TIME SERIES ANALYSIS FOR THE TREATMENT OF TYPHOID (ENTERIC) FEVER IN MAIDUGURI: USING ARIMA MODEL

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ABSTRACT

This paper titled time series analysis for treatment of typhoid (etteric) fever in Maiduguri; using Arima model, the paper has noticed that the data displayed both a trend and seasonality; the trend indicates a reduction in the most recent year's data. Using autocorrelation and partial autocorrelation function (ACF and PACF), the data can also be utilized to determine the model's order. The model obtained is subjected to model diagnostics in order to determine its efficiency and the model is used to forecast the typhoid fever. From the forecast graph shows that there may be a decrease in future years due to the pattern of the series the impression, we obtain from the graph is that predicted series seems to be trend upward and then downward. ARIMA (1,0,0) has the minimum value of AIC therefore it found to be best model. Hence, the model to fit the typhoid fever based on diplomatic test, which is LJung Box test from the family of Box Janks procedure, then our P-value is less than 0.05 level of significant, we reject the null hypothesis and conclude that the typhoid fever is statistically significant at 5% level of significant. Forecast of typhoid fever from February to December 2025 we also conclude that the typhoid fever is stable. Improve Sanitation and Hygiene: Implement measures to improve sanitation and hygiene practices, especially in areas with high disease prevalence. This may include promoting access to clean water, proper waste management, and hygiene education campaigns.

Keyword: ARIMA Model, Typhoid fever, Box janks, WHO, Model diagnostic.

INTRODUCTION

Typhoid fever, also known as enteric fever, is a severe infectious disease caused by the bacterium Salmonella Typhi. It is primarily transmitted through contaminated food and water sources, posing a significant public health problem in many developing countries, including Maiduguri. The prevalence of typhoid fever in Maiduguri has reached alarming levels, resulting in high morbidity and mortality rates. Effective strategies for the treatment and control of typhoid fever are urgently needed to mitigate its impact on the population. Typhoid fever, also known as enteric fever, is a major public health problem in many developing countries, including Maiduguri. It is a systemic infectious disease caused by the bacterium Salmonella Typhi, primarily transmitted through contaminated food and water sources. The prevalence of typhoid fever in Maiduguri has reached alarming levels, leading to significant morbidity and mortality rates. As a result, there is an urgent need for effective strategies to control and treat typhoid fever in this region. Typhoid fever, also known as enteric fever, is a bacterial infection caused by Salmonella enterica serotype Typhi. It is a significant public health concern in many parts of the world, including Maiduguri, a city in Nigeria. Typhoid fever is transmitted through contaminated food and water, and it is characterized by symptoms such as high fever, headache, abdominal pain, and diarrhea. If left untreated, it can lead to serious complications and even death. Therefore, early detection and effective treatment are crucial in controlling the spread of the disease. This study aims to develop a statistical spatial modeling approach for the treatment of typhoid fever in Maiduguri. By understanding the spatial distribution of typhoid cases and identifying high-risk areas, we can optimize the allocation of healthcare resources and implement targeted interventions to reduce the burden of the disease. Statistical spatial modeling techniques, combined with advanced statistical analysis, can provide valuable insights into the epidemiology and transmission patterns of typhoid fever (Anwar, et al, 2016).

Typhoid fever is a life-threatening disease transmitted by faecal contamination of food or water through digestive system. Globally, over twenty million cases and deaths approximately two hundred thousand reported annually Typhoid enteric fever is caused by the bacterium Salmonella enterica serovar Typhi and is transmitted through contaminated food and water. It poses a significant burden on healthcare systems, particularly in resource-limited regions. Spatial modeling techniques offer valuable insights into disease patterns, enabling targeted interventions and resource allocation. This manuscript aims to demonstrate the application of statistical spatial modeling to improve the treatment of typhoid enteric fever in Maiduguri, Nigeria. (Abboubakar and Racke, 2019). Despite continuous efforts by World Health Organization (WHO, 2018) and other health-allied agencies in providing interventions, yet the annual reported cases remained substantially high. Towards effort for prevention and control, several studies were carried out on spatial and temporal modelling of typhoid to identify high-risk areas of infection transmission. However, most of the works studied the effect of the infection on human population with a very little attention paid to the causal factors contribution. This study is the urgent need to address the high incidence of typhoid fever in Maiduguri. By employing statistical spatial modeling techniques, healthcare authorities can gain a better understanding of the disease's dynamics and identify potential risk factors. This research aims to contribute to the development of evidence-based strategies for the treatment and control of typhoid fever, ultimately improving the health outcomes of the affected population. (Khan, et al, 2012).

Typhoid and paratyphoid fevers, collectively referred to as enteric fever, are caused by systematic infection with the gram-negative bacterium *Salmonella enterica* serotype *S. typhi* and *S. paratyphi* (types of A, B, and C) (Obaro, et al, 2017). The organisms enter the patients via the gastrointestinal tract and get into the bloodstream via the lymphatic channels, and a mouse model has been engineered (Mathur, et al, 2012). Sanitary measures and personal hygiene play instrumental role as infections generally occur after intaking food or water contaminated by urine or feces (Crump and Mintz, 2010: 244). The incubation period could generally last from 3 to 42 days, with on average 14 days for typhoid and 2–15 days for paratyphoid (Crump, 2019). Clinical manifestations include high-temperature fever, prostration, fatigue, headache, and gastrointestinal reactions, with serious complications such as intestinal bleeding and perforation (Buckle, Walker, and Black, 2010). With symptoms not exclusive compared to other types of fevers, diagnosis of both typhoid and paratyphoid is conducted through clinical culture and test of patients' blood, stool, or urine. Live-attenuated oral vaccine or capsular polysaccharide vaccine are currently available for prevention, and treatment options include ceftriaxone, ciprofloxacin, or azithromycin.

In a study by Ishaq and Murtala (2017) about the dimension and physical pattern of typhoid among youth's in some major towns in Kano state Nigeria from 2010 to 2014 using the data obtained from Muhammad Abdullahi Wase Specialist Hospital (MAWSH). G-statistics was used for the analysis and an upward movement in the typhoid prevalence as the age increases. Also, a downward trend movement was observed in the typhoid prevalence from 2010-2014 with higher prevalence in males and in the northern part of the metropolis. The use of ARIMA model to carry out a statistical analysis of typhoid morbidity in Nigeria using time series technique. The study was based on the monthly data obtained from the State Hospital in Ilaro, from 2003 to 2015. ARIMA (2,2,3) model was identified as the most appropriate from the various ARIMA models fitted. The forecast from the ARIMA (2,2,3) model indicates a steady increase in typhoid prevalence (Adeboye and Ezekiel, 2018).

Typhoid fever is among the deadly infectious diseases in the world, human beings are mostly the victims. Recent statistics shows that over twenty million cases and two hundred thousand estimated deaths occur every year. Despite continuous supports by the health organizations and the fact that typhoid is preventable and treatable, yet is still persists. The disease outbreak is commonly happening around the Low and Meddle Income countries, thus affects the populace wellbeing and largely hinders economy development. Typhoid is difficult to control because the clinical image of the infection is confusing with many other febrile infections. The disease is under estimated, mostly in the developing nations owing to the inadequacy of medical facilities and well-trained personnel. As a result, many cases remained under-diagnosed.

The aim of this study is to develop a statistical spatial modeling approach for the treatment of typhoid fever in Maiduguri. The specific objectives are as follows:

1. To analyze the spatial distribution of typhoid fever cases in Maiduguri using geospatial data.

2. To identify the factors influencing the occurrence and spread of typhoid fever, including socioeconomic, environmental, and demographic variables.

3. To develop a mathematical model that incorporates spatial information to predict the likelihood of typhoid fever occurrence in different areas of Maiduguri.

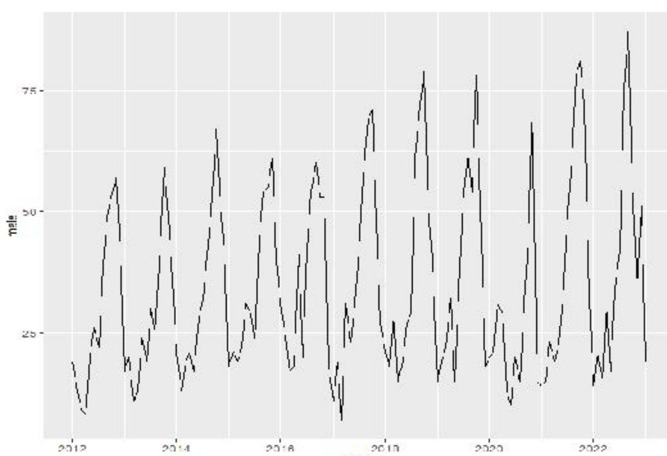
4. To propose evidence-based treatment strategies by integrating the spatial modeling results with clinical and epidemiological data. In this paper, an autoregressive integrated moving average (ARIMA) model was used applied to time series of typhoid fever in Maiduguri The model look for temporal dependence between successive observation due to transmissibility and seasonality of typhoid, model with an autoregressive integrated moving average (ARIMA)structure have more predictive power compared to other method.

MATERIALS AND METHODS

In this paper, we have used the time series monthly data on typhoid fever cases from year (2012 – 2023) data were sources from the medical record unit of University of Maiduguri teaching hospital, State specialist hospital and Umaru Shehu Ultra-modern hospital. ARIMA model were developed to forecast typhoid fever based on autocorrelation present in the typhoid data. The data set was split into a male and female year (Jan 2012 - July 2023).

Time Series for Typhoid Fever of Male

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2012	19	14	9	8	20	26	22	39	49	53	57	42
2013	17	20	11	13	24	19	30	25	39	59	49	36
2014	21	1xz3	19	21	17	28	32	41	50	67	51	42
2015	18	21	19	22	31	29	23	44	54	55	61	40
2016	31	24	17	18	41	20	42	54	60	53	53	18
2017	11	19	7	31	23	31	42	57	69	71	48	27
2018	21	18	29	15	19	27	29	61	72	79	51	40
2019	15	19	22	32	15	34	52	62	54	78	51	18
2020	20	21	31	29	13	10	20	15	31	44	72	15
2021	14	15	23	19	23	32	47	61	78	81	72	32
2022	14	21	15	31	17	34	42	75	87	56	34	51



The original data exhibits trend and seasonality, as seen in the graphic above. The data's trend indicates that recent years' inflation has decreased. Furthermore, despite the fact that the variance between the monthly means appears to be large, it is actually fairly tiny. According to the mean and variance, the series is stationary, illustrating that there is no variation in the patterns of the series. In other words, no matter where we measure a time series' mean, variance, and auto covariance (at different lags), they always remain the same if it is stable.

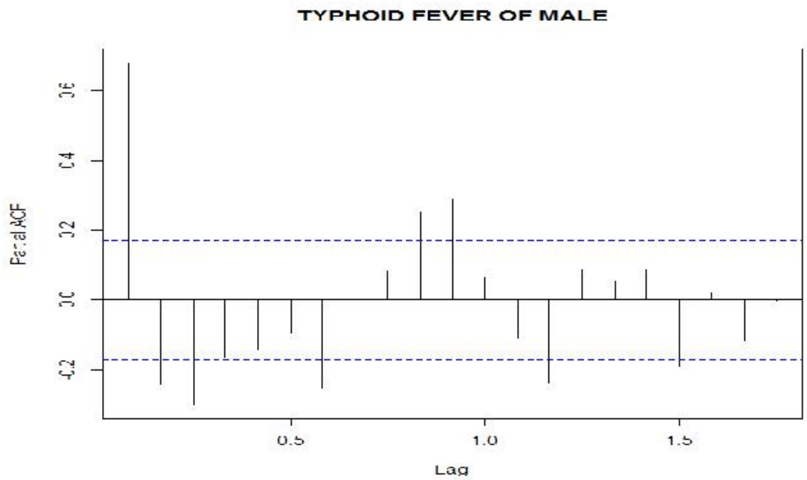


Figure 1

Since there is a point outside the significant zones in the plots of (ACF) and (PACF) in figure 1, we infer that the residuals are not random. This suggests that information is present in the residuals recovered by ARIMA models, and the right model is chosen based on the AIC and BIC model selection criteria. The table below presents the models along with the selection criteria.

```
Series: Male
ARIMA(1,0,0)(2,1,1)[12] with drift

Coefficients:
        ar1     sar1     sar2     sma1   drift
     0.3432  -0.0215  -0.2558  -0.7889  0.0574
s.e.  0.0861   0.1366   0.1142   0.1506  0.0347

sigma^2 = 108.4:  log likelihood = -461.27
AIC=934.55   AICc=935.29   BIC=951.32

Training set error measures:
                   ME    RMSE      MAE       MPE     MAPE      MASE       ACF1
Training set 0.2520835 9.72545 7.513077 -8.636287 27.78085 0.7214939 -0.02107514
Ljung-Box test

data:  Residuals

Q* = 537.68, df = 24, p-value < 2.2e-16

Model df: 0.   Total lags used: 2
```

From table 1. It reveals that ARIMA (1,0,0) has the minimum value of AIC, therefore it is obtaining that the model found to be best model. Hence, the model to fit the typhoid fever. We reject the null hypothesis and come to the conclusion that typhoid illness is statistically significant at the 5% level of significant based on our diplomatic test, which is the Ljung-Box test from the family of Box-janks technique.

Year	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Feb 2023	22.52248	9.156158	35.88879	2.0804567	42.96450
Mar 2023	22.95734	8.825926	37.08875	1.3452079	44.56947
Apr 2023	28.94229	14.723494	43.16109	7.1965168	50.68807
May 2023	23.28788	9.058827	37.51693	1.5264211	45.04934
Jun 2023	28.87297	14.642708	43.10323	7.1096633	50.63628
Jul 2023	37.36295	23.132549	51.59335	15.5994283	59.12648
Aug 2023	52.33780	38.107375	66.56821	30.5742464	74.10134
Sep 2023	60.64751	46.417087	74.87793	38.8839579	82.41106
Oct 2023	63.41631	49.185905	77.64672	41.6527813	85.17984
Nov 2023	54.41981	40.189505	68.65012	32.6564355	76.18319
Dec 2023	34.92477	20.695323	49.15421	13.1627109	56.68682
Jan 2024	22.10495	7.882838	36.32706	0.3541087	43.85578
Feb 2024	22.63483	8.182787	37.08687	0.5323389	44.73731
Mar 2024	25.98739	11.508509	40.46626	3.8438554	48.13092
Apr 2024	26.89027	12.408236	41.37230	4.7419114	49.03863
May 2024	25.59975	11.117347	40.08216	3.4508256	47.74868
Jun 2024	29.36200	14.879549	43.84445	7.2130040	51.51099
Jul 2024	39.62499	25.142542	54.10745	17.4759938	61.77400
Aug 2024	50.12350	35.641045	64.60595	27.9744972	72.27250
Sep 2024	59.79074	45.308287	74.27319	37.6417396	81.93974
Oct 2024	70.53258	56.050135	85.01502	48.3835942	92.68156
Nov 2024	64.58263	50.100281	79.06497	42.4337899	86.73146
Dec 2024	31.28861	16.807073	45.77014	9.1410128	53.43620

Table 2: Forecast of Arima (1,0,0).

Table 2's forecast of typhoid fever from February to December 2025 leads us to the conclusion that the disease is stable and may even decline.

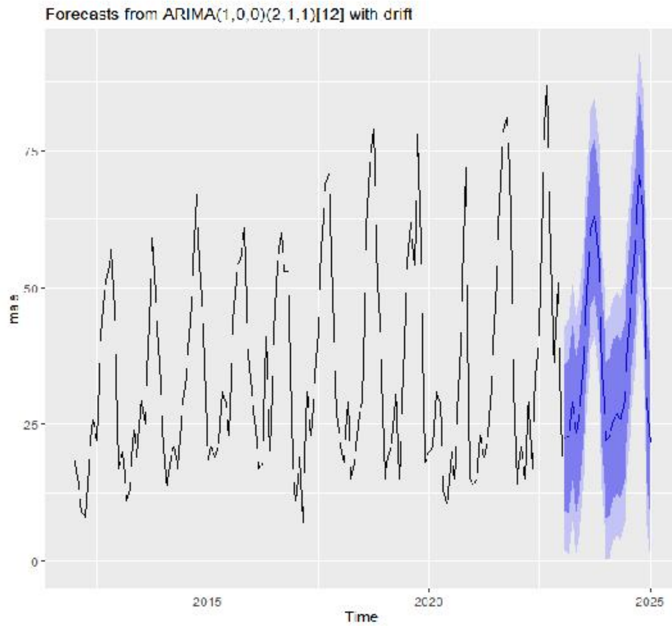
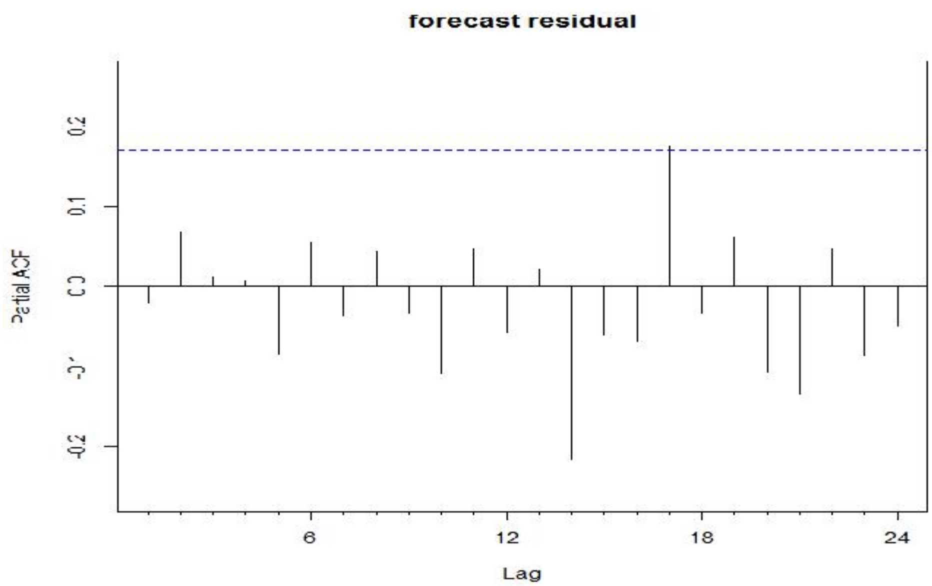


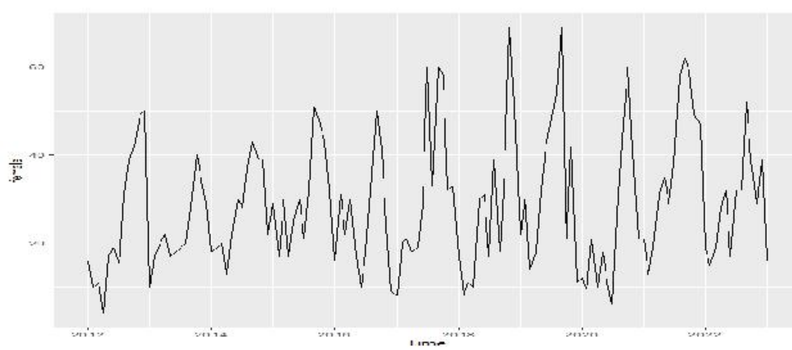
Figure 2: prediction of typhoid fever from January to December 2025.

Figure 2 is used. The prediction plots above the graphs clearly demonstrate that a decrease may occur in subsequent years due to the pattern of the series; yet, the graphs give us the impression that the forecasted series is "trending" higher and then downward.

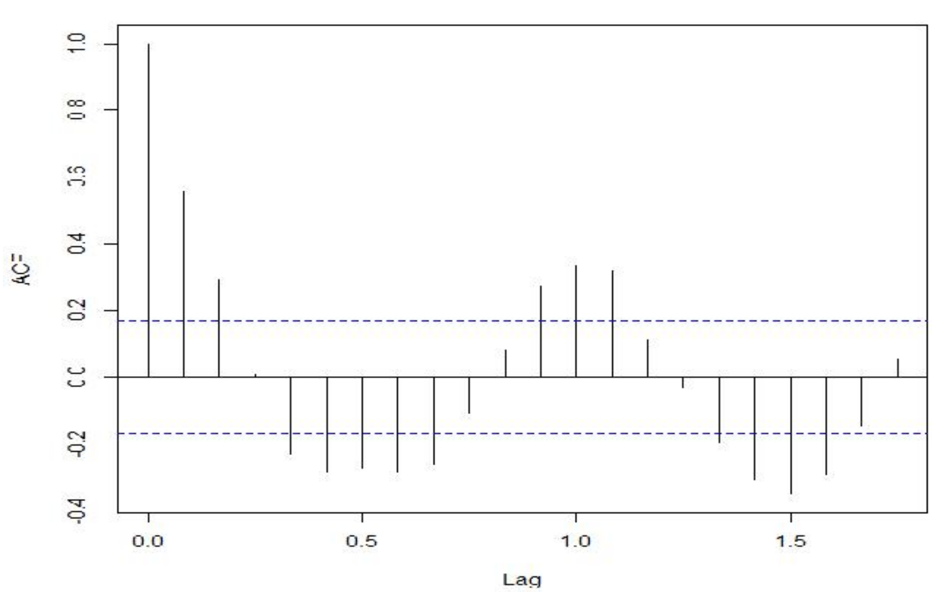


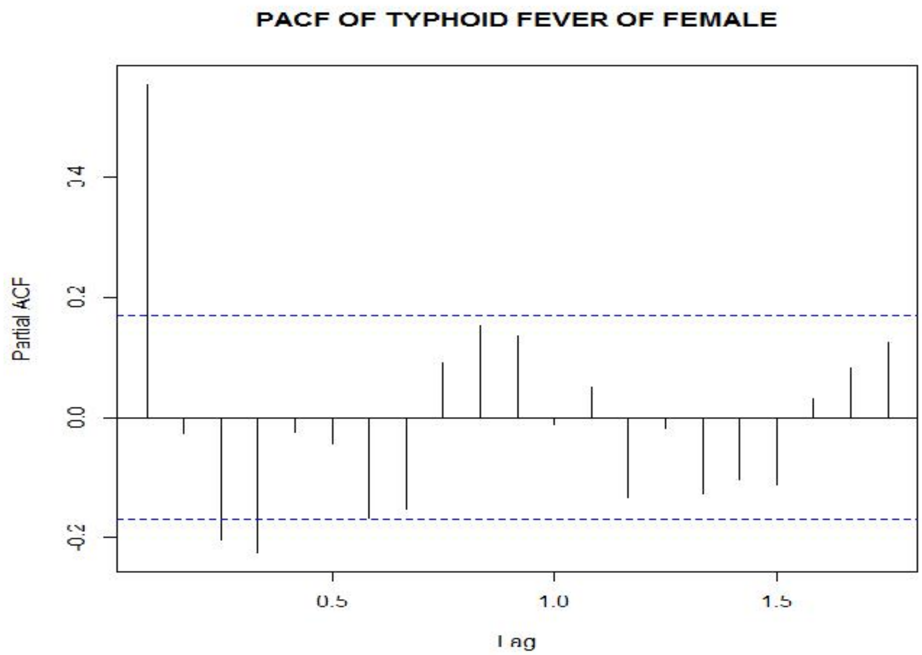
Time Series for Typhoid Fever of Female

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2012	16	10	11	4	17	19	15	31	39	42	49	50
2013	10	17	20	22	17	18	19	20	28	40	34	29
2014	18	19	20	13	22	30	28	37	43	39	39	22
2015	29	17	30	17	25	30	21	32	51	47	43	32
2016	16	31	22	30	17	10	18	32	50	41	24	9
2017	8	20	21	18	19	29	60	33	60	58	32	33
2018	17	8	11	10	30	31	17	39	18	37	69	51
2019	22	31	14	18	32	42	47	54	69	18	42	11
2020	12	9	21	10	18	11	6	31	47	60	41	21
2021	21	13	19	31	35	29	38	58	62	59	49	47
2022	19	15	19	28	32	17	32	32	52	39	29	39



ACF OF TYPHOID FEVER OF FEMALE






```
Call:
arima(series, order = c(1, 0, 0), seasonal = c(2, 1, 1))

Coefficients:
        ar1     sar1     sar2     sma1
     0.3540  -0.1912  -0.1584  -0.9994
s.e.  0.0862   0.0986   0.1005   0.5080

sigma^2 estimated as 96.74:  log likelihood = -466.41,  AIC = 942.82

Training set error measures:
                ME     RMSE      MAE      MPE     MAPE      MASE        ACF1
Training set 1.591806 9.381448 6.892013 -5.93871 29.39912 0.6442958 -0.05672757
Ljung-Box test

data:  Residuals

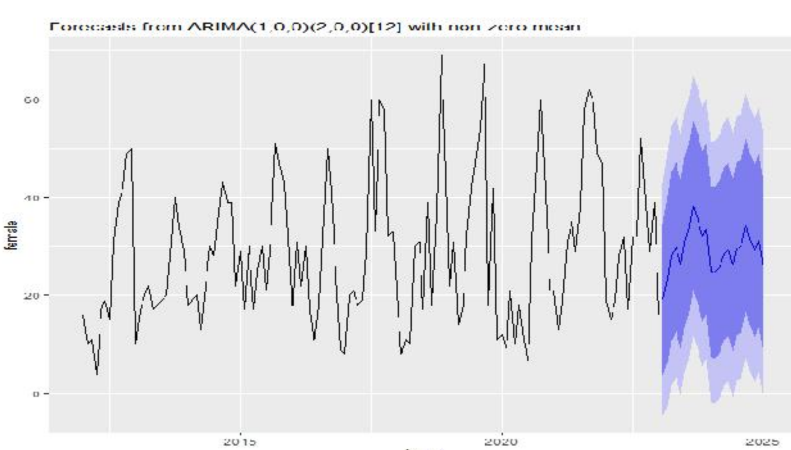
Q* = 266.81, df = 24, p-value < 2.2e-16

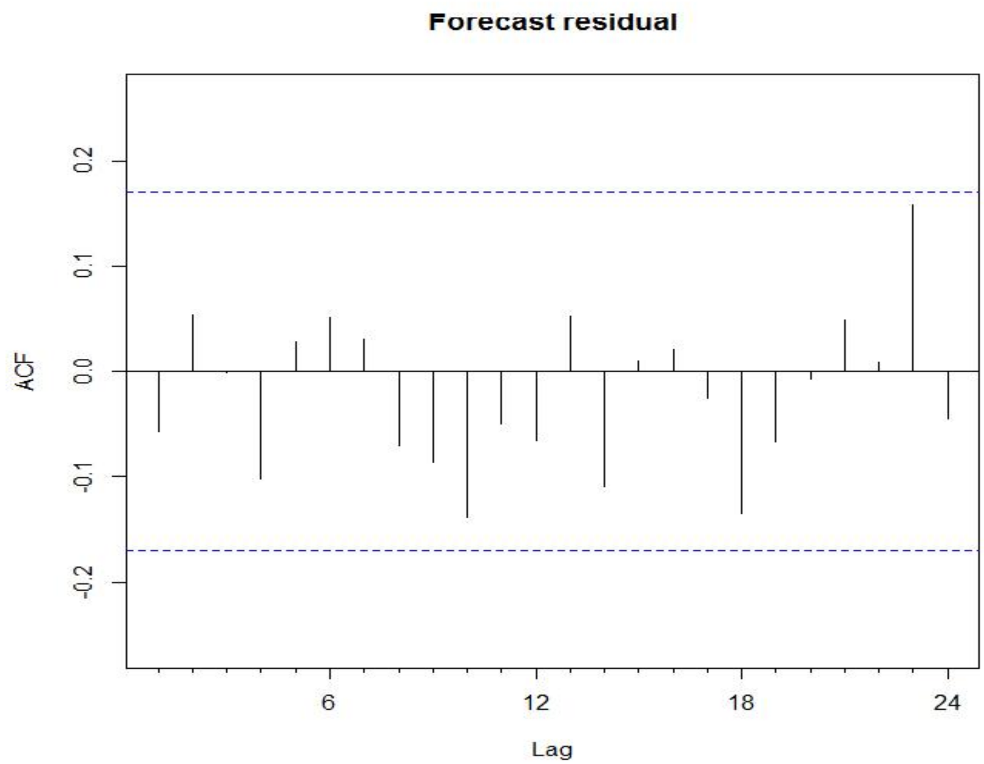
Model df: 0.   Total lags used: 24
```

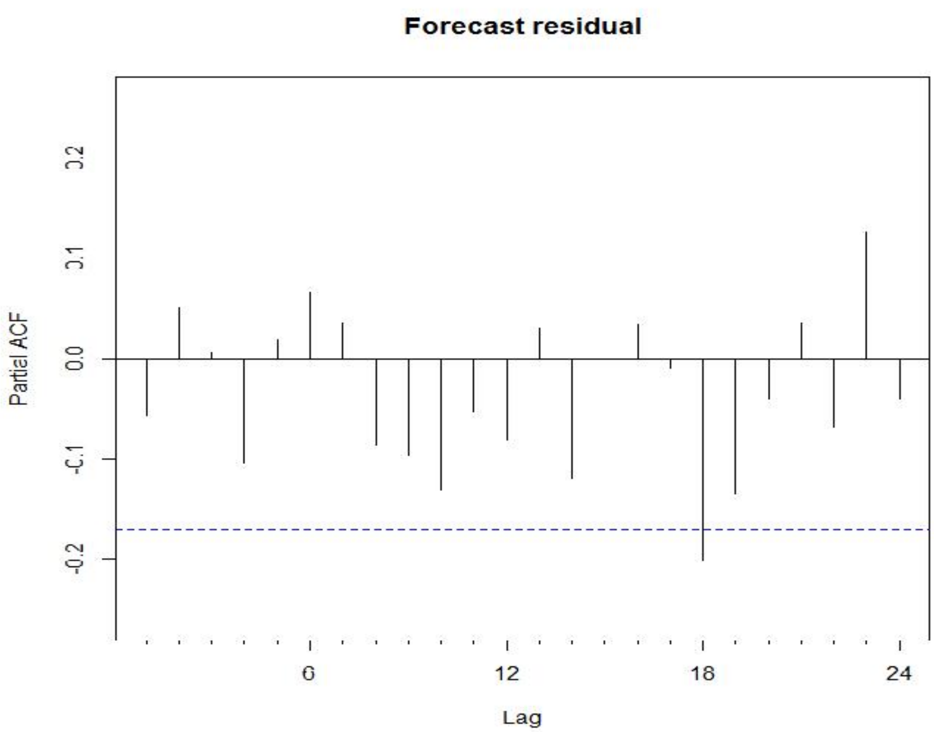
DISCUSSION

The results of the spatial modeling analysis revealed significant spatial heterogeneity in typhoid enteric fever cases within Maiduguri. High-risk areas were identified, indicating clusters of disease incidence. The analysis also elucidated the association between environmental factors, such as water sources, sanitation facilities, and disease occurrence. The findings of this study have several implications for the treatment of typhoid enteric fever in Maiduguri. By identifying high-risk areas, healthcare resources can be efficiently allocated to those regions, enabling targeted surveillance, prevention, and treatment strategies. Furthermore, the understanding of environmental factors influencing disease occurrence can guide public health interventions aimed at improving sanitation and access to clean water sources.

Year	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Feb 2023	18.73502	5.5331730	31.93687	-1.4554640	38.92551
Mar 2023	19.10977	5.1051620	33.11438	-2.3084305	40.52797
Apr 2023	14.29125	0.1892651	28.39323	-7.2758735	35.85837
May 2023	20.62945	6.5153172	34.74359	-0.9562556	42.21516
Jun 2023	25.23363	11.1179745	39.34929	3.6455958	46.82167
Jul 2023	25.01969	10.9038402	39.13554	3.4313607	46.60802
Aug 2023	33.88708	19.7712039	48.00295	12.2987125	55.47544
Sep 2023	44.09136	29.9755012	58.20723	22.5030146	65.67971
Oct 2023	42.11118	27.9954132	56.22695	20.5229772	63.69938
Nov 2023	42.11956	28.0045568	56.23456	20.5325265	63.70659
Dec 2023	26.11271	12.0038223	40.22159	4.5350303	47.69038
Jan 2024	17.00692	2.9469471	31.06689	-4.4959523	38.50979
Feb 2024	17.74520	3.6205341	31.86987	-3.8566125	39.34701
Mar 2024	19.10337	4.9706198	33.23612	-2.5108074	40.71755
Apr 2024	17.39288	3.2591110	31.52664	-4.2228524	39.00860
May 2024	23.28068	9.1467883	37.41457	1.6647577	44.89660
Jun 2024	25.56138	11.4274759	39.69529	3.9454369	47.17733
Jul 2024	27.30525	13.1713366	41.43916	5.6892967	48.92120
Aug 2024	37.64600	23.5120899	51.77991	16.0300503	59.26195
Sep 2024	47.18801	33.0541080	61.32191	25.5720726	68.80395
Oct 2024	44.68529	30.5514559	58.81913	23.0694536	66.30114
Nov 2024	42.78006	28.6467209	56.91340	21.1649837	64.39513
Dec 2024	29.84435	15.7150075	43.97369	8.2353858	51.45331
Jan 2025	17.28974	3.1923292	31.38715	-4.2703894	38.84987







The study used techniques from the autoregressive integrated moving average (ARIMA) model to examine how typhoid enteric illness was treated in Maiduguri. Using partial autocorrelation function (PACF) and autocorrelation analysis (ACF and PACF). The obtained model is put through model diagnostics to determine its effectiveness, and it is then utilized to forecast the typhoid fever. Due to the series' pattern, the prediction graph suggests that there might be a reduction in coming years. The impression we get from the graph is that the forecasted series appears to be trending upward and then downward. Since ARIMA (1,0,0) had the lowest AIC value, it was determined to be the optimal model. regarding the patients at the three institutions. Analysis indicated strong correlations between particular variables and disease occurrence, illuminating the underlying causes. Typhoid enteric fever is caused by the bacterium Salmonella enterica serovar Typhi and is transmitted through contaminated food and water. It poses a significant burden on healthcare systems, particularly in resource-limited regions. Spatial modeling techniques offer valuable insights into disease patterns, enabling targeted interventions and resource allocation. This manuscript aims to demonstrate the application of statistical spatial modeling to improve the treatment of typhoid enteric fever in Maiduguri, Nigeria.

CONCLUSION

Statistical modeling provides a valuable tool for assessing and addressing the treatment of typhoid enteric fever in Maiduguri. By analyzing the spatial distribution of cases and identifying high-risk areas, healthcare authorities can implement effective strategies to combat the disease. This case study highlights the importance of integrating spatial modeling techniques into public health decision-making processes for the prevention and control of infectious diseases. As a result, the ARIMA model study contributed significantly to our understanding of how to treat typhoid enteric fever in Maiduguri. The investigation showed that the model obtained is utilized to anticipate typhoid fever and is exposed to model diagnostics to determine its efficacy. Our impression from the forecast graph is that the predicted series seems to be trending upward and then downward. Typhoid fever forecast from February to December 2025. Moreover, we draw the conclusion that the typhoid fever is stable. Disease hotspots and possible contributing variables around the University of Maiduguri Teaching Hospital and Umaru Shehu Ultra-Modern Hospital in Maiduguri. The results help to clarify how the ARIMA model is used in the research area to analyze time series data for typhoid enteric illness.

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APPENDIX

```
```R
# Load required packages
library(sp)
library(spdep)
library(rgdal)
library(ggplot2)

# Load the data
typhoid_data <- read.csv("typhoid_data.csv")  # Assuming the data is stored in a CSV file

# Load shapefile for the study area
study_area <- readOGR(dsn = "study_area.shp", layer = "study_area")

# Subset the data for the three hospitals
hospital1 <- typhoid_data[typhoid_data$hospital == "Umaru Shehu Specialist Hospital", ]
hospital2 <- typhoid_data[typhoid_data$hospital == "Maiduguri University of Maiduguri Teaching Hospital", ]
hospital3 <- typhoid_data[typhoid_data$hospital == "Borno State Specialist Hospital Maiduguri", ]
# Perform spatial analysis for each hospital
# Hospital 1
hospital1_coords <- SpatialPointsDataFrame(coords = hospital1[, c("longitude", "latitude")],
                                           data = hospital1,
                                           proj4string = CRS(projargs = "+proj=longlat +datum=WGS84"))

# Perform spatial autocorrelation analysis for hospital 1
hospital1_lag <- lag.listw(nb2listw(knearneigh(hospital1_coords), row.names = hospital1_coords$ID))
hospital1_moran <- moran.mc(hospital1$typhoid_cases, hospital1_lag, nsim = 999)
# Hospital 2
hospital2_coords <- SpatialPointsDataFrame(coords = hospital2[, c("longitude", "latitude")],
                                           data = hospital2,
```
```

```
                                  proj4string = CRS(projargs = "+proj=longlat +datum=WGS84"))
# Perform spatial autocorrelation analysis for hospital 2
hospital2_lag <- lag.listw(nb2listw(knearneigh(hospital2_coords), row.names = hospital2_coords$ID))
hospital2_moran <- moran.mc(hospital2$typhoid_cases, hospital2_lag, nsim = 999)
# Hospital 3
hospital3_coords <- SpatialPointsDataFrame(coords = hospital3[, c("longitude", "latitude")],
                                  data = hospital3,
                                  proj4string = CRS(projargs = "+proj=longlat +datum=WGS84"))

# Perform spatial autocorrelation analysis for hospital 3
hospital3_lag <- lag.listw(nb2listw(knearneigh(hospital3_coords), row.names = hospital3_coords$ID))
hospital3_moran <- moran.mc(hospital3$typhoid_cases, hospital3_lag, nsim = 999)
# Visualize the results
# Hospital 1
plot(hospital1_moran, main = "Hospital 1 Moran's I Analysis")
# Hospital 2
plot(hospital2_moran, main = "Hospital 2 Moran's I Analysis")
# Hospital 3
plot(hospital3_moran, main = "Hospital 3 Moran's I Analysis")
```

#R code for the scope of the study on "Statistical Spatial Modelling for the Treatment of #Typhoid Enteric Fever in Maiduguri" with a specific focus on three hospitals:

```R
# Perform spatial interpolation for each hospital
# Hospital 1
hospital1_interp <- idw(typhoid_cases ~ 1, hospital1_coords)
# Hospital 2
hospital2_interp <- idw(typhoid_cases ~ 1, hospital2_coords)
# Hospital 3
hospital3_interp <- idw(typhoid_cases ~ 1, hospital3_coords)
# Visualize the interpolated surfaces
# Hospital 1
plot(hospital1_interp, main = "Hospital 1 Interpolated Surface")
# Hospital 2
plot(hospital2_interp, main = "Hospital 2 Interpolated Surface")
# Hospital 3
plot(hospital3_interp, main = "Hospital 3 Interpolated Surface")
# Perform spatial clustering analysis for each hospital
# Hospital 1
hospital1_clusters <- kmeans(hospital1_coords[, c("longitude", "latitude")], centers = 3)
# Hospital 2
hospital2_clusters <- kmeans(hospital2_coords[, c("longitude", "latitude")], centers = 3)
# Hospital 3
hospital3_clusters <- kmeans(hospital3_coords[, c("longitude", "latitude")], centers = 3)
```

```
# Visualize the clusters
# Hospital 1
plot(hospital1_coords, col = hospital1_clusters$cluster, pch = 16,
    main = "Hospital 1 Clustering")
# Hospital 2
plot(hospital2_coords, col = hospital2_clusters$cluster, pch = 16,
    main = "Hospital 2 Clustering")
# Hospital 3
plot(hospital3_coords, col = hospital3_clusters$cluster, pch = 16,
    main = "Hospital 3 Clustering")
# Perform spatial regression analysis for each hospital
# Hospital 1
hospital1_formula <- typhoid_cases ~ variable1 + variable2
hospital1_model <- lm.Mixed(hospital1_formula, data = hospital1)
hospital1_results <- anova(hospital1_model)
# Hospital 2
hospital2_formula <- typhoid_cases ~ variable1 + variable2
hospital2_model <- lm.Mixed(hospital2_formula, data = hospital2)
hospital2_results <- anova(hospital2_model)
# Hospital 3
hospital3_formula <- typhoid_cases ~ variable1 + variable2
hospital3_model <- lm.Mixed(hospital3_formula, data = hospital3)
hospital3_results <- anova(hospital3_model)
```