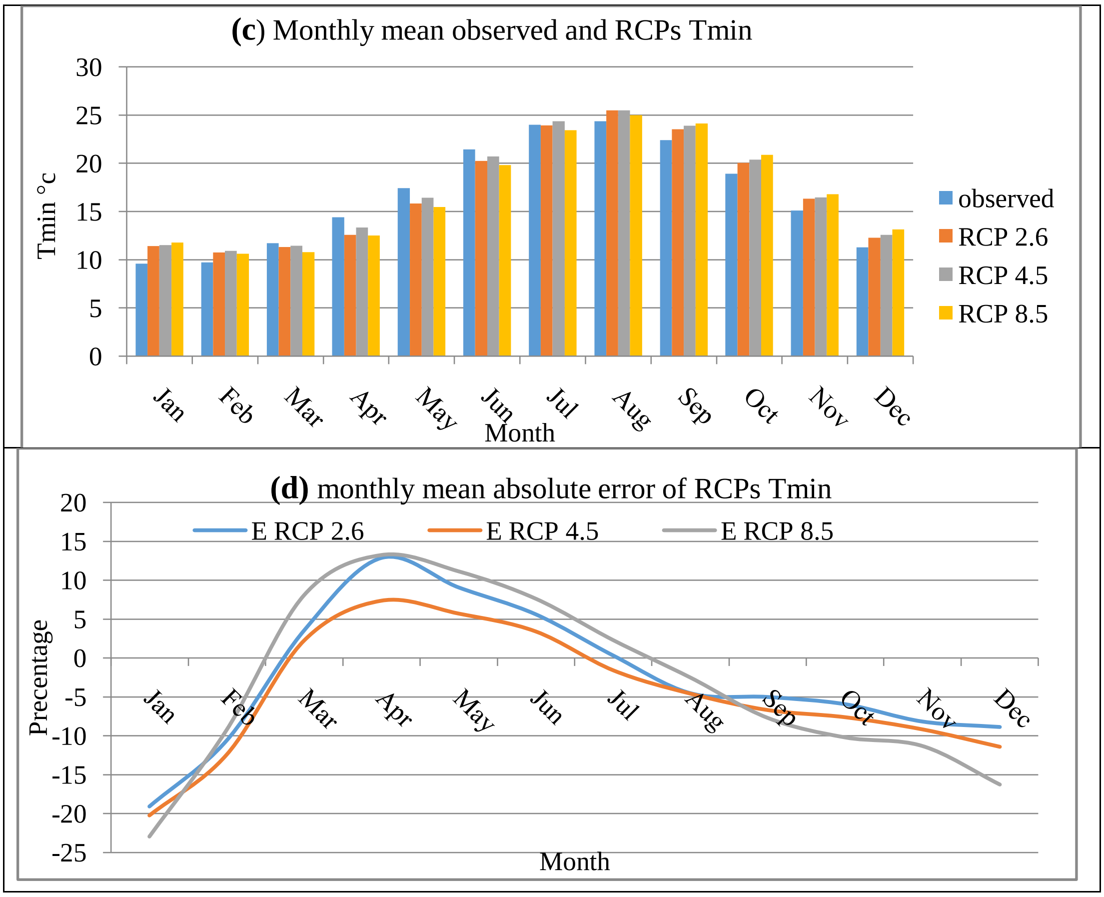


Fig 7:Monthly means of observed and simulated data output from RCPs for Tmax and Tmin during period (2006-2014)

3.3.1 Projection of maximum temperature

The downscaled maximum temperature clearly shows an increasing trend in mean annual maximum temperature in all the future time horizons and also for all the scenarios not shown. In Alexandria, the mean annual maximum temperature under the RCP 2.6 scenario will be increased by 0.76 °Cin the 2011-2040 and 1.14 °C in the 2041-2070and 1.23°C in the 2071-2100from baseline (1980-2009) and the seasonal variation can be shown in table 5 and monthly variation can be shown in Figure 8.

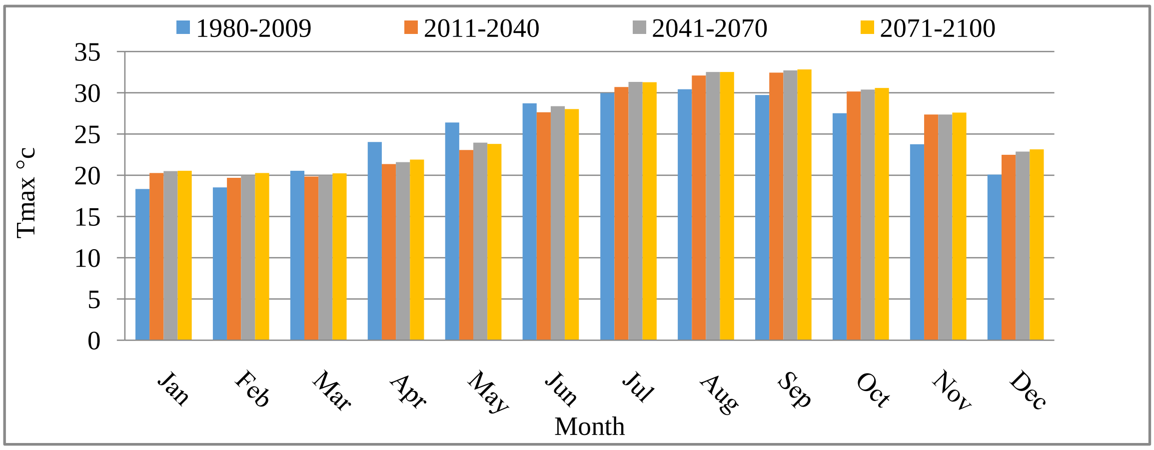


Fig 8:Monthly mean observed (1981-2010) RCP2.6 Tmaxforthe future three periods.

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Table 5.RCP 2.6 Seasonal variation of Tmaxfor the three periods.

Seasonal	Periods				
	2011-2040	2041-2070		2071-2100	
	Form baseline	Form baseline	Previous period	Form baseline	Previous period
Winter	1.853538	2.168018	0.31448	2.354038	0.18602
Spring	-2.22234	-1.79176	0.430584	-1.65953	0.132229
Summer	0.463249	1.066514	0.603264	0.935492	-0.13102
Autumn	2.974792	3.14462	0.169828	3.324153	0.179534

Under the RCP 4.5stabilization scenario, the maximum temperature will increase by 0.88°C in the 2011-2040, 1.62°C in 2041-2070 and 1.98°C by the end of the century. The seasonal variation can be shown in table 6 and monthly variation can be shown in Figure 9.

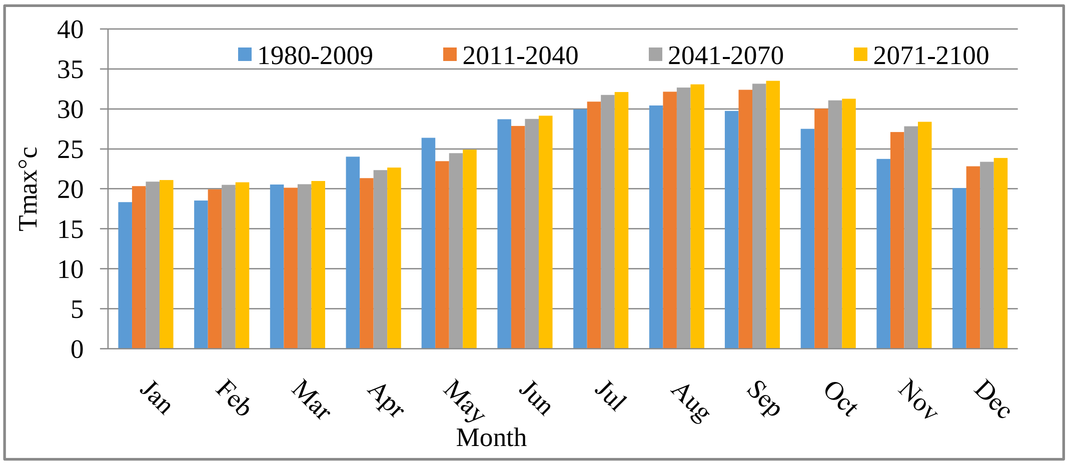

Fig 9. Monthly mean observed (1981-2010) RCP 4.5 Tmax for the future three periods.

Table 6: RCP 4.5 Seasonal variation of Tmax for the three periods.

Seasonal	Periods				
	2011-2040	2041-2070		2071-2100	
	Form baseline	Form baseline	Previous period	Form baseline	Previous period
Winter	2.074011	2.644512	0.570501	2.983735	0.339223
Spring	-1.99832	-1.19181	0.806518	-0.81071	0.381092
Summer	0.638807	1.378406	0.739599	1.767716	0.38931
Autumn	2.838264	3.676277	0.838013	4.041642	0.365365

Under the RCP 8.5 scenario, this scenario shows the highest increase compared to the other two scenarios for all time windows.The maximum temperature will increase by 0.96°C in the 2011-2040, 2.16°C in 2041-2070 and 3.85°C by the end of the century. The seasonal variation can be shown in table 7 and monthly variation can be shown in Figure 10.

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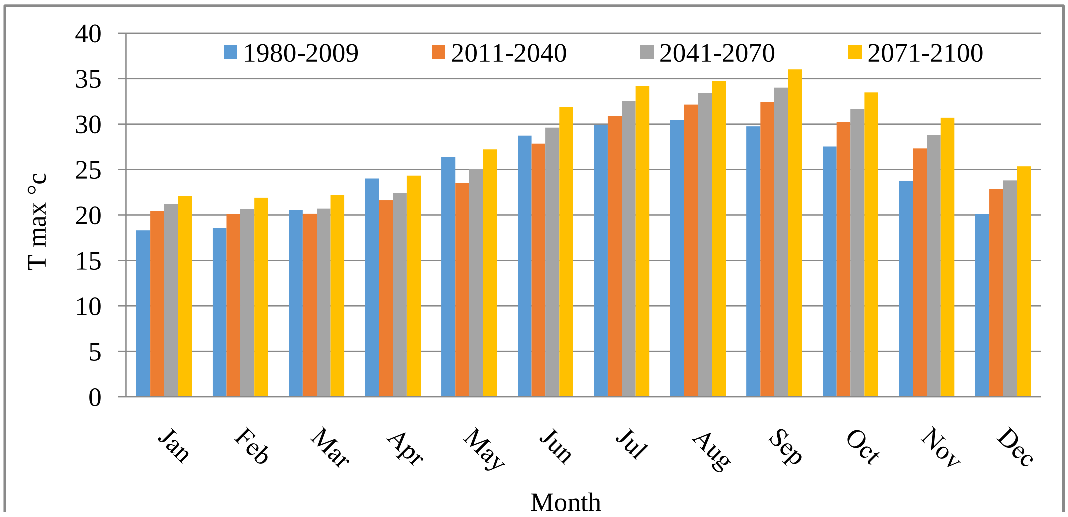

Fig 10. Monthly mean observed (1981-2010) RCP 8.5 Tmax for the future three periods.

Table 7: RCP 8.5 Seasonal variation of Tmax for the three periods.

Seasonal	Periods				
	2011-2040	2041-2070		2071-2100	
	Form baseline	Form baseline	Previous period	Form baseline	Previous period
Winter	2.155771	2.928399	0.772628	4.163265	1.234866
Spring	-1.88137	-0.91167	0.969701	0.951569	1.863237
Summer	0.624555	2.179223	1.554667	3.924306	1.745084
Autumn	2.974479	4.486538	1.512059	6.385661	1.899123

3.3.2 Projection of minimum temperature

The same to the maximum temperature, the projection showed the increasing trend of minimum temperature across all the periods. In Alexandria, the mean annual minimum temperature under the RCP 2.6 scenario will be increased by 1.43°C in the 2011-4020 and 1.8°C in the 2041-2070 and 1.92°C in the 2071-2100 from baseline (1980-2009) and the seasonal variation can be shown in table 8 and monthly variation can be shown in Figure 11.

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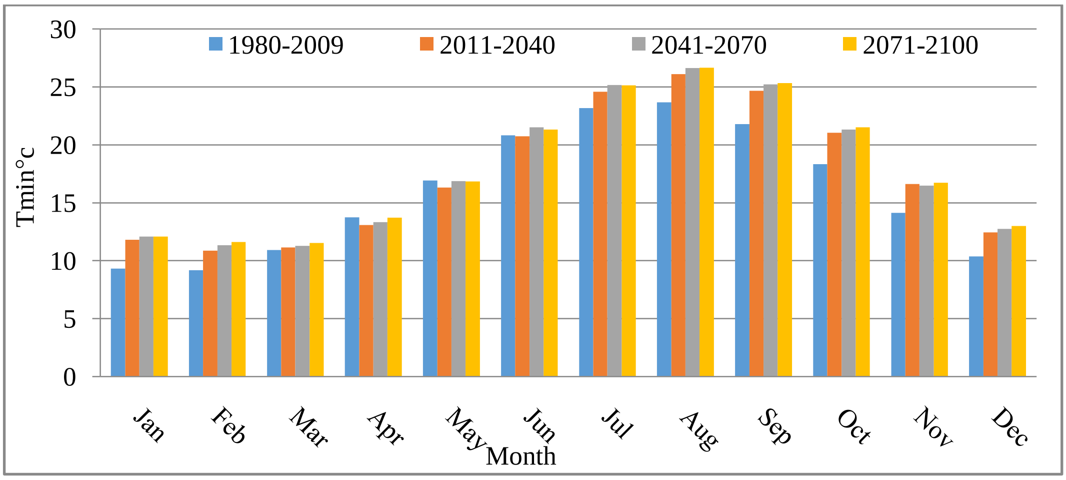

Fig 11: Monthly mean observed (1981-2010) RCP 2.6 Tmin for the future three periods.

Table 8.RCP 2.6 Seasonal variation of Tmin for the three periods.

Seasonal	Periods				
	2011-2040	2041-2070		2071-2100	
	Form baseline	Form baseline	Previous period	Form baseline	Previous period
Winter	2.109504	2.457049	0.347545	2.624219	0.16717
Spring	-0.3425	-0.03156	0.310939	0.16953	0.201093
Summer	1.262034	1.888887	0.626853	1.826786	-0.0621
Autumn	2.698458	2.919335	0.220878	3.099288	0.179952

Under the RCP 4.5 stabilization scenario, the minimum temperature will increase by 1.52°C in the 2011-2040, 2.34°C in 2041-2070 and 2.75°C by the end of the century. The seasonal variation can be shown in table 9 and monthly variation can be shown in Figure 12.

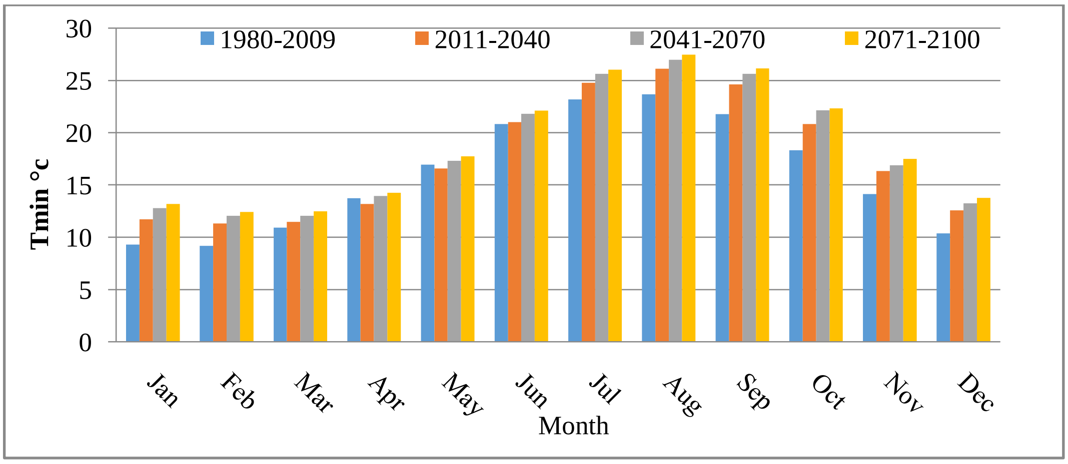

Fig 12: Monthly mean observed (1981-2010) RCP 4.5 Tmin for the future three periods.

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Table 9.RCP 4.5 Seasonal variation of Tmin for the three periods.

Seasonal	Periods				
	2011-2040	2041-2070		2071-2100	
	Form baseline	Form baseline	Previous period	Form baseline	Previous period
Winter	2.269133	3.086293	0.81716	3.510324	0.42403
Spring	-0.11467	0.573597	0.68827	0.960225	0.386629
Summer	1.432615	2.258793	0.826178	2.656101	0.397308
Autumn	2.521204	3.467021	0.945817	3.90842	0.441399

Under the RCP 8.5 scenario, this scenario shows the highest increase compared to the other two scenarios for all time windows.The minimum temperature will increase by 1.62°C in the 2011-2040, 2.96°C in 2041-2070 and 4.86°C by the end of the century. The seasonal variation can be shown in table 10 and monthly variation can be shown in Figure 13.

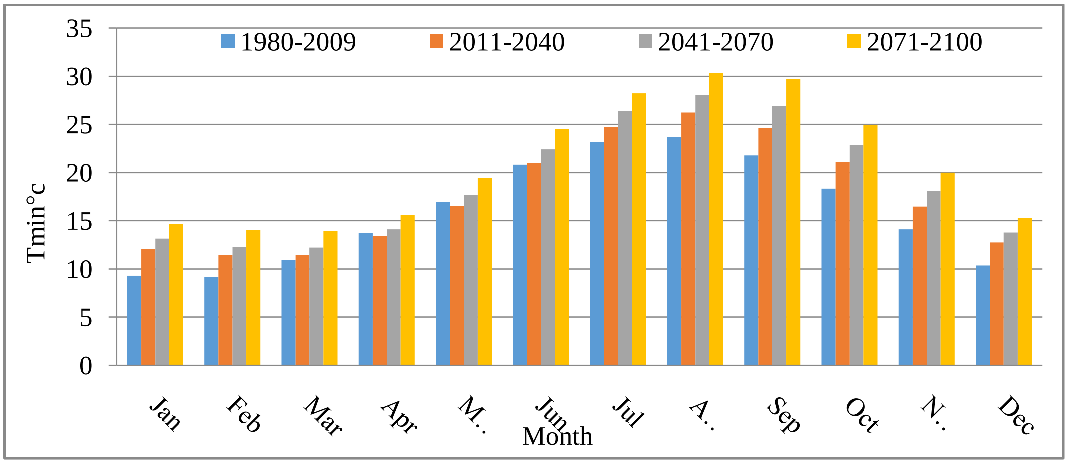

Fig 13: Monthly mean observed (1981-2010) RCP 8.5 Tmin for the future three periods.

Table 10.RCP 8.5 Seasonal variation of Tmin for the three periods.

Seasonal	Periods				
	2011-2040	2041-2070		2071-2100	
	Form baseline	Form baseline	Previous period	Form baseline	Previous period
Winter	2.467202	3.465414	5.06757	5.06757	1.602156
Spring	-0.05625	0.816531	2.450443	2.450443	1.633912
Summer	1.443407	3.05498	5.159456	5.159456	2.104476
Autumn	2.639091	4.536436	6.787578	6.787578	2.251142

4 CONCLUSION

The objectives of this study are to analyze the temporal variations of maximum, and minimum daily temperature data for Alexandria to describe the development of the widely used SDSM linkage between the climate simulations given by the CanESM2 and the local temperature records. The 30 year (1980-2009) temperature data at Alexandriastation has been considered. Obtained analysis and development resultsare concluded as follows:

- The maximum dailytemperatures of Alexandria tend to slightly decrease during 1980-1994 period while the trend of the 1995-2009 interval increases.
- The minimum daily temperatures of Alexandria tend to increase during the whole period.
- The commonly significant NCEP variables for the SDSMs ofthe daily maximum temperature are surface Meridional wind component, mean temperature at 2 m and 500 hPageopotentialheights. While, the commonly significant NCEP variables for

daily minimum temperature are surface divergence lag data by one day, Surface specific humidity and Mean temperature at 2 m lag data by one day.

- The calibration and validation of the developed SDSMs for the temperature occurrences have demonstrated that the observed and downscaled temperature means and variances generally agree with each other.
- After evaluation of the different three RCPs scenarios, it is concluded that RCP 4.5 is the best one with increasing in both Tmax and Tmin based on baseline period (1980-2009) exceptin spring season the most periods are under estimation in all scenarios.

5 REFERENCES

[1] Alcamo, J., et al., Europe: IPCC AR4. Climate Change 2007: Impacts, Adaptation and Vulnerability., 2007. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, M.L. Parry, O.F. Canziani, J.P. Palutikof, P.J. van der Linden and CE. Hanson, Eds., Cambridge University Press, Cambridge, UK,: p. 541- 580.

[2] Amr H. El-Shafie, A. El-Shafie, Hasan G. El Mazoghi, A. Shehata and Mohd. R. Taha (2011): Artificial neural network technique for rainfall forecasting applied to Alexandria, Egypt. International Journal of the Physical Sciences Vol. 6(6), 1306-1316. DOI: 10.5897/IJPS11.143

[3] Ayalew, D., Tesfaye, K., Mamo, G., Yitaferu, B. and Bayu, W. 2012. Outlook of future climate in northwestern Ethiopia, Agricultural Sciences 3, Vol.3, No.4, 608-624.

[4] B´ardossy A, Plate EJ. 1992. Space-time model for daily rainfall using atmospheric circulation patterns. Water Resources Research 28: 1247–1259.

[5] Babel, M.S. and Turyatunga, E. 2015. Evaluation of climate change impacts and adaptationmeasures for maize cultivation in the western Uganda agro-ecological zone. Theoretical and Applied Climatology, 119, 239-254.

[6] Beckmann BR, Buishand TA. 2002. Downscaling relationships for precipitation for the Netherlands and North Germany. International Journal of Climatology 22: 15–32.

[7] Busuioc A, Chen D, Hellstr¨om C. 2001. Performance of statistical downscaling models in GCM validation and regional climate change estimates: application for Swedish precipitation. International journal of Climatology 21: 557–578.

[8] Chaleeraktrakoon, C. and Punlun, P. 2010. Statistical analysis and downscaling for the minimum, average, and maximum daily temperatures of the Chi and Mun River basins. Thammasat International Journal of Science and Technology, 15, 64-81.

[9] Cheema, S.B., Rasul, G., Ali, G. and Kazmi, D.H. 2011. A comparison of minimum temperature trends with model projections. Pakistan Journal of Meteorology, 8, 39-52.

[10] Christensen JH, Hewitson B, Busuioc A, Chen A, Gao X, Held I, Jones R, Kolli RK, Kwon WT, Laprise R, Maga˜na Rueda V, Mearns L, Men´endez CG, R¨ais¨anen J, Rinke A, Sarr A, Whetton P. 2007. Regional climate projections. Climate Change 2007: The Physical Science Basis, Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press: Cambridge

[11] Cubasch U, von Storch H, Waszkewitz J, Zorita E. 1996. Estimates of climate change in Southern Europe derived from dynamical climate model output. Climate Research 7: 129–149.

[12] Diaz-Nieto J, Wilby RL. 2005. A comparison of statistical downscaling and climate change factor methods: impacts on low flows in the river Thames, United Kingdom. Climatic Change 69: 245–268.

[13] Dibike YB, Coulibaly P. 2005. Hydrologic impact of climate change in the Saguenay watershed: comparison of downscaling methods and hydrologic models. Journal of Hydrology 307: 145–163. Forney GD Jr. 1978. The Viterbi algorithm. Proceedings of the IEEE 61: 268–278.

[14] Fowler HJ, Blenkinsop S, Tebaldi C. 2007. Linking climate modeling to impacts studies: recent advances in downscaling techniques for hydrological modeling. International journal of Climatology 27: 1547–1578.

[15] Gachon P, Dibike Y. 2007. Temperature change signals in northern Canada: convergence of statistical downscaling results using two driving GCMs. International Journal of Climatology 27: 1623–1641.

GLOBAL JOURNAL OF ADVANCED RESEARCH
(Scholarly Peer Review Publishing System)

[16] Hassan, Z., Shamsudin, S. and Harun, S. 2014. Application of SDSM and LARS-WG for simulating and downscaling of rainfall and temperature. Theoretical and Applied Climatology, 116, 243-257.

[17] Hewitson BC, Crane R (1996) Climate downscaling: techniques and application. Clim Res 7(2):85–95. doi:10.3354/cr0007085

[18] 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. Cambridge University Press, Cambridge, UK, and New York, USA

[19] Karl TR, Wang WC, Schlesinger ME, Knight RW, Portman D. 1990. A method of relating general circulation model simulated climate to observed local climate. Part I: seasonal statistics. Journal of Climate 3: 1053–1079.

[20] Khan MS, Coulibaly P, Dibike Y. 2006. Uncertainty analysis of statistical downscaling methods. Journal of Hydrology 319: 357–382.

[21] Liu, L., Liu, Z., Ren, X., Fischer, T., and Xu, Y., 2011. Hydrological impacts of climate change in the Yellow River Basin for the 21st century using hydrological model and statistical downscaling model. Quaternary International, 244 (2), 211–220.

[22] Prudhomme C, Davies H. 2009. Assessing uncertainties in climate change impact analyses on the river flow regimes in the UK. Part 1: baseline climate. Climate Change 93: 177–195, DOI: 10.1007/s10584-008-9464-3.

[23] Sayad T. A., S. Ouda, M. Morsy and F. El Hussieny 2015: Robust statistical procedure to determine suitable scenario of some CMIP5 models for four locations in Egypt, Global Journal of Advanced Research, Vol-2, Issue-6 PP. 1009-1019.

[24] Schubert S, Sellers AH. 1997. A statistical model to downscale local daily temperature extremes from synoptic-scale atmospheric circulation patterns in the Australian region. Climate Dynamics 13: 223–234.

[25] Thorpe A.J., 2005, Climate Change Prediction: A challenging scientific problem. Institute of physics,availableat:http://www.iop.org/activity/policy/Publications/file_4 147.pdf [accessed 14 Sep 2010]

[26] Timbal B, Dufour A, McAvaney B. 2003. An estimate of future climate change for western France using a statistical downscaling technique. Climate Dynamics 20: 807–823, DOI: 10.1007/s00382-002-0298-9.

[27] Von Storch H, Zorita E, Cubasch U. 1993. Downscaling of global climate change estimates to regional scales: an application to Iberian rainfall in wintertime. Journal of Climate 6: 1161–1171.

[28] Wetterhall F, B´ardossy A, Chen DL, Halldin S, Xu CY. 2006. Daily precipitation-downscaling techniques in three Chinese regions. Water Resources Research 42: W11423, DOI:10.1029/2005WR004573.

[29] Wilby RL, Charles SP, Zorita E, Timbal B, Whetton P, Mearns LO (2004) Guidelines for use of climate scenarios developed from statistical downscaling methods. Supporting material to the Intergovernmental Panel on Climate Change 27

[30] Wilby RL, Dawson CW, Barrow EM (2002) SDSM—a decision support tool for the assessment of regional climate change impacts. Environ Modell Softw 17(2):145–157. doi:10.1016/S1364-8152(01)00060-3

[31] Wilby, R.L., Hassan, H., Hanaki, K., 1998b. Statistical downscaling of hydrometeorological variables using general circulation model output. Journal of Hydrology 205, 1–19.

[32] Wilby, R.L., Wigley, T.M.L., 1997. Downscaling general circulation model output: a review of methods and limitations. Progress in Physical Geography 21, 530e548.

[33] Wilby, R.L., Wigley, T.M.L., Conway, D., Jones, P.D., Hewitson, B.C., Main, J., Wilks, D.S., 1998a. Statistical downscaling of general circulation model output: a comparison of methods. Water Resources Research 34, 2995–3008.

[34] Wise EK. 2009. Climate-based sensitivity of air quality to climate change scenarios for the southwestern United States. International Journal of Climatology 29: 87–97.

[35] Wood AW, Leung LR, Sridhar V, Lettenmaier DP. 2004. Hydrologic implications of dynamical and statistical approaches to downscaling climate model outputs. Climatic Change 62: 189–216.

[36] Yehun D. (2009). Hydrological Modeling to Assess Climate Change Impact at GilgelAbbay River, Lake Tana Basin, MSC Thesis degree at Lund University, Sweden.

[37] Zorita E, von Storch H. 1999. The analog method as a simple statistical downscaling technique: Comparison with more complicated methods. Journal of Climate 12: 2474–2489.