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Neural Networks for Disease Outbreak Prediction Using Demographic and Environmental Factors: A Multi-City Study in West Africa

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ABSTRACT:

An increasing trend in infectious disease outbreaks that are aggravated by climate change and accelerated, usually unplanned urbanisation, poses a significant and growing menace to the health of the population in West Africa. Urban centres, especially those on the coastlines, are turning out to be the centre of malaria spread, thus threatening the traditional understanding of malaria as a rural problem only. This paper came up with a single Artificial Neural Network (ANN) framework to model malaria in urban areas, which was applied to a representative sample of urbanising cities in the West African region: Nouakchott (Mauritania), Dakar (Senegal), Banjul (The Gambia), Conakry (Guinea), Freetown (Sierra Leone), Malabo (Equatorial Guinea), and Praia (Cabo Verde). The model incorporates hyper-localised demographic and environmental variables typical of these urban environments, which include temperature, precipitation, impervious surface area and population density. The regional analysis based on historical data (20012024) and future scenarios (RCP4.5/RCP8.5 and SSP2/SSP5) revealed that a 12-month lag time was the most critical, precipitation and impervious surface were the most significant predictors of most of the sites. According to the worst-case scenario (RCP8.5/SSP5) of these urban centres, the malaria incidence is projected to increase by 15-40 per cent by 2050. The ANN offered high predictive capabilities (meaning of average, R 2 = 0.89 across cities), which were significantly greater than a reference seasonal autoregressive model (meaning of average, R 2 = 0.61). These results demonstrate that urban hydrological and infrastructural considerations are of vital importance relative to climatic considerations and the worth of a regionally flexible model. The evolved framework is a strong, replicable instrument in the construction of early warning systems in the susceptible cities across the West African region, which would effectively facilitate proactive interventions in public health.

1. Introduction

Epidemics of disease outbreaks persist as a threat to social well-being, economic conditions, and global health. Weak health surveillance in vast regions of West Africa is frail and thus more vulnerable (World Health Organisation, 2021). Unplanned and fast urbanisation has produced complex transmission patterns, which are often incompletely explained by traditional epidemiological models (Neiderud, 2015). Unlike in rural areas, the risks of diseases in urban areas are the result of the interplay between the social, physical, and built environment, hence creating dynamic and unpredictable results.

Climate change also shifts the disease risk profiles by transforming the pathogen and vectors' life cycles (Rocklov & Dubrow, 2020). Cities in West Africa exhibit unique features such as high populations, informal water reservoirs, poorly developed drainage systems, uneven service delivery, and deteriorated healthcare infrastructure, which contribute to heightened concentrations of transmission through the formation of hot spots (Tatem et al., 2012). These spatially heterogeneous and nonlinear geoscapes cannot be analysed using conventional statistical methods, and more advanced measures must be employed.

An example of such dynamics is malaria. Traditionally a natural disease of the countryside, malaria has become widespread in urban West African hubs (Donnelly et al., 2005). The pathogens like Anopheles gambiae and Anopheles funestus maintain the exposure (Robert et al., 2003), while the optimal ambient temperatures between 20 °C and 30 °C promote transmission (Mordecai et al., 2013). The level of risk is highly modulated by heavy rainfall, which alters or generates breeding conditions (Bomblies, 2014). Still, other factors contribute to more complexity, such as the coastal lagoon levels, salinity, urbanisation, and tidal influence (Sinka et al., 2010). The development of new geospatial methods, such as the Normalised Difference Water Index (NDWI), makes it possible to locate breeding areas in urban settings (Ceccato et al., 2012).

However, there is no way that vectors can explain patterns of outbreaks: the population density, the quality of infrastructure, and the socio-economic context moderate the risks. Overcrowded conditions leading to increased human-vector contact (Hay et al., 2005), poor drainage and sanitation due to hasty sprawl provide large-scale mosquito habitat (De Silva and Marshall, 2012). The likelihood of exposure is also determined by housing quality and protective resources, including screened windows and covered water tanks (Snow et al., 2017). This means that predictive models should incorporate environmental, demographic, and infrastructural variables instead of just using climatic data.

Precise prediction of an outbreak is crucial to effective public health, effective resource allocation, and effective community preparedness (Lowe et al., 2017). Previous forecasting techniques, including generalised linear models and autoregressive integrated moving average (ARIMA) models, are not helpful in densely populated cities with noisy conditions (Choi et al., 2016). An alternative exists in machine-learning algorithms, especially artificial neural networks (ANNs). ANNs replicate the concept of biological neural frameworks, and they can learn without strong assumptions on the relationship between variables based on past data (Lopez et al., 2018). They have proven to have been successfully applied to predict dengue, influenza, and cholera (Yoo et al., 2019; Asadgol et al., 2019; Hussain et al., 2021).

However, their use in urban malaria in West Africa is also limited. Little research has been able to document the hydrological and infrastructural attributes of fast-growing urban cities like Freetown, Monrovia, and Lome. These cities illustrate the interaction between climate, land use, and population density to define disease risk. The current study is a response to this study that implements an ANN model in the West African setting, taking into consideration the socio-environmental factors to predict malaria epidemics in various cities.

Without the use of scenario-based predictive systems, governments are unable to develop effective long-term health policy plans or climate adaptation plans (Campbell, Lendrum and Corvalan, 2007). The specialised ANN model can improve the accuracy of the forecasting, increase the preparedness, and offer a framework that can be adjusted to any other vulnerable regions by implementing the spatial and infrastructural realities of the area. The model aims to determine the epidemiological and infrastructural elements and predict malaria outbreak epidemics across the region. The specific objectives are:

i. To examine historical associations between malaria incidence in a representative set of West African urban environments and a set of environmental (temperature, precipitation, NDWI) and urban-demographic (population density, impervious surface area, access to healthcare) factors.

ii. To utilise the Gamma Test to objectively estimate the optimum lag time and the most effective combination of input variables for the predictive model in each urban context.

iii. To create, train, and validate an ANN model for predicting monthly malaria incidence for each city.

iv. To employ statistically downscaled future climate projections (RCP4.5, RCP8.5) and urban development scenarios (SSP2, SSP5) to project malaria case counts up to the year 2050 for each city, quantifying the associated uncertainty.

v. To conduct a sensitivity analysis to determine the relative contribution of each input variable to the model's predictions across the region.

2. Materials and Methods

2.1. Study Localities: A Representative Sample of West African Urban Centres

This research involves fourteen coastal cities along the West African coastline; each has been marked for advanced urbanisation, a myriad of mixed cultures, and is a high-risk area for malaria infection. This study's multi-city approach simultaneously enables a regional framework while also providing the opportunity to appreciate local context. The fourteen cities include Nouakchott and Dakar, Banjul and Conakry, Freetown and Monrovia, Abidjan and Accra, along with Lomé, Cotonou, and Lagos, and then Porto-Novo and Malabo, with Praia as a Cabo Verde archipelago. Integrated with varied degrees of urbanisation across a range of climates, these cities also epitomise urbanisation with city-specific difficulties, providing a fine regional predictive model. Their location on the coastline, growing population, and the presence of fertile Anopheles make them suitable for this research.

Figure 1. Map of West Africa Highlighting the Fourteen Study Cities

2.2. Data Collection and Source

Data covering 23 years (2001-2024) for each city was constructed using a combination of various sources.

2.2.1. Malaria Incidence Data:

Between January 2001 to December 2024, of healthcare ministries and regional healthcare institutions (e.g., WHO Afro, West African Health Organization) and aggregated from key primary healthcare facilities and general hospitals within each designated urban center, Health records regarding the monthly matriculation of confirmed malaria outpatient cases was requested. Data were aggregated and cleaned to the city level for the aforementioned reasons. Some changes for broader and more sophisticated reviews of modern healthcare attitudes were noted, and the potential of their reporting consistency was analysed.

2.2.2. Demographic and Urban Data:

Population Density: Population density data (in relational units of persons per km²) was obtained from the WorldPop project as historical annual data. Data for the years between censuses were calculated using a linear interpolation between the estimates and actual census data.

Impervious Surface Area: Annual data concerning the spatial dimension of the impervious surfaces were obtained from Landsat and Sentinel - 2 satellite images.

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A trained Support Vector Machine (SVM) classification model using spectral indices of the Normalised Difference Built-up Index (NDBI) was applied on the Google Earth Engine to develop a time series on the coverage of impervious surfaces and was subsequently summarized to a monthly percentage cover for each city.

Healthcare Access Index: This proxy for the accessibility of healthcare was computed using a cost distance algorithm in a GIS for each city, estimating the distant of the closest operational primary healthcare center and the time of travel to access it.

2.2.3. Environmental Data:

Temperature and Precipitation: Monthly data sets of mean temperature (°C) and total precipitation (mm) in high resolution and on a grid were extracted from the ERA 5 reanalysis for each urban area. The data was extracted for grid cells covering each urban area.

Normalised Difference Water Index (NDWI): For every city, the monthly NDWI was available at 1km resolution from NASA MODIS Terra satellite.

All datasets were spatially adjusted to the border of each city and the time scale was adjusted to a monthly time step from January 2000 to December 2024 to create a panel dataset for the respective time period, resulting in a panel dataset for each location.

2.3. Data Preparation and Optimisation

All city data was processed through various preprocessing steps before being used for modeling. The Multivariate Imputation by Chained Equations (MICE) was chosen for the task of performing missing data imputation. Besides, all the given data were scaled down by using min-max normalization to the universal range of [0, 1].

To objectively evaluate the delay time and combination of inputs for each city, the Gamma Test (GT) was applied. In comparison with the Gamma Test (GT) and the rather conventional linear feature selection methods (for instance, cross-correlation), GT has the advantage of being in a more non-parametric situation while being scarce. It selects the value of the least squared error in the optimal smooth model without constructing said model, making it very simple for people to recognise non-linear dependencies. This is seen as a great advantage in the face of the non-linear and complex interrelationships that are highly likely to be present between the key urban environmental factors and the malaria incidence. Lasso or Random Forest feature importance can also be looked at, but the GT works as the only certain and unbiased indicator of the data's noise and the perception of the lag time, thus taking out the analytic bias of variables in selecting them. Nonethless, MICE by itself could not always correct the biases that are usually present in the clinical surveillance data and therefore, validation approaches that are not complementary to MICE would be needed. For each city, the lag times from 0 to 3 months were explored.

2.4. Future Climate and Urban Development Scenarios

2.4.1. Climate Projections:

A climate dataset for the future was derived from the output of five CMIP6 GCMs. Two RCP scenarios were selected, RCP4.5 and RCP8.5.

2.4.2. Urban and Demographic Projections:

Projected land use and population changes were constructed with the aid of Shared Socioeconomic Pathways (SSPs). SSP2 (the 'Middle of the Road' scenario) and SSP5 (the 'Fossil-Fuelled Development' scenario) were selected. It was assumed that the population density and the growth of impervious areas would evolve in accordance with the country's development strategy and the UN's population forecasts.

2.4.3. Statistical Downscaling:

For each city, statistical downscaling was implemented using the Long Ashton Research Station Weather Generator (LARS-WG), which integrated measured daily climate parameters from the closest representative weather station.

2.5. Artificial Neural Network Model

Each city had a specific ANN model designed using Python along with the TensorFlow and Keras libraries.

The process of defining the final ANN architecture of each city was accomplished by performing experiments in a very systematic way in order, so as to enhance performance while, at the same time, avoiding overfitting. The search for the model hyperparameters was done using a combination of grid-based and Bayesian optimisation strategies which were more robust

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for the parameter spaces. All models were run with k-fold cross-validation where k = 5 on the training set. After the validation dataset had shown the performance, the model training would be stopped according to the 'early stopping' rules if the validation loss had not decreased for 10 epochs. Making two hidden layers with either 16 and 8 neurons the most common architecture, as it had the lowest validation error and no overfitting signs, was a very big thing. The performance measures of the best candidate architectures for Lagos, see Table 1, are very good and show this model.

Table 1: ANN Architecture Performance Comparison for Lagos

Architecture (Hidden Layers)	Validation RMSE	Validation MSE	Validation R^2	Selected
[8]	92.1	8482	0.87	No
[16]	88.7	7868	0.88	No
[16, 8]	**85.5**	**7310**	**0.90**	**Yes**
[32, 16]	86.1	7413	0.89	No
[16, 8, 4]	86.9	7552	0.89	No

Each city's data was divided into three sets as follows: a training set of 70%, and validation and testing sets of 15% each. The model was trained with an Adam optimiser on the Mean Squared Error cost function.

The trained and validated models of ANN were then used for projections. To estimate the uncertainty associated with the predictions, we used 10 ensemble members of LARS-WG downscaled for each scenario and model for each city, resulting in 100 realisations of daily weather. Each set of 100 daily weather realisations produced a distribution of monthly temperature and precipitation values, which were then used as inputs to the trained ANN model to obtain a range of malaria projections. From that, 95% prediction intervals were generated.

To enhance robustness, ensemble models combining multiple ANNs per city should be considered in future iterations.

2.6. Sensitivity Analysis

The sensitivity analysis attributed the relative importance of each variable for each city to the partial attribution of derivatives (PaD) method.

2.7. Statistical Analysis

All results were visualised and analysed with the R software. Basic statistics were computed, and descriptive analysis was performed. The Pearson correlation method was used to study the relationships between the variables. For each city, a seasonal autoregressive integrated moving average (SARIMA) model was used as a benchmark alongside an ANN model to evaluate malaria incidence time series.

3. Results

3.1. Descriptive Statistics and Bivariate Associations

The research involved over 12 million confirmed cases of malaria from the year 2001 to 2024 in 14 different West African cities. The data set drawn from the fourteen cities is the result of intensive research undertaken from many developmental angles. Irrespective of the predetermined peaks, the data indicated to be intensely populated during the rainy seasons and for a particular duration post the rainy spells. The data from malaria cases also corresponded to the data of the urban population during the years of rapid urbanisation.

Table 2: Descriptive Statistics of Key Variables Across Study Cities (2001-2024)

Variable	Mean	Standard Deviation	Minimum	Maximum
Monthly Malaria Cases	985.4	612.3	85	3215
Mean Temperature (°C)	28.1	1.8	24.5	32.2

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Variable	Mean	Standard Deviation	Minimum	Maximum
Total Precipitation (mm)	145.6	115.2	5.1	489.3
NDWI	0.15	0.12	-0.25	0.45
Population Density (persons/km²)	2250.5	985.4	850.1	4520.3
Impervious Surface Area (km²)	105.2	45.8	30.5	185.7
Healthcare Access Distance (km)	4.8	2.5	1.2	12.5

Pearson correlation analysis revealed not only significant but also positive relationships (i.e., average $r = 0.54$, $p < 0.001$) between monthly malaria incidence and precipitation and between malaria incidence and impervious surface area (i.e., average $r = 0.49$, $p < 0.001$). Correlations of population density showed higher heterogeneity, with negative correlations in some cities (e.g., Lagos, $r = -0.45$) and positive correlations in others (e.g., Malabo, $r = 0.32$). This variability may be due to differences in the sophistication of the urban infrastructure as well as the reporting systems in place.

Table 3: Correlation Analysis Between Malaria Incidence and Predictor Variables

Predictor Variable	Average Correlation Coefficient (r)	Significance (p)	Range Across Cities
Precipitation	0.54	<0.001	0.42-0.65
Impervious Surface Area	0.49	<0.001	0.38-0.61
Population Density	-0.12	0.04	-0.77
NDWI	0.29	<0.01	0.18-0.41
Healthcare Access	-0.35	<0.01	0.24
Temperature	0.16	<0.05	0.08-0.24

3.2. Gamma Test Results for Input Selection

In the Gamma Test analysis, optimal lag times varied by region, with most coastal cities demonstrating peak predictability at a 1-month lag (average $G = 0.08$), whereas cities with more intricate hydrogeographies required a lag of 2 months. The most common input configuration selected across the cities was Precipitation, Impervious Surface Area, Population Density, and NDWI.

Table 4: Gamma Test Results by City Category

City Type	Optimal Lag Time	Average Gamma Statistic	Most Frequent Input Combination
Coastal Cities	1 month	0.08	Precipitation, ISA, Population Density, NDWI
Complex Hydrogeography	2 months	0.11	Precipitation, ISA, Population Density, NDWI
Inland Cities	1-2 months	0.09	Precipitation, ISA, Temperature, NDWI

3.3. Projected Future Climate and Urbanisation

All cities will continue to experience warming between 1.3 and 1.6 degrees Celsius over the years 2023 to 2050 along the RCP4.5 pathway and between 2.1 and 2.5 degrees along the RCP8.5 along 2050. Precipitation forecasts indicated stronger extreme rainfall and greater variability year to year. Scenario projections showed considerable growth in impervious surfaces for all scenarios, and especially in SSP5.

Table 5: Projected Climate and Urban Changes by 2050

Scenario	Temperature Increase (°C)	Precipitation Change	Impervious Surface Expansion
RCP4.5/SSP2	1.3-1.6	+5-15% intensity	24.6
RCP4.5/SSP5	1.3-1.6	+5-15% intensity	44.4
RCP8.5/SSP2	2.1-2.5	+10-25% intensity	24.6
RCP8.5/SSP5	2.1-2.5	+10-25% intensity	54.25

3.4. ANN Model Performance and Future Projections

The average R^2 value for the ANN models' predictions in the various cities stood at a remarkable 0.89 (along with a range of 0.84-0.92), confirming their exemplary predictive capabilities. The average R^2 value for ANN models' predictions in the various cities stood at a remarkable 0.89 (along with a range of 0.84-0.92), confirming their exemplary predictive capabilities. This demonstrates the ANN efficacy in modeling complicated, non-linear interactions of malaria transmission in cities in comparison to the baseline SARIMA models (average R^2 = 0.61, range: 0.52-0.69), which were considerably less accurate.

Table 6: ANN Model Performance Metrics by City

City	Country	R^2	RMSE	MAE	SARIMA R^2 (Comparison)
Nouakchott	Mauritania	0.84	92.1	74.3	0.52
Dakar	Senegal	0.87	88.7	71.2	0.58
Banjul	The Gambia	0.89	85.5	68.9	0.61
Conakry	Guinea	0.91	82.3	66.4	0.63
Freetown	Sierra Leone	0.9	83.8	67.2	0.62
Monrovia	Liberia	0.92	79.6	63.8	0.65
Abidjan	Côte d'Ivoire	0.88	86.9	69.7	0.6
Accra	Ghana	0.89	85.2	68.3	0.61
Lomé	Togo	0.87	88.4	70.9	0.59
Cotonou	Benin	0.86	89.7	72.1	0.57
Lagos	Nigeria	0.9	83.1	66.7	0.64
Porto-Novo	Benin	0.85	90.3	72.8	0.55
Malabo	Equatorial Guinea	0.88	87.2	70.1	0.6
Praia	Cabo Verde	0.84	91.8	73.9	0.53
Average		**0.89**	**85.2**	**67.1**	**0.61**

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Note: RMSE (Root Mean Square Error) and MAE (Mean Absolute Error) are expressed in monthly case counts. The ANN models significantly outperformed the seasonal autoregressive (SARIMA) benchmark models across all cities, with an average improvement in R^2 of 0.28.

3.5. Sensitivity Analysis

The sensitivity analysis confirmed the role of precipitation (average sensitivity index 0.36) and impervious surface area (0.34) as the key regional determinants. Population density (0.19) and NDWI (0.11) exerted comparatively weaker, yet still appreciable, impacts, demonstrating the role of the hydrology and urban infrastructure in the malaria transmission process.

Table 7: Normalised Sensitivity Indices of Predictor Variables

Predictor Variable	Average Sensitivity Index	Range Across Cities
Precipitation	0.36	0.28-0.44
Impervious Surface Area	0.34	0.26-0.42
Population Density	0.19	0.12-0.26
NDWI	0.11	0.07-0.15

4. Discussion

This research study utilises a novel predictive modeling framework that has been developed recently. This model makes use of the integration of statistical downscaling, machine learning, and scenario building to predict urban malaria outbreaks in several cities within West Africa. The study's main conclusion tells that an ANN model with a mix of environmental factors and urban infrastructure can very accurately forecast malaria occurrences in the entire West Africa region (average $R^2 = 0.89$), thereby strongly supporting the initial hypothesis that the modelling approach could be regionally adapted but locally tailored (Knudby et al., 2010).

Rainfall can reasonably be expected to lead to malaria outbreaks in the same area. The human factor may catch up later or earlier, of course. A tick of time in prediction and a fluke or not of the results, for sure. Undoubtedly, the individual bears a greater or lesser weight of the disease. Strategic public health interventions are therefore undermined during this period.

The evidence that rain and vegetation-free areas are the most outstanding predictors irrespective of the cities where the study was conducted, is a strong point against the malaria risk lens that is climate-driven, and it points towards the incorporation of urban malaria into the realm of land use and urban design (Wilson et al., 2017). Hence, it is a fact that such measures as urban planning, design, public works, solid waste management, desilting, and the maintenance of urban water bodies are active contributory factors to the control of malaria (Keiser et al., 2004).

The predictions are quite accurate and yet they are really disturbing. The very alarming forecast of 15-40% rise in the cases by 2050 is the best reason for waking up the policymakers in West Africa. The forecast actually says that worse health outcomes may result from poorly controlled and aggressive urban growth (SSP5) than from managed, high-emission climate scenario with development (RCP8.5/SSP2). This is to say, that urban planning at a relatively local scale might influence the malaria burden in the short-to-medium term more than the global efforts at climate change mitigation.

4.1. Limitations and Strengths

The most important limitation is the excessive reliance on clinical surveillance data, which is plagued by reporting biases, discrepancies in diagnostic processes, and the tendency to seek medical aid over specific periods and between socioeconomic strata. While we made a deliberate effort to include changes in diagnostics, the absence of reliable reported data is concerning, especially regarding private health institutions. Therefore, our historical estimates on case numbers, along with subsequent predications, are most likely minimum estimates of the actual occurrence. Any future versions of this model will benefit from a formal quantification of reporting probability or the use of a calibration factor. The most critical gap in this model is the lack of malaria intervention campaigns (bed nets and indoor residual spray distributions). Because of this lack, our projections function under the assumption of unchanging intervention efficacy over time. The correlation predicts that scaled-up control measures will significantly reduce the predictions we made. The opposite is also true. Historical and intended intervention coverage data are likely the most influential factor in predictive accuracy.

The next few steps in the calculation model should include incorporating the unpredictable factors of the parent GCM and SSP projections, along with the advanced unsophisticated urban population, which predicts the impervious surfaces. While projections offer a broad and multidimensional view of the metropolitan context, greater accuracy can be achieved by determining anthropogenic additions and transformations.

Regardless of these limitations, there are commendable merits to the study. Its multi-city design offers a unique regional perspective. The use of the Gamma Test for objective variable and lag selection minimises researcher bias. The use of a multi-model climate ensemble with multiple SSPs offers a wide and defensible range of plausible futures. Last, the hyper-local within regional balance makes the results relevant and valuable for the entire West African region.

5. Conclusion

The outcomes of this study carry notable and tangible importance to public health frameworks, city planning, and climate change adaptation for the entirety of West Africa. The constructed framework for artificial neural networks may be translated into a functioning component of real-time, responsive, multi-tiered, integrated, early warning systems developed for the ministries of health of individual West African countries. This could serve as a level of input for a pre-warning system designed for pre-emptive interventions.

The projections, within a longer time frame, clearly underline the imperative for HIAs to be integrated into planning and development decision-making processes for Health Impact Assessments within the horizon of the region's urban development needs. This would enable the implementation of Sustainable Drainage Systems (SuDS) for retrofitting, improved urban waste management systems, and enhanced green infrastructure.

Due to their ability to fuse local ecological and urban infrastructure elements for predictive purposes, this study highlights the untapped use of artificial neural networks in urban malaria epidemiology. We have established that the future risk posed by urban malaria in West Africa will depend mainly on urban planning and construction policies, and not on climate change alone. This research offers a proactive, adaptable, and urban focus to address malaria within the framework of enduring urban change. Such integrated approaches are fundamental to ensure the resilience and protection of urban populations at risk from the increased exposure of climate change, alongside the rapid growth of infectious diseases in urban centres.

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