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Article

Classical methods used for predicting temperature as a relevant variable of climate change

Métodos Clásicos utilizados para la predicción de la temperatura como variable relevante del cambio climático

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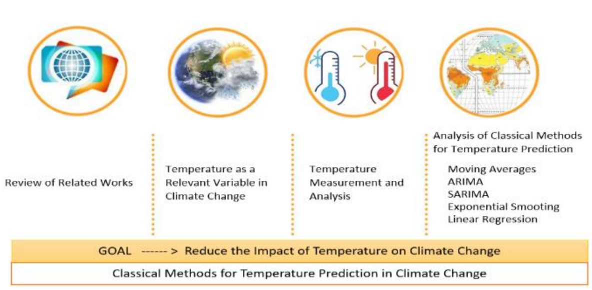
Abstract

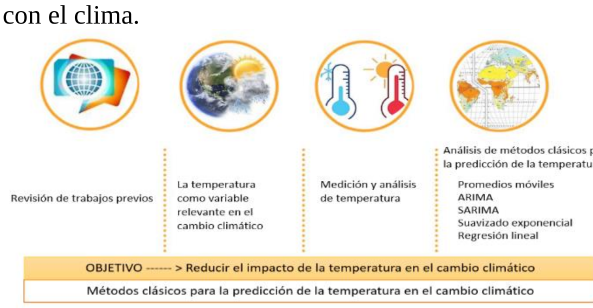
Temperature prediction has become a very important area of research in the context of climate change. Classical prediction methods have been highlighted as fundamental tools to address this problem. This work includes a state of the art on temperature prediction as an important variable of climate change, where we seek to identify the strengths and limitations of the methods used such as moving averages, ARIMA, SARIMA, exponential smoothing and linear regression. These methods continue to be valuable tools in temperature prediction, providing a solid basis for analysis and decision making in meteorology and other climate-related areas.



Climate change, Temperature analysis, Related works, Classical methods

Resumen

La predicción de la temperatura se ha convertido en un área de investigación muy importante en el contexto del cambio climático. Los métodos clásicos de predicción se han destacado como herramientas fundamentales para abordar esta problemática. En este trabajo se incluye un estado del arte sobre la predicción de la temperatura como variable importante del cambio climático, donde se busca identificar las fortalezas y limitaciones de los métodos usados como son los métodos de promedios móviles, ARIMA, SARIMA, suavizamiento exponencial y regresión lineal. Estos métodos continúan siendo herramientas valiosas en la predicción de la temperatura, proporcionando una base sólida para el análisis y la toma de decisiones en meteorología y otras áreas relacionadas con el clima.



Cambio climático, Análisis de temperatura, Trabajos relacionados, Metodos clásicos

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Introduction

The climate changes over the years, due to processes that occur within or outside the climate system, such as emissions of gases caused by human activities, which we call anthropogenic changes. The seriousness of the current climate change is that it is so fast (compared to historical changes) that natural ecosystems and we, humans, are not prepared to change at the same pace and be able to cope with it. This change is a variation of the average climate in the medium and long term, and can last for decades or longer periods.

In terms of prediction or forecasting, climate models try to simplify reality and use historical climate records (data from years ago) and global emissions trends (depending on how society evolves and how we behave) to project what may happen in the future. Therefore, the models can generate different results that must be interpreted with caution. Climate warming is unequivocal; unprecedented changes have been observed since the 1950s [1].

We can expect three types of fundamental climate changes: One is changes in the mean, meaning that the average value of a variable changes, causing the value to increase or decrease; another change is an increase in variability or amplitude, where the average value remains the same, but the range will be wider and more variable. The other is the one that involves both changes (mean + variability) [2].

The analysis of classical methods for temperature prediction involves evaluating and comparing statistical and time series techniques that have been widely used before the advent of machine and deep learning models. Below we describe some of the most commonly used classical methods and how they can be applied in temperature prediction.

Review of Related Works

Temperature prediction is one of the most studied areas in meteorology and time series analysis. Over the years, numerous studies have explored the use of classical methods for temperature prediction. This review summarizes some relevant works that have applied and evaluated classical methods such as moving averages, ARIMA, SARIMA, exponential smoothing, and linear regression.

Shahid et al. [3] conducted a study in which they propose to achieve traffic forecasting using air pollution data (carbon monoxide CO, carbon dioxide CO2, volatile organic compounds VOCs, hydrocarbons HCs, nitrogen oxides NOx, and particulate matter PM), since, as they mention, these have a great relationship, by the emissions of certain gases one can know the concentration of cars in a certain place. In this study they performed a comparative analysis of 7 different regression models to find which model gives better accuracy. Of these, the one that gave the best result was found to be the Multi-Layer Perceptron model. But in addition to this, the authors proposed a regression model that gives better results than the 7 previously used. This is an ensemble between MLP and SVR (Support Vector Regression). The experimental results show its effectiveness, indicating that the forecast error with this new model is reduced by 2.47%.

On the other hand, to compare forecast models, and in particular to evaluate these methods for climate change, several approaches are used, among the most common are the one known as AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) which use measures of how likely it is that a method obtains better predictions than another with which it is compared; for this, metrics known as AUC (area under the curve) or MaxEnt (Max entropy) are used[4]. It is not yet known which of the numerous approaches is the best criterion for evaluating the combination of several forecast models, much less for climate change. However, a recent evaluation found that for the M4 competition the BIC approach is among the best approaches for such a comparison; in addition, the metrics of this approach can be used to obtain a combination of forecast methods and to select the combination of the highest quality [5].

Another research example is that of Ibarra and Huerta [6], whose objective was to build a spatial model to generate a fire prediction scenario for the year 2050 in the La Primavera Forest, taking as a reference the data of the climate projections for western Mexico and the historical occurrences of fires in recent years.

This model was taken from a subset of the best 10 models with less than 10% error by omission.

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The spatial model in this work had an AUC (area under the curve, which is the graphic output in which the ability to discriminate an occurrence "sensitivity" against the ability to discriminate an absence "specificity") of 0.81, indicating that the robustness to classify the presence of fires in the APFFLP was good. In conclusion, the spatial model developed with MaxEnt [7], under the climate change scenario, proved to be a reliable tool to predict the APFFLP for the year 2050. Also using MaxEnt, is the work of Qin, et al. in Truja, China [8]. the areas to be burned

On another occasion, K. Krishna Rani Samal, et al. [9], conducted a research study that explores a new pollutant forecasting model called Multi-output temporal convolutional network autoencoder (MO-TCNA). The MO-TCNA network serves both PM2.5 and PM10 pollutant forecasting for multiple locations, rather than performing single-output and site-specific pollutant forecasts. Consequently, the experimental results show that the MO-TCNA network saves time and performs better than traditional site-specific forecasting models. It has also shown its satisfactory long-term prediction results for PM2.5 and PM10 pollution at multiple sites. An absolute error (MAE) of 32 was obtained.

Temperature as a Relevant Variable in Climate Change

Temperature is one of the most important and sensitive variables in the study of climate change. Its variation affects various aspects of the climate and the environment, influencing ecosystems, the water cycle, and human activities. Below, we describe its relevance, how it is measured and analyzed in the context of climate change.

Main Indicator of Global Warming: The average global temperature has increased significantly since the beginning of the industrial era, mainly due to greenhouse gas (GHG) emissions such as carbon dioxide (CO_2). This increase in temperature is a direct indicator of global warming and its effects on the climate.

- Impact on Ecosystems: Changes in temperature affect the distribution and behavior of species, altering entire ecosystems. The melting of glaciers and rising sea levels are directly related to the increase in global temperature.
- Effects on Climate Phenomena: Increase in the frequency and intensity of extreme events such as heat waves, storms, and floods. Changes in precipitation patterns and the appearance of more severe droughts in some regions.
- Repercussions on Human Health: The increase in temperature can cause health problems such as heat stroke, respiratory and cardiovascular diseases. It also influences the spread of vector-borne infectious diseases, such as dengue and malaria.

Temperature Measurement and Analysis

Temperature measurement requires meteorological stations that collect temperature data at specific locations, providing detailed and accurate information. Satellites also measure the temperature of the land and ocean surface on a global scale, offering a broad and continuous view; while buoys and ocean soundings collect temperature data at different depths of the ocean.

Temperature analysis involves studying temperature trends over time, identifying patterns of increase or decrease.

This allows current temperatures to be compared with historical averages to identify anomalies that indicate unusual warming or cooling. Mathematical and simulation models are used with the collected data to predict future temperature variations and their possible impacts.

Regarding the prediction of temperature as a relevant variable in climate change, works such as that carried out by Lin et al. [20], which performs the forecast of the maximum temperature in the climate change area in the metropolitan region of the city of Tapei in Taiwan, using a hybrid method of a complementary multi-dimensional ensemble and a neural network, called in English as Multi-dimensional Complementary Ensemble Empirical Mode Decomposition and Radial Basis Function Neural Network (MCEEMD-RBFNN). With this, it is possible to forecast the maximum daily temperature for the next 7 days. In the results of this work, it was obtained that its average error according to MAPE tests was 2–4.5%. It should be noted that a low error is achieved because it is a very short-term prediction.

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On the other hand, Morid et al. [21], carried out a study where he makes an integrated framework for the prediction of the impact of climate change on a simulated river, taking into account the water temperature and other hydrological parameters.

The configuration of this model is based on a combination of two models called Soil and Water Assessment Tool (SWAT) and the international river interface cooperative (iRIC). The water temperature module in SWAT was modified to observe the effectiveness of the method. With this method, it was obtained that the prediction of this temperature obtained a mean square error RMSE of approximately 2 to 3 °C.

Continuing with the water temperature, Mercado-Bettín, Clayer et al. [21], made a forecast of the water temperature in lakes and dams taking into account the climatic seasons.

They used the seasonal climate forecast system (SEAS5) and reanalysis (ERA5) of the European Centre for Medium Range Weather Forecasts (ECMWF). According to the results, no significant progress was made in the forecast.

Al Sayah, et al.[22] , made a contribution to the evaluation of climate change in a hydrological basin in the Mediterranean by obtaining information from a distance and using an ARIMA forecast model for the average, minimum and maximum temperature in the area. For the average temperature forecast, it was found that the temperature trend will increase by more than 0.9 °C by 2030, with the adjusted SARIMA (2,0,0) (0,1,1)12 model. From this, an R2 in the model of 0.823 and a goodness of fit R2 of 0.825 were achieved.

Another study in which the SARIMA model was used is that of Farsi M, et al. [23] where a genetic algorithm was used to optimize it. This was used to predict as a test mean temperature data in India from 2000 to 2017 and an RMSE of 1.16 was obtained in the best case.

Within the prediction by classical methods, Su, Y, et al. [24] made a forecast of the urban ecological footprint of water with double exponential smoothing, where they used an adjustment of α=0.3 achieving a squared sum of residuals (SSE) of 0.005.

Indriani R., et al. [25] also performed a forecast with exponential smoothing, but they used the additive Holt-Winter method to predict the maximum and minimum air temperature. For the maximum temperature they used $\alpha = 0.4$, $\delta = 0.1$, and $\gamma = 0.1$, obtaining a MAPE = 1.62917%. On the other hand, to predict the minimum temperature they used $\alpha = 0.7$, $\delta = 0.1$, and $\gamma = 0.1$, obtaining a MAPE = 1.92473%.

To predict the monthly ambient temperature and precipitation, Papacharalampous, G, et al. [26] used several automatic prediction methods, including ARFIMA, Naive method, ARMA, BATS, and an exponential smoothing method, which had the lowest RMSE error globally of 1.68.

Another study that uses exponential smoothing is that of Mahajan, S., et al. [27] but in this model a drift (ESD) is added to predict PM 2.5 in the short term. They obtained a mean error of 0.16, the lowest compared to ARIMA which was 11.47 and NNAR of 1.19. ESD also gained in the shortest computing time.

In summary, there are many prediction methods and ensembles between these to reduce the error, and numerous studies, but none has been found for temperature as a relevant variable of climate change in the regions of Tampico, Tamaulipas and Xalapa, Veracruz in Mexico. The aim is to apply the classic methods proposed in this work such as SARIMA and exponential smoothing also used by Liu, et al. [28].

Analysis of Classical Methods for Temperature Prediction

Classical methods for temperature prediction are valuable tools that offer a balance between simplicity and effectiveness. Each method has its own advantages and limitations, and the choice of the appropriate method depends on the characteristics of the data and the specific objectives of the prediction. By understanding and applying these methods, valuable insights into temperature trends and patterns can be obtained, contributing to better planning and decision making in various areas. Classical prediction methods have been used for decades due to their simplicity and effectiveness. This section presents an analysis of the most common classical methods for temperature prediction, evaluating their characteristics, advantages and limitations.

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The Moving Averages method Smooths a time series to identify underlying trends and is based on calculating the average of subsets of data. Its advantages include being simple and easy to implement and reducing noise and highlighting general trends. On the other hand, it cannot capture complex seasonal patterns and it delays the response to rapid changes in the trend, so it is mainly used to identify short-term trends and for smoothing noisy data.

The ARIMA (AutoRegressive Integrated Moving Average) method combines autoregressive (AR), integrated difference (I) and moving average (MA) components and is suitable for stationary time series. It records temporal dependencies and autocorrelation patterns and is flexible and applicable to a wide range of time series. However, it requires the series to be stationary or to be adequately differenced and can be complex to fit. Widely used in economic and weather forecasts where the time series show autocorrelation.

The SARIMA (Seasonal ARIMA) method extends ARIMA to capture seasonal patterns by means of additional seasonal components with a given period. It captures both seasonality and temporal dependencies and is suitable for time series with strong seasonal patterns. It is more complex to fit than ARIMA due to the additional seasonal components and requires a sufficient series length to capture seasonality. It is used for time series with clear seasonality, such as annual weather data.

The Exponential Smoothing method predicts the time series by exponentially weighting past data and includes variants such as Single Exponential Smoothing, Double Exponential Smoothing and Triple Exponential Smoothing (Holt-Winters). It is simple to implement and tune and captures trends and seasonality effectively in more advanced variants (Holt-Winters). Its limitations include that the simple version does not record trends or seasonality and that more advanced versions require careful tuning of smoothing parameters. It is used for short and medium term predictions where trends and seasonality are evident.

The Linear Regression method models the linear relationship between temperature and one or more independent variables (predictors). It is divided into simple and multiple linear regression models that are easy to interpret and implement.

It is suitable for understanding the influence of multiple factors on temperature, although it assumes a linear relationship between variables, which may not be realistic for all time series and does not record complex non-linear or seasonal patterns, so it is used for predictions where a linear relationship between temperature and other variables is known or assumed.

Based on the review of previous work, Table 1 presents an analysis of the methods with an ensemble, whether machine learning, SES, ARIMA.

Box 1

Table 1

Comparison of forecasting methods

Method	1	2	3	4	5	6
SE double [24]	X	X	X	✓	X	X
SE triple additive [25].	X	X	✓	✓	X	X
SED [27].	✓	✓	X	✓	X	X
Ensemble-Neural Network. [20]	✓	✓	✓	X	X	X
Ensemble Wavelet transform [11]	✓	✓	X	✓	X	X
CMIP5 and GCM [10]	✓	X	✓	✓	X	X
MLP and SVR [3].	✓	✓	X	X	X	X
MaxEnt [8]	✓	✓	✓	X	X	✓
SES-Hurst [16]	✓	✓	X	✓	X	X
FCTA [17]	✓	✓	X	✓	X	X
ARIMA [23]	X	✓	✓	X	✓	X
SARIMA [26]	X	✓	✓	X	✓	X

Features:

1) Ensemble
2) Machine Learning
3) Predicts temperature
4) SES
5) ARIMA
6) Applies to regions of Mexico

Conclusions

Temperature is a crucial variable for the study of climate change due to its direct impact on the environment, ecosystems and human society.

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Measuring and analyzing temperature trends is essential to understand the extent of climate change and develop mitigation and adaptation strategies. Using data analysis tools and techniques, valuable scenarios can be obtained to help address this global challenge. Classical methods such as SMA, EMA, ARIMA and Holt-Winters are valuable tools for temperature prediction. Each method has its strengths and weaknesses, and the choice of the appropriate model depends on the nature of the data and the specific objectives of the analysis. These methods provide a solid basis for time series analysis and can be complemented with more advanced machine learning techniques to improve the accuracy of predictions. The methods described can be applied to other climate variables and results can be improved by using more advanced models and a more complete data set. Furthermore, the combination of machine learning techniques with spatial analysis can provide more accurate and useful predictions for the study of climate change.

Conflict of interest

The authors declare no interest conflict. They have no known competing financial interests or personal relationships that could have appeared to influence the article reported in this article.

Authors' Contribution

The contribution of each researcher in each of the points developed in this research, was defined based on:

Alarcón-Ruiz, Erika: contributed to the research design, the type of research, the approach, the method and the writing of the article.

González-Barbosa, Juan Javier: Carried out the systematisation of the background for the state of the art. He also contributed to the writing of the article.

Frausto-Solis, Juan: Contributed to the project idea, research method and technique. He supported the design of the field instrument.

Rángel-González, Javier Alberto: worked on the application of the field instrument, data collection and systematisation of the results. He also worked on the writing of the paper.

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Background

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