RESEARCH ARTICLE

Climate change in the UAE: Modeling air temperature using ARIMA and STI across four bio-climatic zones [version 1; peer review: peer review discontinued]

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Abstract

Background: Standardizing climate-related indices and models across spatial and temporal scales presents a challenge. Especially when predicting climatic conditions in the era of climate change. The present work aims to assess the use of ARIMA (Auto Regressive Integrated Moving Average) modeling approach coupled with STI (Standardized Temperature Index) to predict temperature anomalies across four bio-climatic regions within the United Arab Emirates (UAE).

Methods: We used monthly temperature data from NOAA Land-Based Station Data for Abu Dhabi, Al-Ain, Dubai and Sharjah. ARIMA modeling and STI assessment of climatic events were used to predict and study the dynamics of climate of the four zones. The use of such forecasting powers was intended for an ultimate aim to study the impact of climate change on land use and land cover changes.

Results: Data were not auto-correlated as shown by the Box-Ljung test. Additionally, the box-plots showed that Abu Dhabi had the highest median temperature. The ARIMA forecasting suggested that Dubai is predicted to have increasing trend of average temperatures until 2030. "Extremely hot" events were highest for Al-Ain (i.e. 9), followed by Abu Dhabi, Dubai and Sharjah. Dubai had the highest occurrences of "Moderately hot" events, when compared to all other studied zones. Further, events classified as "very cold" were in the order of 20, 10, and 8, for Dubai, Sharjah, and for each of Abu Dhabi and Al-Ain, respectively.

Conclusions: The temperature is predicted to increase in Dubai and Sharjah, with each representing a different bio-climatic zone. This was also reflected in the STI assessment of the historical temperature. "Moderately hot" and "very cold" events for Dubai were the highest as compared to the other studied zones in the UAE. It is therefore believed that ARIMA, coupled with STI, may be a valid approach to forecast temperature and analyse extreme events.

Keywords
Anomalies, ARIMA, Climate Change, Extreme Temperature.
Introduction
Climate change affects ecosystems, communities and individual organisms. Plants, for instance, are primary producers which often adapt to extreme environmental conditions with different strategies, especially in arid areas. Many plant species in the region exhibit adaptation to extremes of heat and drought. In the United Arab Emirates (UAE), for example, vegetation may be considered already highly resilient to climate change. However, some of these species may be close to their physiological tolerance limits. This presents a natural challenge to living organisms. As such, the present study attempted to assess temperature patterns, in order to further investigate the overall impact of climate change on land cover and land use dynamics.

With the expected change in climate, such species will experience additional stressors, leading to reduced land cover and therefore degradation due to overgrazing and land use change. The UAE climate is classified as hyper-arid, with different bio-climatic zones and hence a variety of environmental challenges, including very low land cover coupled with major shifts in land use. In the north-eastern regions of the UAE, the average precipitation is higher while the temperatures are lower. Additionally, and in comparison, these conditions are similar to those of other areas in the Arabian Gulf, where the mean annual temperatures increase along a north–south gradient from Kuwait and Riyadh towards Dibba and Muscat. But there may be patterns in rainfall as well as temperature. Consequently, there exists a need to assess patterns in climatic conditions, especially with the potential impact of climate change regionally as well as globally.

Climate change has also been impacting the UAE. The UAE’s tropical and dry climate is subject to impacts from the Indian Ocean across the Sea of Oman. Across the UAE, using 2012 statistics performed by the Ministry of Environment and Water, the temperature increased by 0.6°C to 2.7°C. Raising temperature, for instance, has been observed in Abu Dhabi with an increase of around 2.3°C between 1982 and 2013, while an increase of 2.7°C between 2013 and 1975 in Dubai. Other cities have also experienced increases between 0.6 and 1.8°C during the past 30–40 years. The Gulf temperatures are also changing. During the last 50 years, the Arabian gulf surface temperature increased 0.2°C per decade. In other parts of the Arabian Gulf, the increase was estimated to be thrice the global average or 0.6°C per decade. Additionally, sea surface temperatures, sea surface salinity and sea level were projected to change. Wind patterns were also estimated to change across the region, which normally affects temperature. Further, and in terms of energy supply, for instance, the UAE 2030 strategic plan envisages to generate more than quarter of its electricity from clean energy sources. It is therefore believed that predicting temperature changes in different parts of the UAE is necessary, especially with the widespread use of time series analyses.

Auto Regressive Integrated Moving Average (ARIMA) based models are used in time series analyses to predict changes in climatic conditions. ARIMA is a class of models that predicts a given time series based on historical values. It is a modeling approach in which three predictors (i.e. p, d and q) are calculated to be the basis for the forecasting process. ARIMA has been used to predict solar radiation, weather, evapotranspiration, wind speed and rain & temperature. Generally, the goodness of fit of the model is tested against standardized residuals, the auto-correlation function (ACF), and the partial autocorrelation function (PACF). The ACF plot shows the correlation of the series with itself at different lags, while the PACF plot shows the amount of auto-correlation at a given lag that is not explained by lower-order auto-correlations. For evaluation purposes, the model is compared with Monte Carlo simulations, using mean absolute error, R-square error, root mean square error and sum of square error. ARIMA performed better than Adaptive Network Based Fuzzy Inference System in a study to forecast weather in Bangladesh; however, a lower performance in modeling evapo-transpiration when compared to other modeling approaches was reported. The relationship between circulation type frequencies and temperature anomalies revealed a warming effect for both winter and summer. The number of days with extreme high temperatures in the wheat growing regions of the Netherlands, for instance, significantly increased since the early 1900s, while the number of extreme low temperature events dropped during the same period. It is therefore useful to use standardized indices such as STI (standardized temperature index) to compare historical values across and within years.

STI is calculated in the same way as was reported by McKee and Kleist for the standardized precipitation index (SPI). Specifically, SPI was calculated based on the Palmer Drought Severity Index, which is widely used for drought forecasting and evapo-transpiration assessment. Such standardization process allows for comparison across space and time at any location. Both SPI and STI have been developed into RStudio packages, and in the present work we limit our analyses to STI. The basis of which has been that assessing temperature anomalies may be useful for climate forecasting purposes. Temperature anomalies may also be used as indicators of climate change. Trends in annual mean temperature anomalies for the globe show rapid and steady warming through the early 1940s. As a consequence, the present study aimed to assess the use of ARIMA modeling approach coupled with STI to predict temperature anomalies across four bio-climatic UAE regions. Historical data is used for the ARIMA forecasting and STI categorization of climatic events.

Methods
Study location
The present investigation centers around average monthly temperatures collected from NOAA Land-Based Station Data for Abu Dhabi (24.45N, 54.38E), Al-Ain (24.13N, 55.80E), Dubai (25.20N, 55.27E) and Sharjah (25.35N, 55.42E). Each of these locations was intended to represent a different bio-climatic zone within the UAE; they have different climatic conditions and represent different soil/vegetation associations as classified in the UAE soils Atlas. The time frame of the historical data is between January 1997 and December 2017 (as was available...
from NOAA station data), while the forecast is planned for 2030, or 13 years into the future. The year 2030 constitutes a major important target, for which the UAE set a strategic plan in relation to various development aspects, including expectations for efficient climate change mitigation and adaptation.

Modeling approach using ARIMA
The data for each of the four bio-climatic regions was transformed into a time series data frame using RStudio “forecast” and “tseries” packages. The data was then converted into a differencing series \( Y_t' = Y_t - Y_{t-1} \) to make it stationary on mean and remove the trend. Additionally, it was log transformed \( Y_{t, \text{new}} = \log(Y_t) \) in order to make the data stationary on variance. The plotting of the ACF and PACF to identify potential AR and MA model predictors (i.e. \( p \) and \( q \)). The idea is to identify the presence of AR and MA components in the residuals. The “d” predictor is used to reflect differencing in the ARIMA model. Where \( p \) is the number of autoregressive terms; \( d \) is the number of nonseasonal differences and \( q \) is the the number of moving-average terms.

The “csv” files for each zone were loaded into RStudio, then the “forecast” package was loaded. The residuals of the ARIMA analyses were graphed using the “plot.ts” function in the “tseries” package. The “acf” and “pacf” functions were executed for all studied zones. In order to identify the best fit, the “auto.arima” function was used and the best model predictors (\( p, d \) and \( q \)) were then identified. The plots presented here for each location is a forecast for 13 years (until 2030) using the best fit, and a range between \( \pm \) two standard errors.

Modeling approach using STI
The standardized temperature index (STI) was used to categorize the changes in temperature across all four bio-climatic zones. STI was calculated using the historical climate data (i.e. 1997–2017). STI is an index representing the probability of occurrence of a temperature value when compared with values on a longer period. It is calculated based on the Palmer Drought Severity Index. The median is used as a point of reference to identify the STI events. These events are relative to the temperatures at a given location, but STI permits for comparisons at different locations. To classify temperature anomalies, the STI events are categorized as detailed in Table 1.

Raw data was first processed for all four bio-climatic zones using the pivot table option in Excel (Version 16.0.4266.1001). The “csv” file for each zone was then uploaded to RStudio to analyse the data using “STI” package (Version 0.1). STI command was used and the time scale was set to 12. That is the average of the eleven first months is used for month twelve (i.e. the first eleven values will be “NA”). The “stiEvents” function was then used to quantify the number of entries in each of the STI categories listed in Table 1. The “scatter.smooth” command was finally used to draw the scatter plots referred to in Figure 10.

Results
Data distribution across regions
Boxplots were generated using RStudio from the original temperature data (Figure 1). Abu Dhabi (top) tended to have highest median temperature when compared to Al-Ain, Dubai and Sharjah with averages of 36.2°C, 29.9°C, 29.6°C and 28.6°C, respectively. While Al-Ain, with 12.5°C, has the largest inter-quartile range (IQR) vs 12.1°C, 10.6°C and 11.4°C, for Abu Dhabi, Dubai and Sharjah, respectively.

| STI Categories     | Range of STI Values |
|--------------------|---------------------|
| Extremely hot      | \( STI > 2.0 \)     |
| Very hot           | \( 1.5 \leq STI \leq 2.0 \) |
| Moderately hot     | \( 1.0 \leq STI \leq 1.5 \) |
| Near normal        | \( 1.0 \leq STI \leq -1.0 \) |
| Moderately cold    | \( -1.0 \leq STI \leq -1.5 \) |
| Very cold          | \( -1.5 \leq STI \leq -2.0 \) |
| Extremely cold     | \( STI < -2.0 \)    |

Figure 1. Boxplots for temperature distribution, across all years, for (listed top to bottom) Abu Dhabi, Al-Ain, Dubai, and Sharjah.
The lowest minimum temperature recorded was 16.8°C for Al-Ain, while the highest minimum was for Abu Dhabi (22.5°C). The pattern observed for the highest value of maximum temperatures were 46.1°C, 39.2°C, 38.2°C and 37.3°C for Abu Dhabi, Al-Ain, Dubai and Sharjah, respectively.

**ARIMA consistency and forecast**

First the variance and mean are stationary as shown in the differentiated temperature in Figure 2–Figure 4 and Figure 5 (top left insets). This also gives us the idea that the “I” term (or integrative part) in the ARIMA model will be equal to 1 as 1st level was making the series stationary, for all four bio-climatic regions.

The residual graphs for all four zones also suggest stationary data. This is shown in Figure 2–Figure 4 and Figure 5 (bottom left insets). Additionally, the Box-Ljung test, which is used to test for auto-correlation at P> 0.05, is presented in Table 2. For all four zones, the Box-Ljung test was carried at three different lags (5, 10 and 15). All runs were not significant at P> 0.05; which is an indication of the absence of auto-correlation. The x-squared for 5 lags were 3.7, 9.7, 5.8 and 5.2 for Abu Dhabi, Al-Ain, Dubai and Sharjah, respectively (Table 2).

The ARIMA forecasting assessment suggests that all zones under investigation, except Dubai, are predicted to have constant trend of average temperatures until 2030. For Dubai (Figure 4 lower right inset), however, there is a slightly increasing trend. The ARIMA predictors (i.e. p,d and q) are in the order of 2,0,2 (Figure 4 lower right inset).

**ACF and PACF assessment**

The ACF and PACF graphs are shown in Figure 6–Figure 8 and Figure 9 for Abu Dhabi, Al-Ain, Dubai and Sharjah, respectively. Since mostly there are no spikes outside the insignificant zone for both ACF and PACF plots, it can be concluded that residuals are random. In other words, our ARIMA models are appropriate in forecasting UAE bio-climatic zones. It is important to note that ACF plots can help determine the order of the MA (q) component of the model. While PACF plots assist in identifying the order of the AR (p) component of the model.

**Historical STI assessment**

STI events from historical climatic data (1997–2017) are summarized in Table 3. All four bio-climatic zones had high proportions of “near normal” events between 1997 and 2017. Sharjah and Al-Ain had the highest occurrences of such events, with averages of 171 and 168, respectively. Extremely hot events are highest for Al-Ain (i.e. 9), followed by Abu Dhabi, Dubai and Sharjah (8, 7 and 5, respectively). What is noteworthy are the differences among the studied zones for “moderately hot” events. Dubai has the highest number of such events (i.e. 34), while Abu Dhabi has experienced only 12 “moderately hot” events. The average number of events classified as “very cold” are predicted to be 20, 10, and 8, for Dubai, Sharjah, and for each of Abu Dhabi and Al-Ain, respectively.
Figure 3. ARIMA modeling output for Al-Ain: Differenced temperature (top left), the decomposition graphs (top right), residuals (bottom left) and the forecast (bottom right) extended from the actual data (black vs blue lines).

Figure 4. ARIMA modeling output for Dubai: Differenced temperature (top left), the decomposition graphs (top right), residuals (bottom left) and the forecast (bottom right) extended from the actual data (black vs blue lines).
and Sharjah had more STI values to the positive range direction (Figure 10 bottom two insets), toward the end of the study period (1997–2017). It may be an indication that historically, both Dubai and Sharjah have experienced more proportions of climatic categories toward “very hot” and “extremely hot” conditions.

**Discussion**

Here, we assessed the use of ARIMA modeling approach coupled with STI to predict temperature anomalies across four UAE bio-climatic regions. ARIMA modeling proved to be valid to assess such predictive powers. Drought forecasting was validated through ARIMA modeling [28]. In the present study, the ARIMA forecasting assessment showed that all zones, except Dubai, were predicted to have constant trend of average temperatures until 2030. For Dubai, however, there was a slight increasing trend. The ARIMA predictors (i.e. p, d and q) were in the order of 2,0,2. The estimates reported by Koenker and Schorfheide [29] suggest a generally upward sloping trend of the temperature series during their study period. ACF and PACF trends showed that the data were not autocorrelated. Weather data were used in similar attempts (e.g. [30,31]). It was also used to predict long-term variability in solar irradiation and surface air temperature [32]. Surface air temperature was closely predicted by ARIMA modeling [32]. Increasing trends were also reported about the maximum temperature in north-eastern
**Figure 6.** ACF and PACF residuals for ARIMA modeling to forecast temperature in Abu Dhabi.

**Figure 7.** ACF and PACF residuals for ARIMA modeling to forecast temperature in Al-Ain.
Figure 8. ACF and PACF residuals for ARIMA modeling to forecast temperature in Dubai.

Figure 9. ACF and PACF residuals for ARIMA modeling to forecast temperature in Sharjah.
Table 3. Outcome from the STI events modeling for the historical data (1997-2017) for four bio-climatic zones in the UAE.

| STI Events          | Abu Dhabi | Al-Ain | Dubai | Sharjah |
|---------------------|-----------|--------|-------|---------|
| Extremely hot       | 8         | 9      | 7     | 5       |
| Moderately hot      | 12        | 19     | 34    | 16      |
| Near normal         | 162       | 168    | 163   | 171     |
| Moderately cold     | 34        | 25     | 6     | 13      |
| Very cold           | 8         | 8      | 20    | 10      |
| Extremely cold      | 5         | 5      | 4     | 7       |

Figure 10. Scatter plots of STI values (solid line is the general trend) from historical temperatures (1997–2017) for Abu Dhabi, Al-Ain, Dubai and Sharjah. X-axis is time: in months between 01/199712/2017.

Bangladesh. Globally, temperature changes had similar ranges when compared to various climate sensitivities. When using various variants of ARIMA, some outperformed others based on Mean Absolute Percentage Error, Maximum Absolute Percentage Error and Mean Absolute Error. It is important to highlight that ARIMA was used by Corchado and Fyfe for comparisons with other modeling approaches.

The STI assessment of the historical data for all four bio-climatic zones showed that “near normal” events were the highest in Sharjah and Al-Ain (171 and 168, respectively). Further, Dubai had 34 “moderately hot” events, while Abu Dhabi has experienced only 12 such events.

Increased frequencies of warm days and warm nights, higher extreme temperature values were reported by Donat et al. They added that the warming trends were stronger in the 1970s. In the present assessment, the scatter plots of the STI values were around zero for both Abu Dhabi and Al-Ain, while these values were skewed toward the upper limits for Dubai and
Sharjah. An STI assessment in the Himalayas revealed significant positive trends of extreme monsoonal temperatures in most regions studied.

Extreme events were reported to be impacted by the changing climate. It was projected that temperatures in the Arabian Gulf are likely to come close or even exceed critical limits. It was also highlighted that this region will be a regional hot spot if no major mitigation measures are in place. Significant negative trends of the number of days when temperature was below its 10th percentile and daily temperature range was also reported.

The spatial and temporal variations of the extreme events and the changing temperature reported in the present work are critical. They impact various facets of our environment. Such impact can be detrimental to human health, coral assemblages, coral survival, plants, birds, butterflies, wheat stress, and much more. Targeting climate change causes (mitigation) and addressing its impact (adaptation) are urgently needed; locally, regionally and globally, as the region will remain a hot spot, if no major mitigation measures are in place.

Conclusions

ARIMA is a valid model to forecast temperature. This was true using the UAE historical data to predict temperature into the future. Much of the findings reported here agreed with previously published work. Some parts of the UAE will suffer more in terms of increased extreme events than others. STI can be used to further analyse temperature events and support ARIMA modeling approaches. Further assessments are needed to link between historical temperature data and the extracted ARIMA and STI outputs on the one hand and projected changes in daily/monthly temperatures on the other hand. Further, a detailed analysis of temperature fluctuations at finer spatial and temporal scales are also needed to strengthen any modeling approach.

Data availability

Underlying data

This project contains the following underlying data:
- RStudio code for ARIMA and STI analyses performed
- STI data (CSV)
- ARIMA data (CSV)

Data are available under the terms of the Creative Commons Attribution 4.0 International license (CC-BY 4.0).

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