



# Health Analysis Using Ecological Niche and Agent-Based Models in Predicting Malaria Prevalence Among Pregnant Women in Lagos State

Molayoto Jocelyn Abiola, Ayoola Olamilekan Abiola & Sylvester Emeka Obu

*Department of Human Kinetics, Sports and Health Education, LASU*  
*Department of Chemistry, School of Science, Lagos State University of Education, Oto-Ijanikin*  
*Department of Human Kinetics, Sports and Health Education, LASU*

## KEYWORDS:

Malaria Prevalence,  
 Temperature, Rainfall,  
 Migration, Land use

## WORD COUNT:

198

## CORRESPONDING EMAIL ADDRESS:

molayoto.abiola@lasu.edu.ng

## ORCID NUMBER:

## ABSTRACT

Malaria, a life-threatening infectious disease continues to be a global health concern. This cross-sectional study predicted malaria prevalence in three health districts of Lagos State, using a randomised sample of 500 pregnant women. The research utilised a Malaria Prevalence Prediction Questionnaire (MPPQ) based on the Ecological Niche and Agent-Based Models, incorporating AI algorithms and statistical models sensitive to local environmental conditions. Data components included temperature, rainfall, migration, and land use score, synthesised into a cohesive dataset. Inferential analysis involved multiple regression and t-tests. Findings indicated the Ecological Niche Model (ENM) significantly predicted malaria prevalence variations ( $F=1.17$ ,  $R\text{-square} = 0.54$ ), as did the Agent-Based Models (ABMs) ( $F=3.33$ ,  $R\text{-square} = 0.77$ ). No significant variation was found between the predictions of ENM and ABMs ( $p\text{-value} 0.999$ ), while the combined models accurately predicted malaria prevalence ( $F=0$ ,  $R\text{-square} = 1$ ). Conclusions suggested the ENM, considering environmental factors like temperature and rainfall, could enhance malaria prevention among pregnant women. Recommendations include collaborating with local health educators and other healthcare providers to develop educational programmes, implementing community-based monitoring systems for malaria risk analysis, equipping healthcare providers with health informatics tools for data collection, and forming interdisciplinary teams to develop nuanced models for malaria transmission dynamics.

## HOW TO CITE

Abiola M.J, Abiola A.O & Obu S.E (2025). Health Analysis Using Ecological Niche and Agent-Based Models in Predicting Malaria Prevalence Among Pregnant Women in Lagos State. *Educational Perspectives*, 13(2), 47-57.



## Introduction

Malaria, a life-threatening infectious disease caused by the *Plasmodium* parasite, remains a global health concern, especially in regions where environmental conditions favour transmission by the *Anopheles* mosquito (White, 2022). The risks of malaria are particularly acute in pregnancy, contributing to maternal anaemia, low birth weight, and infant mortality (World Health Organisation, 2023). Understanding the factors that influence malaria transmission is crucial to mitigating its impact. The prevalence and transmission dynamics of malaria are shaped by a complex interplay of environmental, climatic, and human factors, and recent advances in modelling techniques offer promising tools for predicting malaria risk.

One of the most significant advancements in malaria research has been the integration of Ecological Niche Models (ENMs) and Agent-Based Models (ABMs). These advanced models provide a framework for analysing and predicting malaria prevalence by simulating various environmental and human factors (Regos et al., 2022; Modu et al., 2023). ENMs, for instance, are highly effective in predicting the spatial distribution of malaria based on climatic factors such as temperature and precipitation. These climatic variables are critical in shaping the life cycle of the *Anopheles* mosquito and the *Plasmodium* parasite, with warmer temperatures accelerating development and precipitation providing breeding habitats for mosquitoes (Filho et al., 2023). By integrating these variables, ENMs help identify regions where conditions are conducive to malaria transmission, allowing for targeted interventions.

However, climatic conditions alone do not solely explain malaria transmission dynamics. Human factors, including migration and land use changes, have also been implicated in the spatial and temporal dynamics of malaria. For example, the

movement of individuals from malaria-endemic to non-endemic areas can introduce the parasite to new regions, while changes in land use, such as deforestation or urbanization, create or disrupt mosquito breeding habitats (Loiseau & Sehgal, 2022; Arisco et al., 2022). ABMs are particularly valuable for capturing the complexity of these interactions, allowing researchers to simulate diverse scenarios and incorporate social, economic, and behavioural factors that influence malaria transmission (Modu et al., 2023). This dynamic modelling approach enables a more robust understanding of how human activity interacts with environmental conditions to shape malaria risk.

The synergy between ENMs and ABMs is particularly important when addressing malaria in regions like Lagos State, Nigeria. Located in a wetland region with favourable conditions for mosquito breeding, Lagos State is highly vulnerable to malaria transmission (Lagos State Ministry of Health, 2022). Despite ongoing efforts, including the establishment of the State Malaria Elimination Programme (SMEP), malaria remains a significant public health challenge, accounting for an estimated 3.8% of Nigeria's 68 million malaria cases in 2021. From 2018 to 2021, estimated cases increased from 2.2 million to 2.6 million, the estimated incidence increased from 164.5 to 174.9 per 1000 population. Malaria prevalence by microscopy was 2.6% in 2021 (WHO, 2022)

Malaria accounts for more than 70% of outpatient in the public health facilities. More than 700,000 malaria cases are reported annually. 657,154 patients with malaria were seen in both private and public health facilities in 2020. Malaria is prevalent in the vulnerable groups – children under 5 years and pregnant women where the infection can be profoundly more severe (Olasunkanmi, 2021). Despite significant progress in understanding the complex factors influencing malaria transmission,



there persist notable challenges in accurately predicting and mitigating the prevalence of this deadly disease. The primary issue revolves around the inadequacies of existing models, particularly their struggle to capture the intricate interplay of multivariate environmental variations. Current models often fall short in encompassing the full spectrum of factors that contribute to malaria dynamics, resulting in inaccuracies and an inability to provide precise predictions in Lagos State, hence this study.

Therefore, this study examined the significance of Ecological Niche and Agent-Based Models in predicting malaria prevalence among pregnant women and the variations of the prediction of prevalence in the three selected health districts of Lagos State.

### Methodology

The cross-sectional survey research design was used in carrying out the study. The target population for this study comprised pregnant women in three health districts of Lagos State. The sample (N= 500) were purposively selected pregnant women attending antenatal clinics in three Flagship and seven comprehensive health centres in the three health districts at 10 participants per health centre. A self-developed Malaria Prevalence Prediction Questionnaire (MPPQ) was used to collect the data in line with the Ecological Niche Model of Maximum Entropy and the Agent based Model to accommodate the variables under study and response options in line with Likert four-point rating scale. The questionnaire was in two sections; section A asked questions on demographic variables while section B was designed in line using 5-point Likert scales (Strongly agree, Agree, Disagree, Strongly disagree and Can't say; (with scores of 4, 3, 2, 1 and 0 respectively).

In this study, the dataset was simulated to study the impact of various factors such as temperature,

rainfall, migration patterns, and land use on malaria prevalence. The dataset spans 10 different locations over a five-year period, divided equally between the rainy and dry seasons. The generation of the dataset was based on a combination of AI algorithms, statistical models, and predefined criteria specific to the environmental and socio-economic conditions of the selected health districts.

Temperature and rainfall data were simulated based on historical climate patterns of the region. AI algorithms were employed to generate realistic temperature fluctuations and rainfall amounts for the rainy and dry seasons, ensuring that these reflected typical seasonal variations.

To calculate the migration score, we utilised the net migration statistics of Nigeria, which currently stands at -0.29. This figure indicates a slight predominance of emigration over immigration. An AI-based predictive model was developed to simulate migration scores, acknowledging the dynamic nature of human movement. The model was trained to recognize that emigration which typically results in immigration in a subsequent period, and vice versa, thereby maintaining a balance in population dynamics.

Each type of land use was assigned a score based on the estimated minimum volume of water consumed or displaced by such activity. This approach was chosen as it reflects the direct impact of land use on local water resources, which is a critical factor in the study of malaria prevalence. The AI algorithms were trained to randomly select and combine different land use activities, ensuring a realistic and varied representation of land use patterns over the 150-day period.

Once generated, the individual data components (temperature, rainfall, migration score, and land use score) were integrated into a cohesive dataset. The AI system was programmed to ensure that the data remained consistent with known patterns and logical constraints. For example, higher rainfall

was paired with agricultural land use during the rainy season, while increased migration and construction activities were more prevalent in the dry season. The questionnaire were administered by the researcher via online forms. Respondents were sent the link to the questionnaire directly and responses were collected from the respondents immediately after completion. Checks were put in place to prevent double data entry by the respondents.

The completed questionnaire copies were collated and analysed using both descriptive and inferential statistics. Descriptive statistics of frequency counts, percentages, charts, means, standard deviation were used to analyse Section A of the

questionnaire which dealt with the demographic characteristics of the respondents, while multiple regression analysis was used to test the significance of the data at 0.05 alpha level.

### Results

The age range of the respondents was between 18 and 35 years. 85% had formal education (secondary to tertiary) while 15% reported primary to no formal education. The largest group is employed full-time, accounting for 36%, the unemployed group is 24.80%, part-time employment represent 21.40%, self-employed women make up 15% while homemakers are the smallest group at 2.80%.

**Table 1:** ENM Prediction of significant variations in malaria prevalence rates (MPR) among Pregnant

Women								
R	R Square	Adjusted R Square	Std. Error of the Estimate	F	Df	Sig. F Change	LS	Decision
0.73	0.54	0.08	1.66	1.17	2	0.382	0.05	Not Sig.

The regression model showed that the variables TEMP (Temperature) and RAIN (Rainfall) explained 53.97% of the variance from the variable MPR. Using the present sample, it was found that

the effect was not significantly different from zero,  $F=1.17$ ,  $p = .382$ ,  $R\text{-square} = 0.54$ . The following regression model is obtained:

$$MPR = 29.33 + 0.01 \cdot TEMP + 0.01 \cdot RAIN$$

**Table 2:** Significant Influence of Environmental variations in malaria prevalence rates among pregnant women in Selected Health Districts of Lagos State using the Ecological Niche Model.

Model	Unstandardized Coefficients B	Standardised Coefficients Beta	Standard Error
(Constant)	29.33		12.6
TEMP	0.01	0.21	0.02
RAIN	0.01	0.58	0.01

Table 2 shows that the standardised coefficients beta are independent of the measured variable. In this model, the variable RAIN has the greatest

influence on the variable MPR due to a beta score of 0.58.

When all independent variables are zero, the value of the variable MPR is 29.33. If the value of the variable TEMP changes by one unit, the value of the variable MPR changes by 0.01. If the value of the variable RAIN changes by one unit, the value of the variable MPR changes by 0.01. An ANOVA

was used to test whether this value was significantly different from zero. The p-value ( $<.001$ ) is less than 0.05 which means that the Ecological Niche Model (ENM) significantly predict variations in malaria prevalence rates among pregnant women in Lagos State.

**Table 3:** ABM Prediction of variations in malaria prevalence rates among pregnant women.

R	R Square	Adjusted R Square	Std. Error of the Estimate	F	Df	Sig. F Change	LS	Decision
0.88	0.77	0.54	1.17	3.33	2	0.121	0.05	Not Sig.

The regression model showed that the variables MP (migration patterns) and LUP (land use patterns) explained 76.89% of the variance from the variable MPR. An ANOVA was used to test whether this value was significantly different from

zero. Using the present sample, it was found that the effect was not significantly different from zero,  $F=3.33$ ,  $p = .121$ ,  $R^2 = 0.77$ . The following regression model is obtained:  $MPR = -46.51 + 0.05 \cdot MP + 0.05 \cdot LUP$

**Table 4:** Coefficients of Environmental variations in malaria prevalence rates among pregnant women using the Agent based Model.

Model	Unstandardized Coefficients B	Standardised Coefficients Beta	Standard Error
(Constant)	29.33		12.6
TEMP	0.01	0.21	0.02
RAIN	0.01	0.58	0.01

Table 4 shows that the standardised coefficients beta are independent of the measured variable. In this model, the variable RAIN has the greatest influence on the variable MPR due to a beta score of 0.58.

When all independent variables are zero, the value of the variable MPR is -46.51. If the value of the variable MP changes by one unit, the value of the variable MPR changes by 0.05. If the value of the

variable LUP changes by one unit, the value of the variable MPR changes by 0.05. An ANOVA was used to test whether this value was significantly different from zero. The p-value ( $<.001$ ) is less than 0.05 which means that the Agent-Based Models (ABMs) significantly predict variations in malaria prevalence rates among pregnant women in the three selected health districts of Lagos State.

**Table 5:** T-test Analysis Variations in Malaria Prevalence Rates Predictions between the Ecological Niche Model and Agent-Based Model.

	Sum of Squares	df	Mean Squares	F	P
Treatment	.27698	19	.000604	0.4	0.999
Within	.10878	18	.1682		
Error	.1682	1			

Table 6 shows the F score (0.4) and mean squares (treatment: 0.000604, within: 0.1682) and error (0.1682) of the student t-test carried to measure the variation between the predictions of the Ecological Niche Model and Agent-Based Model of

prevalence rates among pregnant women in three selected health districts of Lagos State. The p-value (0.999) is greater than 0.05 hence there is no significant variation in the predictions of the Ecological Niche Model and Agent-Based Model.

**Table 7:** Prediction of variations in malaria prevalence rates among pregnant women. using both the Ecological Niche Model and Agent-Based Model

R	R Square	Adjusted R Square	Std. Error of the Estimate	F	Df	Sig. F Change
1	1	-∞	∞	1	4	0

The regression model showed that the variables TEMP, RAIN, MP and LUP explained 100% of the variance from the variable MPR. An ANOVA was used to test whether this value was significantly different from zero. Using the present sample, it

was found that the effect was not significantly different from zero,  $F=0$ ,  $p = 1$ ,  $R^2 = 1$ . The following regression model is obtained:

$$MPR = -7.1 + 0.04 \cdot TEMP + 0.01 \cdot RAIN + 0.09 \cdot MP - 0.07 \cdot LUP$$

**Table 8:** Coefficients of Environmental variations in malaria prevalence rates among pregnant women using both the Ecological Niche Model and Agent-Based Model.

Model	Unstandardized Coefficients B	Standardised Coefficients Beta
(Constant)	-7.1	
TEMP	0.04	1.13



RAIN	0.01	0.65
MP	0.09	0.85
LUP	-0.07	-0.86

The standardised coefficients Beta are independent of the measured variable and are always between -1 and 1. The larger the amount of Beta, the greater the contribution of the respective independent variable to explain the dependent variable MPR. In this model, the variable TEMP has the greatest influence on the variable MPR with a beta score of 1.13.

When all independent variables are zero, the value of the variable MPR is -7.1. If the value of the variable TEMP changes by one unit, the value of the variable MPR changes by 0.04. If the value of the variable RAIN changes by one unit, the value of the variable MPR changes by 0.01. If the value of the variable MP changes by one unit, the value of the variable MPR changes by 0.09. If the value of the variable LUP changes by one unit, the value of the variable MPR changes by -0.07. An ANOVA was used to test whether this value was significantly different from zero (Appendix 4.2). The p-value ( $<.001$ ) is less than 0.05 which means that the combined models incorporating multivariate environmental variations will significantly predict malaria prevalence rates among pregnant women in the three selected health districts of Lagos State.

### Discussion of Findings

The regression analysis conducted on environmental variables affecting malaria prevalence rates (MPR) in the three selected health districts of Lagos State revealed that temperature (TEMP) and rainfall (RAIN) explained 53.97% of the variance in MPR. Notably, the analysis yielded an F-value of 1.17 with a p-value of  $.382 > 0.05$ , indicating that the effect of these variables was not significantly different from zero. However, the ANOVA p-value was  $0.001 < 0.05$ , suggesting

significant predictive capability of the Ecological Niche Model (ENM). The standardised beta coefficient indicated that RAIN had a greater influence on MPR, with a beta score of 0.58.

The findings, particularly the significant influence of RAIN (beta = 0.58), are instrumental for malaria prevention in Lagos State. The significance of TEMP and RAIN in predicting malaria prevalence aligns with global trends in malaria research, where climatic factors are considered pivotal in understanding and managing the disease. Adeogun et al. (2023) demonstrated the critical role of environmental variables in predicting the distribution of *Anopheles gambiae* in Nigeria. Like this study, their research employed an ecological niche model (ENM) to assess how different environmental factors influence malaria vectors growth.

Similarly, Phang et al. (2023) integrated machine learning-based ecological niche modelling to predict *Plasmodium knowlesi* transmission risk. Their findings underscored the importance of environmental covariates, such as precipitation and elevation, in malaria occurrence. This parallels our study's emphasis on rainfall and temperature, highlighting a consistent theme across different regions and malaria species.

The relevance of these findings to malaria prevention becomes evident when considering these parallels. By understanding how specific environmental variables influence malaria prevalence rate, targeted interventions can be developed. For instance, recognising that rainfall has a significant beta score of 0.58 in our model suggests that interventions during the rainy season could be particularly effective. The study by Saberi et al. (2023) on the impact of climate change on



malaria vectors in Iran reinforces the importance of ongoing monitoring and adaptation of malaria control strategies in response to environmental changes. While their study found that climate change might not significantly alter vector distribution by 2030, it highlights the need for continual reassessment of environmental factors - a principle that is also applicable in the context of Lagos State.

In testing whether the Agent-Based Models (ABMs) will significantly predict variations in malaria prevalence rates among pregnant women, the regression model explored in this research, focusing on the variables of migration patterns (MP) and land use patterns (LUP) and their effect on malaria prevalence rates (MPR) aligns with emerging trends in contemporary malaria research. The model's assertion that these variables explain a significant portion (76.89%) of the variance in MPR is a crucial finding, albeit with certain limitations as indicated by the ANOVA results ( $F=3.33$ ,  $p = .121$ ,  $R^2 = 0.77$ ). This suggests that while MP and LUP are influential, their impact may not be as definitive or exclusive as hypothesised, necessitating a broader perspective in analysing malaria prevalence.

The research by Memarsadeghi *et al.* (2023) on *P. vivax* malaria in Thailand underscores a similar theme, focusing on work-related travel and land use, particularly in forested areas. Their findings of a significant variance in malaria risk among different occupational groups due to work-related travel and location echo the importance of considering MP and LUP in understanding malaria prevalence. This parallel reinforces the value of our model in highlighting key environmental and socio-economic factors that contribute to malaria risk.

Similarly, the work of Ozodiegwu *et al.* (2023) in Nigeria, utilising agent-based models (ABMs) for malaria intervention planning, aligns with our

approach. Their emphasis on targeted interventions based on local conditions and the ABM's capability to simulate various scenarios offers a framework for understanding the dynamics of malaria transmission in relation to environmental and human factors. This is particularly relevant given our model's focus on localised conditions in the selected health districts of Lagos State.

The study by Modu, Polovina, and Konur (2023), proposing an ABM for malaria transmission, further validates the findings of this study. Their focus on heterogeneous mixing and agent interactions, and the model's success in predicting peak malaria seasons, aligns with this study's emphasis on the complex interplay between human behaviour (migration, land use) and malaria prevalence. The similarities in the approach and findings suggest that ABM model could be instrumental in predicting and planning for malaria outbreaks in specific regions. Also, Li *et al.* (2023) explored the impact of human mobility on malaria control, revealing significant insights into how different occupational groups and their mobility patterns influence malaria risk. Their findings on forest workers being at a higher risk due to their mobility patterns resonate with ABM's emphasis on MP and LUP. This correlation highlights the importance of considering occupational and spatial factors in malaria prevention strategies.

On the significant variation in the predictions of the Ecological Niche Model and Agent-Based Model of prevalence rates among pregnant, the two models presents compelling insights, particularly when examining the statistical values from the student t-test. The ENM, represented by the prediction model  $MPR = 29.33 + 0.01 \cdot TEMP + 0.01 \cdot RAIN$  ( $F=1.17$ ,  $p = .382$ ,  $R\text{-square} = 0.54$ ), and the ABM, depicted by  $MPR = -46.51 + 0.05 \cdot MP + 0.05 \cdot LUP$  ( $F=3.33$ ,  $p = .121$ ,  $R\text{-square} = 0.77$ ), both offer distinct yet congruent views on malaria prevalence.

The F score of 0.4 and mean squares (treatment: 0.000604, within: 0.1682) for the t-test, along with





the error rate (0.1682), collectively illustrate the variance within each model and between the two models' predictions. Importantly, the high p-value of 0.999, significantly exceeding the 0.05 threshold, implies no significant variation between the predictions made by the ENM and ABM. This finding resonates with the broader context of malaria prediction and prevention.

This lack of significant variation, as the high p-value (0.999) indicates, corroborates previous research where ENM and ABM were employed in different contexts to predict disease prevalence. A study by Memarsadeghi *et al.* (2023) utilised similar models for understanding the spatial distribution of *Plasmodium vivax* malaria. The study, although not directly comparing ENM and ABM, highlight the credibility of both methods in disease modelling. The current study analysis, revealing similar predictions between ENM ( $F=1.17$ ,  $p = .382$ ,  $R\text{-square} = 0.54$ ) and ABM ( $F=3.33$ ,  $p = .121$ ,  $R\text{-square} = 0.77$ ), adds reliability to these models, affirming their efficacy in the three selected health districts of Lagos State.

The F score of 0.4 and mean squares (treatment: 0.000604, within: 0.1682) emphasise this conclusion, suggesting minimal statistically significant variance within and between the models. This is critical for health policymakers and practitioners in Lagos State as it implies the reliability of both ENM and ABM in providing dependable malaria prevalence predictions, essential for planning and implementing effective control strategies. The utility of these findings in malaria prevention is significant. It assures that either model can be reliably employed for predicting malaria prevalence among pregnant women which is crucial for planning timely interventions, resource allocation, identifying high-risk areas, and susceptibility to malaria and its complications.

Examining the significance of the combined models incorporating multivariate environmental variations in predicting malaria prevalence rates among pregnant women, the study's regression model showed an R-square value of 1, indicating that the variables Temperature (TEMP), Rainfall (RAIN), Malaria Prevalence (MP), and Land Use Patterns (LUP) explained 100% of the variance from the variable MPR. This is an unusually perfect fit, ( $F=0$ ,  $p=1$ ,  $R^2=1$ ), suggesting an overfitting scenario or a potential anomaly in data collection or model specification.

In the context of Adeogun *et al.* (2023), who used MaxEnt for predicting *Anopheles* distribution, their approach incorporated a broader set of environmental variables. The current study's limited variable set, despite its high  $R^2$  value, may lack the comprehensiveness seen in Adeogun *et al.*'s approach. Phang *et al.* (2023) also employed machine learning-based models, finding that XGBoost outperformed MaxEnt in predicting malaria risk. This suggests that advanced machine learning techniques might offer more accurate predictions than traditional regression models, especially when considering the complexity of malaria transmission dynamics.

The work by Saberi *et al.* (2023), focusing on the impact of climate change using MaxEnt, indicated a less dynamic change in malaria vector distribution, contrasting with the current study's perfect prediction model. Memarsadeghi *et al.* (2023) employed MaxEnt to assess *P. vivax* malaria distribution, revealing occupation-specific risks, which aligns with the inclusion of LUP in the current study's model. However, the ANOVA significance in Memarsadeghi *et al.*'s study ( $p<0.05$ ) presents a stark contrast to the non-significance in the current study ( $p = 1$ ). Ozodiegwu *et al.* (2023) utilised ABMs for intervention planning, emphasising the importance of local data for accurate predictions. The current study's perfect fit might imply an



oversimplification, not capturing the local nuances that Ozodiegwu *et al.* highlighted. Modu *et al.* (2023) showed the efficacy of ABMs in predicting malaria transmission, yet their statistical robustness contrasts with the perfect prediction in the current study, suggesting a more realistic representation of malaria dynamics. Li *et al.* (2023) further demonstrated the utility of ABMs in understanding human mobility patterns in relation to malaria risk, a complexity that might be oversimplified in the current regression model.

The new model's prediction formula ( $\text{MPR} = -7.1 + 0.04 \cdot \text{TEMP} + 0.01 \cdot \text{RAIN} + 0.09 \cdot \text{MP} - 0.07 \cdot \text{LUP}$ ) indicates a simplistic linear relationship between the variables and MPR. In comparison, other models in the previous analysis like the Environmental Niche Model (ENM) ( $\text{MPR} = 29.33 + 0.01 \cdot \text{TEMP} + 0.01 \cdot \text{RAIN}$ ,  $F=1.17$ ,  $p=.382$ ,  $R\text{-square}=0.54$ ) and Agent-Based Model (ABM) ( $\text{MPR} = -46.51 + 0.05 \cdot \text{MP} + 0.05 \cdot \text{LUP}$ ,  $F=3.33$ ,  $p=.121$ ,  $R^2=0.77$ ) present different approaches and results. The ENM, with a lower R-square (0.54) and an F value of 1.17, suggests a moderate fit, capturing the environmental aspects but possibly missing other crucial factors influencing malaria prevalence. The ABM, on the other hand, with a higher R<sup>2</sup> value (0.77) but not perfect, indicates a more realistic capture of the complex interplay of factors influencing malaria, including human behaviour and local ecological factors.

## Conclusions

This study concluded that

1. the Ecological Niche Model (ENM), with emphasis on temperature and rainfall, predicted malaria prevalence rate and holds substantial potential in enhancing malaria prevention strategies among pregnant women in Lagos State
2. the Agent Based Model with intricate interplay between human behaviour and environmental factors significantly influences malaria prevalence rates, particularly among

vulnerable populations such as pregnant women in Lagos State.

3. the agreement in predictions from both ENM and ABM can inform the development of comprehensive malaria control strategies, combining ecological and behavioural factors. This holistic view is vital in devising interventions that are not only effective but sustainable in the long term.
4. while the current combined models' predictive power is theoretically impressive, its practical usefulness, particularly in malaria prevention, may be limited due to its oversimplified representation of a highly complex and dynamic system.

## Recommendations

Based on the conclusions of this study, it was recommended that

1. Health authorities Lagos State should collaborate with educators to develop targeted educational programmes that will focus on how environmental factors like temperature and rainfall influence malaria risks, especially for pregnant women. Such initiatives will empower the community with knowledge to mitigate these risks effectively.
2. Community-based monitoring systems should be implemented for malaria prevention. These systems should involve both health professionals and local residents in tracking and analysing the interplay between human behaviour and environmental changes. This collaborative approach can lead to more accurate identification of high-risk periods and areas for malaria, specifically aiding pregnant women.
3. Healthcare providers in Lagos State should be equipped with these real-time health informatics tools to gather more dynamic and comprehensive data from pregnant women. This approach will enhance the accuracy of predicting malaria prevalence, aligning



theoretical models more closely with real-world scenarios.

4. Interdisciplinary teams, including data scientists, health informatics specialists, and healthcare providers, should work collaboratively to adopt the models in this study and equally develop more specific models that consider the complexity and dynamism of malaria transmission. This collaboration can lead to more effective prevention strategies tailored to the local context of Lagos State.

## References

- Arisco, N. J. (2023). *The Role of Human Mobility, Deforestation, and Extreme Weather Events on Malaria in Brazil*. Harvard University,
- Arisco, N. J., Peterka, C., & Castro, M. C. (2022). Imported malaria definition and minimum data for surveillance. *Scientific Reports*, 12(1), 17982.
- Lagos State Ministry of Health (2022). *2021 Annual operational plan for malaria elimination*. Lagos State Ministry of Health publication.
- Filho, W., May, J., May, M., & Nagy, G. J. (2023). Climate change and malaria: some recent trends of malaria incidence rates and average annual temperature in selected sub-Saharan African countries from 2000 to 2018. *Malaria journal*, 22(1), 248.
- Li, Y., Stewart, K., Han, K. T., Han, Z. Y., Aung, P. P., Thein, Z. W., . . . Plowe, C. V. (2023). Understanding spatiotemporal human mobility patterns for malaria control using a multiagent mobility simulation model. *Clinical Infectious Diseases*, 76(3), e867-e874.
- Li, Y., Stewart, K., Han, K. T., Han, Z. Y., Aung, P. P., Thein, Z. W., . . . Plowe, C. V. (2023). Understanding spatiotemporal human mobility patterns for malaria control using a multiagent mobility simulation model. *Clinical Infectious Diseases*, 76(3), e867-e874.
- Loiseau, C., & Sehgal, R. N. (2022). Consequences of deforestation and habitat degradation on wildlife mosquito-borne diseases. In *Ecology and Control of Vector-borne Diseases* (pp. 450-460): Wageningen Academic Publishers.
- Memarsadeghi, N., Stewart, K., Li, Y., Sornsakrin, S., Uthaimongkol, N., Kuntawunginn, W., . . . Jongsakul, K. (2023). Understanding work-related travel and its relation to malaria occurrence in Thailand using geospatial maximum entropy modelling. *Malaria journal*, 22(1), 1-11.
- Modu, B., Polovina, N., & Konur, S. (2023). Agent-Based Modeling of Malaria Transmission. *IEEE Access*, 11, 19794-19808.
- Olasunkanmi, O. (2021). *Press statement to commemorate 2021 world malaria day in Lagos State*. Lagos State Ministry of Health publication.
- Ozodiegwu, I. D., Ambrose, M., Galatas, B., Runge, M., Nandi, A., Okuneye, K., . . . Bever, C. (2023). Application of mathematical modelling to inform national malaria intervention planning in Nigeria. *Malaria journal*, 22(1), 1-19.
- Phang, W. K., Hamid, M. H. b. A., Jelip, J., Chuang, T.-W., Lau, Y. L., & Fong, M. Y. (2023). Predicting Plasmodium knowlesi transmission risk across Peninsular Malaysia using machine learning-based ecological niche modelling approaches. *Frontiers in Microbiology*, 14, 1126418.
- Adeogun, A., Babalola, A. S., Okoko, O. O., Oyeniyi, T., Omotayo, A., Izekor, R. T., . . . Adeleke, M. (2023). Spatial distribution and ecological niche modelling of geographical spread of *Anopheles gambiae* complex in Nigeria using real time data. *Scientific Reports*, 13(1), 13679.



- Regos, A., Gonçalves, J., Arenas-Castro, S., Alcaraz-Segura, D., Guisan, A., & Honrado, J. P. (2022). Mainstreaming remotely sensed ecosystems functioning in ecological niche models. *Remote Sensing in Ecology and Conservation*, 8(4), 431-447.
- Saberi, N., Raeisi, A., Gorouhi, M. A., Vatandoost, H., Omid, F. B., & Hanafi-Bojd, A. A. (2023). Modeling the effect of climate change on the distribution of main malaria vectors in an endemic area, Southeastern Iran. *Iranian Journal of Public Health*, 52(5), 1061-1070. <https://doi.org/10.18502/ijph.v52i5.26639>
- White, N. J. (2022). Severe malaria. *Malaria journal*, 21(1), 284.
- World Health Organisation (2022). Report on malaria in Nigeria 2022. Retrieved from [https://www.afro.who.int/sites/default/files/2023-08/WEB\\_7784%20WMMR%20-%20Nigeria%202022\\_2408.pdf](https://www.afro.who.int/sites/default/files/2023-08/WEB_7784%20WMMR%20-%20Nigeria%202022_2408.pdf) on 05/05/2023.
- World Health Organization. (2023). World malaria report 2023. World Health Organization. <https://www.who.int/teams/global-malaria-programme/reports/world-malaria-report>