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Environmental Health Situation: A Case Study of Childhood Diseases in Southwest Nigeria

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ABSTRACT
Childhood diseases in the Southwest region of Nigeria remain a pressing public health concern. An in-depth analysis of disease prevalence, trends, and forecasting is essential for informed interventions. This study draws upon a dataset encompassing a 32-year period, from 1990 to 2022, detailing the prevalence of various childhood diseases. Data collection and curation processes ensured comprehensive coverage of the region's health landscape. Employing a combination of descriptive statistics and time series modeling, we examined disease prevalence, temporal patterns, and stationarity transformations. ARIMA models, augmented Dickey-Fuller tests, and stationarity differencing techniques were instrumental in the analysis. The analysis revealed persistent prevalence of Diarrhoea, fluctuating patterns in Malaria and Kidney disease, stability in Whooping cough and Measles, and fluctuations in Skin disease. These temporal patterns were corroborated by ARIMA models, uncovering intricate relationships and predicting future trends. Notably, targeted interventions, adaptable strategies, vigilance in vaccination programs, and environmental health initiatives emerged as essential strategies for the Southwest region. The study offers a comprehensive understanding of childhood disease dynamics, with implications for public health planning and interventions.
KEYWORDS: Childhood Disease, Time Series Modeling, ARIMA Models, Whooping Cough, Malaria and Kidney Disease
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1. INTRODUCTION

Childhood diseases are a significant public health concern worldwide, with a substantial impact on child morbidity and mortality (Bhutta & Saeed, 2018). In developing countries like Nigeria, the burden of childhood diseases remains a critical issue, particularly in the Southwest region (Ugboko et al., 2020). The Southwest region, comprising states such as Lagos, Ogun, Oyo, Osun, Ekiti, and Ondo, is one of the most densely populated regions in Nigeria, and it faces numerous health challenges, including the high prevalence of childhood diseases (He et al., 2018).

Childhood diseases encompass a wide range of conditions, including malaria, pneumonia, diarrhea, measles, and malnutrition, among others. These diseases often lead to severe health consequences, contributing to a considerable number of childhood deaths in the region (Walson & Berkley, 2018). Understanding the temporal patterns and trends in the prevalence of these diseases is essential for public health planning, resource allocation, and the development of effective interventions (Lederberg, 2016).

Diseases can be devastating for anyone, but seems particularly unfair when they attack children (Nwachuku & Gerba, 2006). Unfortunately, many diseases seem to have interest in infecting children more frequently and vigorously than the adults (Nwachuku & Gerba, 2006). Children are more susceptible to diseases for a number of reasons. The major reason for children’s increased susceptibility is that they are often exposed to diseases, yet they have not built the immunological defenses required to fend off certain diseases (Perlin & Cohen, 2002) three diseases were considered in this research work (Measles, Fever in children (Malaria), Whooping cough). Time series analysis is a powerful statistical method that can be employed to study the temporal behavior of data points collected at regular intervals (Ozaki, 2012). In the context of childhood diseases, time series analysis allows us to examine how the prevalence of these diseases has evolved over time, identify underlying patterns, and make forecasts for future disease prevalence (Yadav & Akhter, 2021). This predictive capability can assist healthcare authorities, policymakers, and healthcare practitioners in the Southwest region in planning and implementing targeted interventions to mitigate the impact of childhood diseases.

Childhood diseases represent a complex and multifaceted challenge that affects not only the health of young individuals but also has broader implications for communities and societies. The Southwest region of Nigeria, with its mix of urban and rural areas, faces a unique set of circumstances in the battle against childhood diseases (Antai & Moradi, 2010). The Southwest region is characterized by significant socioeconomic disparities. While urban areas like Lagos boast relatively better access to healthcare facilities, rural areas may struggle with limited resources, infrastructure, and access to essential healthcare services (Oladipo, 2014). The availability and quality of healthcare infrastructure, including hospitals, clinics, and vaccination programs, vary across the Southwest region. This infrastructure influences not only disease detection and treatment but also vaccination coverage, which is critical in preventing diseases like measles, polio, and others. Analyzing the relationship between healthcare infrastructure and disease prevalence is crucial for improving healthcare delivery. The population composition of the Southwest region, including factors such as birth rates, population density, and migration patterns, can impact disease prevalence. Understanding how demographic changes influence disease dynamics can aid in resource allocation and preparedness for potential outbreaks.

This study is motivated by the urgent need to address the high prevalence of childhood diseases in the Southwest region of Nigeria. By leveraging time series analysis techniques, we aim to provide valuable insights into disease trends and develop predictive models that can support evidence-based decision-making in public health. Ultimately, our goal is to contribute to the reduction of childhood disease burden and enhance the overall health outcomes of children in the Southwest region.

2. LITERATURE REVIEW

Overview of Childhood Diseases

Childhood diseases encompass a wide spectrum of illnesses and conditions that affect infants, children, and adolescents (Ezeonwu et al., 2014). They represent a significant public health concern globally, with a particular impact on developing regions such as Nigeria (Ezeonwu et al., 2014). Understanding the types and characteristics of childhood diseases is essential for effective disease prevention and management. These diseases are caused by microorganisms such as bacteria, viruses, and parasites. They include but are not limited to malaria, pneumonia, diarrhea, measles, and tuberculosis. Understanding the transmission dynamics, risk factors, and prevention strategies for these diseases is crucial. Childhood non-infectious diseases, such as malnutrition, obesity, and chronic conditions like asthma and diabetes, pose a significant health burden (Boutayeb, 2010). Examining the prevalence, determinants, and long-term health effects of these conditions is vital. Vaccination programs are a cornerstone of public health efforts to combat childhood diseases.

Factors Influencing the Prevalence of Childhood Diseases

Childhood diseases are not isolated occurrences but rather complex outcomes that result from a web of interconnected factors and processes. Most childhood diseases do not have a single, direct cause. Instead, they typically result from a combination of factors working together (Church, 2004). For example, a child's susceptibility to an infectious disease like pneumonia may depend on genetic factors, immune system strength, exposure to pathogens, and environmental conditions.

Environmental Factors

Environmental factors have a significant impact on the prevalence of childhood diseases, especially in regions like the Southwest of Nigeria. These factors include:

i. Climate and Seasonal Variations: Weather patterns and seasonal changes can influence disease transmission, particularly in vector-borne diseases like malaria. Understanding the link between climate and disease prevalence is essential for proactive disease management.
ii. Water Quality: Access to clean and safe drinking water is crucial for preventing waterborne diseases such as cholera and diarrhea. Contaminated water sources can contribute to disease outbreaks.
iii. Sanitation and Hygiene: Proper sanitation practices, including the availability of toilets and waste disposal facilities, are essential for reducing the transmission of diseases caused by fecal-oral contamination.
iv. Vector Habitats: Diseases transmitted by vectors (e.g., mosquitoes) are influenced by the availability of breeding sites. Stagnant water and poor waste management can create breeding grounds for disease-carrying vectors.
v. Air Quality: Environmental factors like air pollution and indoor air quality can impact respiratory diseases in children. Exposure to indoor pollutants, such as tobacco smoke, can worsen disease outcomes.

Prevalence of Childhood Diseases in the Southwest Region of Nigeria

[i] Cough and Respiratory Infections

In the Southwest region of Nigeria, as in many parts of the world, cough and respiratory infections are common among children, particularly during the cooler and drier months. The Harmattan season, which brings dry and dusty winds, can exacerbate respiratory issues. While these infections are generally mild, they can contribute to school absenteeism and place a strain on healthcare resources, especially in densely populated areas.

[ii] Measles

Measles remains a concern in some parts of Nigeria, including the Southwest region. The prevalence of measles can vary within the region, influenced by factors such as vaccination coverage and population density. Areas with higher vaccine coverage tend to have lower measles prevalence. However, pockets of low vaccination rates can make some communities vulnerable to measles outbreaks.

[iii] Chickenpox (Varicella)

Chickenpox is a childhood disease that still occurs in the Southwest region, although its prevalence has reduced due to vaccination efforts. The effectiveness of vaccination campaigns can vary by location and community awareness. Those who are not vaccinated or have not had chickenpox before remain at risk of contracting the virus.

[iv] Whooping Cough (Pertussis)

Pertussis outbreaks can occur in the Southwest region and other parts of Nigeria. Vaccine coverage and healthcare infrastructure influence prevalence. Periodic outbreaks can strain local healthcare systems and emphasize the importance of vaccination in reducing the spread of the disease.

[v]Asthma

Asthma prevalence in children in the Southwest region may be influenced by environmental factors, such as air quality, allergens, and exposure to indoor smoke from cooking. The region's urban areas, including Lagos, may have a higher prevalence due to air pollution and other environmental factors.

[vi] Diarrheal Diseases

Diarrheal diseases remain a public health concern, particularly in areas with inadequate access to clean water and sanitation facilities. In some parts of the Southwest region, urbanization has improved infrastructure, reducing the prevalence of diarrheal diseases. However, rural areas may still face challenges in this regard.

[vii] Malaria

Malaria is a significant concern in the Southwest region, especially during the rainy season when mosquito populations increase. While malaria prevalence varies within the region, preventive measures like insecticide-treated bed nets and antimalarial medication distribution play a vital role in reducing the burden of the disease.

3. METHODOLOGY

We employed time series approach in the study to predict the prevalence of childhood diseases in the Southwest Region of Nigeria.. An exploratory data analysis (EDA) was conducted to visually examine the historical data using time series plots. The primary goal of this step is to unveil potential trends, seasonality, and patterns in the prevalence of childhood diseases, which will provide crucial insights for the subsequent modeling. The model selection and fitting process was carried out, with a focus on determining the appropriate ARIMA model order (p, d, q) for each specific disease.

Following the fitting of ARIMA models, comprehensive model evaluation and diagnosis were performed. This involved diagnostic tests such as the Ljung-Box test to examine residual autocorrelation and the Jarque-Bera test to assess the normality of residuals. Additionally, the quality of model fit were assessed using statistical metrics such as the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) for model comparison. The final step involved leveraging the fitted ARIMA models to provide forecasts of future disease prevalence for the specified time period.

3.3 Data Collection

For this research project, the primary data source is the UNICEF Data Explorer https://data.unicef.org/resources/data_explorer/unicef., a comprehensive platform managed by the United Nations Children's Fund (UNICEF). The UNICEF Data Explorer offers a rich repository of datasets encompassing a diverse array of indicators related to child and maternal health, nutrition, education, and various socio-economic factors. Access to this platform allows for the extraction of valuable insights and statistical information crucial for understanding the prevalence of specific childhood diseases, including Diarrhoea, Malaria, Kidney diseases, Whooping Cough, Measles, and Skin diseases, in the Southwest region of Nigeria. The data collected spans from 1990 to 2022, capturing a comprehensive view of the evolving trends over this significant time period. The data retrieved from UNICEF serves as a foundation for the time series analysis conducted in this study, offering a reliable and globally recognized source for child-focused data.

3.4 Data Analysis

The data analysis section delves into the techniques and methods used to process and analyze the collected data. It discusses the software or tools employed for data analysis, the specific statistical or computational methods used, and how these methods align with the research questions and objectives. The section provides transparency on how the time series approach is utilized to predict the prevalence of childhood diseases and the variables considered in the analysis.

3.4.1 ARIMA Time Series Models and Their Assumptions

Autoregressive Integrated Moving Average (ARIMA) models are a class of time series forecasting techniques widely used in various fields, including economics, finance, and epidemiology. ARIMA models are powerful tools for analyzing and predicting time-dependent data. They combine autoregressive (AR) and moving average (MA) components with differencing to achieve stationarity. To use ARIMA effectively, it's crucial to understand the underlying assumptions and structure of the model.

Components of ARIMA:

i. Autoregressive (AR) Component: This part of the model captures the relationship between the current value and previous values of the time series. It assumes that past values of the series are useful in predicting the future.

ii. Integrated (I) Component: Differencing the time series data is the integration component. It makes the data stationary by removing trends and seasonality.

iii. Moving Average (MA) Component: This component models the relationship between the current value and past error terms or "shocks" of the time series.

Assumptions:

i. Stationarity: ARIMA assumes that the time series is stationary. Stationarity means that the statistical properties of the series, such as mean and variance, do not change over time. If the series is not stationary, differencing is applied until stationarity is achieved.

ii. Independence: ARIMA assumes that observations at different time points are independent. In other words, the value at one time doesn't depend on the values at other times, except through the specified AR and MA terms.

iii. Constant Variance: The variance of the errors or residuals (the differences between observed and predicted values) should be constant over time.

iv. No Seasonality: Basic ARIMA models do not account for seasonality in the data. For seasonal time series, seasonal decomposition or seasonal ARIMA (SARIMA) models should be considered.

3.4.2 Box-Jenkins ARIMA Process of Model Analysis

Box-Jenkins forecasting models consist of a four-step iterative procedure as follows; Model Identification, Model Estimation, Model Checking (Goodness of fit) and Model Forecasting. The four iterative steps are not straight forward but are embodied in a continuous flow chart depending on the set of data under study.

3.4.3 Stationary Test (Augmented Dickey Fuller, ADF)

A time series data is said to be stationary when its properties like mean, variance and co-variance do not change over time (Shrestha & Bhatta, 2018). The ADF model tests the unit root as follows:

$$\Delta y_t = \mu + \delta y_{t-1} + \sum_{i=1}^{k} \beta_i \Delta y_{t-1} + \varepsilon_t \qquad (5)$$

Where:

$\delta = \alpha - 1$,

α = coefficient of y_{t-1}; and

Δy_{t-1} = first difference of y_t

The hypothesis for the Augmented Dickey Fuller (ADF) test is given as;

H_0: *there is no unit root (the series is non stationary)*

H_1: *there is unit root (the series is stationary)*

3.4.4 Model Identification (Selecting an initial model)

We first Determine whether the series is stationary or not by considering the graph of ACF. If a graph of ACF of the time series values either cuts off fairly quickly or dies down fairly quickly, then the time series values should be considered stationary. Differencing is done until a plot of the data indicates the series varies about a fixed level, and the graph of ACF either cuts off fairly quickly or dies down fairly quickly. Once a stationary series has been obtained, then the form of the model to be used can be identified.

3.4.5 Differencing in Time series Analysis

Differencing is a common technique used in time series analysis to remove trend and seasonality from a data series. It involves taking the difference between consecutive observations in the series. This can be done one or more times, depending on the degree of trend or seasonality in the data.

3.4.6 Model Estimation and Evaluation
Once a model is identified, the next stage for Box-Jenkins approach is to Estimate the parameters. In this research, the estimation of parameters was done using maximum likelihood estimation (MLE) with the help of the R-Console statistical package.

3.5 Information Criterion
3.5.1 Akaike Information Criterion (AIC)
The final model after estimation can be selected using a penalty function statistic such as the Akaike Information Criterion (AIC), a measure of the goodness of fit an estimated statistical model. Given a data set, several competing models may be ranked according to their AIC with one having the lowest information criterion value being the best. These information criterion judges a model by how close its fitted values, in terms of certain expected values.

Then the AIC value of the model is given as.

$$AIC = 2k - 2\ln(\widehat{L})$$

3.5.2 Bayesian Information Criterion (BIC)

$$BIC = \ln(n)\,k - 2ln\,(\widehat{L})$$

Where;

$\hat{L}$ = the maximum value of the likelihood function of the model M, i.e., $\hat{L} = p(x|\hat{\theta}, M)$, where $\hat{\theta}$ are the parameter values that maximize the likelihood function;

x = the observed data; n = the number of data points in x, the number of observations, or equivalently, the sample size; k = the number of parameters estimated by the model.

4. ANALYSIS AND RESULTS
4.1 Descriptive Statistics of Data
Table 4.1 presents summary statistics for various diseases for predicting the prevalence of childhood diseases in the Southwest region of Nigeria. The mean values provide an average estimate of the reported cases for each disease. For instance, Diarrhoea cases show an average of 41,625, and Malaria cases have an average of 63,187. These mean values serve as central tendencies for the respective diseases. The standard deviation (Sd) measures the variability or spread around the mean. Diseases like Diarrhoea and Kidney disease exhibit relatively low variability, suggesting that reported cases tend to cluster closely around the average. On the other hand, diseases like Malaria, Whooping cough, Measles, and Skin disease show moderate variability. The minimum and maximum values indicate the range of reported cases. For instance, the minimum and maximum Diarrhoea cases are 41,013 and 42,141, respectively. Furthermore, Skewness measures the asymmetry of the distribution. Negative skewness, as seen in Diarrhoea, Kidney disease, Whooping cough, Measles, and Skin disease, suggests a longer tail on the left side of the distribution.

Table 4.1: Summary statistics of the disease's cases

Diseases cases	Mean	Sd	Min	Max	Skewness
Diarrhoea	41625.18	290.86	41013	42141	-0.2
Malaria	63187.36	643.04	62028	64329	0.08
Kidney disease	4057.36	29.85	4003	4105	-0.16
Whooping cough	10117.36	55.04	100000	10207	-0.36
Measles	16221.45	98.99	16053	16371	-0.21
Skin disease	20357.67	109.03	20144	20496	-0.49

4.2 Prevalence of Diseases among children between 1990 to 2022

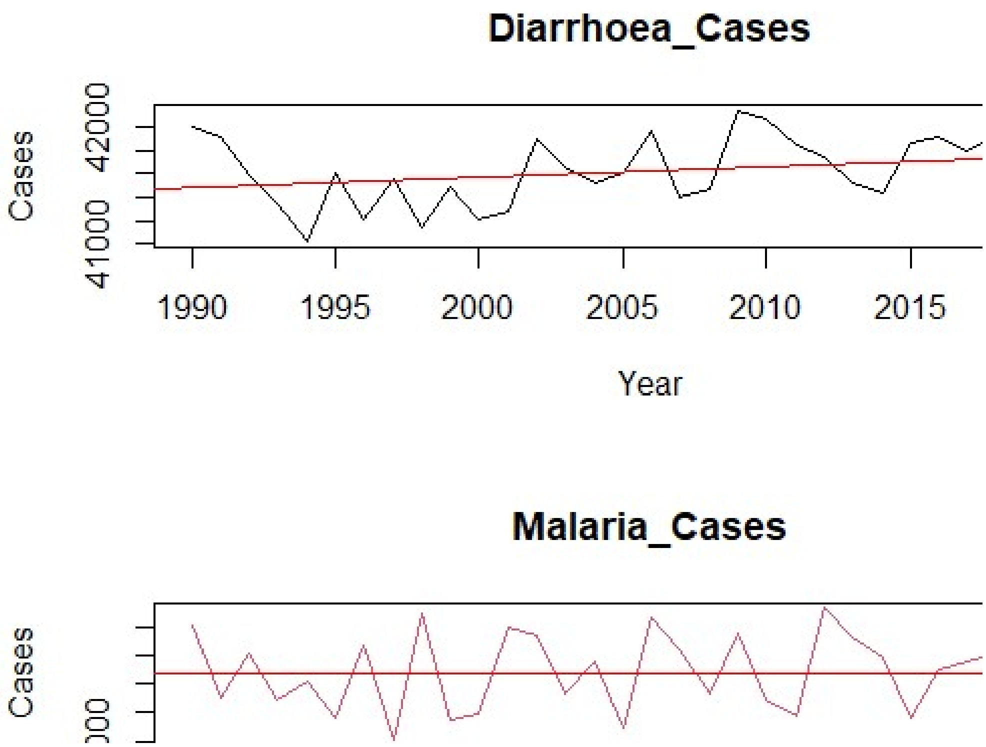


Figure 4.1: Trend line showing prevalence of Diarrhoea and Malaria case (1990-2022)

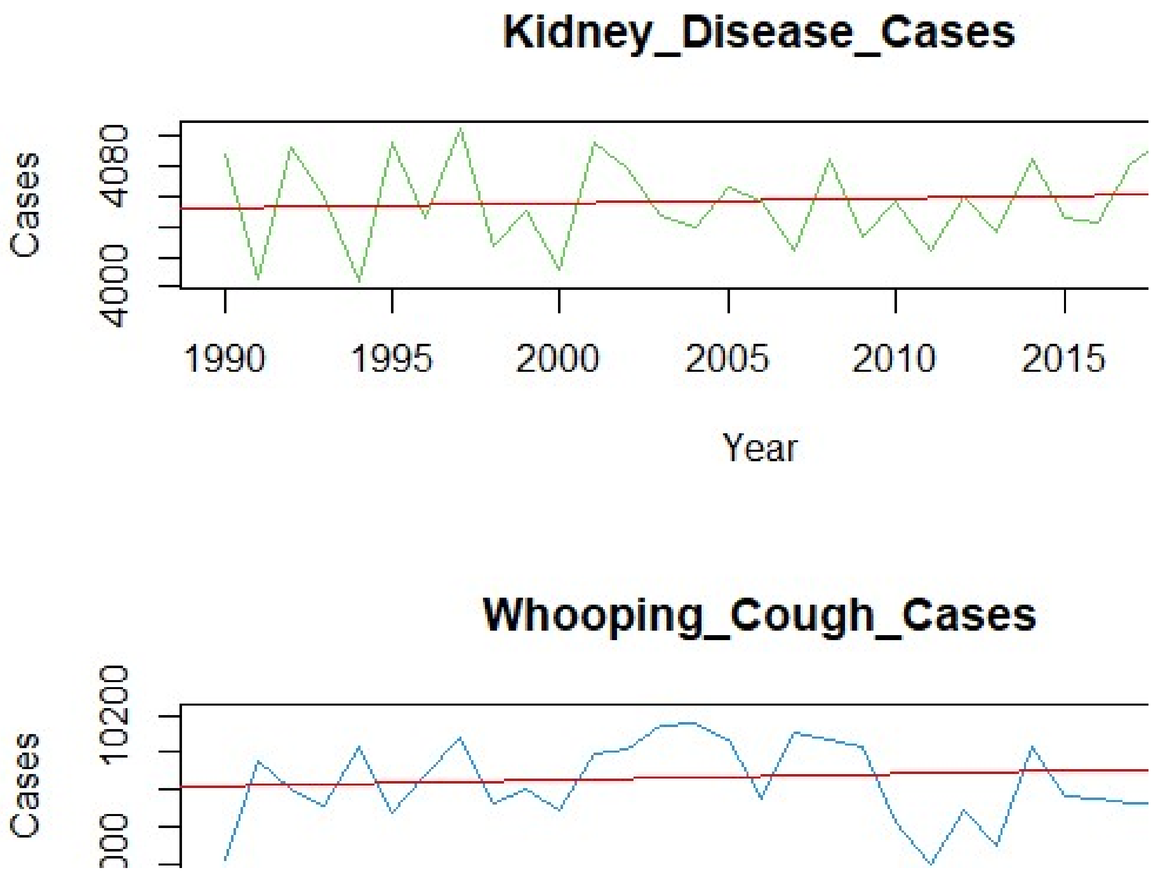
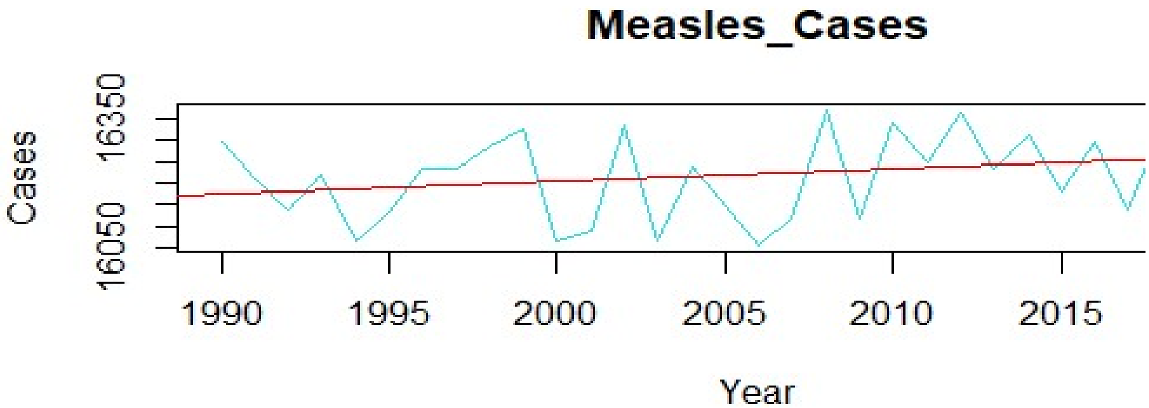


Figure 4.2: Trend line showing prevalence of kidney disease and whooping cough case (1990-2022)



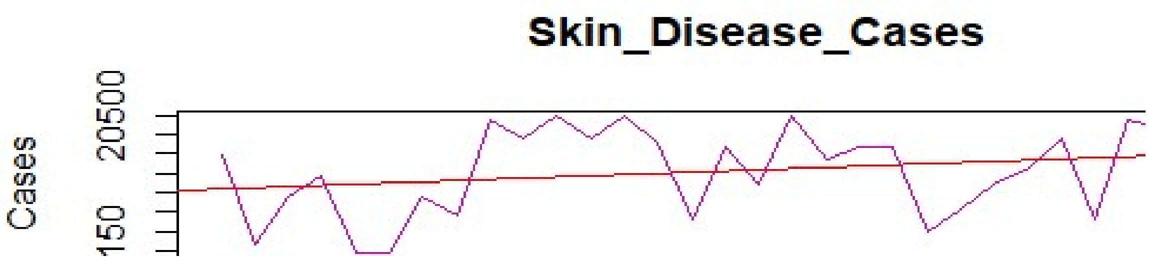


Figure 4.3: Trend line showing prevalence of measles and skin disease case (1990-2022)

Figure 4.1 to 4.3 presents the prevalence of childhood diseases in Nigeria's Southwest region from 1990 to 2022. Notably, Diarrhoea cases remain consistently prevalent, ranging from 41,013 to 42,141 annually, indicating a persistent burden. Malaria cases exhibit a fluctuating pattern with an overall increasing trend, ranging from 62,028 to 64,329, emphasizing the enduring impact of malaria in the region. Reported cases of kidney disease remain relatively low and stable, fluctuating between 4,003 and 4,105, suggesting a consistent but not pervasive occurrence. Whooping cough cases demonstrate stability with a slight upward trend, ranging from 10,000 to 10,207. Measles cases show stability with a slight increase in recent years, ranging from 16,053 to 16,371, indicating potential impacts of vaccination efforts. Skin diseases maintain a relatively stable prevalence, ranging from 20,144 to 20,496, emphasizing a consistent burden over the analyzed period

4.3 Stationarity of the data (Unit root test)

Table 4.2 presents the results of the Augmented Dickey-Fuller (ADF) test, assessing the stationarity of the variables before and after differencing for childhood diseases in Nigeria's Southwest region.

Before differencing, Diarrhoea, Kidney disease, Whooping cough, Measles, and Skin disease exhibit non-stationary behavior with p-values above the significance level of 0.05, implying a failure to reject the null hypothesis of non-stationarity. Malaria, however, shows some evidence of stationarity with a p-value of 0.03729, although still above the 0.01 significance level.

After differencing, all variables become stationary. Diarrhoea, Kidney disease, Whooping cough, Measles, and Skin disease exhibit ADF test statistics with p-values of 0.01, satisfying the significance threshold for stationarity. Malaria also becomes stationary, with an ADF test statistic of -5.1941 and a p-value of 0.01.

Table 4.2: Stationary test (ADF test)

	Before Differencing			After Differencing		
Variables	ADF test	p-value	Conclusion	ADF test	p-value	Conclusion
Diarrhoea	-3.122	0.1391	NS	-4.3884	0.01	Stationary
Malaria	-3.7428	0.03729	S	-5.1941	0.01	Stationary
Kidney disease	-3.3999	0.0747	NS	-6.9901	0.01	Stationary
Whooping cough	-2.4894	0.3837	NS	-4.6594	0.01	Stationary
Measles	-2.9429	0.2084	NS	-4.4245	0.01	Stationary
Skin disease	-2.4663	0.3926	NS	-3.5424	0.04	Stationary

**Significance at 5% level; **significance at 10% level; ***significance at 1% level*

4.4 Time Series Modeling of the Diseases Prevalence

In the ARIMA (1,0,0) model estimated for Diarrhoea prevalence (Table 4.3.1), the coefficient for the autoregressive term (AR(1)) is 0.3169. This indicates a positive relationship between the current prevalence of Diarrhoea and its past value, suggesting that the occurrence of Diarrhoea in one time period influences its occurrence in the subsequent period. The mean estimate for Diarrhoea prevalence is 41,631.6973. This represents the average level of Diarrhoea cases when the autoregressive effect is taken into account. The Akaike Information Criterion (AIC) is 456.59, and the Bayesian Information Criterion (BIC) is 460.99. These information criteria serve as indicators of the model's goodness of fit. In this context, the lower the AIC and BIC values, the better the model. Therefore, the AIC of 456.59 suggests a relatively good fit of the ARIMA (1,0,0) model to the Diarrhoea prevalence data.

Table 4.3: Estimation of ARIMA (1,0,0) for modeling Diarrhoea Prevalence

Coefficients	
AR (1)	Mean
0.3169	41631.6973
AIC	456.59
BIC	460.99

Table 4.3.2 presented the ARIMA (0,0,1) model estimated for Malaria prevalence, the coefficient for the moving average term (MA(1)) is -0.4878. This negative coefficient suggests that the current prevalence of Malaria is influenced by the past residual errors, indicating a corrective mechanism in response to previous forecasting errors. The mean estimate for Malaria prevalence is 63,100.17, representing the average level of cases when considering the impact of the moving average effect. The Akaike Information Criterion (AIC) is 504.31, and the Bayesian Information Criterion (BIC) is 508.71.

Table 4.4: Estimation of ARIMA (0,0,1) for modeling Malaria Prevalence

Coefficients	
MA (1)	Mean
-0.4878	63100.17
AIC	504.31
BIC	508.71

In the ARIMA (0,0,1) model estimated for Kidney diseases prevalence, the coefficient for the moving average term (MA(1)) is -0.6007. This negative coefficient suggests that the current prevalence of Kidney diseases is influenced by the past residual errors, indicating a corrective mechanism in response to previous forecasting errors. The mean estimate for Kidney diseases prevalence is 4,055.7347, representing the average level of cases when considering the impact of the moving average effect. The Akaike Information Criterion (AIC) is 303.48, and the Bayesian Information Criterion (BIC) is 307.88.

Table 4.5: Estimation of ARIMA (0,0,1) for modeling Kidney diseases Prevalence

Coefficients	
MA (1)	Mean
-0.6007	4055.7347
AIC	303.48
BIC	307.88

4.5 Predicted future Trends of Diseases Prevalence among children in Nigeria

Table 4.5 provides the anticipated trends in diseases prevalence among children in Nigeria. Diarrhoea is projected to increase from 41,694 in 2023 to 51,651 in 2024, followed by a slight decrease in 2025 and 2026, suggesting potential fluctuations in prevalence and the need for targeted interventions during peak periods. Also, Malaria cases are expected to remain relatively stable, with a marginal decrease from 63,412 in 2023. Whooping cough prevalence is forecasted to decrease gradually from 10,114 in 2023 to 10,072 in 2026, suggesting the potential effectiveness of existing vaccination programs, while emphasizing the importance of ongoing vigilance. Measles cases are projected to vary, reaching a peak of 17,841 in 2025, followed by a slight decrease in 2026, signaling the importance of maintaining high vaccination coverage to prevent outbreaks. Lastly, Skin disease prevalence is expected to fluctuate, peaking in 2024 at 22,441, with a subsequent decrease in 2025 and 2026, warranting attention to environmental factors and skin health education.

Table 4.6: Predicted future Trends of Diseases Prevalence among children in Nigeria

Year	Diarrhoea	Malaria	Kidney disease	Whooping cough	Measles	Skin disease
2023	41694.21	63412.89	4046.63	10114.56	16220.16	20357.12
2024	51651.51	63199.18	4055.74	10108.24	16218.02	22441.83
2025	41637.97	63204.23	4013.21	10098.54	17841.21	21321.24
2026	41633.69	62122.14	3008.09	10072.76	16342.66	21187.09

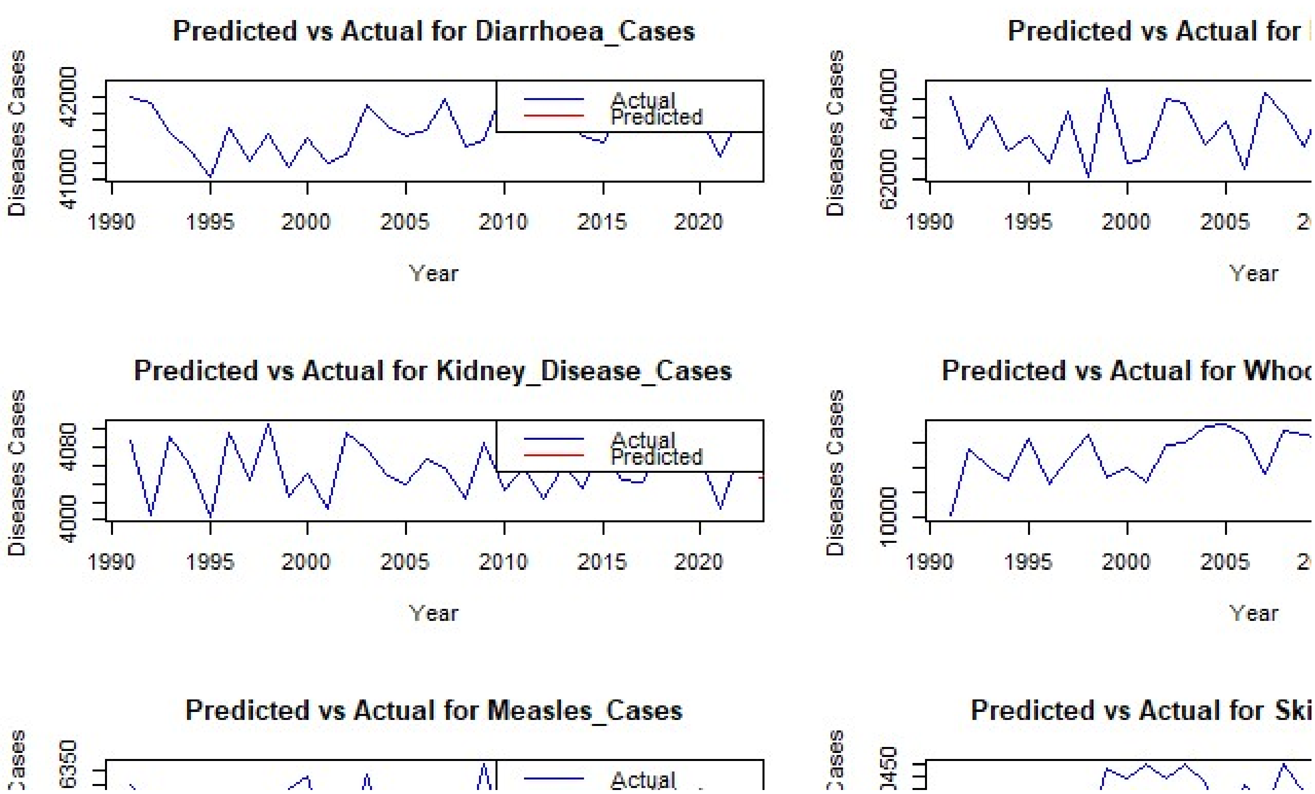


Figure 4.4: Prediction versus actual prevalence plot

5. CONCLUSION AND RECOMMENDATION

5.1 Summary of Findings

The comprehensive analysis of childhood disease prevalence in Nigeria's Southwest region yielded significant insights into the dynamics of various diseases. The study revealed a persistent and consistent prevalence of Diarrhoea over the years. Diarrhoea cases consistently ranged from 41,013 to 42,141 annually. The mean value of 41,625 serves as a central tendency, indicating the average reported cases. The low standard deviation and skewness, coupled with the stability in the minimum and maximum values, highlight a robust and enduring burden of Diarrhoea in the region. The ARIMA (1,0,0) model provided additional insights, indicating a positive relationship between current and past Diarrhoea prevalence, emphasizing the influence of past occurrences on present cases. Furthermore, malaria cases exhibited a fluctuating pattern over the years, showcasing an overall increasing trend from 62,028 to 64,329. The variability in Malaria cases suggests ongoing challenges in malaria prevention and control efforts. The ARIMA (0,0,1) model for Malaria with a negative MA(1) coefficient underscores the corrective mechanisms in response to previous forecasting errors, indicating a level of adaptability in addressing the disease's dynamics.

Similarly, Kidney disease prevalence demonstrated a fluctuating pattern within the range of 4,003 to 4,105 cases. The ARIMA (0,0,1) model for Kidney diseases, with a negative MA(1) coefficient, suggests corrective mechanisms responding to past errors. This implies that the occurrence of Kidney diseases is influenced by corrective actions taken in response to previous forecasting errors.

Unlike Diarrhoea, Malaria, and Kidney disease, Whooping cough and Measles exhibited a degree of stability in their prevalence. Whooping cough cases demonstrated a slight upward trend, ranging from 10,000 to 10,207, indicating stability in reported cases. The low variability, as indicated by the standard deviation, further emphasizes the consistent occurrence of Whooping cough.

Measles cases remained stable with a slight increase in recent years, ranging from 16,053 to 16,371. The stability in reported cases, coupled with the ARIMA (1,0,0) model's positive AR(1) coefficient, implies that past occurrences of Measles influence the current prevalence. This underscores the importance of sustained efforts in vaccination programs to maintain stability and prevent outbreaks. Lastly, skin disease prevalence exhibited fluctuations within the range of 20,144 to 20,496 cases. The ARIMA (0,0,1) model for Skin diseases with a negative MA(1) coefficient suggests corrective mechanisms, indicating adaptability in response to past forecasting errors. This fluctuation in Skin disease prevalence emphasizes the need for attention to environmental factors and skin health education to address the varying trends.

5.2 Conclusion

The culmination of extensive data analysis and modeling efforts presents a comprehensive understanding of childhood disease prevalence in Nigeria's Southwest region. The integration of descriptive statistics, as evidenced in Table 4.1, facilitated a holistic view of the dynamics surrounding childhood diseases. Mean values, standard deviations, minimum and maximum cases, and skewness collectively depicted the central tendencies, variability, and distribution characteristics of Diarrhoea, Malaria, Kidney disease, Whooping cough, Measles, and Skin disease. The resulting nuanced portrayal laid the foundation for a detailed examination of each disease's prevalence. The temporal patterns of diseases, as depicted in Figures 4.1 to 4.3, illuminated the prevalence trajectories from 1990 to 2022. The persistently prevalent nature of Diarrhoea, fluctuating patterns in Malaria and Kidney disease, stability in Whooping cough and Measles, and fluctuations in Skin disease emerged as prominent themes. These patterns, when juxtaposed with the predictions derived from ARIMA models (Table 4.5), furnish a valuable predictive lens for understanding future disease trends. The application of ARIMA models (Tables 4.3.1, 4.3.2, and 4.3.3) unearthed relationships between current and past disease prevalence, capturing autoregressive and moving average effects. Coefficients such as AR(1) for Diarrhoea, MA(1) for Malaria, and MA(1) for Kidney disease unraveled the intricate interplay of historical occurrences in shaping present disease burdens. AIC and BIC values in these models served as indicators of goodness of fit, facilitating the identification of models that best capture the underlying dynamics.

5.3 Recommendation

The following recommendation were made from the findings from the study;

Given the persistent prevalence of Diarrhoea, public health initiatives should focus on targeted interventions, including improved sanitation, hygiene practices, and access to clean water sources. Fluctuations in Malaria prevalence call for adaptable strategies in malaria control. These may include responsive distribution of bed nets, access to antimalarial drugs, and ongoing educational campaigns. The stability observed in Whooping cough and Measles prevalence suggests the efficacy of vaccination programs. Continued vigilance, maintenance of high vaccination coverage, and addressing potential barriers to vaccination are recommended.

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