

Long-Term Trends and Its Best Functional Form Estimation of Yearly Maximum and Minimum Temperatures at Cotonou City by Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise Method

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Abstract

The understanding of the long-term trend in climatic variables is necessary for the climate change impacts studies and for modeling several processes in environmental engineering. However, for climatic variables, long-term trend is usually unknown whether there is a trend component and, if so, the functional form of this trend is also unknown. In this context, a conventional strategy consists to assume randomly the shape of the local trends in the time series. For example, the polynomial forms with random order are arbitrarily chosen as the shape of the trend without any previous justification. This study aims to 1) estimate the real long-term nonlinear trend and the changing rate of the yearly high temperature among the daily minimum (YHTaDMinT) and maximum temperatures (YHTaDMaxT) observed at Cotonou city, 2) find out for these real trend and trend increment, the best polynomial trend model among four trend models (linear, quadratic, third-order and fourth-order polynomial function). For both time series, the results show that YHTaDMinT and YHTaDMaxT time series are characterized by nonlinear and monotonically increasing trend. The trend increments present different phases in their nonmonotone variations. Among the four trend estimations models, the trend obtained by third-order and fourth-order polynomial functions ex-

hibits a close pattern with the real long-term nonlinear trend given by the Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (ICEEMDAN). But, the fourth-order polynomial function is optimal, therefore, it can be used as the functional form of trend. In the trend increment case, for the YHTaDMaxT time series, the fourth-order fit is systematically the best among the four proposed trend models. Whereas for the YHTaDMinT time series, the third-order and fourth-order polynomial functions present the same performance. They can both be used as the functional form of trend increments. Overall, the fourth-order polynomial function presents a good performance in terms of trend and trend increments estimation.

Keywords

Long-Term Trends, Polynomial Trend Models, Trend Increment, ICEEMDAN, Extrema Temperature

1. Introduction

To modelize several processes in environmental engineering, agriculture, climatology and hydrology, the understanding of the real nonlinear trend and trend model's estimation of climate variables as extrema temperatures are necessary [1]. Moreover, climate change impacts are evaluated through trend analysis of climate variables [2]. Climate change is marked with variation in temperature, which can directly influence the hydrological processes [3] [4] [5]. In Benin Republic, a sub-Saharan country affected by climate change effects, few studies are focused on the real nonlinear trend investigation and on the estimation of the functional form of this trend in the extrema temperatures during historical period. In this country, one of the major challenges for hydrologists and meteorologists is the estimation of the real functional form of historical climate variables trend. Indeed, if there is a trend in a real-time series of historical climatic variables, the functional form of this trend is usually unknown. In this context, certain authors assume randomly the form of the local trends as a polynomial function with arbitrarily chosen order (Abaje and Oladipo [6], Gadedjisso-Tossou *et al.* [7], Agbazo *et al.* [8]). Generally, linear regression technique is used to analyze the trends in the climatic variables time series. This situation can lead to erroneous conclusions.

Nowadays, to overcome these difficulties and to correctly represent the trend in climatic variables, with higher accuracy without ignorance of its nonstationarity and nonlinearity characteristics, some improved methods are developed in literature. Among these methods one can cite, the Empirical Mode Decomposition (EMD) developed by Huang *et al.* [9], and its variations, such as the Ensemble Empirical Mode Decomposition (EEMD) developed by Wu and Huang [10], Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) developed by Torres *et al.* [11] and Improve Complete Ensemble

Empirical Mode Decomposition with Adaptive Noise (ICEEMDAN) developed by Colominas *et al.* [12]. The CEEMDAN is an important improvement of EEMD and ICEEMDAN is a further improvement of CEEMDAN [11] [12].

Based on ICEEMDAN method, the purpose of this article is, firstly to estimate the real long-term nonlinear trend and the changing rate of the yearly high temperature among the daily minimum (YHTaDMinT) and maximum temperatures (YHTaDMaxT) observed at Cotonou city, the most industrialized and developed city in Benin Republic, secondly, to find out the best (optimal) polynomial forms of these nonlinear trends and trend increments. The article is structured as follows: Section 2 describes data sets and the methods involved. The results are presented and interpreted in Section 3. Finally, a summary with concluding remarks forms and outlook for further research ends the study in Section 4.

2. Materials and Methods

2.1. Materials

Cotonou is located in the southern part of Benin Republic (West Africa), closer to the Atlantic Ocean. It is characterized by four seasons each year: a long rainy season (April to July) followed by a short dry season (August to September) and a short rainy season (October to November) followed by long dry season (December to March). In this study, the daily maximum temperature and minimum temperature data are recorded from 1953 to 2019 at Cotonou Airport's synoptic station and provided by "Météo-Benin". From these data, one generates the yearly high temperature among the daily minimum (YHTaDMinT) and the yearly high temperature among the daily maximum temperatures (YHTaDMaxT) observed during each year. **Figure 1** shows that YHTaDMinT and YHTaDMaxT time series vary regarding to the year. The minimum values of YHTaDMinT and YHTaDMaxT are respectively greater than 27°C and 32°C.

2.2. Methods

Improved Complete Ensemble Empirical Mode Decomposition with adaptive noise, namely ICEEMDAN, developed by Colominas *et al.* [9] is used for estimating nonlinear trends and trend increments in YHTaDMinT and YHTaDMaxT time series. The ICEEMDAN is an important improved version of the complete ensemble empirical mode decomposition with adaptive noise, CEEMDAN (developed by Torres *et al.* [11]). It is an expansion algorithm of Empirical Mode Decomposition (EMD), which is an adaptive (data-driven) method developed by Huang *et al.* [9] to analyze nonstationary time series stemming from nonlinear systems. According to Colominas *et al.* [12], ICEEMDAN's main steps can be described as follows:

1) Construct the signal $x^{(i)}(n)$ which is obtained after the specific white noise is added into the original signal $x(n)$:

$$x^{(i)}(n) = x(n) + \alpha_0 E_1(\mu^{(i)}(n)) \quad (1)$$

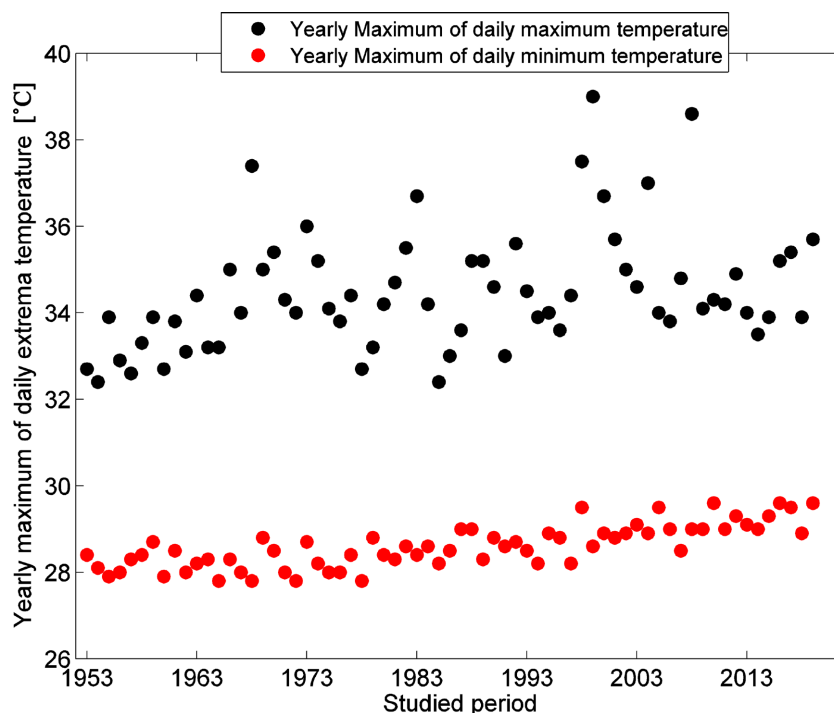


Figure 1. Temporal variation of YHTaDMinT and YHTaDMaxT temperature. YHTaDMinT and YHTaDMaxT time series are respectively in red and black.

α_0 is the level of noise; i is the added times of noise; $i = 1, 2, \dots, N$; $\mu^{(i)}(n)$ is the noise with zero-mean and unit variance; and $E_1(\mu^{(i)}(n))$ is the first EMD component of the white noise $\mu^{(i)}(n)$.

2) Decompose the N signals by EMD method to obtain the first intrinsic mode function (IMF) component of ICEEMDAN as:

$$imf_1(n) = x(n) - \left\langle M(x^{(i)}(n)) \right\rangle \quad (2)$$

where $\langle \cdot \rangle$ represents the mean value, $M(\cdot)$ is the operation which produces the local average of the envelope that satisfies the IMF sifting threshold and imf_1 is the first IMF.

3) Construct the second signal $\left\langle M(x^{(i)}(n)) \right\rangle + \alpha_1 E_2(\mu^{(i)}(n))$. This signal is decomposed by EMD and one obtains the second IMF component of ICEEMDAN:

$$imf_2(n) = r_1(n) - r_2(n) = r_1(n) - \left\langle M(r_1(n) + \alpha_1 E_2(\mu^{(i)}(n))) \right\rangle \quad (3)$$

where $r_1(n) = \left\langle M(x^{(i)}(n)) \right\rangle$ is the residual obtained after the first decomposition.

4) Construct the k th signal $r_{k-1}(n) + \alpha_{k-1} E_k(\mu^{(i)}(n))$. This signal is decomposed by EMD and obtains the k th IMF component of ICEEMDAN:

$$imf_k(n) = r_{k-1}(n) - r_k(n) = r_{k-1}(n) - \left\langle M(r_{k-1}(n) + \alpha_{k-1} E_k(\mu^{(i)}(n))) \right\rangle \quad (4)$$

$r_k(n)$ is the further residual after the k th decomposition, and $k = 1, 2, \dots, K$.

5) Repeat step 4 for the next k until the residual cannot be decomposed any further, the residual is monotonous, or its amplitude is less than the indicated

threshold. Then, the decomposition stops.

To evaluate the sensitivity of the nonlinear trend obtained by ICEEMDAN to the α_k values, the ICEEMDAN algorithm has been implemented for different values of α_k . Colominas *et al.* [12] have recommended α_k values between 0.1 and 0.3. In this study, α_k values vary from 0.1 to 0.5 with step of 0.1 to evaluate the effect of large interval.

In order to find out the best (optimal) functional form of the real long-term nonlinear trend and its changing rate, different polynomials functions (linear, quadratic, third-order and fourth-order) are used to modelize this trend. Four main indicators are used to clearly reflect the error of each polynomial function's result and evaluate the fitting accuracy: the deterministic coefficient (DC), the mean squared error (MSE), the mean absolute error (MAE) and the weighted mean absolute percentage error (WMAPE). According to Chen *et al.* [13], Tao *et al.* [14], Xia and Bo [15], these parameters are calculated respectively as follows:

$$DC = 1 - \frac{\sum_{t=1}^N [d_t - D_t]^2}{\sum_{t=1}^N [D_t - \bar{D}_o]^2} \quad (5)$$

$$MSE = \frac{1}{N} \sum_{t=1}^N (D_t - d_t)^2 \quad (6)$$

$$MAE = \frac{1}{N} \sum_{t=1}^N |D_t - d_t| \quad (7)$$

$$WMAPE = \frac{\frac{1}{N} \sum_{t=1}^N |D_t - d_t|}{\sum_{t=1}^N D_t} * 100 \quad (8)$$

where N is the series length; D_t represents the real long-term nonlinear trend or trend increment's value at time t ; d_t is the predicted long-term nonlinear trend or trend increment's value at time t . $\bar{D}_o$ is the mean value of the real long-term nonlinear trend or trend increment's value. Statistically, the tinier the values of the MSE, MAE and WMAPE are, the more precise the prediction accuracy of the model is. However, the closer the DC value is to 1, the better is the model's prediction, and when $DC < 0.5$, the prediction is unreliable.

3. Results and Discussion

Figure 2 compares the trend obtains from ICEEMDAN decomposition with different α_k values for yearly high temperature among the daily minimum (YHTaDMinT) and maximum temperatures (YHTaDMaxT) time series. From **Figure 2(a)**, it is noted that whatever the α_k values considered, the YHTaDMaxT time series trends obtained present similar pattern.

From **Figure 2(b)**, it's observed that the YHTaDMinT time series trends obtained change slowly with α_k values. Therefore, when α_k values are chosen between 0.1 and 0.5, the obtained trends patterns don't change significantly. **Figure 3** presents the same results as in **Figure 2**, but for the corresponding trend increments. From these figures, it is shown that 1) the trend increments

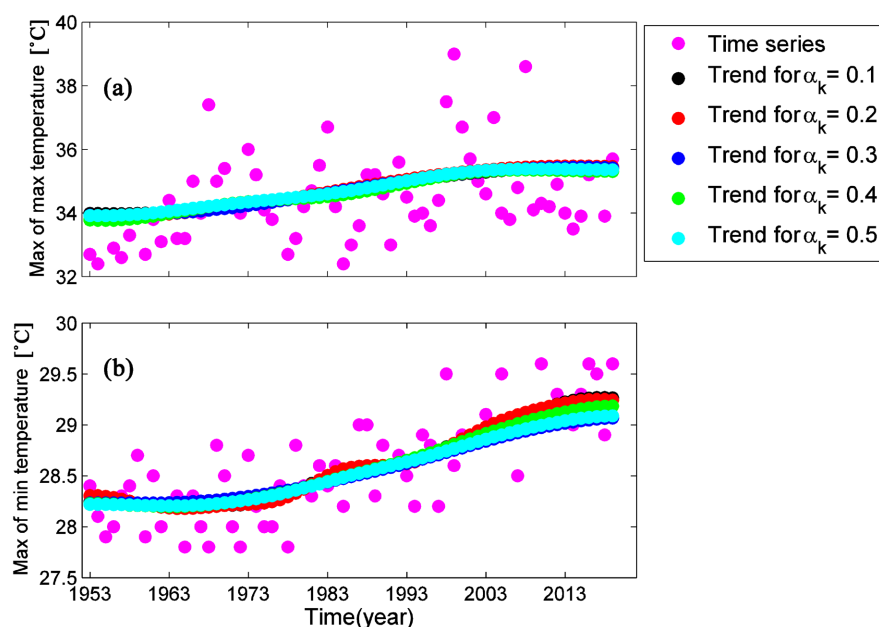


Figure 2. Trends from ICEEMDAN for YHTaDMinT and YHTaDMaxT time series. (a) For YHTaDMaxT time series; (b) for YHTaDMinT time series. Trends are shown for different α_k values.

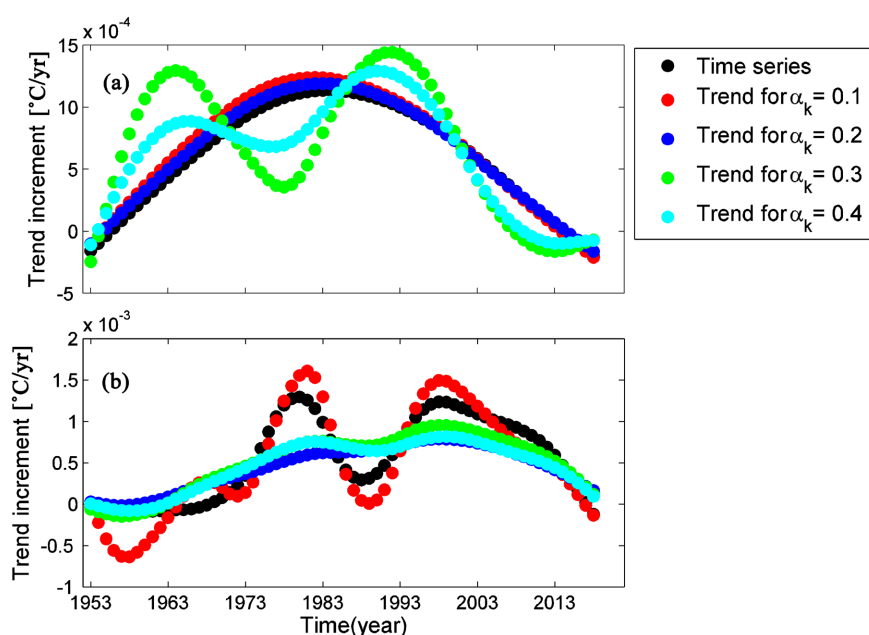


Figure 3. Same as Figure 2, but for the corresponding trend increments. (a) For YHTaDMaxT time series; (b) for YHTaDMinT time series.

don't vary monotonically like trend curves, 2) the trend increments present different forms from one α_k value to another. Thus, the trend increments patterns change significantly with α_k values.

Figure 4 compares the long-term trend obtained from ICEEMDAN for YHTaDMinT and YHTaDMaxT time series and the four chosen trend models (linear, quadratic, third-order, and fourth-order polynomials). The results reveal

that YHTaDMinT and YHTaDMaxT time series are characterized by nonlinear increasing trend. Monotonically increasing trends are observed. The results have shown an increasing temperature trend in the last seventy years (1953–2019). Findings are in agreement with the global increase in temperatures indicated by IPCC [16], Trenberth *et al.* [17], Hartmann *et al.* [18], and Tang and Zhang [19]. They are also in agreement with the findings of (Trenberth *et al.* [17]), global temperatures are rising and will continue to do so throughout the 21st century.

It is clearly noted that the natural trend of YHTaDMinT and YHTaDMaxT time series cannot be modeling by linear trend model, but it seems that the quadratic, third-order, and fourth-order polynomials are the good candidates to fit these trends, however, their fitting accuracy cannot be evaluated visually. Thus, to find out the functional forms of these nonlinear trends, the fitting errors of each proposed trend model are calculated and shown in Table 1.

Table 1 presents the values obtained of MSE, MAE, WMAPE and DC for the

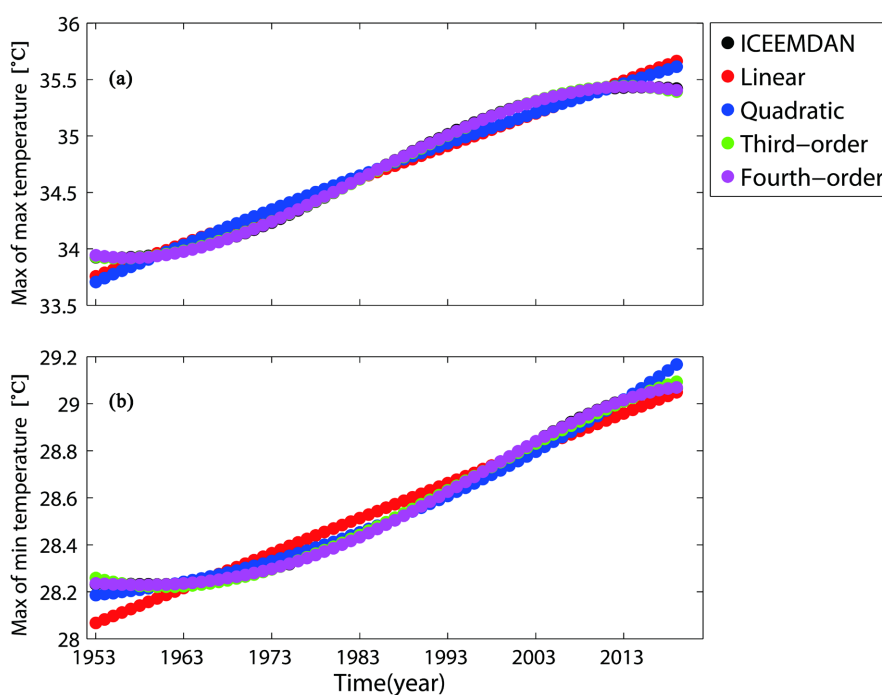


Figure 4. Trends obtained from ICEEMDAN, linear, quadratic, third-order and fourth-order polynomial fits. (a) For YHTaDMaxT time series; (b) for YHTaDMinT time series.

Table 1. Comparison of the fitting errors of each proposed models. The case of YHTaDMinT time series are highlighted in bold.

Models	MSE	MAE	WMAPE (%)	DC
Linear	0.0090 (0.0041)	0.0821 (0.0550)	0.0035 (0.0029)	0.9720 (0.9530)
Quadratic	0.0085 (0.0010)	0.0801 (0.0265)	0.0034 (0.0014)	0.9737 (0.9884)
Third-order	6.7 * 10⁻⁵ (8.9 * 10⁻⁵)	0.0067 (0.0079)	2.90 * 10 ⁻⁴ (4.1 * 10 ⁻⁴)	0.9998 (0.9990)
Fourth-order	4.2 * 10⁻⁵ (7 * 10⁻⁵)	0.0057 (0.0022)	2.44 * 10 ⁻⁵ (1.2 * 10 ⁻⁴)	0.9999 (0.9999)

proposed models to fit the nonlinear trend of YHTaDMinT and YHTaDMaxT time series. These values in case of YHTaDMinT time series are highlighted in bold.

It can be observed that whatever the model, the time series (YHTaDMinT or YHTaDMaxT) considered the MSE, MAE, WMAPE values (**Table 1**) of the third-order polynomial and fourth-order polynomial are significantly smaller than those of quadratic polynomial function. Therefore, the third-order and fourth-order polynomial are both the good candidates to modelize the functional form of the real long-term nonlinear trend of YHTaDMinT and YHTaDMaxT time series at Cotonou city. Moreover, the DC values obtained for both functions are closer to 1, therefore, the better are their fitting. However, the DC values of the fourth-order polynomial are greater than those of the third-order polynomial. Thus, fourth-order polynomial function is optimal among the four trend models proposed in this study.

Figure 5 compares the long-term trend increment obtained from ICEEMDAN for YHTaDMinT and YHTaDMaxT time series and four trend increment models (linear, quadratic, third-order, and fourth-order polynomials). The real trend increment obtained from ICEEMDAN for YHTaDMaxT time series (**Figure 5(a)**, curve in black) increases from 1953 to 1983 and decreases from 1984 to 2019. However, for the YHTaDMinT time series, it increases from 1963 to 1983 and decreases from 1993 to 2019. For the both time series, the trend increments are not the monotonic functions. It is clearly noted that the natural trend increments of YHTaDMinT and YHTaDMaxT time series cannot be modeling by linear

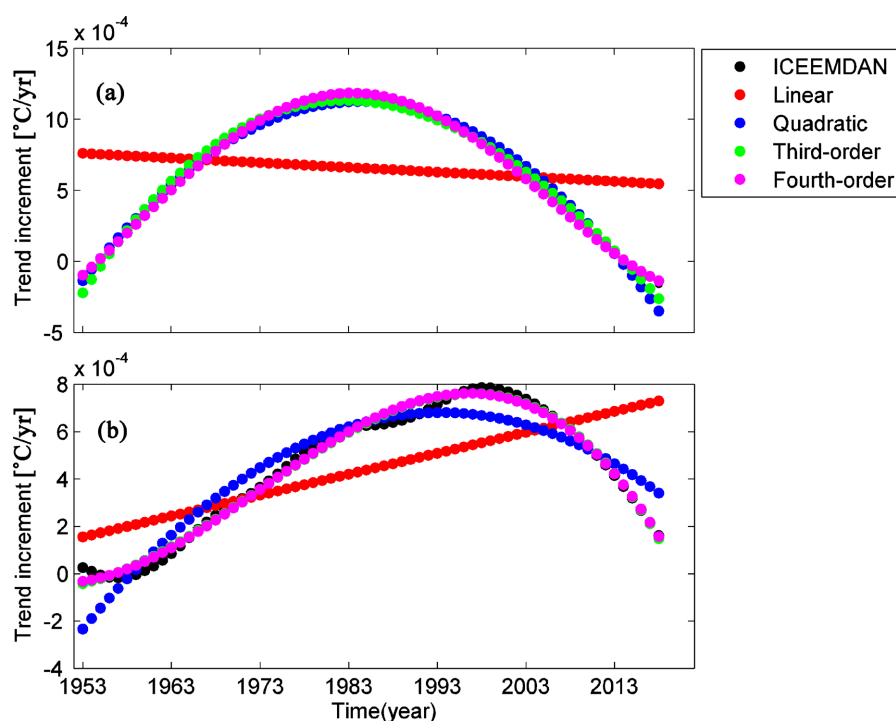


Figure 5. Same as in **Figure 4** but for trend increment. (a) For YHTaDMaxT time series; (b) for YHTaDMinT time series.

Table 2. Same as **Table 1**, but for the trend increment.

Models	MSE	MAE	WMAPE (%)	DC
Linear	$1.8 * 10^{-7}$ ($4.02 * 10^{-8}$)	$3.7 * 10^{-4}$ ($1.7 * 10^{-4}$)	0.8641 (0.5831)	0.0214 (0.4136)
Quadratic	$3.7 * 10^{-9}$ ($7.1 * 10^{-9}$)	$5.1 * 10^{-5}$ ($6.74 * 10^{-5}$)	0.1174 (0.2313)	0.9798 (0.8965)
Third-order	$2.4 * 10^{-9}$ ($7.33 * 10^{-10}$)	$4.3 * 10^{-5}$ ($2.20 * 10^{-5}$)	0.0989 (0.0755)	0.9868 (0.9893)
Fourth-order	$6.4 * 10^{-11}$ ($7.21 * 10^{-10}$)	$6.7 * 10^{-6}$ ($2.18 * 10^{-5}$)	0.0156 (0.0749)	0.9997 (0.9895)

trend model, but it seems that the quadratic, third-order, and fourth-order polynomials are good candidates for YHTaDMaxT time series. Thus, to find out the functional form of these trend increments, the fitting errors of each proposed trend increments model are calculated and shown in **Table 2**.

Table 2 presents the MSE, MAE, WMAPE and DC values for the proposed models to fit the nonlinear trend increment of YHTaDMinT and YHTaDMaxT time series. The values of the MSE, MAE, WMAPE and DC values in case of YHTaDMinT time series are highlighted in bold. It can be observed that whatever the model, the time series (YHTaDMinT or YHTaDMaxT) considered, the MSE, MAE, WMAPE values (**Table 2**) of the third-order polynomial and fourth-order polynomial are significantly smaller than those of quadratic polynomial function. Therefore, the third-order and fourth-order polynomial are the good candidates to modelize the functional form of the real long-term nonlinear trend increment of YHTaDMinT and YHTaDMaxT time series at Cotonou city. The DC values of the fourth-order polynomial function are closer to 1 and greater than those of the third-order polynomial. Thus, fourth-order polynomial function is optimal among the four trend increment models.

4. Summary and Conclusions

In this paper, the real long-term nonlinear trend and the changing rate of the yearly high temperature among the daily minimum (YHTaDMinT) and maximum temperatures (YHaDMaxT) observed from 1953 to 2019 at Cotonou city, the most industrialized and developed city in Benin Republic are estimated by ICEEMDAN method and, the best polynomial trend model among four trend models and trend increment of these nonlinear trends and trend increment is found out. The major remarks are summarized as follows: 1) YHTaDMinT and YHTaDMaxT time series are characterized by nonlinear and monotonically increasing trends. The trend increments don't vary monotonically; they present different phases in their variation. 2) Based on four indicators, such as the deterministic coefficient (DC), mean squared error (MSE), mean absolute error (MAE) and weighted mean absolute percentage error (WMAPE), for both time series, the fourth-order polynomial is optimal among the four chosen trend models (linear, quadratic, third-order and fourth-order polynomial function). For the trend increment, the fourth-order polynomial function presents a good performance in terms of trend increments estimation. This study reveals the

evidence of climate change in Cotonou, Benin republic. The findings of the present research can be used in climate change impacts studies and in assessing environmental heat stress on the health of the population in Cotonou city. Future works will be focused on the investigation of the long-term trends in the climatic variables simulated by regional climate models in Benin republic and its best functional forms.

Data Availability

The data used in this study are supplied by the local service of Météo-Bénin in Cotonou. The data are not available online in any data base, so that we cannot provide a link to reach them. They are provided when researchers address requests to Météo-Bénin (<http://www.asecna.aero>).

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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