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Spatial and Temporal Simulation of Typhoid Fever Transmission in Yobe State

Babagana Modu [a*], Sheriff Wakil [b], Umar Y. Madaki [a] and Audu M. Mabu [c]

[a] *Department of Mathematics and Statistics, Yobe State University, Nigeria.*
[b] *Department of Microbiology, Yobe State University, Nigeria.*
[c] *Department of Computer Science, Yobe State University, Nigeria.*

Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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Abstract

Aims / Objectives: Typhoid fever is a threat to human race and perhaps not much research is conducted towards mitigating it menace in Yobe State. A classical epidemic model SIR is deployed into GLEaMviz software to simulate typhoid spread and spatially analysed the trend.
Study Design: Computational modeling and simulation.
Place and Duration of Study: Computational Laboratory, Department of Mathematics and Statistics Yobe State University, Damaturu, Nigeria. The duration of the study is between May 2021 and December 2021.
Methodology: SIR epidemic model was used to simulate typhoid spread and time series model was explored to investigate the disease trend.
Results: The model predicts mild seasonal fluctuations in the trend which coincides with rainy season. The agents causing the disease transmission is possibly being transported through flowing water.
Conclusion: A mild seasonality is present in the fluctuations of the trend of typhoid, hence the pattern shows strong evidence of perennial tendency with likelihood of high cases during rainy season. Further work is needed to validate this findings by using real data.

**Corresponding author: E-mail: modubabagana70@yahoo.com;*

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2010 Mathematics Subject Classification: 53C25; 83C05; 57N16.

1 Introduction

Typhoid fever is a serious public health challenge in Nigeria. The most vulnerable people are those dwelling in rural and semi-rural areas. Poor healthcare delivery, lack of portable water, poor drainage, poverty and general environmental hygiene are few amongst other factors contributing to the typhoid fever transmission in Nigeria. Globally, the typhoid is classified among the deadly infectious diseases that affecting human beings [1]. Despite typhoid is preventable and treatable, yet is persisting. This is attributed to the poor handling of the disease combined with lack of mechanism for reporting cases as they occur. Besides underreporting of the disease in the developing countries, the shortages of medical facilities and well-trained healthcare workers is also another issue hindering prevention and control. Towards investigating typhoid fever spread globally, several works have been carried out by exploring various modelling techniques. For instance [2] used bayesian approach to study large-scale facility based typhoid fever spread to estimate the disease incidence from passive surveillance data. The results provides a platform that can be updated with additional data as they become available and adapted to other contexts, thus used to adjust for underreporting in other diseases. Spatio-temporal spreads of typhoid fever trends in Uganda between 2012-2017 was analyzed by [3]. Furthermore, spatial and temporal transmission of typhoid and paratyphoid fever was studied in Yunnan province of China [4]. The results exacerbated by the fact that rainwater canals were being used for disposal of polluted waste from hospitals and residential areas. Similarly, the incidence of Influenze-Like Illness was spatio-temporally analyzed and predicted the high-risk regions in the United State between 2011-2020 [5]. The study identified high-risk clusters which is concentrated in the southeast. G_i^* statistics was used to evaluate clusters of typhoid fever outbreaks in Washington DC from recorded data 1906-1909 [6]. The results showed new insights into the urban patterns of typhoid outbreaks during the early part of the twentieth century. Seasonality of typhoid and paratyphoid dynamics investigated by [7] and found the underlying mechanisms that influencing the seasonality of enteric fever are likely dependent on the local context. The findings showed the northern region of the country was the safest based on the data analyzed. A study by [8] predicted the impact of vaccination on the transmission dynamics of typhoid in south Asia. The model predicts the overall and indirect effects of vaccination depend strongly on the role of chronic carriers in transmission. However, district-level spatial and temporal heterogeneities of typhoid fever morbidities investigated in Ghana by [9]. The study indicates temporal dependencies of typhoid risk with incidences in the previous months with varying magnitudes across the different regions. Mathematical models are used to investigate dynamics in typhoid fever prevention, control and intervention. This methods is used to assess the drivers of the emergence of typhoid fever in Blantyre of Malawi [10].

The remaining sections of this paper is organised as follows. Section 2 presents some previous works on typhoid fever transmission and the methodologies used for modelling the transmission including materials and methods presented in Section 3. In section 4, we presented the results and discussion of our findings accordingly. We presented the conclusions and unravel an area for further study in Section 5.

2 Theoretical Framework

In this section, we presents in detail the theoretical concepts of the typhoid fever transmission and its characteristics.

This include global perspective of the typhoid fever spread and epidemiological transition model.

2.1 Geographical distribution

Recent statistics shows that more than 22 million cases and estimated deaths of 200,000 due to typhoid have been occurring each year globally [11]. In which, there are several cases not officially captured [12] and thus rendered the published statistics underestimated. The underreporting is perhaps occurring in endemic countries, especially the Saharan and sub-Saharan Africa in which the facilities for testing and confirming the infection is inadequate [13]. Endemic areas like Asia, Africa, Latin America, Caribbean and Oceania are having highest incidence rate of more than 100 persons per 100,000 per year [14]. The global incidence rate of typhoid fever spread could be found in Fig. 1.

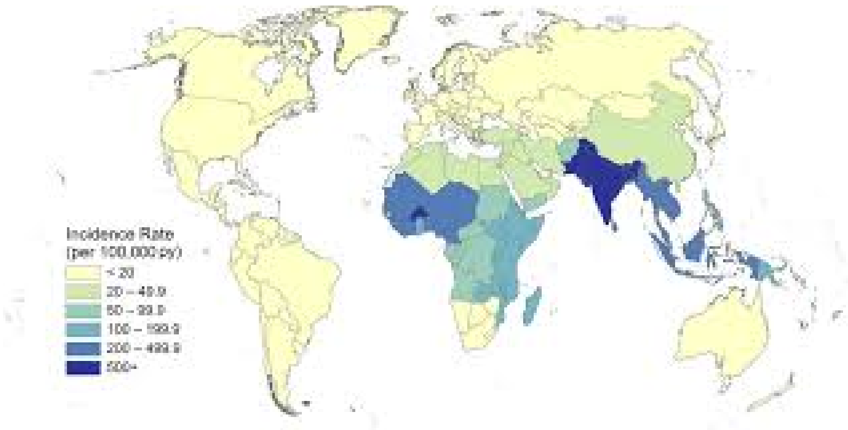


Fig. 1. Typhoid Fever Incidence Rate

2.2 Typhoid Pathogens

Salmonella typhi causes the typhoid fever infection and remains a serious public health issues in the world despite prevention and control efforts by governments and other health donor agencies. Substantially, the typhoid fever is negatively affect socio-economic activities and general wellbeing of human beings. The infection in humans can range from a self-limited gastroenteritis, that is usually associated with non-typhoidal *Salmonella* (NTS) to typhoid fever, which has fatal complications that leads to perforation [15]. Non-typhoidal *Salmonella* is one of the principal causes of food poisoning worldwide with an estimated annual incidence of 1.3 billion cases and about 3 million deaths each year [16].

2.2.1 Species

The commonly known species and strains of Salmonella that causing typhoid fever in human are *Salmonella paratyphi A; Salmonella paratyphi B; Salmonella paratyphoid C and Salmonella paratyphi D* [17]. These serotypes of *Salmonella* can co-infect an individual or causes infection in different form [18]. The *Salmonella Typhi* is causes infection in human beings only, that is person with typhoid fever carry the bacteria in their bloodstream and intestinal tract. The typhoid fever infection is characterized by the following symptoms: these are prolonged high fever, fatigue, headache, nausea, abdominal pain, and constipation or diarrhoea. However, in some situation a patient may have a rash, also when the condition is severe a person will possibly die. Typhoid fever can be confirmed through blood screening [19].

2.2.2 Incubation

As human beings are the sole reservoir and natural hosts of the typhoid fever, the infection is transmitted through ingestion of contaminated food or water. The epidemic of typhoid occur where water source for serving a large population is contaminated. Studies have shown that incubation period of typhoid fever takes 8-14 days, but sometimes my range from 3 days up to 60 days [20]. About 25% of people infected are becoming chronic carriers harbouring *S. typhi* in their gall bladder. The chronic carriers are the class of people or agent for spreading the typhoid fever infection to the susceptible individuals. However, many mild and a typical infections occur and relapses as common. A HIV patients are at a significantly increased risk of severe disease when exposed to *S. typhi and S. paratype* [21].

2.2.3 Transmission route

Typhoid transmitted from person-person is through oral route, that is eating or drinking contaminated food or water are the commonly channel. The *S. Typhi* is mostly found in urine and vomit and sometimes could be traced to the contaminated food or water. A shellfish or vegetables grown in a contaminated sewages are potential vehicles driving the infection. Furthermore, a flies can transfer or import the organism causing the infection to food or water, where the bacteria would remained replicating until it reaches an infective dose [21]. However, environmental consequences through urbanization and climate change have the potential to increase the global burden of typhoid. In addition, increasing resistance to antibiotic treatment is making it easier for typhoid to spread through overcrowded populations in cities and inadequate and or flooded water and sanitation systems [22]. One of the most important reasons that developed countries have become as productive as they are today is that the population remains healthy and disease free.

2.3 Epidemic Model

An infectious disease model SIR (Susceptible, Infected and Recovered) is considered as basic the epidemic model [23]. The model is used to syncronize infectious diseases with SIR representation such as influenza, measles, malaria, typhoid among other. Originally, Kermack and Mckendrick developed this model [24] and thereafter, many epidemiological components were built on the model to aid better understandings toward prevention, control and vaccine efficacy in disease dynamics. The SIR model is described by the following differential equations (2.1).

$$
\begin{aligned}
S' &= \pi N - \beta \frac{SI}{N} - \mu S + \alpha R, \\
I' &= \beta \frac{SI}{N} - (\mu + \gamma + \delta) I, \\
R' &= \gamma I - (\mu + \alpha) R,
\end{aligned}
\tag{2.1}
$$

where: S = Susceptible human, I = Infected human, R = Recovered human, μ = Natural death rate, β = Average contact rate, γ = Recovery rate and π = Rate of natural increase. The parameters μ, β, γ and π are positive constant. The natural death rate μ and natural increase rate π are not same, hence making N to be variable. A susceptible human will move to I compartment when contacted with an infected human, while an infected human will then move to R compartment through recovery and hence returning to the susceptible compartment through immunity lost. The value of the parameters used for simulating the differential equations (2.1) and their sources could be found in Table 1.

Table 1. The values of the parameters used in the model and their sources

Parameter description	Parameter symbol	Parameter value	Reference
Recruitment rate	π	0.0817	Estimated
Average contact rate	β	0.0002	[25]
Transmission probability	μ	0.0011	[25]
Natural death rate	μ	0.0003	Estimated
Disease-induced death rate	μ	0.0010	[26]
Recovery rate	γ	0.9	[25]
Immunity lost rate	ρ	0.0096	[27]

3 Materials and Methods

In this section, we describe in detail the methodologies used in this paper. This comprises of the study area of the research, data and their sources, statistical techniques deployed including the computational software used.

3.1 Study Area

This study is conducted in Yobe State located in Northeastern part of Nigeria. The state is lies within latitude 11° N and longitude 13.5° E with a total land area of 47,153 km^2 and sharing boundary with Borno state towards east and southeast, Jigawa state towards northwest; Bauchi and Gombe states towards southwest. Furthermore, the state shared international border with the Republic of Niger. This boundary stretches over 323km to the north of the State. The population of the State according to the 2006 census is about 2.6 million. The state was created on August 27, 1991 having been carved out of the old Borno State in the year 1991 with Damaturu as the state capital. Yobe's terrain consists of plains that are drained by the seasonal Komadugu Yobe River and its tributaries in the north and by the Gongola River in the south.

3.2 Data Collection

Complete data on reported cases of typhoid fever across the Yobe state hospitals is inaccessible or readily not available, hence we resorted to the use of Google Trend data (see, https://trends.google.com). Several studies have been conducted by exploring the Google Trend data as an option to the lack of real data [28, 29]. Using the platform, we generated a weekly trending pattern on how people living in the state searching to find information about typhoid fever transmission, treatment and preventive measures (between 30/12/2019 – 21/12/2020). In Fig. 2, we presented the time-dependent weekly interest trend of the populace searches behaviour and used log-transformation to standardized the fluctuations. A naive normality plot of the typhoid trend is depicted in Fig. 3 which shows the trending pattern of the typhoid is assumed normal. This has evidenced by critical value, $\chi^2_{v=2} = 2.469$ and $P_{value} = 0.0025$ with parametric confidence interval CI: [0.29 – 10]. Furthermore, the results presented in Table 2 reaffirms the normality of the trend data through different testing techniques. Hence, in each case of the tests, $\alpha = 5\%$ was used and therefore the null hypothesis has to be rejected and conclude that normality criteria is satisfied. The demographic data for Yobe state population is retrieved from the link: https://nigerianstat.gov.ng to compute crude birth and crude death rates. The estimates of the birth and death rates derived will be use for simulating the potential pattern of the typhoid fever transmission in the state. Throughout the simulation study, we assumed the crude birth and crude death rates remained constant.

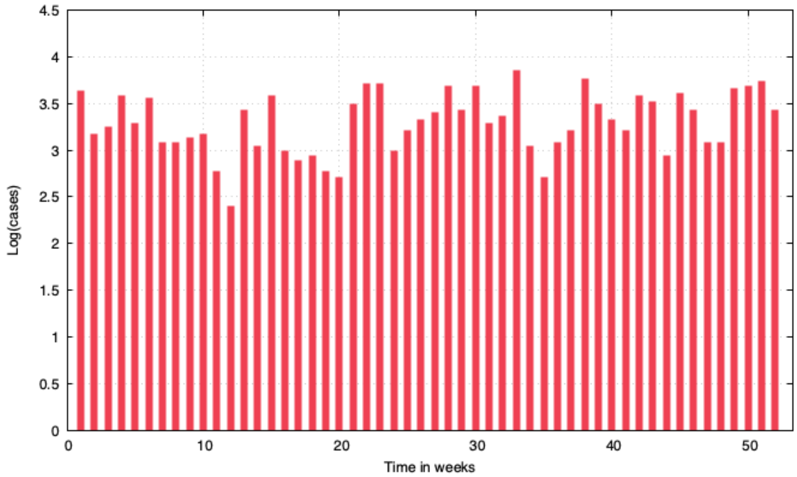


Fig. 2. Plot of log-transformed of Typhoid fever pattern in Yobe State

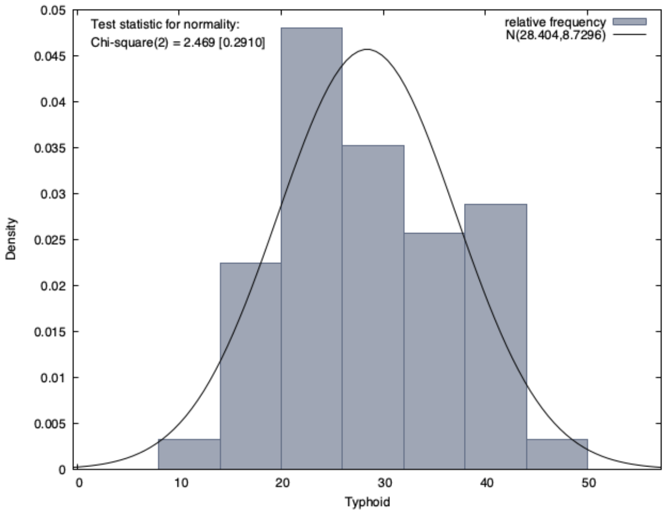


Fig. 3. Normality tests plot

Table 2. Expository analysis of the typhoid fever trend

Test	Critical threshold	P_{value}	Inference	Summary statistics
Doornik-Hanseen	2.4686	0.2910	approximately normal	-
Shapiro-Wilk	0.9730	0.2815	approximately normal	-
Lilliefors	0.0953	0.2700	approximately normal	-
Jargue-Bera	2.0614	0.3568	approximately normal	-
Mean	-	-	-	28.4040
Standard deviation	-	-	-	8.7296
Coefficient of variation	-	-	-	0.3073
Skewness	-	-	-	0.1491
Ex. kurtosis	-	-	-	-0.9287

3.3 Statistical Methods

As this study is plan to investigate spatial transmission of typhoid fever incidence in a closed population. The following methodologies are to be used, these include: serial correlation, test of significance and time series modeling for the Google trend data.

3.4 Software

Gretl and GLEaMviz computational software will be use for modeling and simulation of the typhoid fever transmission respectively. Particularly, the GLEaMviz has been extensively used to simulate infectious disease transmission, for instance see, [30, 31]. The epidemic model represented in equation (2.1) will be simulated using the parameterized values (see Table 1), thus the flow diagram of the model is shown in Fig. 5. The GLEaMviz client bring together different modules that allow the management of the entire process flow from the definition of the model to the visualization of the results.

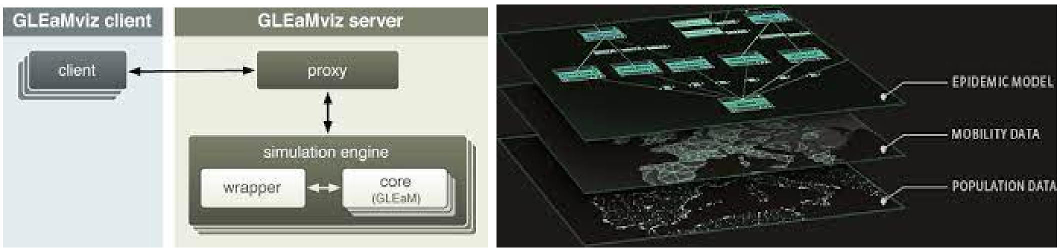


Fig. 4. GLEaMviz

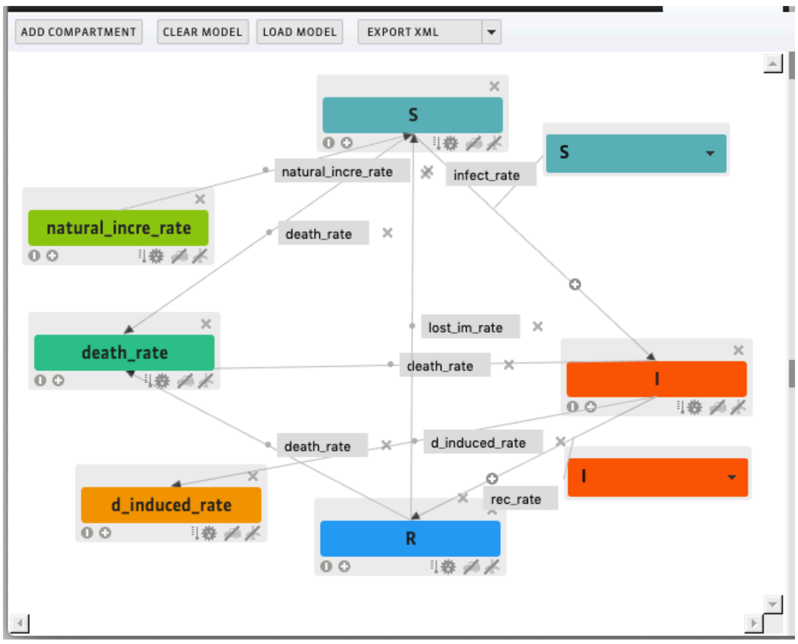


Fig. 5. SIR flow with GLEaMviz

4 Results and Discussion

From the expository analysis presented in Fig. 3 and Tables 2 and 3, the typhoid fever trend is significant at lag 1, $\rho = 0.2461$, $Q - stat = 3.3356$ and $P_{value} = 0.0280$. Thus indicating the degree of association of the typhoid fever trend is positive and approximately normal. Furthermore, lagged regression with autoregressive structure was fitted to the Google trend dataset on typhoid fever follows: $y_t = 30.3934 + 0.0203829y_{t-1} + \epsilon_t$, where $\epsilon_t \sim \mathcal{N}\ (0.062, 0.001)$. The models performance is 62.8% accurate in predicting typhoid fever in Yobe state. The results showed mild seasonal fluctuation in the pattern which coincides with rainfall season, thus the agents causing the disease transmission is possibly being transported through flowing water. Also, the results shows strong evidence of perennial incidence with likelihood of high cases during raining season. Furthermore, an epidemic model SIR was deployed into GLEaMviz (see Fig. 5) and simulate the typhoid fever cases by tuning model parameters to the referenced demographic characteristics of the study area. Two independent samples test was conducted against Google trend data (Fig. 2) and the simulated data (Fig. 7(a)), at 5% level significant of significant there is a fair evidence the two samples are relatively similar. The simulation results further reveals age-dependent of typhoid (see Fig. 6), which indicating less risk of being infected as age increases [32]. The infected and recovery pattern simulated by the GLEaMviz are presented in Fig. 7(a) and (b) respectively.

Table 3. Serial correlation testing of the Google trend typhoid data

Lag	Autocorrelation function (ACF)	Partial autocorrelation function (PACF)	Q-stat	P_{value}
1	**0.2461**	**0.2461**	**3.3356**	**0.0280**
2	-0.0012	-0.0657	3.3357	0.1890
3	-0.0632	-0.0500	3.5646	0.3120
4	-0.0412	-0.0135	3.6639	0.4530
5	0.1430	0.1646	4.8861	0.4300
6	0.0299	-0.0576	4.9406	0.5510
7	0.1219	0.1435	5.8677	0.5550
8	0.0864	0.0377	6.3441	0.6090
9	0.0597	0.0519	6.5767	0.6810
10	0.0202	-0.0209	6.6041	0.7620

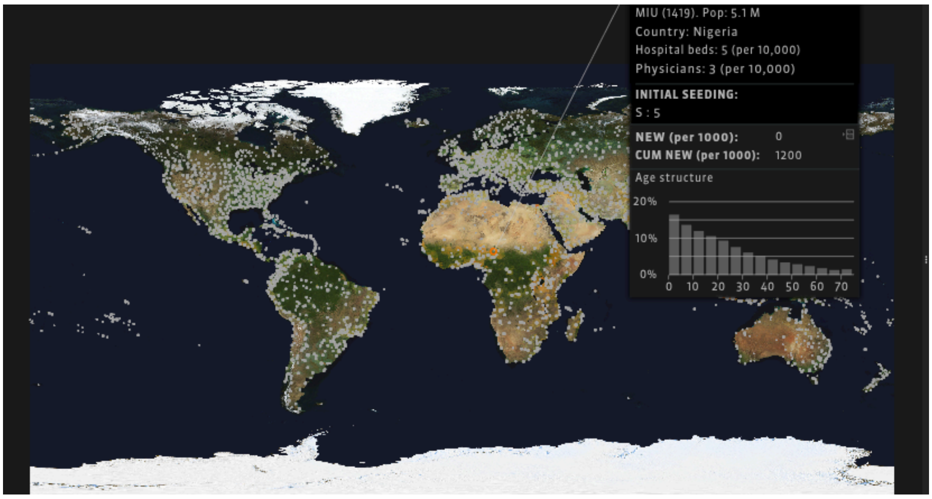
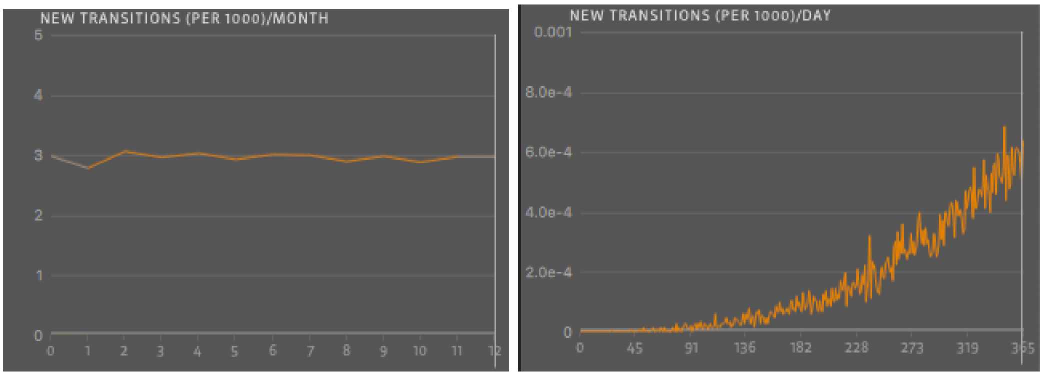


Fig. 6. Typhoid Fever spread decreases by age structure in Yobe



(a) (b)

Fig. 7. The plots show time-dependent pattern of (a) human infectiousness, and (b) recovery from typhoid

5 Conclusion

Typhoid fever is a threat to human race and perhaps not much research is conducted to investigate the disease dynamics in Yobe State. In this study, we used the classical epidemic model SIR into GLEaMviz computational software and simulated the annual pattern of the typhoid fever spread. Below The following are major findings of this study

a The results showed mild seasonal fluctuation in the pattern which coincides with rainfall season, thus the agents causing the disease transmission is possibly being transported through flowing water.

b Also, the results shows strong evidence of perennial incidence with likelihood of high cases during raining season. Further work is needed to validate this findings by using real data.

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Competing Interests

Authors have declared that no competing interests exist.

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