



FORECASTING MENINGITIS OUTBREAK WITH A CLIMATE-INSPIRED MODEL

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ABSTRACT: *Recently, meningitis outbreaks have posed substantial public health issues across the world, prompting effective preventative and control measures. Therefore, this work proposes a unique method for estimating meningitis incidence by incorporating atmospheric data into a predictive model, christened as climate-based predictive meningitis model (CBPMM). The CBPMM is created using machine learning formalities, with meteorological data serving as a key component of the predictor. The model incorporates powerful prediction techniques that analyze historical data and environmental patterns comprehensively and thus, provide useful insights for early identification and proactive intervention strategies. With infection transmission rate (β) at 0.88, carrier natural recovery rate 0.06, and the efficacy of treatment (η) is 0.001, $R_0 = 1.623668904$; it implies that the infectious disease persists in the community. However, when $R_0 = 0.4265309$; that is, the disease is controllable. The CBPMM marks a huge step forward in meningitis surveillance, providing healthcare authorities with information to promptly limit the effect of outbreaks.*

KEYWORDS: Forecasting; Meningitis outbreaks; Environmental factors; Machine learning technique.



INTRODUCTION

Meningitis is an inflammation of the meninges membranes that surround the brain and the spinal cord, and which protects the central nervous system, together with the cerebrospinal fluid [1]. Meningitis is caused by different types of organisms; bacteria and viruses are the most common causes of meningitis. When these organisms are in the cerebrospinal fluid, everything in the immediate area will be inflamed. [5] Bacterial meningitis occurs more often than viral. More than 80% of all meningitis cases are caused by three distinct types of bacteria, namely: *Neisseria meningitidis*, *Haemophilus influenzae* and *Streptococcus pneumoniae* ([7]. According to Molesworth [9], humans are the sole hosts of *Neisseria meningitidis* and it has been responsible for the outbreak of the disease every year particularly in the northern part of Nigeria. In most people, antibodies kill the bacteria, preventing them from causing the disease. Meningitis can spread quickly among people who live in close spaces like schools, daycare centers, military barracks and college dormitories [7]. Meningitis usually occurs as epidemics, and has posed a major health problem since it was first recognized and thus, the problem is studied with a view to gain insight into how to curb the spread. In this regard, many researchers have developed different meningitis SIR, SEIR and SVCIR models in a bid at studying the disease.

[8] developed three compartmental deterministic models of seasonal hyperendemicity. The models were parameterized based on current knowledge on meningococcal biology and pathophysiology. The three models' performance were compared in reproducing weekly incidence of suspected cases of acute bacterial meningitis surveillance system. The result suggests that a combination of seasonal changes increase the risk of invasive disease, and carriage transmission is involved in the hyperendemic seasonality of meningitis in the Africa meningitis belt.

[12] in his paper proposed a combination of Double Exponential Smoothing and Adjacent Accumulation Grey Double Exponential Smoothing techniques to further improve prediction accuracy. The Hybrid model was applied along with the ARIMA Method and Holt-Winters Exponential Moving Average Method (H-WEMA) and comparing these three methods, the new model, H-WEST, has a higher prediction accuracy measured using the MAPE (Mean Absolute Percentage Error). In this study, a model incorporating the climatic factors that can trigger the outbreak of meningitis in the Meningitis Belt of Africa was formulated and the sensitivity analysis was carried out to establish that the recovery rate of carriers is the most sensitive parameter in the model. From our knowledge, this is the first model to incorporate climatic factors into a meningococcal meningitis model.

METHODOLOGY

The methodology comprises representation of the model in compartments with a view to study the influence of some environmental factors on meningitis outbreak.

Description of the Model

The population in the model is divided into five compartments. The susceptible $S(t)$, the Exposed $E(t)$, the carrier $C(t)$, the Infected $I(t)$ and $R(t)$ is the whole human population after Recovery. All individuals, whatever their status, are subject to natural death which occurs at the rate μ . The susceptible population is reduced by infection following the effective contact with the carrier and infected individuals as a rate α define by

$\alpha = \beta \frac{(C+I)}{N}$, where β is the infection transmission rate and N , is the population size. The flowchart for the disease progression is depicted in Figure 1

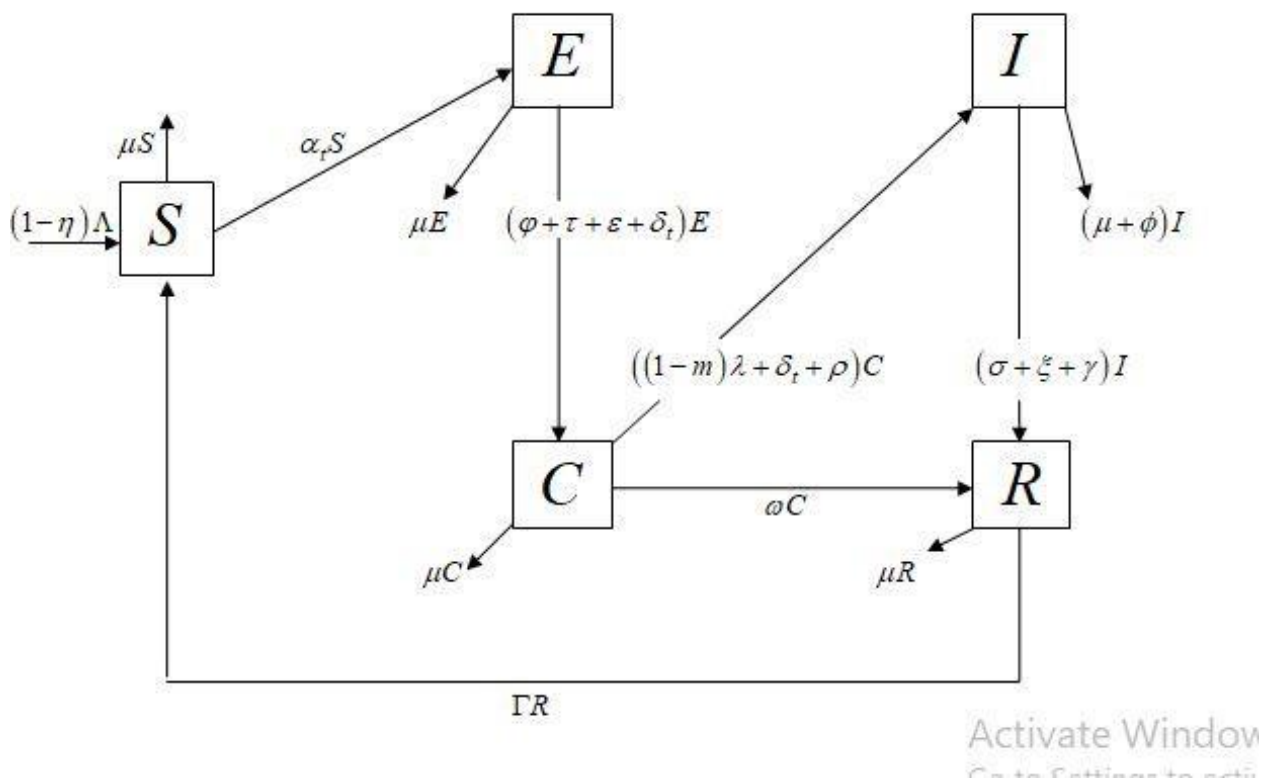


FIGURE 1: THE SCHEMATIC DIAGRAM OF THE MODEL



MODEL FORMULATION

The state equations, which is the model, is as follows:

$$\frac{dS}{dt} = (1 - \eta)\Lambda + \Gamma R - \alpha S - \mu S$$

$$\frac{dE}{dt} = \alpha S - (\varphi + \mu + \tau + \varepsilon)E - \delta_t E$$

$$\frac{dC}{dt} = (\varphi + \tau + \varepsilon)E + \delta_t E - (\rho + \mu + \omega) C - (1 - m)\lambda C - \delta C$$

$$\frac{dI}{dt} = \rho C - (\sigma + \xi + \mu + \phi + \gamma)I + (1-m)\lambda C + \delta C$$

$$\frac{dR}{dt} = \omega C + (\sigma + \xi + \gamma)I + (\Gamma + \mu)R$$

$$\alpha = \beta \frac{(C+I)}{N},$$

$$\delta = T + h + a$$

Table 1: Table of Description of Variables and Parameters

| Variables | Descriptions |
|--------------------|--|
| <i>S</i> | The entire number of humanity that are vulnerable |
| <i>E</i> | Unprotected humans as a whole do not exhibit any symptoms |
| <i>I</i> | The total number of persons who are either infected or suggestive |
| <i>C</i> | Asymptomatic carrier population |
| <i>R</i> | The whole human population after recovery |
| Parameters | |
| δ_t | Infiltration parameter due to seasonal changes |
| γ | Infectious individual recovery rate |
| Γ | Natural immunity of the inhabitants is lost |
| <i>N</i> | The whole human population |
| ε | Humans' pace of advancement from the exposed class |
| ω | Carrier natural recovery rate |
| Λ | Proportion of unvaccinated individuals |
| ξ | A recovered human population's rate of re-infection |
| τ | The rate at which an infected person exhibits signs of the infection |
| μ | Human population decline through natural deaths |
| φ | The vulnerable are protected |
| <i>N</i> | Incidence of mass actions (population size) |
| β_t | Infection transmission rate |
| $\beta_t S(C + I)$ | New infection rates |
| β_t / N | The newly identified meningitis infections sparked the identification of further meningitis infections |
| <i>S/N</i> | Enough residents typically come into contact to spread an infection. |
| λ | Infections rate of carriers |



| | |
|-----------|---|
| m | Fraction of carriers |
| η | Vaccination efficacy |
| ϕ | Disease induced mortality rate |
| ρ | Progression rate from Carrier to Infections |
| T, h, a | Temperature, Humidity, Aerosols |

MODEL ANALYSIS

Disease Free Equilibrium

Let Γ_0 denotes the disease free periodic solution of the model (1), which is the equilibrium point in the absence of infection, and is given for the population to be deprived of the infection, the infected state will be assumed to be zero, that is $\Gamma_0 = 0$. Solving the system of equations simultaneously to obtain a parameter for the disease-free equilibrium state, yield as follows:

$$\Gamma_0 (S_0, E_0, C_0, I_0, R_0) = \left(\frac{(1-\eta\Lambda)}{\mu}, 0, 0, 0, 0 \right) \tag{2}$$

COMPUTATION OF REPRODUCTION NUMBER

The next generation matrix approach is employed to compute the reproduction number for the non-autonomous model (1), using the notation in [13]. The matrices for the new infection terms and the transition terms for model (1) are denoted respectively as F(t) and V(t)

$$F(t) = \begin{pmatrix} 0 & \beta & \beta \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} \tag{3}$$

$$V(t) = \begin{pmatrix} \varphi + \mu + \tau + \epsilon + \delta_t & 0 & 0 \\ -(\mu + \tau + \epsilon + \delta_t) & \mu + \rho + (1 - m)\lambda + \omega + \delta_t & 0 \\ 0 & -\rho + (1 - m)\lambda + \delta_t & \sigma + \xi + \mu + \phi + \gamma \end{pmatrix} \tag{4}$$

$$\lambda = \begin{pmatrix} 0 \\ 0 \\ \frac{\beta S^0 G_2 (G_5 + G_4)}{N G_1 G_3 G_5} \end{pmatrix},$$

From the eigenvalues $\lambda_1 - \lambda_3$ above, the dominant largest eigenvalues is λ_3 . Therefore, the basic reproduction number which is given by the largest eigenvalue for the model is denoted by R_0 , and given as

$$G_1 = \varphi + \mu + \tau + \epsilon + \delta;$$

$$G_2 = \varphi + \tau + \epsilon + \delta;$$



$$G_3 = \rho + \mu + \omega + (1 - m)\lambda + \delta;$$

$$G_4 = \rho + (1 - m)\lambda + \delta;$$

$$G_5 = \sigma + \zeta + \phi + \gamma + \mu$$

$$S^0 = \frac{(1 - \eta)\Lambda}{\mu}$$

Hence,

$$R_0 = \frac{\beta (1 - \eta) \Lambda (\varphi + \tau + \epsilon + \delta) (\sigma + z + \phi + \gamma + \mu + \rho + (1 - m)\lambda + \delta)}{\mu N(\varphi + \mu + \tau + \epsilon + \delta) (\rho + \mu + \omega + (1 - m)\lambda + \delta) (\sigma + z + \phi + \gamma + \mu)} \tag{5}$$

ENDEMIC EQUILIBRIUM

At equilibrium point,

$$\frac{dS}{dt} = \frac{dE}{dt} = \frac{dC}{dt} = \frac{dI}{dt} = \frac{dR}{dt} = 0$$

Where,

$$z = (1 - \eta)\Lambda, \quad \alpha = \frac{\beta(C + I)}{N}, \quad K_1 = \varphi + \mu + \tau + \epsilon + \delta, \\ K_2 = \rho + \mu + \omega + (1 - m)\lambda + \delta,$$

$$K_3 = \sigma + \xi + \mu + \phi + \gamma, \quad K_4 = \Gamma + \mu, \quad L_1 = \varphi + \tau + \epsilon + \delta, \\ L_2 = \rho + (1 - m)\lambda + \delta,$$

$$L_3 = \sigma + \xi + \gamma \tag{6}$$

$$S = \frac{A_2 I + G K_4 L_1 L_2}{\mu L_1 L_2 K_4}, \tag{7}$$

Where $A_2 = \Gamma A_1 L_1 - K_1 K_2 K_3 K_4$.

$$N = \frac{A_3 I + K_4 L_1 L_2}{\mu L_1 L_2 K_4}, \tag{8}$$

Where $A_3 = \mu \{K_4 [L_1 (L_2 + K_3) + K_2 K_3] + L_1 A_1\} + A_2$



$$\alpha = \frac{K_1 E}{S} = \frac{\beta(I+C)}{N} \tag{9}$$

and

$$I = \frac{zK_4 L_1 L_2 K_1 K_2 K_3 (R_0 - 1)}{A_3 K_1 K_2 K_3 - \beta A_2 L_1 (K_3 + L_2)} \tag{10}$$

SENSITIVITY ANALYSIS

Sensitivity analysis is the use of certain techniques to determine the effect of individual or group of parameters on the overall behavior of a model. It clears the uncertainties mostly associated with the values of the parameters and builds confidence on the choice of suitable parameters for a model.

Table 2: Parameter values and sensitivity index of the meningitis model

| PARAMETER | VALUE | SOURCE | SENSITIVITY INDEX | PARAMETER | VALUE | SOURCE | SENSITIVITY INDEX |
|------------|--------|---------|-------------------|-----------|--------|---------|-------------------|
| ϕ | 0.4868 | [3] | 0.011194225203 | ρ | 0.56 | Assumed | -0.1268127295 |
| τ | 0.5 | [3] | -0.04996624353 | μ | 1/56 | [3] | -0.1132256513 |
| ϵ | 0.1 | [3] | 0.002299553245 | λ | 0.0438 | [3] | -0.005951140243 |
| δ | 0.8 | Assumed | -0.1811610421 | M | 0.4 | Assumed | 0.003967426826 |
| σ | 0.88 | [14] | -0.1870518050 | ξ | 0.2 | [3] | -0.07482072200 |
| β | 0.3345 | [2] | 0.8748623434 | γ | 0.001 | [14] | 0.1608645523 |
| ω | 0.06 | [14] | -0.1132256513 | | | | |

After the partially differentiating the R_0 with respect to each of the parameters involved, and substituting the parameter values in table 2, to obtain the sensitivity indices presented in the same table 2 above. The most sensitive parameter is σ That is the recovery rate of carriers, with the highest negative value, while the least is the most positive value β . Also using the above parameter values computed on maple to obtained $R_0 = 1.623668904$. Consequently, when the force of infection is reduced, $\beta = 0.3345$, the recovery rate of carrier is increased, $\sigma = 0.5$ and the vaccination efficacy rate is improved to 0.8, then $R_0 = 0.4265309$. This showed that the meningitis epidemic is controllable.

NUMERICAL SIMULATION

DATA SOURCES

The environmental factors considered are Temperature, Humidity and Aerosols. The data used for the analyses were acquired from the website of the Meteorological State Agency of Spain (AEMET) and various collaborating bodies.



HYBRIDIZED-HOLT WEIGHTED EXPONENTIAL SMOOTHING METHOD (H-WEST)

The CBPMM is created using machine learning formalities, with meteorological data serving as a key component of the predictor. The model incorporates powerful prediction techniques that analyze historical data of the environmental patterns comprehensively and thus, provide useful insights for early identification and proactive intervention strategies. Exponential smoothing was proposed in the late 50's by Brown (1959), Holt (1957) and [10] and is one of the most successful forecasting methods. This method of forecasting is produced with the use of exponential smoothing methods which are weighted averages of past values of the data, with the weights decaying exponentially as the observation expands. The Hybridized Holt-Winter method under consideration takes into account both seasonal changes and trends. It provides better forecasts with simple formulations allowing the incorporation of error, trend, and seasonal components in a comprehensive manner (Holt 2004, lifeng W. et al., 2006). The Table 3 below shows the actual and predicted values using the H-WEST.

Table 3: H-WEST PREDICTION

| WEEKS | TEMPERATURE (°c) | | HUMIDITY(gm ⁻¹) | | AEROSOL (mm) | | MENINGITIS | |
|-------|------------------|-----------------|-----------------------------|-----------------|--------------|-----------------|--------------|-----------------|
| | Actual Value | Predicted Value | Actual Value | Predicted Value | Actual Value | Predicted Value | Actual Value | Predicted Value |
| 1 | 32 | 32 | 12 | 12 | 2 | 2 | 2391 | 2391 |
| 2 | 22 | 22.33 | 5 | 5.28 | 0 | 0 | 562 | 563 |
| 3 | 36 | 36.21 | 3 | 3.14 | 1 | 1.23 | 2659 | 2660 |
| 4 | 27 | 27.11 | 19 | 19.04 | 2 | 2.15 | 3485 | 3486 |
| 5 | 38 | 38.43 | 13 | 13.33 | 2 | 2.07 | 4309 | 4310 |
| 6 | 31 | 31.82 | 3 | 3.77 | 1 | 1.32 | 2368 | 2369 |
| 7 | 30 | 30.96 | 6 | 6.22 | 2 | 2.50 | 3609 | 3611 |
| 8 | 17 | 17.05 | 14 | 14.72 | 0 | 0.90 | 2059 | 2061 |
| 9 | 35 | 35.43 | 3 | 4.06 | 1 | 1.69 | 5565 | 5567 |
| 10 | 17 | 17.41 | 4 | 5.35 | 2 | 2.04 | 1093 | 1095 |

DISCUSSION AND CONCLUSION

Model on transmission dynamics of meningitis under the influence of some environmental factors, temperature, humidity and aerosols, has been presented. The endemic equilibrium of the systems of equations was determined, and the reproduction number was computed to be 1.623668904. The sensitivity indices were calculated from Table 2, which showed that the most sensitive parameter is the recovery rate of carriers. This implies that the lower the recovery rate the more the disease will spread. Infection transmission rate at 0.88 (Asamoah et al., 2018), carrier natural recovery rate is 0.06, and efficacy of treatment is 0.001, then $R_0 = 1.623668904$, when infection transmission rate is fixed at 0.3345, efficacy of treatment is 0.1, delta parameter is 0.6, that is a decrease in temperature and disease induced mortality rate is 0.5, then, $R_0 = 0.4265309$ which implies that the disease is controllable. Numerical simulation was carried out using a miniature proportion of the data on the environment factors and the meningitis cases for the purpose of prediction, using the Hybridized-Holt weighted exponential smoothing



method (H-WEST). From Table 3, it can be seen that the actual value and the predicted value have significantly low differences. The accuracy of the method was further ascertained with a Mean Absolute Percentage Error (MAPE) of 0:00162 which shows a high level of accuracy of the H-WEST method in forecasting of meningitis and the associated environmental factors.

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