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RESEARCH ARTICLE

MODELING RESIDUAL COMPONENTS AND IRREGULAR FLUCTUATIONS IN HEALTH TIME SERIES

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ABSTRACT

This study provides an in-depth analysis of methods for modeling residual components in time series applied to health data. Time series analysis plays a crucial role in many disciplines, particularly in public health. Time series make it possible to study the evolution of phenomena over time in order to identify trends and formulate forecasts. However, beyond the trend and seasonality components, residual components, often perceived as "noise", also contain valuable information that could impact the results of these forecasts if they are not taken into account. After exploring some methods (statistical and machine learning), we applied the first-order autoregressive method AR(1) to health data from the Cameroonian Ministry of Public Health for the period 2018 to 2022. This method successfully captured the relevant information contained in the residuals of our decomposition, achieving a performance of 99% in the test. This result is well beyond those using neural networks (LSTM) and ARIMA-ARCH on the same dataset. The study of the residuals helps to better adjust the general trend of the series and highlights the importance of taking into account the residuals in the modeling of time series in order to improve the accuracy of forecasts. Finally, this study opens up perspectives for the application of other hybrid modeling techniques combining statistical and machine learning methods for a more detailed analysis of health data.

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INTRODUCTION

Time series analysis plays a crucial role in many disciplines, including public health. Time series allow studying the evolution of phenomena over time in order to identify trends and formulate forecasts. Time series are used in statistics (Elizabeth Korevaar *et al*., 2024), signal processing (Dorel Aiordachioaie and Theodor, 2024), pattern recognition (Silvio Barra, 2020), econometrics (James, 2020), finance (Siti Aisyah Mohammed *et al*, 2020), weather forecasting (Rabia Hanif *et al*., 2023), earthquake forecasting (Alireza Jafari *et al*., 2024), electroencephalography (Alireza Jafari *et al*., 2024), control engineering (Kexin Zhang, 2024), astronomy (Suzanne Aigrain and Daniel Foreman-Mackey, 2023), communications engineering (Chunyong Yin, 2020), health (Francesco Piccialli, 2021) and many other fields of applied sciences and engineering that involve temporal measurements (Madan Parajuli *et al*. 2023). Beyond the trend and seasonality components, the residual components, often perceived as "noise", also contain valuable information. An in-depth analysis of the modeling methods of these residual components applied to health data is the subject of this work. Indeed, health time series are statistical data widely used in predictions. These data help not only to prevent deaths (Nasrin Talkhi, 2021) but also in the management of infrastructures such as hospital beds (Abdelhafid Zeroual, 2020). The management of chronic diseases such as heart disease (Sabah Hasan Jasim Alsaedi, 2022) or diabetes (Batoure Bamana *et al*., 2024a) generally relies on the patient histories reported in health time series. It should also be noted that if some countries manage to contain epidemics such as cholera and others, it is because the leaders have good contingency plans that take into account health time series forecasting models (Ahmad Hauwa Amshi and Rajesh Prasad, 2023). In this article, we will propose a residual model to better capture the residuals of the time series. The residual components capture the errors, noises and irregularities that cannot be explained by time (Fadloullah Issam Benboubker Mounir, 2024). We will study the characteristics of this component and propose an autoregressive model of order 1 1) on the series of health data of malaria patients. Indeed, malaria is a rather worrying public health problem (Danis, 2023). To deal with this scourge that continues to cause desolation in families, it is important to propose a decision support system that can help decision-makers in planning responses (Moskolaï Ngossaha *et al*., 2024). We will compare our results with that Batoure Bamana *et al*., 2025a) using machine learning methods, in particular neural networks (LSTM) and that of (Leouro Mbaiossoum *et al*. 2025) using the GARCH method, both applied to the same data set. The proposed model will be tested and evaluated on the basis of real data, with known measurements in the field of residue treatment (Batoure Bamana *et al*. 2024b).

METHODS AND MATERIALS

The objective of modeling residual components and irregular fluctuations of time series is to improve the understanding of temporal data, identify modeling errors and nonlinear structures. We will perform a descriptive analysis to better understand the domain. After this descriptive analysis, we will seek to know if the residual component is autocorrelated, that is, if the observations are time dependent. We will explore the methods of processing residuals and use the autoregressive method to adjust the data studied

Decomposition of time series: A time series is a variant of data points indexed in temporal order. These types of data are collected at the regular time interval. It is therefore a sequence of discrete time data. Decomposition of a time series is a process of separating the components to understand their individual influence and obtain deeper information about the data (Hui Liu, 2001). It helps to isolate the effects of each component, facilitating a more complete understanding of the underlying dynamics (Peter Schmid, 2022). This understanding helps to create more accurate forecasting models that account for specific patterns and trends (Bryan Lim and Stefan Zohren, 2021). Decomposition can also reveal unexpected deviations from the expected trend or seasonal patterns, potentially indicating outliers or structural changes in the data (Jingkun Gao, 2020). The main components are:

- The trend, which represents the long-term behavior of the series. This can be an upward trend, a downward trend, or even a steady state.
- The seasonality, which captures any repeating patterns within the series over specific periods, such as daily, weekly, monthly, or annual cycles.
- The residuals, which represent unexplained fluctuations or random variations in the data after removing the trend and seasonality.

Figure 1 shows an illustration of a time series and its different components.

Decomposition methods: A time series can be decomposed into an additive model and a multiplicative model. The additive model assumes that the components are added together to form the original series. This model is suitable when seasonal fluctuations are independent of the overall level of the series. The multiplicative model assumes that the components are multiplied together to form the original series. This model is more suitable when seasonal fluctuations are proportional to the level of the series.

These decompositions that can be used to estimate and statistically extract the individual components.

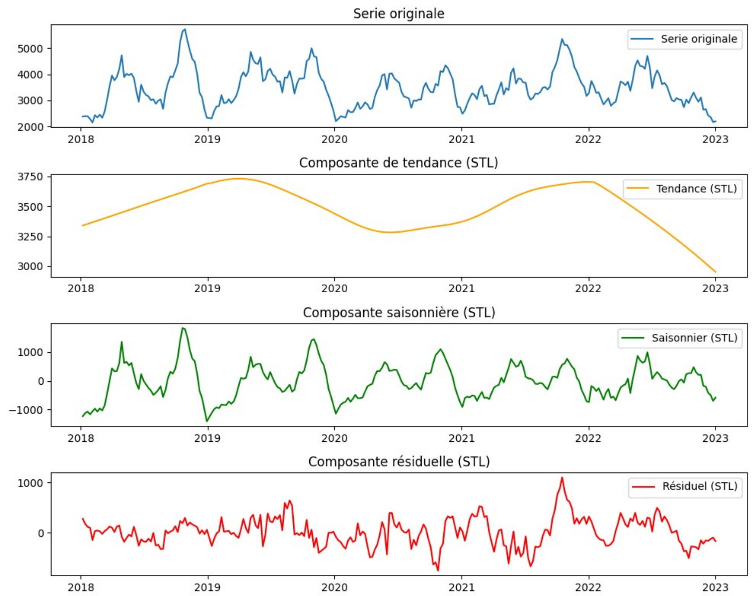

Figure 1. Time decomposition

Residual components of time series: The residuals in a time series represent the difference between the recorded values and the values estimated by the basic model used, thus reflecting irregular or unanticipated fluctuations in the data (Hyndman, R. J., & Athanasopoulos, G. 2021). Called residual movement and noted *εt*, it groups together everything that has not been taken into account by the trend and seasonality (Valery Gitis and Alexander Derendyaev, 2023). It is the result of irregular and unpredictable fluctuations due to non-permanent disturbing factors; these fluctuations are assumed to be of low amplitude and have a zero mean over a small number of consecutive observations. Being a random process, we assimilate it to a stochastic process (Seung Won Lee *et al.*, 2022). We recall that a stochastic process is a mathematical model used to represent the random or unpredictable behavior of a system over time. In the case of a time series, a stochastic process can be used to model fluctuations in the data over time. Stochastic models are of the same type as deterministic models except that the noise variables εt are not identically and independently distributed but have a non-zero correlation structure: εt is a function of past values (± distant depending on the model) and an error term ηt (Dorel Aiordachioaie and Theodor, 2020) i.e.

$$\varepsilon_t = g(\varepsilon_{t-1}, \varepsilon_{t-2}, \dots, \eta_t) \quad (1)$$

The time series is the observation of a stochastic process: the modeling here concerns the form of the process (εt). The special case where the functional relation g is linear is very important and widely used (Lawrence Wong, 2022). It leads to linear autoregressive models, for example a model of order 2 with autoregressive coefficients a_1 ,a_2 is given by:

$$\varepsilon_t = a_1 X_{t-1} + a_2 X_{t-2} + \eta_t \tag{2}$$

where ηt is white noise, i.e. an uncorrelated random variable with zero mean. Both types of models induce very specific forecasting techniques. Schematically, we are first interested in the trend and the possible seasonality (ies) that we isolate beforehand. Then, we try to model and estimate them. Finally, we eliminate them from the series. These two operations are called detrendization and deseasonalization of the series. Once these components are eliminated, we obtain the random series εt.

- For deterministic models, this series will be considered as decorrelated and there is nothing more to do.
- For stochastic models, we obtain a stationary series (which means that the successive observations of the series are identically distributed but not necessarily independent) that we must model.

Stochastic processes are classified into two categories: stationary stochastic processes and non-stationary stochastic processes (Batoure Bamana *et al*. 2025b).

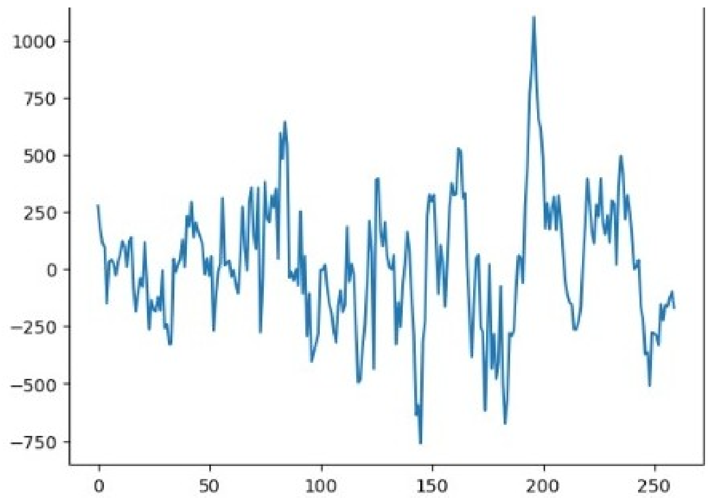

Figure 2. Residual component

Autoregressive Model: Regression is a statistical technique that relates a dependent variable to one or more independent variables (Seung Won Lee *et al*., 2022). It is formally defined by:

$$y_t = b_0 + b_1 * x_t \tag{3}$$

Where y is the dependent variable, b_0 and b_1 are coefficients and x_t is the independent variable.

Autoregressive Process of order p AR(p): Autoregressive processes, constructed from the idea that the observation at time t is explained linearly by the previous observations (Ruey S Tsay, 1989). We say that (Xt) is an autoregressive process of order p (centered) if it is written:

$$X_t = c + \varepsilon_t + \sum_{i=1}^{p} \phi_i X_{t-i}, \forall\, t \in \mathbb{Z} \tag{4}$$

where $c, \phi_i \epsilon \mathbb{R}$ and $\varepsilon_t \in \mathbb{Z}$ a centered white noise of variance σ^2. The observation X_t at time t is the sum of a random shock at time t, ε_t, independent of the history, and of the linear function of its past which is $\sum_{i=1}^{p} \phi_i X_{t-i}$ in a way the prediction of X_t from the last p observations (Alioum Abdoulaye *et al*. 2026).

Moving Average Process MA(q)

$$X_t = m + \varepsilon_t - \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}, \forall\, t \in \mathbb{Z} \tag{5}$$

Moving average methods are smoothing techniques used to estimate short-term trends in time series. A moving average of order q is a process of the form:

with $m, \theta_i \epsilon \mathbb{R}$.
Note that for the moment no condition is necessary on the θ_i for the stationary process. A moving average process is necessarily centered, and its auto-covariance verifies:

$$\sigma(h) = \begin{cases} \sigma^2 \sum_{k=0}^{q-h} b_k b_{k+h}, \forall\, h \leq q \text{ où } b_0 = 1 \\ 0, \forall\, h > q \end{cases} \tag{6}$$

Autoregressive Moving Average Process ARMA(p,q): A moving average autoregressive process of orders p and q is of the form:

$$X_t - \sum_{j=1}^{p} \phi_j X_{t-j} = c + \varepsilon_t - \sum_{h-1}^{q} \theta_h \varepsilon_{t-h}, t \epsilon \mathbb{Z} \tag{7}$$

Where $t \epsilon \mathbb{Z}$ is a centered white noise with variance σ^2; θ_q and ϕ_p are non-zero; the polynomials $\phi(B) = 1 - \sum_{j-1}^{p} \phi_j B^j$ and $\theta(B) = 1 - \sum_{h-1}^{q} \theta_j B^h$ have their roots with moduli different from 1.

Autoregressive Integrated Moving Average Process ARIMA(p,d,q): The ARIMA (AutoRegressive Integrated Moving Average) model is a mathematical model that can be applied to time series to predict future data based on their past values. If a process must be differentiated d times to reach stationarity, it is said to be integrated of order d, we denote by ARIMA(p,d,q). The general formulation of an ARIMA(p,d,q) model is:

$$\left(1-\sum_{i=1}^{d}\phi_i B^i\right)(1-B)^d X_t = \left(1+\sum_{j=1}^{d}\theta_j B^j\right)\varepsilon_t \quad (8)$$

WhereB is the shift operator; ϕ_i are the coefficients of the autoregressive terms; θ_j are the coefficients of the moving average terms; d is the order of differentiation.

$$\phi_p(B)(1-B)^d Y_t = \theta_q(B)\varepsilon_t \quad (9)$$

where Y_t is a chronicle of mean 0.

Autoregressive Conditional Heteroskedasticity (ARCH) Models: ARCH processes are the statistical methods often used to model the volatility of the time series (Sharon Chiang *et al*. 2013). (Brockwell, P. J., & Davis, R. A., 1996) proposes:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p}(\alpha_i \varepsilon_{t-i}^2) \quad (10)$$

where σ_t^2 is the conditional variance at period t; $\alpha_0 > 0$, is a constant parameter called ARCH constant or intercept term; $\alpha_{i,1\le i\le p} > 0$, are the ARCH coefficients that present the impact of the residuals; ε_{t-i}^2 are the squares of the previous residuals. (Caporin, M., & Storti, G. 2020) proposed the generalized form:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p}(\alpha_i \varepsilon_{t-i}^2) + \sum_{j=1}^{q}(\beta_j \sigma_{t-j}^2) \quad (11)$$

where σ_{t-j}^2 are the squares of the previous values of the conditional variance; $\beta_{j,1\le j\le q}$, are GARCH coefficients that represent the impact of the previous conditional variances; p and q are natural numbers.

There are several other methods in the ARCH family that deal with chronicles such as EGARCH (Exponential GARCH) which introduces a logarithmic representation, TGARCH (Threshold GARCH) which introduces the notion of threshold to distinguish the levels of volatility in the observed series. GARCH models assume that volatility evolves over time and can be predicted based on past data unlike traditional models that assume that volatility is constant. They capture the essence of financial markets: volatility depends on past information and does not remain constant. This is in fact a powerful tool to capture the unpredictable nature of stock prices, making forecasts more robust and accurate. GARCH accepts the reality that volatility is not stable: it fluctuates over time. In financial markets, some days are calm, while others are very volatile. GARCH helps to capture and predict these fluctuations.

Dataset: For our experiments, we use data on confirmed malaria cases from the site: https://dhis-minsante-cm. org/ set up by the Cameroonian Ministry of Public Health and managed by the Health Information Unit. It contains data on several diseases collected at the level of health facilities and aggregated each week to obtain information at higher levels of geographical granularity. The maximum level of granularity is the national level, where the data is aggregated for the entire country.

These data are collected weekly over a period of five (05) years, from 2018 to 2022. These datasets stored in csv format have the same number of columns (variables), fifteen (15) in total. The first three columns give the order of the weeks over the years. Since the intention is to work on a single set of the data set, we standardized the variables by renaming them so that all the variables have the same names. After concatenating the set of five (05) data sets, we obtained a set consisting of fifteen (15) variables including four (04) categorical variables and eleven (11) numerical variables on 260 records (lines). All the numerical variables are concatenated into a new variable (explanatory variable) which increases the total number of variables to sixteen (16). Table 1 gives statistics on the data set used.

Table 1. dataset statistics

Variable	Mean	Standard Deviation	Min	25%	Median	75%	Max
District_Bankim	244.2	62.3	107.0	197.0	240.0	279.0	466.0
District_Banyo	245.3	74.5	125.0	195.0	231.0	280.0	559.0
District_Belel	137.3	44.5	11.0	110.0	130.0	161.0	270.0
District_Dang	225.6	81.8	45.0	171.0	226.0	273.0	495.0
District_Djohong	265.0	125.9	79.0	167.0	238.0	356.0	622.0
District_Meiganga	427.6	109.5	198.0	352.0	415.0	494.0	728.0
District_Ngaoundal	329.0	114.5	160.0	265.0	311.0	365.0	1053.0
District_Ngaoundere_ Rural	348.2	93.1	19.0	285.0	328.0	405.0	692.0
District_Ngaoundere_Urbain	697.5	165.7	379.0	595.0	654.0	754.0	1294.0
District_Tibati	293.2	67.4	122.0	242.0	297.0	340.0	488.0
District_Tignere	264.2	83.4	97.0	206.0	256.0	313.0	532.0
Région_Adamaoua	3477.9	710.4	2156.0	2975.0	3416.0	3921.0	5717.0

RESULTS AND DISCUSSIONS

The original series is tested by the Augmented Dicky Fuller (ADF) test and its stationarity is confirmed by the Ljung Box test, before proceeding with the decomposition into different trend, seasonal and residual components. We then recovered the residual component for the rest of our study. After the autocorrelation and stationarity test, it is then divided by two: one part for training and the other for testing. A descriptive analysis allowed us to extract necessary information and describe the variables by their type and content. Figure 3 presents a visualization that gives an idea about the distribution of the dataset. Figure 4 presents the frequency distribution of the dataset values.

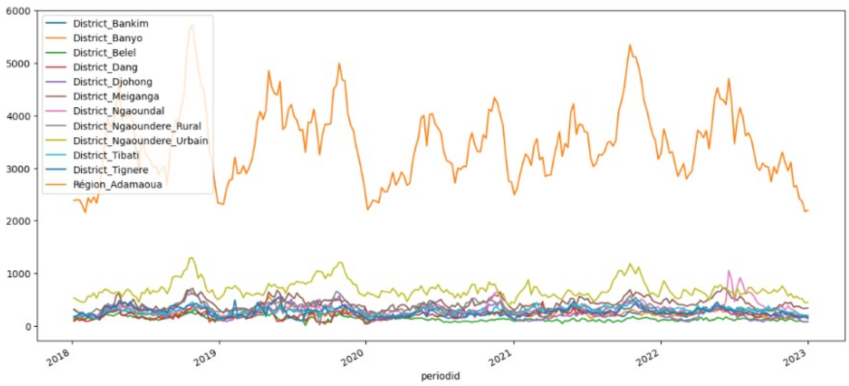

Figure 3. Data distribution graph

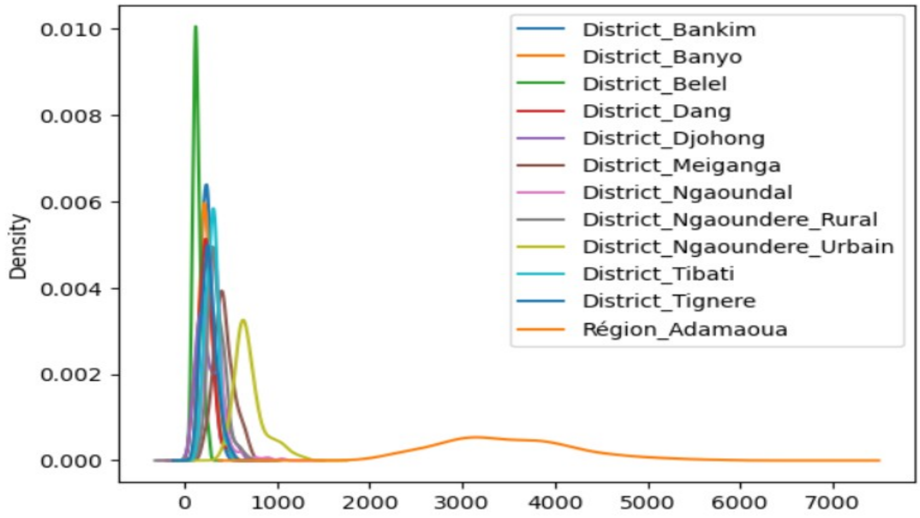

Figure 4. Frequency distribution of values

Figure 5 shows the graph of confirmed malaria cases in the Adamawa region.

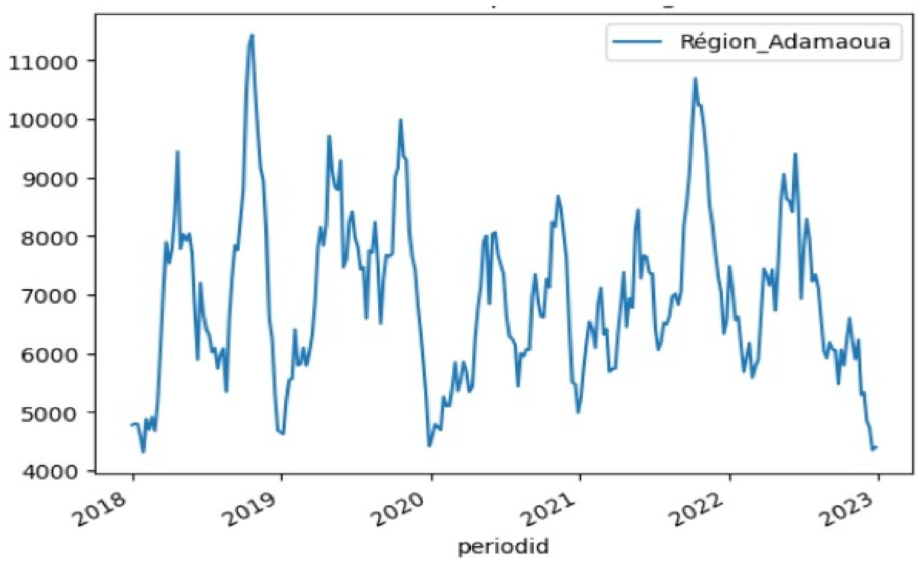

Figure 5. Graph of confirmed malaria cases in the Adamawa region

Figure 6 shows the results of the normality tests. Although the cycles in the residuals suggest that some temporal structures (such as seasonality, rare events, or nonlinear dependencies) might need further modeling, the model seems to capture the general trend well, as the residuals are generally centered around zero. Overall, the graph shows that the residuals oscillate around 0, which is a good indication that the model captures the general trend well. However, there are some large fluctuations (high amplitudes), which could indicate outliers or periods where the model is underperforming.

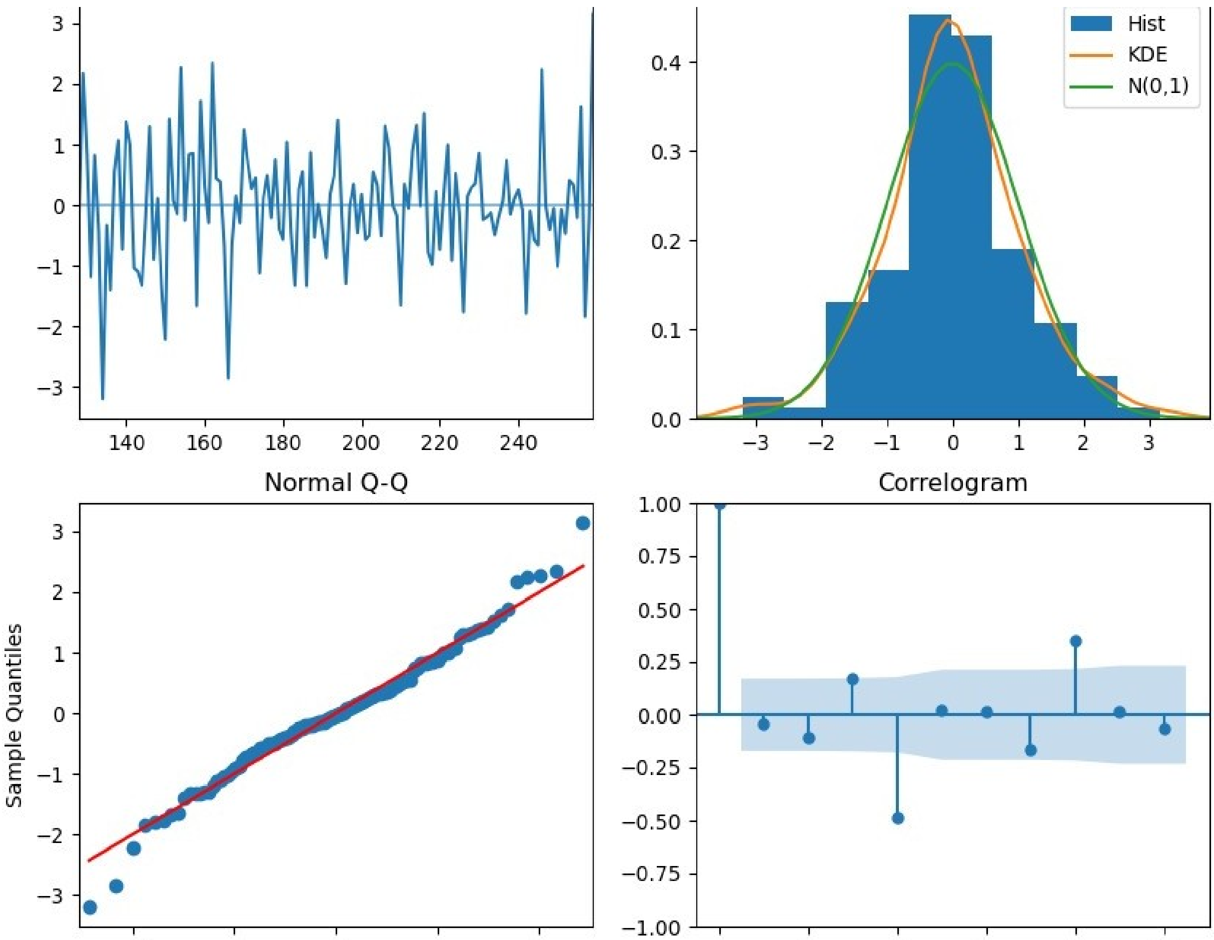

Figure 6. Graph of normality tests

Figure 7 presents the characteristics of ARIMA (1,0,0) applied to the training set consisting of the entire series except the last 30 observations reserved for testing.

```
==============================================================================
Dep. Variable:                residus   No. Observations:                  230
Model:                 ARIMA(1, 0, 0)   Log Likelihood               -1523.728
Date:                Sun, 29 Oct 2023   AIC                           3053.456
Time:                        14:57:54   BIC                           3063.770
Sample:                             0   HQIC                          3057.617
                                - 230
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const         23.1251     49.902      0.463      0.643     -74.682     120.932
ar.L1          0.7617      0.038     19.925      0.000       0.687       0.837
sigma2      3.316e+04   2448.916     13.539      0.000    2.84e+04     3.8e+04
===================================================================================
Ljung-Box (L1) (Q):                   0.78   Jarque-Bera (JB):                15.68
Prob(Q):                              0.38   Prob(JB):                         0.00
Heteroskedasticity (H):               1.55   Skew:                             0.04
Prob(H) (two-sided):                  0.06   Kurtosis:                         4.28
===================================================================================
```

Figure 7. Characteristics of the ARIMA(1,0,0) model

Considering that ARIMA(p,d,q) is the composition of the AutoRegressive AR(p) and Moving Average MA(q) models, by making a differentiation I(d), and noting that the orders d=q=0, we are reduced to an AutoRegressive AR(p) model. The characteristics of the AR(1) model are presented in Figure 8.

Dep. Variable:	residus	No. Observations:	260
Model:	ARIMA(1, 0, 0)	Log Likelihood	-1715.213
Date:	Sat, 04 Nov 2023	AIC	3436.426
Time:	13:24:52	BIC	3447.108
Sample:	0	HQIC	3440.720
	- 260		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
const	16.8560	48.049	0.351	0.726	-77.318	111.030
ar.L1	0.7737	0.036	21.718	0.000	0.704	0.843
sigma2	3.135e+04	2157.930	14.530	0.000	2.71e+04	3.56e+04

Ljung-Box (L1) (Q):	1.14	Jarque-Bera (JB):	20.48
Prob(Q):	0.29	Prob(JB):	0.00
Heteroskedasticity (H):	1.04	Skew:	0.09
Prob(H) (two-sided):	0.84	Kurtosis:	4.36

Figure 8. Characteristics of AR(1)

We therefore have the expression of our model: $X_t = 16.8560 + 0.7737X_{t\text{-}1}$

We can see that the values of σ^2 are exponentially large. The value 0.84 of heteroscedasticity explains the null hypothesis is rejected so there is presence of information. We also note the value of Ljung-Box equal to 0.29 which is less than 5%. These findings lead to the conclusion that the AR(1) model is not the best model in this case, however it has made it possible to prove the existence of information in the residues. Since we have a regression problem, to evaluate our model we use the mean absolute error (MAE), the mean absolute percentage error (MAPE), the mean square error (MSE) and the coefficient of determination R^2. We have in the test R^2-adjusted = 95% and MAPE = 43%. These values show that our model fits the residual series better. Graphically the residuals of our model seem stationary as shown in Figure 9. It is necessary to test its whiteness by performing some tests.

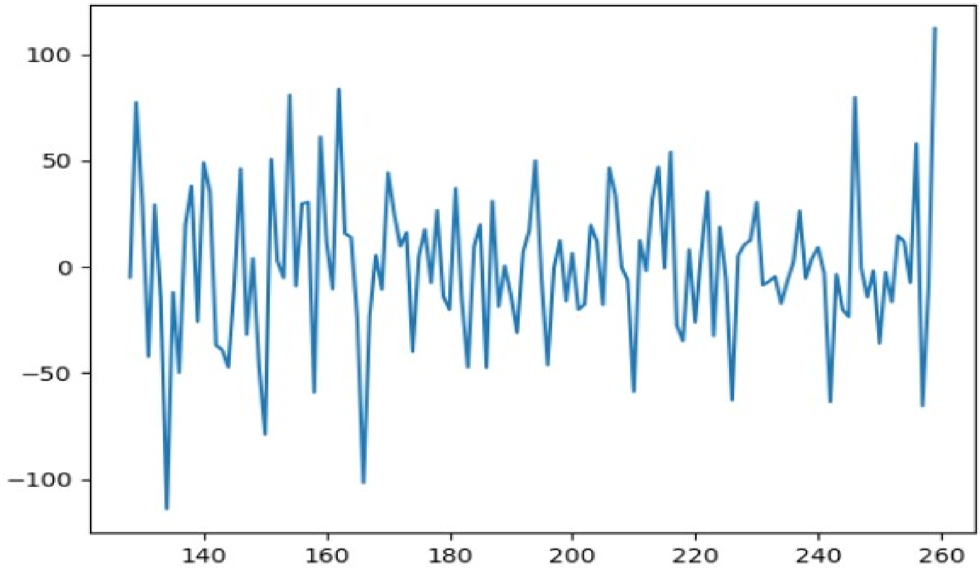

Figure 9. AR(1) model residuals Graph

For autoregressive models the Ljung Box test is used to ensure that all temporal structures have been captured. The Ljung-Box test on residuals is a key step in validating a time series model. It ensures that the residuals behave as white noise, which is crucial for the reliability of model-based forecasts and analyses. Table 2 presents the results of our Ljung Box test.

Table 2. Ljungbox test

Lag	p-valeur
6	0.17932467526273896
12	0.08966237622658224
18	0.0597749175091916

The different p − values are greater than 0.05 so, we can say that the null hypothesis is accepted so our model is adequate. Also, the Shapiro-Wilk test, a statistical test that allows to check if the residuals of a model follow a normal distribution, presented in Table 3, gives us p − value is greater than 0.05. This means that the residuals follow a normal distribution. This is favorable for the validation of the model. In addition, this model is evaluated at R^2 with a precision score of 99% in the test, which is above that of (21) with its RNN / LSTM model achieved a score of 88% in the test and of (22) with ARIMA-ARCH having a score of 74% in the test.

Table 3. Shapiro test

Statistic	0.9742071032524109
p-valeur	0.33667037561535835

The results of our trained model and the prediction are shown in Figure 10. The residual series is subdivided into two parts: the first part was used for training the model and the second part was used for prediction.

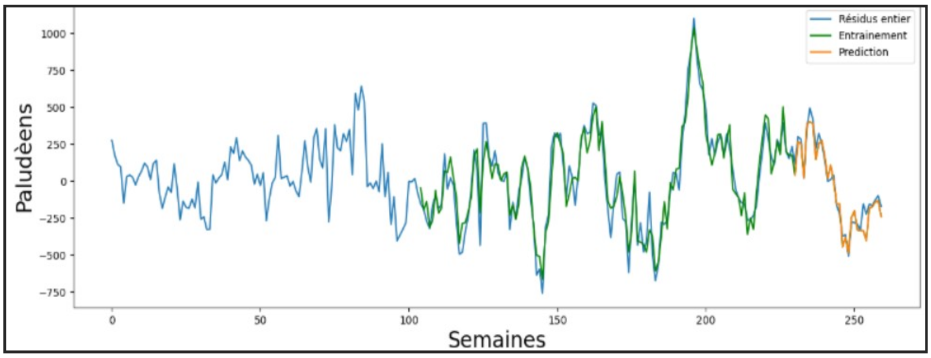

Figure 10. Model Results

The residual tests of this model confirmed that the residuals are white, normally distributed, centered and reduced. Malaria generally seems to reach a seasonal peak at the end of the third quarter of each year. This may be due to the humidity and high rainfall at this time of year which corresponds to the so-called rainy season. Decision-makers should particularly strengthen health systems during this period through awareness campaigns, the distribution of health kits composed of impregnated mosquito nets or any other measure deemed useful. This could significantly reduce the number of malaria cases.

CONCLUSION

The entire health series of confirmed malaria cases in the Adamoua region is studied to understand the statistical characteristics. Then it is decomposed and the residual component is recovered and constitutes a new series to be studied. The autoregressive method is applied to capture the information contained in the residuals. The residuals of the model are tested. The whiteness tests of the residuals of the AR(1) model are positive and allow us to affirm that it is a good model. A good understanding of the residuals is essential to refine the models, detect anomalies and extract hidden information, thus allowing us to better understand and anticipate temporal phenomena. The analysis of irregular fluctuations makes it possible to detect hidden effects, often neglected in traditional studies, and to correct the models accordingly. In the field of health, irregular fluctuations make it possible to quantify the uncertainty in predictions, which is essential for risk-based decisions. Modeling residuals and irregular fluctuations in health time series enriches scientific understanding of complex dynamics, improves predictive tools, and strengthens the ability to respond effectively to public health challenges. For the dataset used in this work, it should be noted that it does not present many notable residuals or irregular fluctuations. It is desirable in perspective to consider an application on large quantities of data with notable residuals or irregular fluctuations and to develop hybrid techniques, combining machine learning (LSTM, transformers) and statistical approaches (ARIMA-GARCH).

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