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Prediction of temperature and relative humidity with AI on the Ecuadorian coast

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Abstract

Artificial intelligence (AI) has established itself as an essential tool in climatology. It facilitates accurate analysis and prediction of variables such as temperature and humidity, which are crucial for understanding global warming and its effects. In this context, this study aims to implement predictive simulations of temperature and relative humidity on the Ecuadorian coast using artificial intelligence (AI). This study adopts a quantitative methodology, utilizing daily historical data collected from 2015 to 2020. Monthly averages for maximum temperature and relative humidity were calculated, based on 72 observations for each variable. The climate simulation employed statistical techniques such as linear regression and simple correlation, along with the implementation of various AI libraries in Rstudio, including readxl, QuantPsyc, and ggplot2, among others. Additionally, the ARIMA model was applied to analyze time series, facilitating detailed simulation and prediction of both climatic variables. The results indicate a significant inverse correlation between maximum temperature and relative humidity, revealing high-temperature variability in recent years. The optimized ARIMA predictive models showed AICC indices of 180.47 for temperature and 283.16 for humidity, after 96 iterations, demonstrating the high reliability of AI in climate prediction for the Ecuadorian coastal region. The study concludes with the importance of integrating advanced technologies such as AI in climatology to improve the accuracy and efficiency of climate predictions.

Keywords: Artificial intelligence, Relative humidity, Maximum temperature, Climate change, Ecuador

1. Introduction

Modeling and predicting climatic conditions through artificial intelligence (AI) are essential tools for studying and understanding the effects of seasonal variations across multiple time scales. There are notable advances in research in this field [1], [2]. However, significant deficiencies are observed in the integration and comprehensive analysis of multivariable data, such as relative humidity and temperature, covering extended periods. The application of machine learning techniques still requires further development and tuning to enhance the accuracy and applicability of predictive models in various climatic contexts [3]. These improvements are vital for a more accurate assessment of future climate patterns and for effectively responding to emerging environmental challenges.

The use of AI tools, particularly the programming language RStudio, has proven effective in quantifying and modeling the behavior of important climatic variables like relative humidity. These tools provide crucial means for the detailed analysis of climatic trends and patterns [4]. Nevertheless, it is critical to expand research to establish an effective correlation between these data and other determining climatic factors, especially temperature, whose variations are key to understanding the dynamics of climate change [5], [6].

The study of relative humidity and temperature is of fundamental importance due to their direct impact on the planet's energy balance and their influence on critical areas such as resource management, agriculture, and public health [7]. A deep understanding of these factors is essential to adapt to the adverse effects of climate change and to formulate and implement effective sustainability policies. The interaction of these climatic elements determines environmental patterns that affect biodiversity and ecosystems, imposing significant pressures on economic and social systems. Thus, deepening their study not only helps mitigate risks but also plans future interventions to ensure long-term sustainable development.

Artificial intelligence has revealed a slow and steady increase in the mean air temperature over recent years [6], [8]. SARIMA models, adjusted to datasets of maximum temperature, have proven suitable through diagnostic verification of correlation using ACF, PACF, IACF, and p-values from the residual statistics of the Ljung-Box test [9], [10], [11]. The model parameters are obtained using the maximum likelihood method, assisted by information criteria such as Akaike (AIC), Bayesian (BIC), and corrected Akaike (AICc) [12], [13], [14].

From previous studies on the simulation and prediction of climatic variables like maximum temperature and relative humidity, the relevance of these indicators in understanding the impact of climate change stands out [15], [16], [17]. The application of artificial intelligence (AI) facilitates the automatic selection of predictive models and the adjustment of parameters, thus optimizing the accuracy of climate predictions [18], [19]. In this context, the following hypotheses have been formulated for the current research:

H1: There is an inverse correlation between relative humidity and maximum temperature, suggesting that variations in one could inversely influence the other.

H2: Artificial intelligence selects the best predictive model for maximum temperature, adjusting parameters to maximize accuracy and capture the observed positive trend and seasonality.

H3: Similarly, AI selects the best predictive model for relative humidity, ensuring that parameter adjustments adequately reflect a positive trend and seasonality.

Therefore, the main objective of this study was to implement predictive simulations of temperature and relative humidity on the Ecuadorian coast using artificial intelligence (AI), in order to explore the interaction between these variables and evaluate their impact on the region's climate dynamics.

2. Theoretical foundations

2.1. Importance of temperature and relative humidity in climatic studies

Temperature and relative humidity are crucial parameters in climatic research, as they directly influence biodiversity, agriculture, public health, and water resource management [20], [21], [22]. A detailed analysis of these variables is essential for understanding climate changes and their effects on specific ecosystems.

2.2. Application of artificial intelligence in meteorology

AI has revolutionized the field of meteorology, facilitating the modeling and prediction of climatic variables with high precision [23], [24]. AI's ability to process large volumes of data and recognize complex patterns enables the prediction of meteorological phenomena in advance, which is crucial for planning and responding to emergencies [25], [26].

2.3. Predictive models in climatology

Within the realm of climate prediction, time series models such as ARIMA and SARIMA are widely used due to their ability to adjust and forecast trends based on historical data [27], [28]. The selection of the most suitable model is verified using statistical criteria such as the AIC, BIC, and Ljung-Box tests, which assess the model's suitability based on correlation and residuals [29], [30].

2.4. Artificial intelligence in predicting temperature and relative humidity

Specifically, in predicting temperature and relative humidity, AI has proven to be an effective tool for capturing and modeling the environmental dynamics of these variables. Studies show that while neural networks have been effective in reproducing patterns of relative humidity, there are still challenges in predicting long-term trends [31], [32]. Additionally, the accuracy of hourly and daily predictions using metrics such as MAPE and RMSE, are key indicators of predictive accuracy [33], [34].

3. Methodology

3.1. Methodological approach

This research adopts a quantitative approach, characterized by being both retrospective, as it is based on historical data, and prospective, by making short-term predictions. Artificial intelligence is used to simulate and predict critical climatic variables, specifically maximum temperature and relative humidity on the coast of Ecuador.

3.2. Data collection

The climatic data analyzed in this study include maximum temperature, recorded in degrees Celsius, and relative humidity, reported in percentage. These were obtained from the meteorological station of the Escuela Superior Politécnica Agropecuaria de Manabí (ESPAM) from the beginning of 2015 to the end of 2020. A total of 13,140 observations were recorded, divided into three periods of the day: morning, midday, and evening. Subsequently, Excel was used to calculate the daily and monthly average of each variable, resulting in 72 monthly observations for each.

3.3. Analysis tools

For statistical analysis and modeling, AI-adapted packages and libraries in RStudio were used, including readxl, QuantPsyc, psych, GGally, xts, ggplot2, tidyverse, colourpicker, and psych for linear regression and correlation analysis. For autoregressive integrated moving average (ARIMA) modeling, packages such as report, reshape2, feasts, fabletools, lfable, tsibble, fpp2, dplyr, lubridate, tidyr, tseries, forecast, and astsA were employed.

3.4. Statistical tests and diagnostics

The augmented Dickey-Fuller test was performed to assess the stationarity of the time series, and Ljung-Box and Bartlett tests were used to analyze the autocorrelation (white noise) and the homogeneity of the variances (homoscedasticity), respectively. The normality of the distributions was verified using the Kolmogorov-Smirnov test. These tests are fundamental for the training, calibration, and evaluation of the models with a 95% confidence interval [35].

3.5. Time series models and model evaluation

Auto-correlograms of the partial autocorrelation function (PACF) and simple (ACF) were analyzed to determine the suitability of time series models, mainly the SARIMA model, which considers components of seasonality and trend. The goodness of fit parameters such as the mean absolute percentage error (MAPE), the mean squared error (MSE), and the stationary correlation were calculated to measure the model's effectiveness in relation to observed values [36], [37]. Additionally, the accuracy of the selected model was evaluated using the Akaike

Information Criterion (AIC and AICc) [38], [39], [40], providing a reliable estimate of the quality of the adjusted model.

4. Results and discussion

This section presents the results obtained through statistical analysis using artificial intelligence to assess maximum temperature (°C) and relative humidity (%) on the coast of Ecuador. The results are displayed through various tables and statistical figures, which facilitate the interpretation of the relationships between the studied variables.

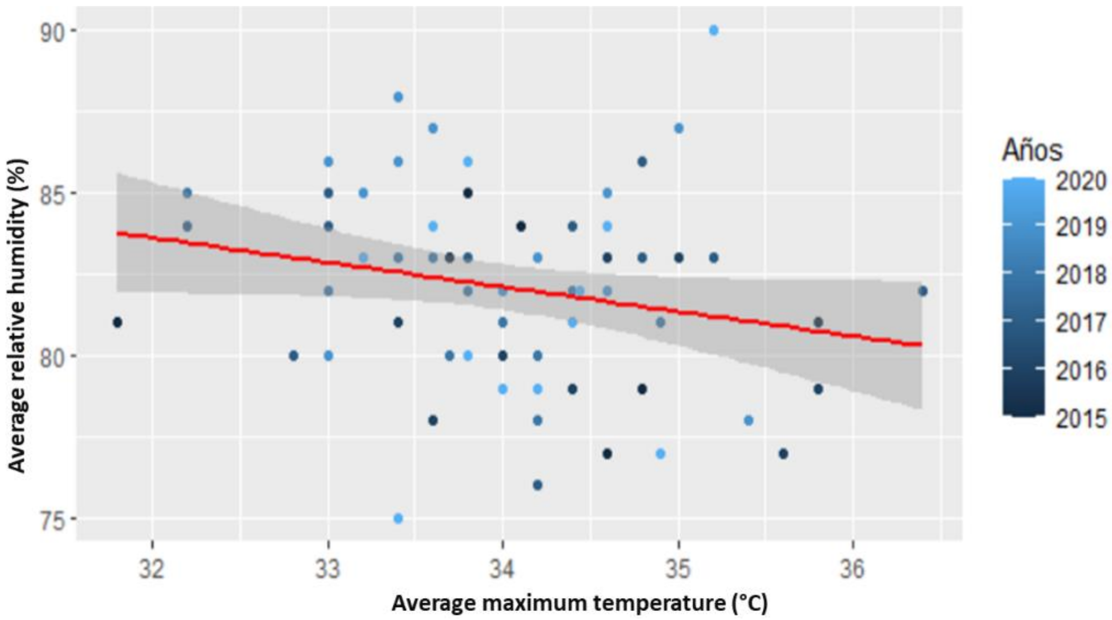

Figure 1. Dynamics of relative humidity in relation to maximum temperature

The chart presented illustrates an inverse correlation between maximum temperature and relative humidity on the Ecuadorian coast during the period 2015-2020. We observe that as maximum temperature increases, the percentage of relative humidity decreases. This pattern becomes more pronounced from 33°C onwards, coinciding with a noticeable decrease in humidity and an increase in the dispersion of humidity values observed in recent years.

Several studies have documented that variations in temperature can significantly influence relative humidity due to the capacity of warm air to contain more water vapor than cold air [41], [42], [43]. Moreover, an increase in temperature is linked with more erratic humidity patterns, reflecting a complex and multifaceted interaction between these climatic elements [44].

The application of robust statistical models has allowed for the quantification of this relationship, revealing that the variability of relative humidity intensifies with the increase of extreme temperatures. This phenomenon underscores the importance of monitoring and understanding climate dynamics in coastal areas, which are particularly vulnerable to the effects of climate change [45]. This analysis provides crucial evidence for the formulation of climate change adaptation policies, especially in preparation for more extreme conditions that could affect both the ecosystem and local communities.

Next, Figure 2 presents a detailed statistical analysis that quantifies the relationship between maximum temperature and relative humidity in a specific context. Through the application of a linear model, this analysis attempts to discern the degree of influence that temperature may have on humidity in a controlled environment.

```
Call:
lm(formula = Relative_humidity ~ Temperature, data = correlations1,
na.action = na.exclude)

Residuals:
   Min     1Q  Median     3Q    Max
-7.5625 -2.3781  0.3908  1.7974  8.7974

Coefficients:
          Estimate Std. Error t value Pr(>|t|)
(Intercept) 107.7968    13.2093   8.161  9.24e-12 ***
Temperature  -0.7555     0.3882  -1.946   0.0556 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 3.01 on 70 degrees of freedom
Multiple R-squared:  0.05134,  Adjusted R-squared: 0.03778
F-statistic: 3.788 on 1 and 70 DF, p-value: 0.05564
```

Figure 2. Climate model coefficients and goodness of fit tests

Figure 2 presents the analysis of the coefficients and goodness of fit tests for a climate model that assesses the relationship between relative humidity and maximum temperature. The adjusted model shows that the intercept is statistically significant at the 0.1% level (p = 0.000942, t = 8.161), suggesting that when the maximum temperature is zero, the expected value of relative humidity is approximately 107.8%. However, this is theoretically impossible given the actual physical conditions, indicating possibly an inappropriate extrapolation of the model or the need for an adjustment in the temperature scale.

On the other hand, the coefficient associated with maximum temperature is -0.7555, with a p-value of 0.0556. This value is marginally above the conventional threshold of 0.05, suggesting a negative trend between temperature and relative humidity, although this relationship does not reach statistical significance at the 5% level. This may indicate a weak relationship or the need for more data to confirm this effect. The model has an adjusted R-squared of 0.0377, indicating that only 3.77% of the variability in relative humidity is explained by variations in maximum temperature. This suggests that other factors not included in the model may be influencing relative humidity [46]. The F-statistic of 3.788 with a p-value of 0.0556 reflects that the model is marginally significant at the global level. That is, a p-value close to the threshold of 0.05 may require a more careful evaluation of the statistical power and sample sizes used in the analysis [47], [48].

```
        Augmented Dickey-Fuller Test

data:  series_tmaxima
Dickey-Fuller = -3.2262, Lag order = 4, p-value = 0.09057
alternative hypothesis: stationary

> adf.test(Difer1)

        Augmented Dickey-Fuller Test

data:  Difer1
Dickey-Fuller = -6.2989, Lag order = 4, p-value = 0.01
alternative hypothesis: stationary

In adf.test(Difer1) : p-value smaller than printed p-value
> ##empleamos el test de dickey fuller
> adf.test(series_humedadre)

        Augmented Dickey-Fuller Test

data:  series_humedadre
Dickey-Fuller = -3.236, Lag order = 4, p-value = 0.08899
alternative hypothesis: stationary

> adf.test(diferenciashr)

        Augmented Dickey-Fuller Test

data:  diferenciashr
Dickey-Fuller = -4.5549, Lag order = 4, p-value = 0.01
alternative hypothesis: stationary
```

Figure 3. Dickey-Fuller test from non-stationary to stationary for temperature and relative humidity

In Figure 3, the results of the augmented Dickey-Fuller test are presented and applied to assess the stationarity of the time series for maximum temperature and relative humidity. This analysis is crucial for identifying the presence of trends or seasonality in the time series, critical aspects for adequately modeling climatic phenomena.

Initially, the tests revealed that both the maximum temperature series and the relative humidity series were non-stationary, with p-values greater than 0.05, indicating the presence of trends and/or seasonal components in the data. This non-stationarity implies that the means and variances of the series can change over time, affecting the accuracy of predictions if not properly handled [49].

To transform the series into stationary ones, a first difference was applied to each series (denoted as Differ1 for temperature and differences for relative humidity). The results after this transformation showed p-values less than 0.05, indicating that the differenced series is stationary and, therefore, suitable for future analysis and modeling.

The transformation of series from non-stationary to stationary is crucial for the application of predictive models like ARIMA, which assume stationarity in the data. By ensuring that the series are stationary, the reliability of the forecasting models is improved [50]. This step is essential to avoid erroneous inferences and improve the accuracy in predicting climatic phenomena.

The need to differentiate time series to achieve stationarity is a common step in the analysis of climatic time series, as demonstrated by previous studies [51]. Applying these techniques facilitates the identification of underlying patterns and responding to questions about climate dynamics and its potential impact, especially in sensitive areas like the Ecuadorian coast.

Table 1. Simulations and iterations of temperature and relative humidity through artificial intelligence

Maximum Temperature Simulations (°C)		Relative Humidity Simulations (%)	
N°	Number of iterations	N°	Number of iterations
1	ARIMA(0,1,0)(0,1,0)[12] : 220.7055	1	ARIMA(0,1,0)(0,1,0)[12] : 317.106
2	ARIMA(0,1,0)(0,1,1)[12] : 209.9701	2	ARIMA(0,1,0)(0,1,1)[12] : 297.2272
3	ARIMA(0,1,0)(0,1,2)[12] : 212.1899	3	ARIMA(0,1,0)(0,1,2)[12] : 299.1942
4	ARIMA(0,1,0)(1,1,0)[12] : 216.0152	4	ARIMA(0,1,0)(1,1,0)[12] : 300.7595
5	ARIMA(0,1,0)(1,1,1)[12] : 212.191	5	ARIMA(0,1,0)(1,1,1)[12] : 299.1541
14	ARIMA(0,1,1)(1,1,1)[12] : Inf	14	ARIMA(0,1,1)(1,1,1)[12] : Inf
15	ARIMA(0,1,1)(1,1,2)[12] : Inf	15	ARIMA(0,1,1)(1,1,2)[12] : Inf
16	ARIMA(0,1,1)(2,1,0)[12] : 180.4718	16	ARIMA(0,1,1)(2,1,0)[12] : 283.8902
17	ARIMA(0,1,1)(2,1,1)[12] : 182.1128	17	ARIMA(0,1,1)(2,1,1)[12] : Inf
38	ARIMA(1,1,0)(0,1,1)[12] : Inf	38	ARIMA(1,1,0)(0,1,1)[12] : Inf
39	ARIMA(1,1,0)(0,1,2)[12] : 193.4651	39	ARIMA(1,1,0)(0,1,2)[12] : 283.2629
88	ARIMA(3,1,1)(0,1,0)[12] : 202.0975	40	ARIMA(1,1,0)(1,1,0)[12] : 286.3039
89	ARIMA(3,1,1)(0,1,1)[12] : Inf	41	ARIMA(1,1,0)(1,1,1)[12] : 283.1664
90	ARIMA(3,1,1)(1,1,0)[12] : Inf	42	ARIMA(1,1,0)(1,1,2)[12] : Inf
91	ARIMA(3,1,2)(0,1,0)[12] : Inf	91	ARIMA(3,1,2)(0,1,0)[12] : 308.273
92	ARIMA(4,1,0)(0,1,0)[12] : 202.416	92	ARIMA(4,1,0)(0,1,0)[12] : 306.392
93	ARIMA(4,1,0)(0,1,1)[12] : Inf	93	ARIMA(4,1,0)(0,1,1)[12] : Inf
94	ARIMA(4,1,0)(1,1,0)[12] : 193.9918	94	ARIMA(4,1,0)(1,1,0)[12] : 288.8698
95	ARIMA(4,1,1)(0,1,0)[12] : 204.7369	95	ARIMA(4,1,1)(0,1,0)[12] : 308.5597
96	ARIMA(5,1,0)(0,1,0)[12] : 204.823	96	ARIMA(5,1,0)(0,1,0)[12] : 307.6009

In Table 1, the process of model selection through the use of the auto.arima function of AI is displayed, which performed 96 iterations to identify the optimal models for maximum temperature and relative humidity on the coast of Ecuador. This automated approach is essential for adjusting time series models that adequately capture the climatic dynamics of the region.

For maximum temperature, artificial intelligence selected the thirteenth iteration, corresponding to the ARIMA model (0,1,1)(2,1,0). This model indicates that after applying one non-seasonal differentiation and another seasonal differentiation, the best approach to capture the seasonality and trend of temperature includes one moving average term in the non-seasonal component and two moving average terms in the seasonal component with annual periodicity. The choice of this model suggests that maximum temperature exhibits clear seasonal patterns, which is consistent with observations of meteorological phenomena that show regular annual fluctuations [52], [53].

For relative humidity, the selected model was ARIMA (1,1,0)(1,1,1) in iteration forty-one. This model combines an autoregressive term and a moving average term in its seasonal and non-seasonal components, which is indicative that relative humidity presents both seasonality and abrupt changes in the mean, required to adequately model its volatile behavior and variations throughout the year.

The selection of these models by artificial intelligence reflects the presence of seasonality, trend, autoregression, and abrupt changes in the mean of the analyzed time series. These elements are crucial for understanding and predicting climatic conditions in the region, which has direct implications for agricultural planning, water resource management, and adaptation to climate change [54], [55]. Furthermore, the use of advanced predictive models, like those based on artificial intelligence, must be guided by a strong ethical framework to ensure the responsible handling of data and decision-making processes. In other fields, such as accounting, ethical responsibility is fundamental to ensuring the integrity of information used in critical decision-making [56].

```
> print(simulacióntm)
Series: series_tmaxima
ARIMA(0,1,1)(2,1,0)[12]

Coefficients:
          ma1     sar1     sar2
      -0.8515  -0.6548  -0.5334
s.e.   0.0925   0.1372   0.1273

sigma^2 = 0.9257:  log likelihood = -85.87
AIC=179.73   AICc=180.47   BIC=188.04
> ##se realiza una revisión de los residuales del mo
delo
> residuales<-checkresiduals(simulacióntm)

        Ljung-Box test

data:  Residuals from ARIMA(0,1,1)(2,1,0)[12]
Q* = 10.413, df = 11, p-value = 0.4937

Model df: 3.   Total lags used: 14

> Box.test(simulacióntm,type = "Ljung-Box")
```

```
Series: series_humedadre
ARIMA(1,1,0)(1,1,1)[12]

Coefficients:
          ar1     sar1     sma1
      -0.5241  -0.1709  -0.8129
s.e.   0.1117   0.2229   0.5394

sigma^2 = 4.966:  log likelihood = -137.21
AIC=282.43   AICc=283.17   BIC=290.74
> ##se realiza una revisión de los residuales del modelo
> residuales<-checkresiduals(simulaciónHR)

        Ljung-Box test

data:  Residuals from ARIMA(1,1,0)(1,1,1)[12]
Q* = 9.0059, df = 11, p-value = 0.6213

Model df: 3.   Total lags used: 14
```

Figure 4. Simulations of maximum temperature and relative humidity on the coast of Ecuador

Figure 4 illustrates the validation of the ARIMA models generated for maximum temperature and relative humidity on the Ecuadorian coast, using the maximum likelihood technique. These models have been selected through a rigorous statistical process that includes the optimization of criteria such as Akaike Information Criterion (AIC), corrected Akaike (AICc), and Bayesian Information Criterion (BIC).

The ARIMA (0,1,1)(2,1,0) model applied to maximum temperature exhibits excellent statistical performance. The AIC values of 179.73 and AICc of 180.47 indicate proper model fit, while the BIC of 188.04 confirms the model's efficiency in terms of penalty for the number of parameters. The Ljung-Box test for the model's residuals shows a p-value of 0.4937, indicating that there is no significant autocorrelation in the residuals, and the model adequately captures the dependency structure in the maximum temperature data [57].

On the other hand, relative humidity is modeled with an ARIMA (1,1,0)(1,1,1). The Akaike and Bayesian criteria also indicate excellent model fit and efficiency, with AICc values of 283.17 and BIC of 290.74. Similar to the maximum temperature model, the Ljung-Box test yields a p-value of 0.6213 for the residuals, suggesting the absence of residual autocorrelation and confirming that the model is appropriate for relative humidity data.

The confirmation of these models' validity through Ljung-Box tests and information criteria indicates that both models are robust and reliable for simulating and predicting climatic conditions. The absence of residual autocorrelation and the adequate capture of the seasonality and underlying trend in the data is essential for making reliable projections that can inform climate change adaptation policies and natural resource management strategies [58], [59].

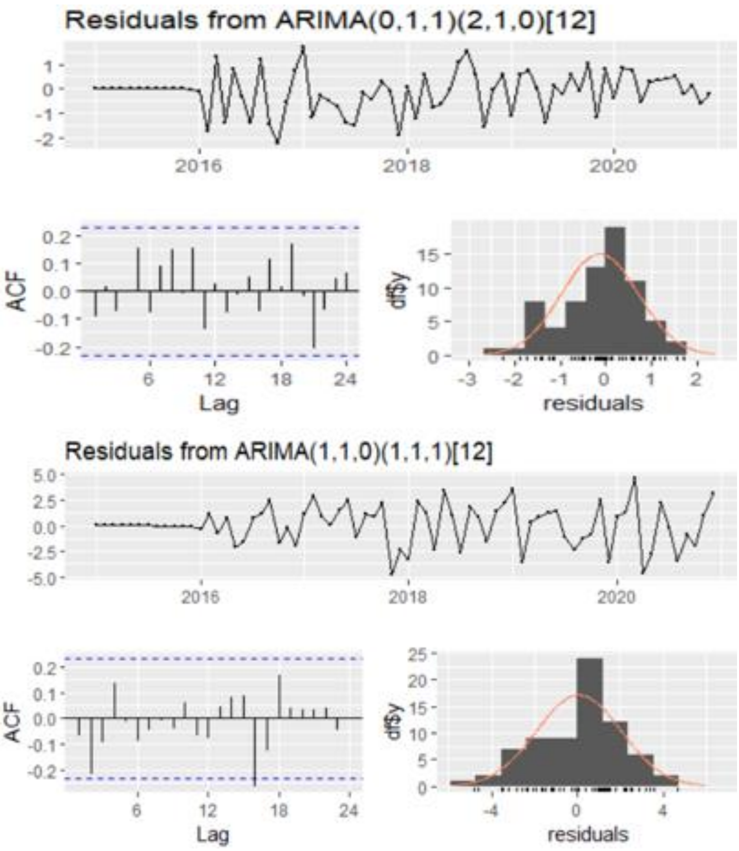

Figure 5. Residual simulations of maximum temperature and relative humidity on the coast of Ecuador

Figure 5 illustrates the analysis of the residuals derived from the ARIMA models selected for maximum temperature and relative humidity. Residuals are crucial for validating the quality of a time series model, as they indicate the amount of information not explained by the model.

The residuals of the ARIMA (0,1,1)(2,1,0) model for maximum temperature show fluctuations that appear not to present clear systematic patterns over time, which is a positive indicator of the model's adequacy. The autocorrelation chart (ACF) for these residuals indicates that all autocorrelations are within the confidence limits, suggesting that there are no significant autocorrelations in the residuals and that the model has adequately captured the dependency structure in the data.

The distribution of the residuals, represented in the density plot, approximates a normal distribution, which is corroborated by the red fit line. This normality is consistent with the underlying assumptions of many statistical tests used for subsequent inferences, strengthening the reliability of the predictions generated by the model [60], [61].

For relative humidity, the ARIMA (1,1,0)(1,1,1) model also shows residuals without clear patterns of autocorrelation over time, as observed in its respective time graph and ACF. This indicates that the model is effective in modeling relative humidity without leaving unexplained autocorrelations [62]. Similar to maximum temperature, the histogram of the residuals with its corresponding normal curve fit shows that the residuals are distributed approximately normally, fulfilling another key assumption for the validation of the statistical model.

The normality and absence of autocorrelation in the residuals are indicative that the models are adequate and complete, which is essential for making accurate and reliable predictions. These results allow researchers and planners to use these models to predict maximum temperature and relative humidity with greater confidence, facilitating planning in response to variable climatic conditions [63].

Table 2. Forecasts for maximum temperature and relative humidity from 2021 to 2024

	Maximum temperature forecasts (°C)			Forecasts relative humidity (%)		
Months/years	Forecast	Forecast Lo 95	Forecast Hi 95	Forecast	Forecast Lo 95	Forecast Hi 95
1/1/2021	34.22623	32.34050	36.11196	82.24920	77.76913	86.72928
1/2/2021	32.96561	31.05921	34.87201	84.35447	79.39970	89.30925
1/3/2021	34.41416	32.48731	36.34101	83.83164	77.85977	89.80351
1/4/2021	34.40953	32.46245	36.35662	81.89022	75.33782	88.44261
1/5/2021	33.85094	31.88382	35.81805	82.03950	74.82015	89.25886
1/6/2021	33.37188	31.38494	35.35882	82.59960	74.83609	90.36310
1/7/2021	33.69443	31.68786	35.70100	82.37683	74.07256	90.68109
1/8/2021	34.07857	32.05256	36.10458	80.87541	72.07983	89.67098
1/9/2021	34.57205	32.52678	36.61731	80.13996	70.87056	89.40937
1/10/2021	34.31540	32.25106	36.37974	80.29411	70.57908	90.00914
1/11/2021	33.87015	31.78691	35.95339	76.56523	66.42013	86.71033
1/12/2021	34.40621	32.30424	36.50818	78.76732	68.21476	89.31988
1/1/2022	33.92280	31.62391	36.22168	82.49701	71.47071	93.52330
1/2/2022	33.28387	30.95434	35.61340	84.14421	72.71959	95.56882
1/3/2022	34.91400	32.55422	37.27378	84.62481	72.80130	96.44831
1/4/2022	34.60193	32.21228	36.99157	81.35646	69.15425	93.55867
1/5/2022	33.77383	31.35469	36.19298	81.71447	69.14127	94.28766
1/6/2022	33.61321	31.16492	36.06149	82.48737	69.55579	95.41895
1/7/2022	33.35593	30.87884	35.83301	82.14921	68.86776	95.43066
1/8/2022	34.25003	31.74448	36.75559	80.21176	66.59030	93.83323
1/9/2022	34.28941	31.75570	36.82311	79.60676	65.65258	93.56093
1/10/2022	34.63012	32.06858	37.19167	79.39034	65.11272	93.66797
1/11/2022	33.44086	30.85177	36.02994	75.95817	61.36168	90.55466
1/12/2022	34.95471	32.33838	37.57105	78.63762	63.73402	93.54122
1/1/2023	34.41282	31.66793	37.15772	82.11471	66.66796	97.56147
1/2/2023	33.61251	30.83195	36.39308	83.83999	68.01725	99.66272
1/3/2023	35.09785	32.28206	37.91363	84.14924	67.90221	100.39627
1/4/2023	34.56281	31.71223	37.41338	81.10756	64.47666	97.73846
1/5/2023	34.23050	31.34556	37.11544	81.42993	64.40871	98.45115
1/6/2023	33.66882	30.74992	36.58772	82.16646	64.77155	99.56137
1/7/2023	33.40578	30.45331	36.35826	81.84802	64.08307	99.61298
1/8/2023	34.29448	31.30881	37.28015	79.98507	61.86013	98.11002
1/9/2023	34.26128	31.24278	37.27978	79.35778	60.87794	97.83762
1/10/2023	34.82784	31.77686	37.87881	79.20468	60.37882	98.03054
1/11/2023	33.56312	30.48001	36.64622	75.72181	56.55287	94.89076
1/12/2023	34.36411	31.24920	37.47902	78.31970	58.81969	97.81971
1/1/2024	34.34576	30.80408	37.88744	81.83995	61.82055	101.85936
1/2/2024	33.31949	29.72251	36.91646	83.55189	63.15053	103.95325

	Maximum temperature forecasts (°C)			Forecasts relative humidity (%)		
Months/years	Forecast	Forecast Lo 95	Forecast Hi 95	Forecast	Forecast Lo 95	Forecast Hi 95
1/3/2024	34.80277	31.15133	38.45421	83.89042	63.06977	104.71106
1/4/2024	34.57774	30.87264	38.28284	80.81001	59.60145	102.01857
1/5/2024	34.06454	30.30655	37.82254	81.13847	59.53709	102.73985
1/6/2024	33.59562	29.78546	37.40578	81.88121	59.90027	103.86216
1/7/2024	33.64566	29.78404	37.50727	81.55941	59.20194	103.91687
1/8/2024	34.26586	30.35346	38.17825	79.68372	56.95809	102.40936
1/9/2024	34.52242	30.55989	38.48495	79.06024	55.97054	102.14995
1/10/2024	34.62243	30.61040	38.63446	78.89632	55.45039	102.34225
1/11/2024	33.80401	29.74308	37.86494	75.42212	51.62180	99.22243
1/12/2024	34.55020	30.44095	38.65945	78.03394	53.89083	102.17705

Table 2 presents the forecasts for maximum temperature and relative humidity on the coast of Ecuador, derived from the ARIMA (0,1,1)(2,1,0) model for temperature and an analogous model for humidity. These forecasts cover the period from 2021 to 2024 and highlight the observed variability across different seasons, a direct reflection of regional climatic patterns.

The analysis reveals significant seasonal fluctuations in temperature. For the year 2023, a maximum temperature of 35.09 °C is forecasted during the rainy season, demonstrating high thermal variability with a range dropping to 32.96 °C in 2021. This variation of 2.13 °C between annual extremes underscores the influence of seasonal meteorological phenomena and their impact on regional temperatures.

Regarding relative humidity, the data projects a maximum peak of 84.62% during the winter season, while the lowest recorded value is 75.42% during the dry season. The observed variability of 9.20% in relative humidity between these seasons reflects environmental responses to changes in precipitation and temperatures.

Forecasts based on ARIMA models are valuable tools for climatic and environmental planning, especially in regions susceptible to significant climatic variations like the Ecuadorian coast. According to studies, the ability to foresee fluctuations in temperature and humidity is crucial for agriculture, water resource management, and public health [64], [65].

Furthermore, the predictive capacity of ARIMA models, particularly in seasonal configurations, allows planners and scientists to anticipate adverse conditions and design appropriate mitigation strategies. The accuracy of these models, as reflected in the confidence intervals and close adherence to historical patterns, strengthens confidence in their practical utility.

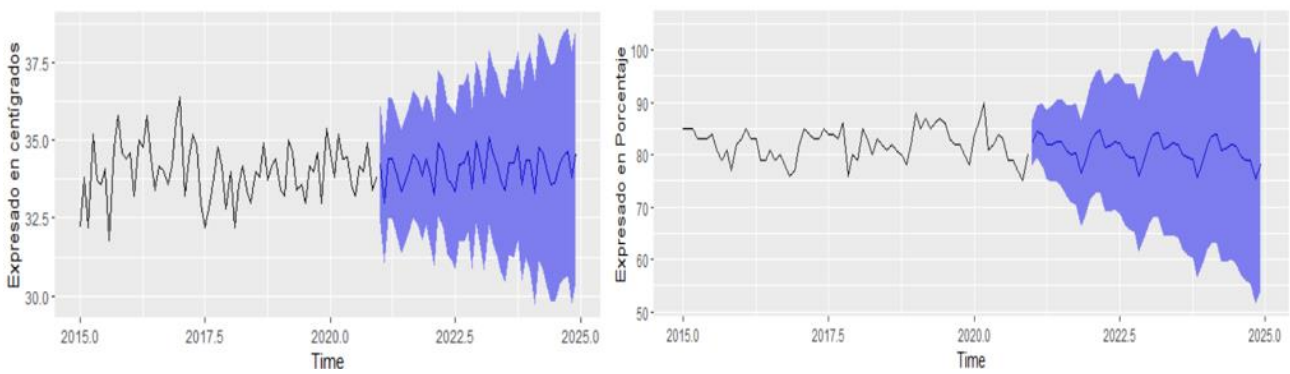

Figure 6. Predictive models for temperature and humidity on the coast of Ecuador

Figure 6 presents the predictive models for maximum temperature and relative humidity on the Ecuadorian coast, extending up to 2024. These models offer a clear visualization of the projected trends and expected fluctuations in both climatic variables over time, allowing for an accurate interpretation of their future behavior under changing climatic conditions.

The model for maximum temperature shows a generally stable trend with significant fluctuations throughout the year, which is typical in tropical regions where interannual variability may be minimal but intra-annual variations are pronounced. The graphical representation includes a confidence interval, denoted by the shaded area, which provides an estimate of the uncertainty associated with the predictions. This feature is crucial for proper planning in response to heatwaves or unusually cold periods that could impact agriculture and public health [66].

As for relative humidity, the model predicts a gradual decrease over the years, with a wide confidence interval that reflects the uncertainty inherent in predicting this variable. This downward trend could be influenced by factors such as rising temperatures and changes in precipitation patterns, suggesting the need for adaptation strategies in sectors such as water management and agriculture to combat the effects of water stress.

The presented models are fundamental for strategic decision-making in natural resource management and urban and rural planning. Understanding the variability and trends in these variables is essential for adapting to climate change, especially in coastal regions susceptible to extreme climatic variations [67].

The ability to foresee changes in temperature and relative humidity in advance allows planners and authorities to implement measures that mitigate the adverse impacts of climate change on local biodiversity, agricultural production, and public health, as studies on the adaptation of ecosystems to changing climates suggest [68].

Table 3. Goodness of fit coefficients for simulation models of maximum temperature and relative humidity

Series: Maximum Temperature (°C): ARIMA(0,1,1)(2,1,0) [12]							
Acronym	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Coefficients	-0.1375942	0.8485132	0.6285502	-0.4349521	1.853311	0.6646636	-0.09364487
Series: Relative Humidity (%): ARIMA(1,1,0)(1,1,1) [12]							
Acronym	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Coefficients	0.05574289	1,965356	1.525231	0.02668258	1.863756	0.5383169	-0.06588713

Table 3 provides a detailed assessment of the reliability of the predictive models for maximum temperature and relative humidity on the coast of Ecuador, using key statistical indicators generated through artificial intelligence. The results demonstrate notable consistency between the models for both climatic variables, reflecting the robustness and precision of the modeling techniques employed.

Key indicators such as mean error (ME), root mean square error (RMSE), mean absolute error (MAE), mean percentage error (MPE), mean absolute percentage error (MAPE), mean absolute scaled error (MASE), and first order autocorrelation of residuals (ACF1) exhibit values very close to zero, indicating a high degree of accuracy in the predictions. These coefficients confirm that the employed ARIMA models are adequately calibrated and capable of effectively capturing the underlying dynamics of the climatic variables.

The similarity in the goodness of fit coefficients for both variables suggests that the artificial intelligence methodology applied, specifically the ARIMA models, is extremely effective for climate analysis in this region. The precision of these models is crucial for making reliable forecasts that can support strategic planning and decision-making in the context of climate change [69].

The effectiveness of artificial intelligence in predicting climatic patterns offers significant advantages for environmental planning and management. With accurate forecasts, planners can better prepare communities for extreme weather events and manage natural resources more effectively, which is vital in regions prone to intense climatic variations like the Ecuadorian coast [70], [71].

In the present study, ARIMA models were applied to predict maximum temperature and relative humidity on the Ecuadorian coast, obtaining significant results regarding the inverse relationship between these climatic variables. To contextualize and validate these findings, a comparison was made with similar studies in the literature that have used advanced statistical approaches and artificial intelligence techniques to model and predict climatic variables. Below is a comparative table summarizing the main relevant studies, the models used, and the key results, which allows us to discuss the coherence and differences between studies, as well as explore the implications of the obtained results.

Table 4. Comparative analysis of predictive models for temperature and humidity

Research topic	Studied variable	Model used	Key results
Stochastic modeling and forecasting of relative humidity and wind speed for different zones of Kerala	Relative humidity and wind speed	Stochastic models	Accurate predictions of relative humidity and wind speed in different areas of Kerala, India [72].
The Investigation and Forecasting of Relative Humidity Variation of Pars Abade-Moghan, North-West of Iran, by ARIMA Model	Relative humidity in Pars Abad-e-Moghan	ARIMA	Effective ARIMA model for forecasting relative humidity variations in northwest Iran [73].
Modeling and Controlling of Temperature and Humidity in Building Heating, Ventilating, and Air Conditioning System Using Model Predictive Control	Temperature and humidity	Model Predictive Control (MPC)	The proposed MPC approach optimizes the control of temperature and humidity, improving energy efficiency and comfort levels [74].
Model Predictive Temperature and Humidity Control of Greenhouse with Ventilation	Temperature and absolute humidity	Model Predictive Control (MPC)	MPC reduced the RMS error of temperature and humidity deficit to 23.5% and 13.1%, respectively, improving plant growth efficiency [75].
Models for Prediction of Daily Mean Indoor Temperature and Relative Humidity: Education Building in Izmir, Turkey	Indoor temperature and relative humidity	Artificial Neural Network (ANN) and multiple regression	ANN models showed better performance than multiple regression for predicting indoor temperature and humidity in educational buildings, with high R^2 values (0.94 for temperature and 0.96 for humidity) [76].
Integration of extreme gradient boosting feature selection approach with machine learning models: application of weather relative humidity prediction	Relative humidity at Kut and Mosul stations, Iraq	XGBoost feature selection with SVR, RF, and MARS	Random forest (RF) model yielded the best prediction at Kut station with RMSE = 4.92, while MARS model performed best at Mosul station with RMSE = 3.80 [77].

When comparing the results of this study with those from previous research (Table 4), significant similarities and differences are identified regarding the predictive models used to estimate temperature and relative humidity.

In terms of relative humidity and wind speed prediction, Gokul, Mehta, and Rail [72] applied stochastic models, obtaining accurate predictions for different zones of Kerala. The ARIMA models used in the study on the

Ecuadorian coast also provided reliable predictions, highlighting the robustness of this approach in environments with moderate climate variability. However, stochastic models might be better suited to capture random fluctuations that ARIMA models may not fully represent.

On the other hand, Shiri et al. [73] also used the ARIMA model to predict variations in relative humidity in Iran, with results similar to those of the present study. Both works corroborate ARIMA's capacity to identify trends and seasonality in relative humidity time series. Nevertheless, it is acknowledged that this model presents limitations in predicting sudden changes or extreme weather events.

In the study by Bahramnia et al. [74] model predictive control (MPC) optimized the control of temperature and humidity in HVAC systems, achieving improvements in energy efficiency and comfort. Although the Ecuadorian study does not focus on control system applications, the analysis of interactions between temperature and relative humidity through ARIMA compares favorably in terms of overall accuracy. However, MPC could be more effective in contexts where climate control optimization is critical.

Ito and Tabei [75] employed MPC for greenhouses, significantly reducing the error in temperature and humidity deficit predictions. In contrast, the results obtained with ARIMA on the Ecuadorian coast focused more on long-term trend prediction, limiting its applicability in scenarios that require precise climate control, such as greenhouses.

Likewise, Özbalta et al. [76] used artificial neural networks (ANN) and multiple regression to predict temperature and humidity in educational buildings, achieving more precise adjustments than ARIMA models. This suggests that, in more complex contexts, ANN models could outperform ARIMA, highlighting the need to consider more advanced approaches in future studies on the Ecuadorian coast.

Finally, Tao et al. [77] demonstrated the effectiveness of machine learning techniques such as XGBoost, SVR, RF, and MARS in predicting relative humidity. The RF model outperformed ARIMA in the present study, indicating that using machine learning-based approaches could improve the accuracy of climate predictions in coastal regions.

5. Conclusion

The study has demonstrated, through the use of advanced artificial intelligence techniques, how maximum temperature and relative humidity are interrelated on the coast of Ecuador. Through comprehensive analysis, which included the application of ARIMA models and the evaluation of their residuals, the reliability of these techniques for predicting climatic changes has been validated. The inverse correlation between maximum temperature and relative humidity, particularly pronounced from 33°C onwards, highlights how relative humidity varies in response to temperature increases, aligning with previous studies that attribute these changes to the ability of warm air to retain more water vapor.

The selected ARIMA models have provided a robust framework for understanding the dynamics of temperature and humidity in a highly variable environment. The goodness of fit coefficients and Ljung-Box tests have corroborated the absence of significant autocorrelations in the residuals, suggesting that these models adequately capture the inherent variability of these climatic phenomena. This is reflected in the consistency of indicators such as ME, RMSE, MAE, and MAPE, which show that both temperature and humidity can be forecasted with a high degree of accuracy.

This study underscores the need for climate change adaptation policies that consider these interactions between temperature and humidity. The ability to foresee extreme conditions is crucial for agricultural planning, water resource management, and public health, especially in a region susceptible to the impacts of climate change. Predictive models, by offering reliable and detailed forecasts, become valuable tools for decision-making regarding infrastructure, emergency response, and sustainable development strategies.

Given that only a small percentage of the variability in relative humidity was explained by changes in maximum temperature, it is recommended to explore other factors that could influence these variables. This could include more detailed studies on precipitation patterns, changes in vegetation cover, and human activities that alter local conditions. Additionally, it is suggested to increase the sample size or use models that integrate more climatic variables to improve the accuracy of the predictions.

Among the most significant limitations of this study is that the variability in relative humidity was only partially explained by changes in maximum temperature. This suggests the probable influence of other factors not considered in the model, which reduces its predictive capacity when only two climatic variables are taken into account. Moreover, while the sample size is adequate for the objectives set, it may not be sufficient to accurately capture seasonal fluctuations or extreme weather events. The absence of other relevant variables, such as wind speed, solar radiation, or precipitation levels, may limit a deeper understanding of the climatic interactions in the region under study.

In future research, it is essential to expand the analysis by incorporating a larger number of climatic variables that may affect the relationship between temperature and humidity, such as precipitation patterns, changes in vegetation cover, and human activities that modify local microclimatic conditions. Additionally, increasing the sample size would allow for the inclusion of longer climatic periods, thereby strengthening the robustness of the models and providing better insights into the long-term dynamics of the phenomena analyzed. Finally, it is suggested to explore more complex predictive models, such as non-linear or hybrid approaches, which combine various prediction techniques to enhance accuracy in forecasting climatic events in areas particularly vulnerable to the effects of climate change.

Declaration of competing interest

The authors declare that they have no any known financial or non-financial competing interests in any material discussed in this paper.

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Author contribution

Ángel Ramón Sabando-García: Data curation, Formal analysis, Investigation, Software, Validation, Visualization, Writing– original draft, Writing – review & editing. Jenniffer Sobeida Moreira-Choez and Luis Javier Castillo-Heredia: Investigation, Conceptualization, Formal analysis, Writing – review & editing. Anthony Andrés Bazurto-Loor: Software, Validation, Visualization and Writing. Rafael Romero-Carazas and Eduardo Espinoza-Solís: Conceptualization, Methodology, Formal analysis, review & editing.

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