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Bridging Climate Science and Public Health: Predicting Asthma for Better Respiratory Health Management in Togo

Essoninam Passike Pokona[1]*, Essohanam Boko[2], Pascal Yaka[3] and Brama Kone[4]

[1]*West African Science Service Centre on Climate Change and Adapted Land Use (WASCAL), University of Lome, Lome, Togo*

[2]*Faculty of Health Sciences, University of Lome, Lome, Togo*

[3]*Climate Services, World Meteorological Organization (WMO) West Africa Sub-regional Office, Dakar, Senegal*

[4]*Department of Research Programs, Ministry of Higher Education and Scientific Research, Abidjan, Cote D'ivoire*

***Corresponding author:** Essoninam Passike Pokona, West African Science Service Centre on Climate Change and Adapted Land Use (WASCAL), University of Lome, Lome, Togo.

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Abstract

Climate change and air pollution are major environmental and public health concerns, particularly in developing countries. Respiratory diseases such as asthma are significantly influenced by variations in temperature, humidity, and air quality. This study examines the relationship between climate, pollution, and asthma prevalence in two distinct regions of Togo: Grand-Lome (urban and coastal) and the Savanes region (rural and arid). We analyse data from 2018 to 2022, including meteorological variables (temperature, humidity, rainfall, wind speed) and air pollutants (CO_2, NO_2, SO_2, O_3), to assess their impact on asthma cases. A Principal Component Analysis (PCA) is conducted for variable selection, followed by two predictive modelling approaches: Random Forest Model (RFM) and Polynomial Regression Model (PRM). Model accuracy is evaluated using statistical indicators such as R^2, Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). Results showed that in the Savones region, PRM explains 36% of asthma variance ($R^2 = 0.36$) but has higher prediction errors, while RFM ($R^2 = 0.13$) better captures seasonal variations. In Grand-Lomé, PRM performs better ($R^2 = 0.41$) compared to RFM ($R^2 = 0.20$). Although PRM offers higher explanatory power, RFM demonstrates superior reliability for seasonal trend forecasting, making it more suitable for asthma prediction in Togo. Furthermore, the impact chain approach highlights the complex interactions between climate, pollution, and asthma prevalence. Rising temperatures and air pollution exacerbate respiratory distress, while socio-economic factors influence healthcare access and exposure levels. Understanding these interdependencies is crucial for designing effective adaptation strategies. These findings emphasize the need for targeted policies to improve air quality and healthcare strategies. Implementing early warning systems based on climate and pollution indicators could help mitigate asthma risks, especially in vulnerable populations.

Keywords: Climate variability, Air pollution, Asthma, Impact chain, Predictive modelling, Togo

Abbreviations: AI: Air Quality Index, CO_2: Carbon Monoxide, SO_2: Sulphur Dioxide, O_3: Ozone, NO_2: Nitrogen Dioxide, PCA: Principal Component Analysis, RFM: Random Forest Model, PRM: Polynomial Regression Model, R^2: Coefficient of Determination, MSE: Mean Squared Error, RMSE: Root Mean Squared Error, NDVI: Normalized Difference Vegetation Index, Tmin: Minimum Temperature, Tmax: Maximum Temperature, Tmoy: Average Temperature, Umin: Minimum Relative Humidity, Umax: Maximum Relative Humidity, Umoy: Average Relative Humidity, Inso: Sunshine, RR: Rainfall, PRM: Polynomial Regression Model

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Introduction

Climate change is now recognized as one of the major global challenges, with profound repercussions for public health. It affects various essential environmental factors such as air quality, access to drinking water, food security, and housing conditions, thereby increasing the risk of diseases and premature deaths. According to the World Health Organization [1], climate change could cause approximately 250,000 additional deaths per year between 2030 and 2050, primarily due to heat stress, malaria, malnutrition, and diarrhoeal diseases. These impacts include direct effects, such as extreme weather events (droughts, floods, storms), as well as indirect effects like the deterioration of water quality and the increase in both infectious and non-communicable diseases [2].

Among the rising respiratory diseases, asthma stands out as one of the most common conditions influenced by environmental changes. The increase in air pollutants, such as fine particulate matter (PM2.5, PM10), Nitrogen Dioxide (NO_2), and Ozone (O_3), as well as the proliferation of airborne allergens exacerbated by climatic changes, contributes to the growing prevalence of this disease [1]. Asthma is a chronic inflammatory condition of the airways, characterized by reversible obstruction and recurrent episodes of breathlessness, wheezing, and coughing. It results from a complex interaction between genetic and environmental factors, including air pollution, allergens, and climatic conditions [2]. Globally, approximately 300 million people are affected by asthma, causing nearly 250,000 deaths annually, according to the Global Initiative for Asthma [3]. In 2019, this figure reached 262 million cases with 455,000 deaths related to the condition [4]. Projections suggest an increase to 400 million patients by 2025 [3], making asthma a major public health concern, particularly in the context of accelerated global warming [5].

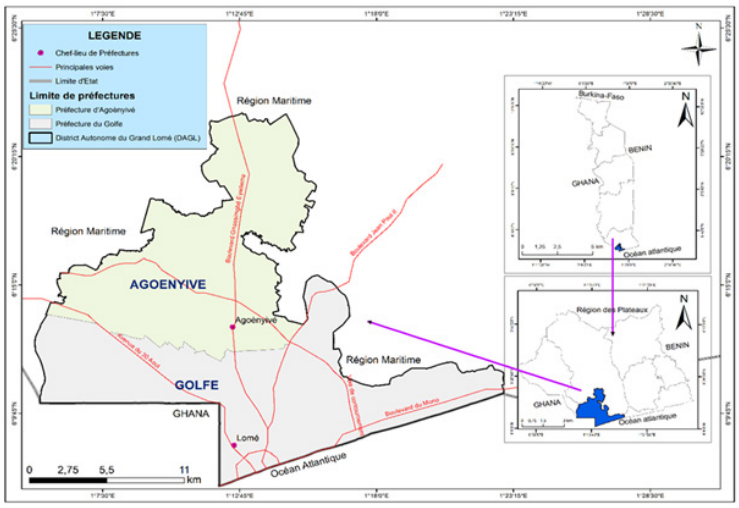
Togo, particularly the regions of Grand-Lome and the Savanes, is not exempt from this issue. Respiratory diseases are among the leading causes of mortality in the country [6]. The vulnerability of Togolese populations to the effects of climate change, combined with rapid urbanization, air pollution, and poor waste management, exacerbates respiratory conditions, including asthma. This situation has led to an increase in asthma attacks, more frequent hospitalizations, and higher mortality rates, impacting not only patients' quality of life but also the country's economic productivity.

Although asthma cannot be cured, it can be effectively controlled through appropriate prevention and management strategies. However, the sharp rise in cases observed in recent decades cannot be solely attributed to genetic factors [7]. Identifying the environmental and climatic triggers of asthma is therefore essential to implementing suitable preventive measures. In this context, the present study aims to deepen the understanding of the links between climate, pollution, and asthma in two distinct regions of Togo by developing a predictive model, to anticipate future trends of this disease and improve the management of respiratory health in the country.

Materials and Methods

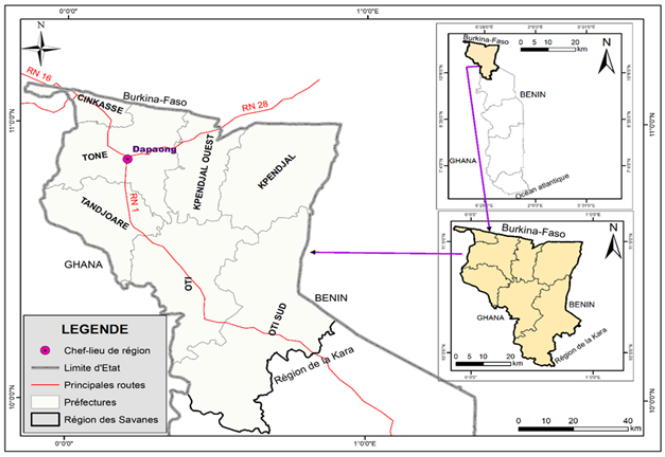
Study Area

Grand-Lome region and Savanes region were the geographical focus of this study. The Grand-Lome region is situated in the extreme southwest of the country, along the Gulf of Guinea coastline, and encompasses the capital city (Figure 1a). With an estimated population of 2,188,376 inhabitants in 2022 [8]. Grand-Lome experiences a Guinean climate and has two rainy seasons. The primary rainy season spans from April to July, followed by a less significant second season starting in September and ending in late November. The average maximum temperature under shelter is 30°C in the afternoon, and the average minimum temperature is 23°C in the morning. From December to February or March, the Harmattan, a dry wind from the Sahara, occasionally blows, lowering the morning temperature to 19°C. The region receives approximately 900 mm of rainfall annually.



Source: Passike, 2023, based on Inseed data.
Figure 1a: Study area (Grand-Lome region).

The Savanah Region (Figure 1b), located between 0°10 and 1°00 East longitude and 9°55 and 11°05 North latitude, with an estimated population of 1,143,520 inhabitants in 2022 [8], is the northernmost region of Togo and covers an area of 8,533 km^2, accounting for 15% of the national territory. It experiences a Sudanian climate characterized by a rainy season from June to September and a dry season from October to May. The average annual rainfall is approximately 1050.0 mm, and the annual average maximum temperature is around 34°C. The annual average minimum temperature hovers around 23°C. The average relative humidity ranges from 50 to 70%. The average wind speed is about 2 m/s, and the average daily duration of sunshine is approximately 7 hours.



Source: Passike, 2023, based on Inseed data.
Figure 1b: Study area (Grand-Lomé region).

Methodology

Data Collection: This study utilizes monthly data from 2018 to 2022, which includes both climatic and environmental parameters. The dependent variable is asthma registered cases, while the explanatory variables encompass environmental and pollution metrics, such as Carbon Monoxide (CO_2), the Air Quality Index (AI), Sulphur Dioxide (SO_2), Ozone (O_3), Nitrogen Dioxide (NO_2), and climate parameters including precipitation (Rainfall), minimum (Tmin), maximum (Tmax), and average (Tmoy) temperatures, relative humidity (Umin, Umax, Umoy), sunshine (Inso), wind speed (windspeed), and the Normalized Difference Vegetation Index (NDVI).

Asthma Impact Chain: An Asthma Impact Chain was developed to capture the complex interactions between climatic, environmental, and socio-economic factors influencing asthma in Northern and Southern Togo based on the Climate Risk Sourcebook [9]. The process (Figure 2) involved defining the geographical and temporal scope of the study and identifying primary climatic hazards like temperature variations, humidity fluctuations, air pollution, and dust storms. Non-climatic drivers (e.g., urbanization, indoor pollution, and limited healthcare access) were incorporated to provide a comprehensive understanding of asthma risk factors. Vulnerable populations (children, elderly, individuals with pre-existing conditions) and healthcare system capacity were central to this analysis, alongside environmental and socio-economic vulnerabilities.

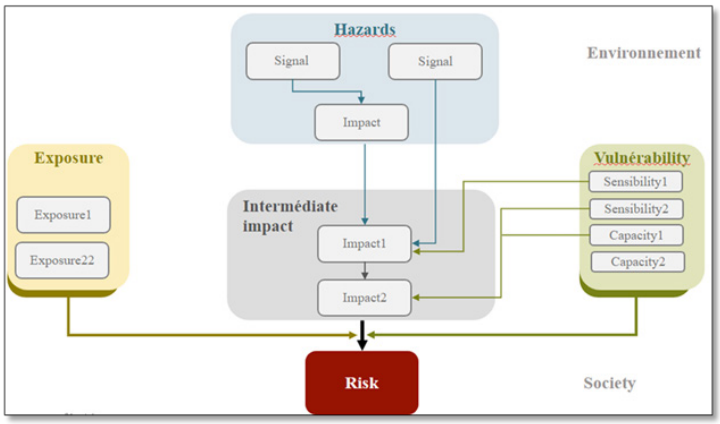


Figure 2: Impact chain framework.

Modeling Process: The modeling process involved several steps: variable selection, model construction, and performance evaluation.

a) Variable Selection

Initial exploratory data analysis was conducted, followed by Principal Component Analysis (PCA) to reduce data dimensionality. PCA helped identify key variables, capturing major variations in the dataset, and enhancing the model's interpretability.

b) Model Construction

Two modeling techniques were employed: Random Forest Model (RFM) and Polynomial Regression Model (PRM).

RFM was chosen due to its ability to capture complex, non-linear relationships, manage correlated variables, and remain robust in the presence of missing data or outliers. The learning algorithm for RFM is represented as:

$$Y = \frac{1}{N}\sum_{i=1}^{N} Ti(X) \quad \text{(Algorithm 1)}$$

Where:

Y is the predicted output;

N is the number of trees in the forest;

Ti(X) is the prediction from the i-th decision tree for the input X.

PRM was selected for its ability to model non-linear relationships using higher-order terms, offering a balance of flexibility and interpretability. The polynomial regression model is expressed as:

$$Y = \beta_0 + \beta_1 X + \beta_2 X^2 + \beta_3 X^3 + \ldots + \beta_h X^h + \varepsilon \quad \text{(Equation 1)}$$

Where:

Y is the dependent variable (the outcome to predict);

β_0 is the intercept of the model (the value of Y when all X variables are zero);

β_1, β_2, β_3, ..., β_h are the coefficients corresponding to each term in the polynomial. They represent the impact of each term on Y;

X is the independent variable (the predictor);

ϵ is Error term, representing the difference between the observed and predicted values.

Model Performance Evaluation

The performance of the models was assessed through two main aspects: statistical performance and seasonal validation.

a) Statistical Performance: Coefficient of Determination (R^2), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) were used to evaluate the explanatory power and accuracy of the models.

b) Seasonal Validation: Models were assessed for their ability to replicate seasonal trends in asthma case incidence, including peak onset and fluctuations.

Results and Discussion

Results

Asthma Impact Chain: The impact chain of asthma (Figure 3) illustrates the primary hazard, exposure, and vulnerability factors that contribute to an increased risk of mortality and morbidity associated with this respiratory condition. Danger factors include air pollution and specific climatic conditions. Pollution is exacerbated by various elements, including wind, vegetation, aerosols, fine particulate matter, arid periods, as well as dust and smoke, creating an environment laden with pollutants that aggravate asthma symptoms. Concurrently, climatic conditions such as variations in temperature, humidity, and sunlight contribute to the exacerbation of symptoms and can trigger asthma attacks. Exposure to these hazards concerns the entire population, meaning that every individual is potentially at risk, although certain groups exhibit heightened vulnerability. This vulnerability manifests in different forms. First, generic susceptibility includes low-income individuals, those living in poorly ventilated or unsanitary environments, who face increased exposure to pollutants. Secondly, biological susceptibility particularly targets asthmatic individuals, who are more sensitive to climatic variations and pollution. Furthermore, a lack of anticipatory capacity, due to insufficient awareness, inadequate hygiene, and the absence of strategic disease management documents, limits these populations' ability to effectively protect themselves against risks. Finally, the inability to recover intensifies the hazards for vulnerable populations, due to limited access to healthcare and medications, as well as a lack of available healthcare personnel to manage crises. In summary, this impact chain highlights how the interaction between exposure and vulnerability leads to an increased risk of mortality and morbidity for asthmatic individuals. Consequently, pollution regulation policies, awareness initiatives, and improved access to healthcare are essential for mitigating the adverse effects of asthma, particularly in heavily polluted areas or those subjected to extreme climatic conditions.

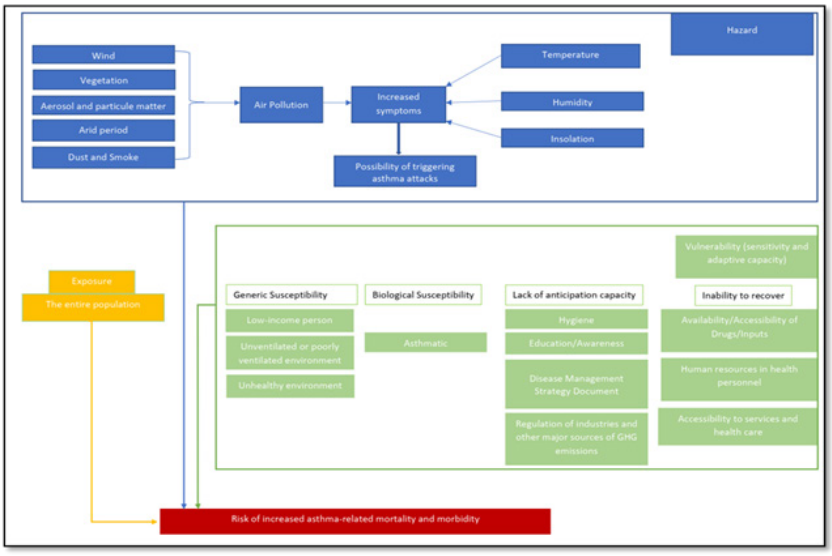


Figure 3: Asthma impact chain.

Results in Savanes Region

Selection of Climate and Environmental Variables Correlated with Asthma through Principal Component Analysis (PCA): The results reveal twelve Principal Components (PCs), each indicating the amount of variance explained within the dataset (Figure 4). The First Principal Component (PC1), with an eigenvalue of 5.02, accounts for 32.80% of the total variance, capturing the most significant variations in the data. The Second Component (PC2), with an eigenvalue of 4.16, explains 27.19% of the variance, underscoring its importance in representing the dataset. Together, PC1 and PC2 account for a cumulative 59.99% of the variance, which is relatively high, justifying the use of these two primary components to simplify the data while retaining substantial information. The subsequent components, from PC3 to PC5, capture progressively smaller proportions of the variance (12.07%, 7.91%, and 5.77%, respectively). Collectively, the first five components explain nearly 85% of the variance. The eigenvalues of the remaining components (PC6 to PC15) are less than 1, suggesting they add minimal information, with relatively low percentages of explained variance. These components may therefore be excluded in a more streamlined model, as they contribute only marginally to the additional information.

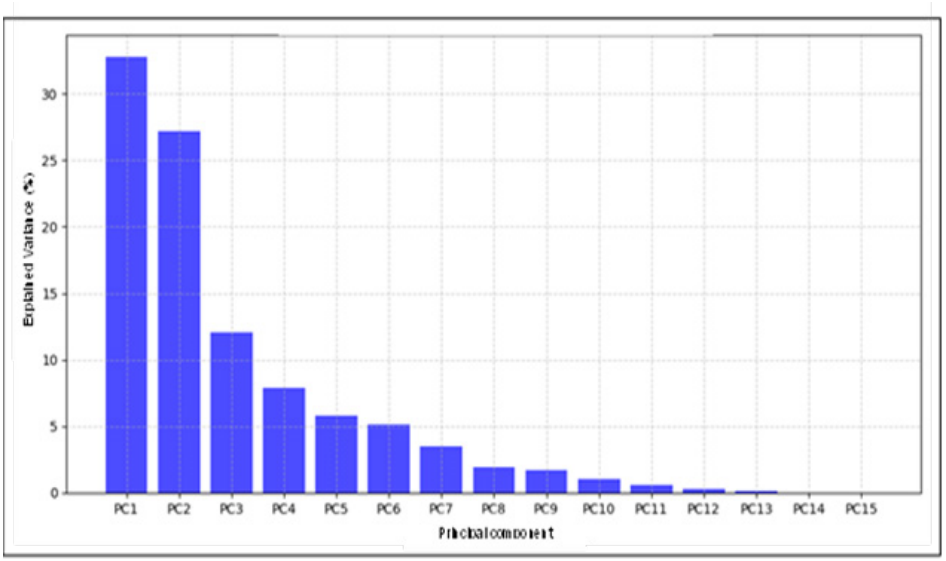


Figure 4: Principal Component Analysis in Savanes region.

The contributions of each variable to the principal components PC1 and PC2 reveal the influence of climatic and environmental factors (Table 1). PC1 is primarily dominated by variables such as AI (72.12%), Tmin (79.77%), Tmax (66.44%), and Tmoy (70.60%), along with humidity parameters including Umin (63.70%), Umax (60.92%), and Umoy (62.09%). Conversely, PC2 is influenced by variables such as CO_2 (80.10%), SO_2 (81.03%), Inso (85.93%), and NDVI (64.04%), with a substantial contribution from RR (69.78%) as well. The wind variable appears balanced between the two components, with respective contributions of 51.17% and 48.82%.

Table 1: Contribution of each variable to PC1 and PC2 in Savanes region.

Variables	PC1 (%)	PC2(%)
CO	19.902008	80.097992
AI	72.123625	27.876375
SO2	18.974867	81.025133
O3	38.350918	61.649082
NO2	40.663646	59.336354
RR	30.217445	69.782555
Tmin	79.773743	20.226257
Tmax	66.436989	33.563011
Tmoy	70.602995	29.397005
Umin	63.699967	36.300033
Umax	60.921564	39.078436
Umoy	62.089945	37.910055
Vent	51.177302	48.822698
NDVI	35.956798	64.043202
Inso	14.073627	85.926373

Model Performance: In this section, the 13 previously selected variables (AI, Tmin, Tmax, Tmoy, Umin, Umax, Umoy, CO_2, SO_2, Inso, NDVI, RR, and wind) were used to generate RFM and PRM models.

Statistical Performance: Analysis of the performance of the RFM and PRM models reveals significant differences in statistical metrics. The RFM model, with a coefficient of determination (R^2) of 0.13, explains only 13% of the variance in asthma cases, indicating limited explanatory power. In contrast, the PRM model has an R^2 of 0.36, accounting for 36% of the variance, which represents a notable improvement over the RFM in terms of explanatory capacity. However, this enhanced ability to explain variance comes at the cost of prediction accuracy: the PRM model shows a Mean Squared Error (MSE) of 352.74 and a Root Mean Squared Error (RMSE) of 18.78, both higher than those of the RFM model, which has an MSE of 225.21 and an RMSE of 15.03. In conclusion, the PRM model proves superior in explaining the variance in asthma cases, while the RFM model remains the most accurate for predictions, with lower associated errors (Table 2).

Table 2: Statistical performance of the models in the Savanes region.

Model	R2	MSE	RMSE
RFM	0.13	225.21	15.03
LPM	0.36	352.74	18.78

Seasonal Representation Capacity: The analysis of the prediction results for the models reveals specific characteristics in terms of seasonal representation (Figure 5). The PRM model demonstrates reasonably good overall performance in capturing peaks and moderate fluctuations. It successfully reproduces the general upward trend from March to October; however, it fails to capture the trend shifts at the end of the year, which marks the major increase from November to December.

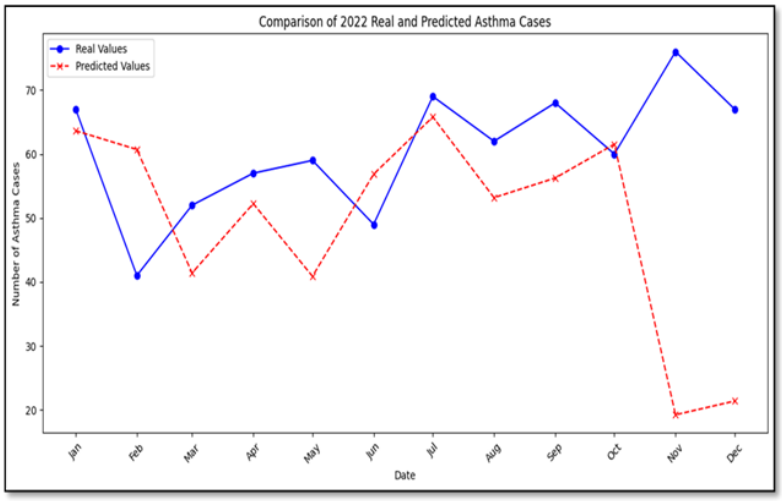


Figure 5: PRM seasonal representation in Savanes region.

The Random Forest model (RFM) demonstrates relatively good performance in capturing peaks, troughs, and seasonal transitions in asthma case incidence (Figure 6). The model accurately detects the asthma peak in May, predicting 70 cases, very close to the observed 75 cases, resulting in a slight underestimation of 6.7%. It also anticipates the October peak with a prediction of 65 cases, compared to an actual count of 70, leading to an underestimation of 7.7%. In March, the model predicts 52 cases against 55 observed cases, amounting to an underestimation of 5.5%. However, the model appears less effective during trough periods; for instance, in January, it predicts 45 cases while 40 were observed, representing an overestimation of 12.5%. Discrepancies during trough periods, such as in January and August, generally show moderate differences, typically around 5 cases, equating to a margin of less than 10%. Overall, the model handles the onset and conclusion of peaks well, adjusting seasonal transitions accurately throughout the year, despite some forecasting errors. The results suggest that the model is effective at capturing seasonal trends.

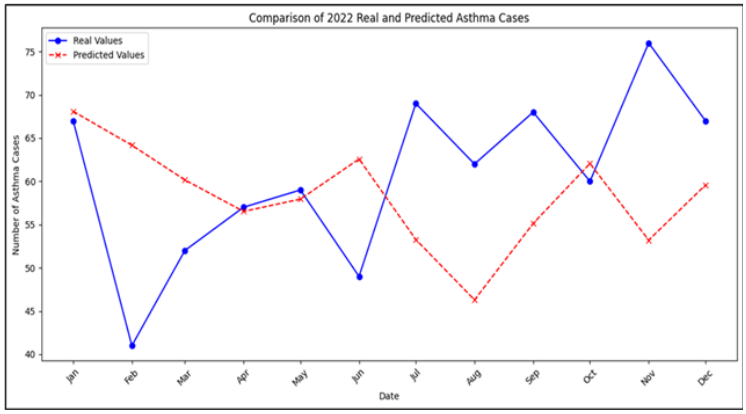


Figure 6: RFM seasonal representation in Savanes region.

Selection of the Best Model: While the Polynomial Regression Model (PRM) achieves the highest R^2 value (0.36), indicating a better ability to explain data variance, it exhibits certain limitations. This model tends to significantly overestimate peaks and misses critical transitions between rising and falling periods, which affects the accuracy of its forecasts. Additionally, its RMSE (18.78) is higher than that of the Random Forest model, reducing its practical reliability. The Random Forest Model (RFM), despite having a lower R^2 (0.13), demonstrates overall solid performance, capturing peaks and troughs and handling seasonal transitions well. It maintains low error levels (RMSE = 15.03), making it the most suitable model to retain.

Results in the Grand-Lome Region

Selection of Climate and Environmental Variables Correlated with Asthma through PCA: The results reveal twelve Principal Components (PCs), each indicating the amount of variance explained in the dataset (Figure 7). The figure shows the variance explained by each principal component derived from a Principal Component Analysis (PCA). The First Principal Component (PC1) stands out by capturing nearly 50% of the total variance, indicating that it summarizes a substantial portion of the key variations in the data. The Second Principal Component (PC2) contributes an additional 10-15% of variance, highlighting its importance as a complementary dimension to the information captured by PC1. Together, PC1 and PC2 explain approximately 60% of the variance, which justifies their use in reducing the dimensionality of the data without significant information loss.

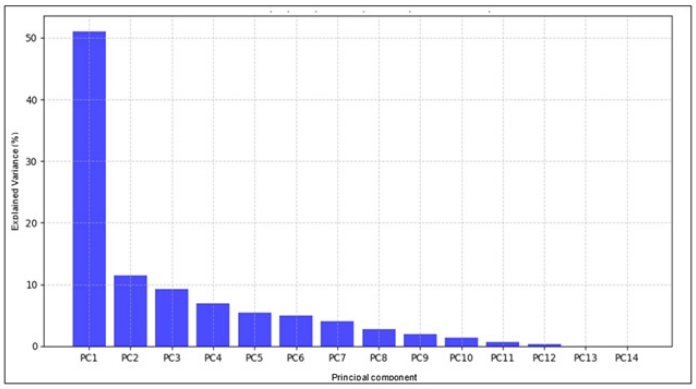


Figure 7: Principal Component Analysis in Grand-Lome region.

The subsequent components, from PC3 to PC5, account for more modest proportions of the variance, each ranging between 5% and 10%. Beyond the fifth component, contributions become increasingly negligible, as evidenced by the small bars on the graph. These components, although containing marginal information, could be disregarded in a simplified modelling approach without substantial information loss. In conclusion, the figure indicates that reducing to two or five principal components is a reasonable approach. Using the first two components (PC1 and PC2) allows for effective simplification while retaining approximately 60% of the variance.

The contributions of each variable to the principal components PC1 and PC2 reveal the influence of climatic and environmental factors (Table 3). PC1 is primarily dominated by variables such as O_3 (99.79%), Umin (99.99%), Umoy (95.82%), NDVI (98.24%), and maximum temperature Tmax (63.20%). In contrast, PC2 is influenced by variables such as RR (72.98%), Tmin (78.94%), and Windspeed (96.88%). The variables CO_2, NO_2, Tmoy, and Umax appear balanced between the two components, with respective contributions of 48.14% and 51.86%; 48.63% and 51.37%; 44.44% and 55.56%; and 44.49% and 55.51%.

Table 3: Contribution of each variable to PC1 and PC2 in Grand-Lomé region.

Variables	PC1	PC2
CO	48.138044	51.861956
AI	41.145159	58.854841
SO_2	40.652213	59.347787
O_3	99.785307	0.214693
NO_2	48.626956	51.373044
Rainfall	27.019991	72.980009
Tmin	21.05674	78.94326
Tmax	63.201794	36.798206
Tmoy	44.437148	55.562852
Umin	95.819235	4.180765
Umax	44.485956	55.514044
Umoy	99.998647	0.001353
windspeed	3.115126	96.884874
NDVI	98.243443	1.756557

Model Performance

Statistical Performance: Analysis of the performance metrics for the RFM and LPM models reveals significant differences in their statistical outcomes (Table 4). The Random Forest Model (RFM), with a coefficient of determination (R^2) of 0.20, explains only 20% of the data variance, indicating its limited explanatory power. Additionally, it exhibits a Mean Squared Error (MSE) of 8501.46 and a Root Mean Squared Error (RMSE) of 92.22, reflecting substantial prediction errors. In contrast, the polynomial regression model (LPM) shows an R^2 of 0.4123, suggesting it explains 41.23% of the variance, which marks a notable improvement in explanatory capability over the RFM. In terms of prediction accuracy, the LPM model has an MSE of 6235.98 and an RMSE of 78.96, both lower than those of the RFM.

Table 4: Statistical performance of the models in the Grand-Lomé region.

Model	R2	MSE	RMSE
RFM	0.2	8501.46	92.22
LPM	0.4123	6235.98	78.96

Seasonal Representation Capacity: The analysis of the seasonal cycle for the models reveals several specific characteristics (Figure 8). The PRM model presents more linear forecasts that are less responsive to observed variations. It demonstrates moderate ability in capturing the seasonality of asthma cases. Incidence peaks, particularly in July, are reasonably well reflected in the forecasts; however, the overall trend of predicted values is less responsive to monthly fluctuations. Although the model successfully captures some peaks and troughs, it shows limitations in precision, with overestimation and underestimation rates ranging between 2.1% and 50%. The RFM model also shows significant limitations in its ability to capture seasonality and monthly variations (Figure 9). Notable discrepancies are observed, particularly during months with high peaks, such as May and October. For instance, in May, real values reach around 550 cases, while the model predicts approximately 400 cases, resulting in an underestimation of 150 cases and an error rate of 27.3%. In October, another peak month, actual values are close to 680 cases, whereas the model predicts only 420 cases, creating an underestimation of 260 cases with an error rate of 38.2%.

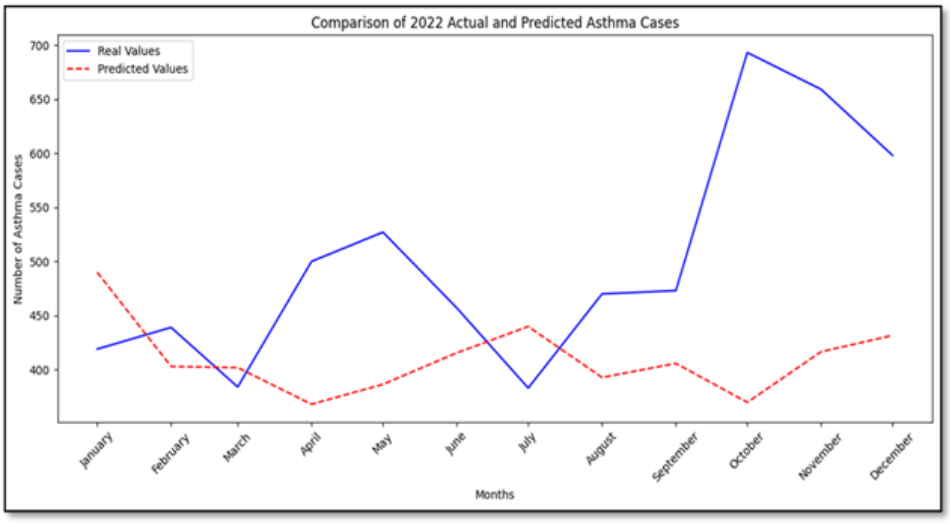


Figure 8: PRM seasonal representation in Grand-Lomé region.

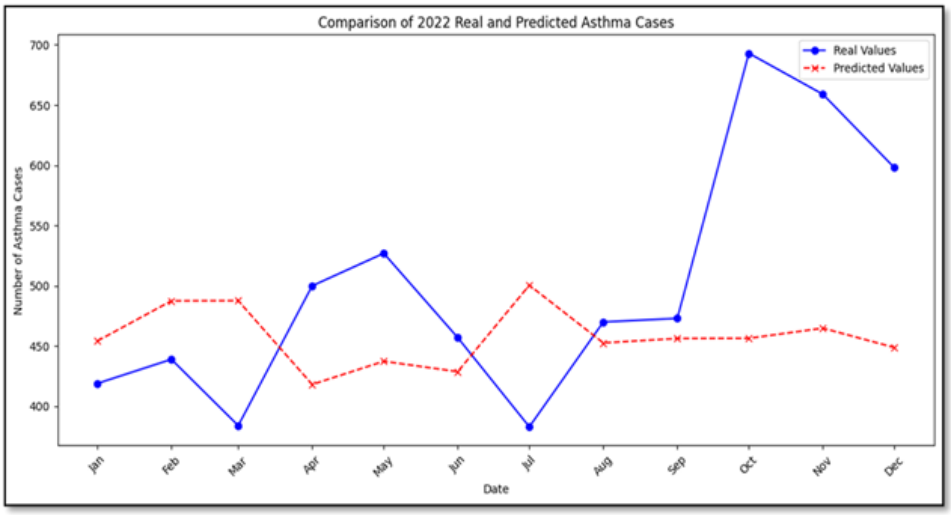


Figure 9: RFM seasonal representation in Grand-Lome region.

In contrast, for months like March and July, where case numbers are more stable, the model slightly overestimates, with moderate but consistent errors around 5-10%. Overall, the model tends to produce flatter predictions, with limited responsiveness to marked seasonal fluctuations. This analysis indicates that the model is less effective during periods of high variation, showing significant errors during peak months (May and October) and moderate overestimations during low-incidence months (January, March, July). Monthly underestimation and overestimation rates vary, often falling between 5% and 38% relative to actual values.

Selection of the Best Model: Although the Polynomial Regression Model (LPM) achieves the highest R^2 value (0.41), indicating a superior ability to explain data variance, it has significant limitations in representing the seasonality of the disease. Unlike the LPM, the Random Forest Model (RFM) better captures critical transitions between periods of increase and decrease. Under these conditions, the RFM emerges as the more reliable choice.

Discussion

Asthma and other respiratory diseases pose a major public health challenge in sub-Saharan Africa, particularly in regions where climate change exacerbates existing vulnerabilities. In Togo, climate variability characterized by rising temperatures, increasing air pollution, and seasonal dust storms has been linked to a rise in respiratory diseases, particularly asthma.

This study aims to enhance the understanding of the link between climate and asthma to improve its monitoring and management. Findings from the Savanes Region highlight the relationship between climatic and environmental variables and asthma incidence. Principal Component Analysis (PCA) identified key influencing factors, including temperature (Tmin, Tmax, Tmoy), humidity

(Umin, Umax, Umoy), and air pollutants (CO_2, SO_2), which significantly impact asthma cases. These results align with previous studies emphasising the role of meteorological conditions and air pollution in asthma exacerbation [10]. PCA results indicate that the First Principal Component (PC1), explaining 32.80% of the variance, is primarily influenced by temperature and humidity, supporting the findings of [11], who demonstrated that these factors play a crucial role in asthma hospitalisations. The Second Principal Component (PC2), accounting for 27.19% of the variance, is dominated by air pollutants (CO_2, SO_2, NO_2), reinforcing established links between air pollution exposure and increased asthma risks, particularly in urban environments [12].

Moreover, the relationship between asthma incidence and climatic conditions fits into a broader global context concerning climate change and respiratory health [13]. Rising temperatures and humidity levels facilitate the proliferation of airborne allergens and pollutants, contributing to increased asthma cases [14]. The study also supports findings from the Aphekom project, which identified traffic related pollution as a major factor in asthma morbidity [15]. Additionally, the Normalised Difference Vegetation Index (NDVI) and Rainfall (RR) influence asthma incidence in the Savanes Region. Higher NDVI values, indicative of denser vegetation, are associated with lower asthma prevalence, supporting the hypothesis that urbanisation and reduced green spaces contribute to increased asthma risks [16]. Similarly, the positive correlation between rainfall and asthma, as highlighted by [17], may be attributed to increased mould growth and allergen dispersion during wet conditions.

Seasonal analysis of asthma incidence reveals that while the PRM model effectively captures general trends, it struggles with abrupt seasonal transitions, particularly towards the end of the year. Additionally, [18] demonstrated the effectiveness of machine learning techniques, such as Random Forest, in predicting asthma trends based on environmental exposures. Furthermore, the ability of these models to forecast asthma peaks, particularly during the harmattan season, highlights their practical application for early warning systems in high-risk areas. These findings align with global research on the effects of climatic and environmental variables on respiratory health. [13] noted that urban areas with high levels of air pollution and frequent extreme weather events experience elevated rates of asthma exacerbations, particularly among vulnerable populations. In Grand-Lomé, where industrialization and vehicular emissions contribute to poor air quality, asthma prevalence increases during periods of high temperatures and humidity. These observations are consistent with the work of [19], who found that heatwaves combined with poor air quality exacerbate asthma attacks and increase hospitalization rates.

Although the predictive models developed in this study require further refinement, they offer a promising tool for healthcare systems in Togo to anticipate asthma surges linked to seasonal climatic patterns. Adapting these predictive tools to Togo's specific climatic and environmental conditions could significantly enhance asthma management and alleviate pressure on healthcare facilities during peak periods, like models successfully used in Europe to predict pollen-induced asthma peaks [13].

Conclusion

This aims to predict asthma occurrences by incorporating climate, environmental, and pollution variables, with the goal of enhancing the management of this climate-sensitive disease in a context where populations are especially vulnerable to climate variability.

The study highlights the impact of climatic and environmental factors on the incidence of asthma, exploring their contributions through principal component analysis and predictive models. The asthma impact chain illustrates how interactions between pollution, climatic conditions, and individual vulnerability exacerbate the risk of morbidity and mortality. The analysis of the Savanes and Grand-Lome regions identified the variables most correlated with variations in asthma incidence, confirming the major influence of air pollution (CO_2, SO_2, O_3), temperature, and humidity.

The findings indicate that the Random Forest Model (RFM) offers the best seasonal prediction capacity, effectively capturing peaks and variations in asthma incidence. However, its explanatory power remains limited (R^2 ranging from 0.13 to 0.20), and its ability to represent the seasonality of asthma remains modest. In contrast, the Polynomial Regression Model (PRM) demonstrates a higher explanatory capacity (higher R^2) but performs less effectively in forecasting seasonal fluctuations.

These findings underscore the importance of adopting a multidimensional approach to anticipate and mitigate the effects of asthma, incorporating pollution reduction policies, climate change adaptation strategies, and awareness-raising initiatives for vulnerable populations. In the long term, enhancing predictive models by integrating new variables and advanced machine learning techniques could improve forecast accuracy and facilitate the implementation of an early warning system for better asthma risk management in the studied regions.

Conflict of Interest

The authors declare no conflicts of interest.

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References

1. WHO (2020) Urgent health challenges for the next decade [Internet]. WHO, Geneva, Switzerland.
2. Mukherjee A B, Zhang Z (2011) Allergic asthma: influence of genetic and environmental factors. J Bio Chem 286(38): 32883-32889.
3. Global burden of 369 diseases and injuries in 204 countries and territories, 1990-2019: a systematic analysis for the Global Burden of Disease Study 2019. Lancet 396(10258):1204-1222.
4. WHO (2018) Climate change and health [Internet]. WHO, Geneva, Switzerland.

5. Asthma, allergies, and the Americans with Disabilities Act (ADA) (2016).

6. Ministère de la Santé, de l Hygiène Publique et de l Accès Universel aux Soins (2023) Plan national de développement sanitaire (PNDS) 2023-2027. Lomé, Togo.

7. Kristeen C (2021) Available from: *https://www.healthline.com/health/asthma/is-asthma-genetic*

8. INSEED (2023) Résultat du cinquième recensement général de la population et de l habitat (RGPH-5) Lomé, Togo.

9. Portnov B A, Reiser B, Karkabi K, Cohen Kastel O, Dubnov J (2012) High prevalence of childhood asthma in Northern Israel is linked to air pollution by particulate matter: Evidence from GIS analysis and Bayesian Model Averaging. Int J Environ Health Res 22(3): 249-269.

10. Kanannejad Z, Goudarzi G, Babaei AA, Geravandi S, Yari AR (2023) Geo-climatic variability and adult asthma hospitalization in Fars province, Iran: A GIS-based analysis. Frontiers Environ Sci 11: 1085103.

11. Zheng XY, Orellano P, Lin HL, Jiang M, Guan WJ (2021) Short-term exposure to ozone, nitrogen dioxide, and sulphur dioxide and emergency department visits and hospital admissions due to asthma: A systematic review and meta-analysis. Environ Int 150: 106435.

12. D Amato G, Pawankar R, Vitale C, Lanza M, Molino A, et al. (2016) Climate change and air pollution: Effects on respiratory allergy. Allergy Asthma & Immunol Res 8(5): 391-395.

13. Deng SZ, Jalaludin BB, Antó J M, Hess JJ, Huang CR (2020) Climate change, air pollution, and allergic respiratory diseases: A call to action for health professionals. Chin Med J (Engl) 133(13): 1552-1560.

14. Kumarihamy RMK, Tripathi NK (2019) Geostatistical predictive modeling for asthma and chronic obstructive pulmonary disease using socioeconomic and environmental determinants. Environ Monit Assess 191(Suppl 2): 366.

15. James G, Witten D, Hastie T, Tibshirani R (2013) An introduction to statistical learning: With applications in R. Springer, New York, USA: 1-426.

16. Jeddi Z, Gryech I, Ghogh M, El Hammoumi M, Mahraoui C (2021) Machine learning for predicting the risk for childhood asthma using prenatal, perinatal, postnatal, and environmental factors. Healthcare (Basel) 9(11): 1464.

17. D Amato G, Holgate ST, Pawankar R, Ledford DK, Cecchi L, et al. (2015) Meteorological conditions, climate change, new emerging factors, and asthma and related allergic disorders: A statement of the World Allergy Organization. World Allergy Organ J 8(1): 1-52.

18. Kinney PL, Pinkerton KE (2022) Heatwaves and air pollution: A deadly combination. Am J Respir Crit Care Med 206(9): 1060-1062.

19. Hastie T, Tibshirani R, Friedman J (2009) The elements of statistical learning: Data mining, inference, and prediction (2nd ed.). Springer, New York, USA: 1-745.