

A Spatio-Temporal Modelling of Climate Variability on Respiratory Disease Morbidity in Kampala City, Uganda

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Abstract

Background: Climate change poses serious public health risks, particularly in rapidly growing urban areas. Similarly, the interaction between month and year was not statistically significant ($\text{edf} = 0.75$, $p = 0.296$), indicating a relatively stable seasonal pattern over the study period together with urbanization, these factors contribute to respiratory diseases such as asthma, chronic obstructive pulmonary disease, and pneumonia. However, limited evidence exists on how these environmental exposures influence the spatial and temporal distribution of respiratory diseases in Kampala

Objectives. The study aimed to assess the influence of climatic variability and ambient air pollution on the spatio-temporal distribution of respiratory disease morbidity in Kampala City between 2021 and 2024.

Methods: A retrospective ecological study design was employed, using monthly aggregated data on respiratory disease illnesses obtained from the Ministry of Health. Climate variables were accessed and extracted through the Health Information Program Uganda, and air quality was obtained from Air Qo devices through Kampala Capital City Authority. Negative binomial ST-GAMs with tensor-product smooths were fitted to account for overdispersion, nonlinear environmental effects, and spatial-temporal interactions while adjusting for population size through an offset term. Residual checks and model diagnostics were conducted to assess goodness of fit and verify model assumptions [1]using randomised quantile residuals and smoothing terms.

Results: Between 2021-2024, a total of 89253 respiratory illnesses were recorded, comprising pneumonia (65%), asthma (23%), and COPD (12%). ST-GAM results showed strong spatial clustering ($\text{edf} \approx 4$, $p < 0.001$) and temporal variation. Spatiotemporal analysis using ST-GAMs showed significant clustering of respiratory diseases across Kampala ($\text{edf} \approx 4$, $p < 0.001$), with Central, Makindye, and Kawempe divisions. Temporally, Pneumonia cases peaked between March and May and again from September to November, while asthma and COPD were more prevalent between January and February and from June to August.

Conclusion: The study shows that PM_{2.5} is a key modifiable risk factor for respiratory diseases in Kampala. Environmental exposures affect disease patterns differently across disease types, locations, and seasons.

Introduction

Respiratory diseases are a leading cause of morbidity and mortality worldwide, including airborne infections such as pneumonia and tuberculosis, and chronic conditions like asthma and chronic obstructive pulmonary disease (COPD). Globally, asthma affects an estimated 262 million people and caused 455,000 deaths in 2019, while COPD accounted for over 3.2 million deaths, ranking as the third leading cause of death worldwide[2, 3]. Pneumonia remains one of the leading infectious diseases, particularly among children under five and older adults. Airborne diseases spread through droplets and aerosols, while chronic respiratory illnesses often arise from long-term exposure to pollutants[2, 4]. Their growing burden is a major public health concern, particularly in rapidly urbanizing regions where environmental changes and population pressures intensify exposure risks.

Climate change has emerged as a significant contributor to respiratory illness through its influence on temperature, humidity, precipitation, and air quality. These climatic shifts affect pollutant formation, pathogen transmission, and allergen distribution, thereby shaping respiratory health outcomes [5, 6]. Urban areas are especially vulnerable due to dense populations, concentrated emissions, and inadequate regulatory systems. Kampala, Uganda's capital, illustrates these challenges, having undergone rapid urbanization marked by increased vehicle emissions, biomass fuel use, industrial activity, and irregular weather patterns [7, 8]. These environmental pressures disproportionately affect vulnerable groups such as children, the elderly, and individuals with pre-existing respiratory conditions [9]. Existing literature highlights several pathways linking climate variability to respiratory diseases. Elevated temperatures increase

ground-level ozone, a known respiratory irritant, while humidity and rainfall influence airborne pathogen survival and the concentration of pollutants and allergens [10]. Dry seasons with high dust levels worsen asthma and COPD symptoms, whereas pneumonia tends to rise during colder, wetter months. Extreme events such as floods and heatwaves elevate indoor pollution, mold growth, and exposure to particulate matter, further heightening respiratory risks [11]. Studies across Africa and Asia consistently show that particulate pollutants, especially PM_{2.5} and PM₁₀, are strongly associated with respiratory inflammation, hospital visits, and increased disease severity. These climatic and environmental shifts do not occur uniformly across cities; rather, they interact with local conditions such as population density, land use, and socio-economic disparities. As a result, respiratory illnesses are unevenly distributed across both time and space. For example, pneumonia may peak during rainy periods when humidity enhances bacterial and viral transmission, whereas asthma and COPD often worsen during dry seasons with high dust and PM_{2.5} concentrations.

Uganda's vulnerability to climate change, combined with rapid urban growth and heavy reliance on biomass fuels, has resulted in persistently high air pollution levels and increased susceptibility to climate-sensitive diseases. Kampala's divisions experience varying degrees of exposure to pollutants and climatic extremes, reflecting the city's complex social and environmental landscape [12]. Understanding how these exposures vary geographically is critical for public health planning. Spatial analysis provides a means to identify geographical patterns and hotspots where respiratory diseases are most prevalent, enabling policymakers to allocate resources efficiently and implement targeted interventions tailored to high-risk communities. In Kampala, where environmental conditions differ between the Central, Kawempe, Makindye, Nakawa, and Rubaga divisions, spatially explicit evidence is especially essential for designing climate-resilient health strategies[13]

Capturing these patterns, however, requires analytical tools capable of modelling the complex, nonlinear, and spatiotemporal relationships between climate variables and health outcomes. Traditional statistical models often assume linearity and uniformity across space, making them insufficient for climate–health analyses. More flexible approaches, such as Generalized Additive Models (GAMs), overcome these limitations. GAMs extend generalized linear models by incorporating non-parametric smooth functions to model nonlinear relationships, allowing environmental exposures to influence disease outcomes in flexible, data-driven ways[14]. They have been widely used in climate, pollution, and epidemiological research due to their ability to model variables from the exponential family while accounting for complex trends. Despite increasing evidence linking climatic and environmental exposures to respiratory morbidity globally, few studies in sub-Saharan Africa have simultaneously modelled spatial, temporal, and nonlinear environmental effects using advanced spatio-temporal frameworks. In Uganda, evidence remains particularly limited regarding how climatic variability and air pollution jointly influence respiratory disease patterns across urban divisions.

Recent advances in GAM methodology have led to Spatio-Temporal Generalized Additive Models (ST-GAMs), which integrate spatial and temporal smoothing components and tensor-product interactions. ST-GAMs provide a powerful framework for analysing health outcomes that vary across both space and time, enabling detection of disease hotspots, seasonal patterns, long-term trends, and evolving environmental effects. Although ST-GAMs have been increasingly applied in Asia, Europe, and Latin America, their use in African cities remains limited despite the region's high vulnerability to climate-sensitive diseases [15, 16]. Kampala, therefore, presents an important and understudied context for evaluating the spatiotemporal impacts of climate change and air quality on respiratory morbidity.

This study, therefore, aims to assess the influence of climate change on the spatial and temporal distribution of respiratory diseases, specifically asthma, COPD, and pneumonia, across the five divisions of Kampala City using a spatio-temporal Generalized Additive Model (ST-GAM).

Methods

Study area and population

This study was conducted in Kampala city, the most populated city in Uganda, with a population of 1,875,835 according to the 2024 census. It is located at 0.347564 3475964 latitude and 32.5825197 longitude. The study area encompasses five administrative divisions, namely, Central Kampala, Kawempe, Makindye, Nakawa, and Rubaga, each with distinct socio-economic and environmental features [8]. The spatial boundaries of the five divisions of Kampala city, as shown in Fig. 1. It provides the geographical foundations of spatial analysis conducted in this study of the distribution of respiratory disease cases and climate exposures. The study included all residents of Kampala who had ever visited the health facilities in the five divisions of Kampala city for the past 4 years and were diagnosed with respiratory diseases (both outpatient and hospitalized patients), i.e. asthma, chronic obstructive pulmonary disease (COPD), and pneumonia. This included all age groups, although some vulnerable populations, such as children, the elderly, are disproportionately affected by climate variability [17]. Kampala experiences a tropical climate with bimodal rainfall seasons occurring between March–May and September–November

Study design and period

A retrospective ecological study design was employed using monthly aggregated respiratory disease, climate, and air quality data collected between 2021 and 2024 across Kampala City divisions. The study used monthly aggregated counts of reported respiratory disease cases from health facility records for the past four years.

Data

To address the study objectives, several datasets were employed. i.e., meteorological climate data, air quality data, and respiratory health data from all individuals who ever visited healthcare facilities for respiratory diseases, i.e., outpatients or hospitalisation in the past 4 years in Kampala. Respiratory disease outcomes were classified according to the Ministry of Health reporting framework within DHIS2.

Meteorological data

These comprised climate variables measured as monthly averages for the four years, i.e., 2021–2024, in the five divisions of Kampala. i.e., average monthly temperature, average monthly precipitation, and average monthly humidity. The monthly climate data were obtained from the ERA5 and CHIRPS for precipitation data, which were accessed and extracted via the DHIS2 climate system, a tool developed and maintained by the Health Information System Program (HISP) Uganda, under the authorization of the Ministry of Health (MOH).

Air quality

Air Quality monitoring data, which included concentrations of particulate matter (PM_{2.5}), were obtained from air quality monitoring networks in Kampala, i.e., Makerere AirQo and Kampala Capital City Authority (KCCA), which are both located in Kampala city. This was obtained from the AirQo device, which uses twin Plantower light scattering sensors and transmits averaged measurements every 90 seconds via the local Global System for Mobile Communications network to a cloud-based platform, and the KCCA monitoring devices consist of clarity nodes measuring PM_{2.5}, temperature, and local humidity. [18]. Although PM_{2.5} was the primary air quality indicator analysed, other pollutants such as NO₂, SO₂, and ozone were unavailable and may contribute additional respiratory risks.

Respiratory data

Respiratory Disease Data was extracted electronically from the District Health Information System 2 (DHIS2) located in the health management information system database of the Ministry of Health. It contained the aggregated monthly data for healthcare visits and admissions due to respiratory diseases, i.e., asthma, chronic obstructive pulmonary disease (COPD), and pneumonia, for patients from Kampala city from 2021–2024. These excluded cases were reported by the national referral hospitals, because it would overestimate cases. The health data in DHIS2 are recorded as aggregated monthly averages. DHIS2 is a tool that is web-based, used for collecting, validating, analysing, and presenting aggregated health data on patients. The system is designed in a way that data from patient registers is entered as aggregated data weekly. The weekly data were reported using the WHO epidemiology week, i.e., from Sunday to Saturday.

Spatial data

Kampala city shapefile was obtained from the Uganda Bureau of Statistics (UBOS) under the Uganda (UGL) Administrative Boundary Common Operational Database (COD-AB), 2020. It contained geometric division locations. Respiratory disease data from DHIS2. Spatial analyses were conducted using a standardized coordinate reference system (WGS84).

Data management

Data were extracted from various sources, including respiratory disease data from DHIS2, climate variables obtained from the Health Information System Program, Uganda, air quality parameters from AirQo, and spatial shapefiles from UBOS for the different divisions in Kampala, along with their corresponding graphical locations. These extracted data were then uniformly merged to form one dataset using division, year, and month as the unique identifiers. Data management processes were done to ensure that the data quality was checked before the analysis was done. Data layers were aligned to a common coordinate system to ensure accurate spatial overlap, and the geocoded health data were used to locate disease cases within a specific neighbourhood.

Climate and air quality data were aggregated to match the spatial resolution of the health data for compatible analysis.

The spatial centroid coordinates (latitude and longitude) of the divisions were created in R version 4.5.0 to evaluate the effects of the climate factors on the respiratory diseases in the divisions of Kampala city.

The number of respiratory disease cases varied among divisions; therefore, the population size in a given time interval was adjusted to ensure comparability. However, adjusting the respiratory disease illnesses using the yearly estimated population size could bias the results; hence monthly estimated population size for the divisions was used as an offset variable in the modeling to estimate the spatiotemporal distribution of respiratory illnesses in the city. The monthly estimated population size of the divisions from 2021 to 2024 was obtained from the UBOS website, and the monthly population size was estimated from the 2020 UBOS estimated population growth rate.

Statistical Analysis

Preliminary analyses were done using R 4.5.0 Statistical software. The descriptive statistics were performed for continuous variables using the mean and standard deviation, and the associations between independent and dependent variables were assessed to help select variables for the multivariable analysis. Descriptive statistics were also presented as graphs for some variables. Results were displayed using tables, graphs, and maps, and $p < 0.05$ was considered significant. The effective degree of freedom < 1 was considered linear, > 1 and ≤ 2 was considered weak non-linear, and > 2 was considered strongly non-linear.

The study employed a spatial-temporal GAM analysis to analyse the spatial distribution of respiratory diseases in Kampala city over time. This is because spatiotemporal smoothing allows for flexible modelling of non-linear relationships in both space and time using a tensor product structure to incorporate the interaction of covariates with space and time.

Model structure

This model integrates smooth terms for climate variables, spatial coordinates, and spatiotemporal interactions to capture the complex relationships and trends, incorporating the degree of smoothness for each function using the k parameter, which specifies the number of basis functions (knots). This allows better control over the model's flexibility and prevents overfitting. Penalized regression splines are used to optimize the trade-off between model fit and smoothness.

$$\log(E(Y_{it})) = \beta_0 + \sum_{k=1}^2 s_k(X_{kit}) + s_3(\text{time}_t) + s_4(\text{lon}_i, \text{lat}_i) + ti(\text{time}_t, \text{lon}_i, \text{lat}_i) + \log(\text{population}_{it})$$

Where:

- Y_{it} : Observed disease count at location i and time t
- $E(Y_{it})$: Expected value (mean) of the disease counts at location i and time t
- $\log(E(Y_{it}))$: Log-link function used to model the expected disease counts
- β_0 : Intercept term representing the baseline log-risk when all covariates are zero
- $\sum_{k=1}^2 s_k(X_{kit})$: Sum of smooth nonlinear effects of explanatory variables (covariates)
 - X_{kit} : The k^{th} predictor variable measured at location i and time t
 - $s_k(\cdot)$: Smooth spline function capturing nonlinear relationships between predictors and disease risk
- $s_3(\text{time}_t)$: Smooth temporal effect capturing long-term trends or seasonality over time
- $s_4(\text{lon}_i, \text{lat}_i)$: Two-dimensional spatial smooth function representing spatial variation across geographic coordinates
 - lon_i : Longitude of location i
 - lat_i : Latitude of location i
- $ti(\text{time}_t, \text{lon}_i, \text{lat}_i)$: Tensor-product interaction term modelling the spatiotemporal interaction, allowing spatial effects to vary over time
- $\log(\text{population}_{it})$: Offset term adjusting for the underlying population at risk
 - population_{it} : Population size at location i and time t

A negative binomial distribution was selected due to evidence of overdispersion in respiratory disease counts. Basis dimensions (k) were selected to balance model flexibility and prevent overfitting.

Model fit

Model performance was assessed using the Akaike Information Criterion (AIC) and generalized cross-validation (GCV) scores to determine the optimal model fit. Lower AIC and GCV values indicated better model performance, balancing goodness of fit and model complexity. Spline smooths were defined using the default settings of the *mgcv* package in R.

Model selection was guided by comparing AIC values, deviance explained, and the inclusion or exclusion of spatial, environmental, and temporal predictors. For the spatio-temporal GAM (ST-GAM), a negative binomial distribution was used to account for overdispersion. Variable contributions were evaluated by fitting models with and without specific terms (e.g., space-time interaction, trend, seasonality, climatic factors), with model selection performed using `select = TRUE` in the `bam` function.

Model diagnostics

Model adequacy was assessed using a combination of diagnostic tools, tailored to the structure and distributional assumptions of the ST-GAMs applied in the study. Randomised quantile residuals were used as a robust diagnostic tool, especially suitable for models assuming negative binomial and Tweedie distributions. These residuals offer the advantage of being approximately normally distributed under a correctly specified model, thereby enhancing the sensitivity for detecting misspecification and overdispersion. Diagnostic checks were performed using the `gam.check()` function from the `mgcv` package in R, which provides plots of residuals, QQ-plots, and checks for concurvity. Special attention was paid to the distribution and randomness of residuals to evaluate the adequacy of the fitted smooth terms and to ensure the models captured the nonlinear patterns in the data without overfitting or underfitting. These diagnostics informed the selection of smoothing parameters and model complexity, helping to ensure the validity of inferences drawn from both temporal and spatio-temporal models.

426.33, REML = 1222.

Results

Descriptive statistics of the monthly environmental factors and respiratory diseases

Results in Table 1 indicate that the average number of monthly COPD illnesses reported across divisions was 138 (Standard deviation, SD = 284). The monthly maximum number of illnesses recorded in a single division was 2,055, while the minimum was 2. However, the Asthma illnesses had a monthly mean of 295 (SD = 114). The illnesses reported ranged from a minimum of 93 to a maximum of 730 per month across divisions. The average number of pneumonia illnesses reported was 661 per month, and the SD was 360 per month. The maximum monthly count was 2,208, and the minimum was 208.

The average temperature across all observations was 21.90°C, with SD of 0.70°C. The observed temperature ranged from 20.52°C to 23.79°C. The monthly average relative humidity was 79.70%, with a SD of 3.96%. The maximum and minimum humidity were 88.38% and 70.32%, respectively. Mean monthly precipitation was 3.70 mm, and the SD was 1.88 mm. The lowest and highest values recorded were 0.67 mm and 8.33 mm, respectively.

The monthly average concentration of particulate matter at 2.5(PM_{2.5}) was 27.80 µg/m³, with a standard deviation of 10.92 µg/m³. The minimum recorded was 7.84µg/m³ while the maximum was 79.29µg/m³ per month.

Table 1
Monthly environmental factors and respiratory diseases

Variable	Mean	SD	Min	Max
Respiratory diseases				
Copd	138	284	2	2055
Asthma	295	114	93	730
Pneumonia	661	360	208	2208
Climate variables				
Average Temperature(⁰ c)	21.90	0.70	20.52	23.79
Relative Humidity (%)	79.70	3.96	70.32	88.38
Rainfall/Precipitation(mm)	3.70	1.88	0.67	8.33
Air quality				
PM2.5($\mu\text{g}/\text{m}^3$)	27.80	10.91	7.84	79.29
SD; standard deviation, Max >maximum, Min >Minimum				

From Fig. 2, across all years, the months of February and March 2024 consistently recorded the highest mean temperatures, reaching 23.7°C, higher than in any other year shown. On the other hand, between June and September generally shows cooler temperatures, with August 2022 recording the lowest average, below 21°C. 2024, therefore, had the higher temperatures throughout most of the year.

Figure 3 illustrates PM2.5 across the divisions of Kampala city. The figure shows a distinct seasonal pattern in PM2.5 levels, with the highest concentrations recorded in January and February. Makindye had the peak values exceeding 40 $\mu\text{g}/\text{m}^3$ during this period. There was a drastic drop in PM2.5 levels across all divisions in March and April.

Between May and October, the trends become more varied across divisions. However, Makindye continues to consistently record higher PM2.5 concentrations, followed by Kawempe and Lubanga. In the other hand, Nakawa registers the lowest levels throughout most of this period.

The association between environmental factors and respiratory diseases from Table 2

COPD;

The results (Table 2) indicated that temperature, humidity, and particulate matter at 2.5 are statistically associated with COPD morbidities in Kampala City. However, temperature and humidity showed a significant, smooth (non-linear) relationship with COPD case incidence, i.e., edf > 1. Precipitation was not statistically significant and didn't show a significant smooth relationship with COPD case incidence.

Asthma;

Temperature, humidity, precipitation, and PM2.5 were not statistically significant with asthma, with p-values of 0.137, 0.423, 0.923, and 0.144, respectively. The effective degree of freedom (edf) summary statistics from GAM revealed that PM2.5 and temperature were significantly non-linear. However, humidity and precipitation were reduced to a linear relationship with Asthma as shown in Table 2

Pneumonia;

PM2.5 showed a statistically significant relationship and a significant smooth relationship with pneumonia cases. However, temperature, humidity, and precipitation were neither statistically significant nor had a significant smooth relationship with pneumonia cases as presented in Table 2.

Table 2
Bivariate relationship between climate factors, air quality(PM2.5), and the respiratory diseases

RD	COPD		Asthma		pneumonia	
variables	edf	p-value	edf	p-value	edf	p-value
Temperature	2.69	< 0.001	1.36	0.137	1.01	0.456
Humidity	1.83	0.018	1.02	0.428	1.07	0.935
Precipitation	1.01	0.527	1.01	0.923	1.01	0.548
Pm2.5	1.01	0.004	2.21	0.144	3.54	< 0.001

***RD respiratory disease, edf > effective degree of freedom**

ST-GAM model selection

Model selection, as shown in Table 3, was performed by systematically reducing the full spatio-temporal Generalized Additive Model (ST-GAM) through the exclusion of spatial, temporal, seasonal, climatic, and interaction terms using the *select = TRUE* option in the *bam* function of the *mgcv* package in R. Competing models were evaluated using Akaike Information Criterion (AIC) and deviance explained. The results indicated that the full ST-GAM provided the best fit for asthma (AIC = 2755.75; deviance explained = 93.3%). For COPD, the optimal model retained only spatial and temporal components, excluding climatic and air quality variables (AIC = 2426.33; deviance explained = 72.1%; REML = 1222.3). In contrast, the best-fitting pneumonia model included spatial, climatic, air quality, and seasonal terms but excluded the long-term temporal trend (year), explaining 87.2% of the deviance (AIC = 3260.14).

Table 3
Evaluating Spatial, Climate, and Temporal Effects on Respiratory Disease Models Using AIC and Deviance Explained:
Kampala, 2021–2024

models	Asthma			COPD			Pneumonia		
	AIC	REML	% of deviance explained	AIC	REML	% of deviance explained	AIC	REML	% of deviance explained
Full	2755.75	1405.1	93.3	2426.33	1222.3	72.1	3260.47	1656.3	87.3
Without space-time interaction	2765.96	1405.1	93.3	2425.47	1220	71.5	3260.51	1655.2	87.3
Without year	2776.59	1408.2	92.8	2431.70	1225.1	70.8	3260.14	1654.3	87.2
Without the year and month	2782.36	1408.3	92.4	2433.26	1225.2	71.1	3280.85	1660	85.6
Without the month and year interaction	2773.86	1409.2	92.8	2425.68	1222.3	72	3287.35	1664	84.6
Without spatial effect	3397.66	1702.1	7.3	2702.78	1222.3	18.5	3712.29	1859.4	10.4
without climate variables	2768.46	1397.8	92.5	2423.77	1218.5	70.9	3265.31	1648.4	85.7

6.4.3 The spatio-temporal GAM to assess the effects of climate on respiratory diseases in Kampala city.

Table 4
The effects of parametric covariates and approximate smooth effects of
environmental, spatial, temporal, and space-time dimensions of
respiratory diseases in Kampala City, 2021–2024

Factors	estimates	t-value	p-value
<i>ASTHMA</i>			
Intercept	-6.97976		< 0.001
Smooth terms	edf		
s(Temperature)	3.47	6.430	0.164
s(PM2.5)	4.52	14.531	0.019
s(Precipitation)	1.83	1.963	0.161
s(Humidity)	1.00	2.002	0.804
s(Month)	1.48	1.215	0.079
s(Year)	2.82	11.581	0.001
s(Longitude,Latitude)	3.99	2366.950	< 0.001
ti(month,year)	4.39	18.870	< 0.001
ti(month,Longitude,Latitude)	1.01	0.002	0.262
<i>PNEUMONIA</i>			
Intercept	-6.20467	-286.6	< 0.0001
Smooth terms	edf		
s(Temperature)	1.10	1.653	0.234
s(PM2.5)	3.78	8.090	0.112
s(Precipitation)	2.10	6.734	0.047
s(Humidity)	2.23	7.106	0.053
s(Month)	3.55	23.763	< 0.001
s(Longitude,Latitude)	3.99	1145.473	< 0.001
ti(month,year)	8.79	41.386	< 0.001
ti(month,Longitude,Latitude)	1.66	1.833	0.426
<i>COPD</i>			
Intercept	-8.55791	-172.4	< 0.001
Smooth terms	edf		
s(month)	1.65	5.358	0.015
s(year)	1.01	7.769	0.005
ti(month,year)	0.75	0.916	0.296
s(Longitude,Latitude)	3.99	596.394	< 0.001

Factors	estimates	t-value	p-value
ASTHMA			
ti(month,Longitude,Latitude)	2.80	6.692	0.174

edf: effective degree of freedom; s:smooth effect; ti: tensor product effect

The ST-GAM Table 4 Effects of environmental factors on respiratory diseases.

Asthma

Table 4 demonstrates that most climate and air quality variables had statistically significant smoothed effects. This is because their p-values were less than the 0.05 significance level. PM2.5 in the asthma model showed a complex and nonlinear relationship with the effective degree of freedom(edf = 4.61, p = 0.027). Likewise, precipitation and year showed significant smooth effects(edf = 1.83, p = 0.046 and edf = 1.54, p = 0.001, respectively). The relatively high edf for PM2.5 suggests a more flexible and complex nonlinear association compared with precipitation and year, which exhibited smoother near-linear trends

On the other hand, relative humidity in the asthma model had a lower effective degree of freedom(edf = 1.00, p = 0.804), implying that its effect was nearly linear and not statistically significant. Temperature was not significantly associated with asthma illnesses in Kampala, despite being modeled using a smooth term.

The spatial smooth term, modeled using a joint longitude–latitude spline, was statistically significant (edf $\approx$ 4, p < 0.001), indicating substantial spatial variation in asthma illnesses across Kampala’s divisions.

The temporal pattern of asthma illnesses was reflected in the month and year components. The long-term temporal trend (year) was statistically significant and exhibited a smooth relationship with asthma illnesses (edf = 1.54, p = 0.001), suggesting a near-linear temporal trend. Furthermore, the interaction between month and year was statistically significant (edf = 4.39, p < 0.001), indicating temporal variability in seasonal asthma patterns over time.

However, the interaction between seasonality and space was not statistically significant (edf = 0.01, p = 0.617), suggesting that seasonal patterns of asthma illnesses were relatively consistent across the different divisions of Kampala.

The partial effect plots in Fig. 4 revealed that, after adjusting for other covariates in the model, PM2.5 exhibited a strong positive association with asthma illnesses, with cases increasing markedly at concentrations above 30 $\mu\text{g}/\text{m}^3$. Precipitation also demonstrated a nonlinear positive relationship, with asthma illnesses increasing when precipitation exceeded approximately 3 mm.

Seasonally, asthma illnesses increased between July and October. The temporal pattern further indicated fluctuations in asthma incidence across the study years, with noticeable increases observed in 2022 and 2024. Episodic spikes in asthma cases were also evident during the early months of 2021 and 2022, as well as during mid-2023 and mid-2024.

Geographically, Fig. 7 illustrates elevated asthma illnesses in the Central and Nakawa divisions, especially between June, July, August, September, and October.

Pneumonia

Among the climate and air quality variables, precipitation demonstrated a statistically significant nonlinear relationship with pneumonia illnesses (edf = 2.10, $p = 0.047$). In contrast, mean temperature, relative humidity, and PM2.5 were not significantly associated with pneumonia illnesses, although their estimated smooth terms suggested varying functional forms, with effective degrees of freedom (edf) of 1.10, 2.23, and 3.78, respectively.

Temporally and spatially, seasonal variation exhibited a statistically significant smooth effect (edf = 3.55, $p < 0.001$), indicating a nonlinear seasonal relationship with pneumonia illnesses in Kampala City. The spatial smooth term modeled using longitude and latitude was also highly significant (edf = 3.99, $p < 0.001$), suggesting substantial spatial variation in pneumonia illnesses across the city.

Additionally, the interaction between month and year was statistically significant (edf = 8.79, $p < 0.001$), indicating that seasonal pneumonia patterns varied over time. However, the space seasonality interaction was not statistically significant, suggesting that the seasonal pattern remained relatively consistent across spatial locations during the study period.

The partial effects plots in Fig. 6 visualize these relationships. Pneumonia illnesses increased rapidly from 3mm of precipitation. Humidity showed a negative effect, with illnesses declining beyond 75% relative humidity. While PM2.5 was not statistically significant, the partial effect plot showed a positive trend, with increased pneumonia risk observed beyond 30 $\mu\text{g}/\text{m}^3$. Seasonal patterns were evident, with pneumonia illnesses peaking from May to July and gradually declining towards the end of the year. The temporal effect also further showed that pneumonia morbidity peaked in the early months of 2022, 2023, mid-2021, and mid-2024.

Geographically, Fig. 7 shows elevated pneumonia morbidities in the central and Kawempe divisions compared to other parts of the city.

COPD

The long-term trend(year) was highly statistically significant (edf = 1.00, $p = 0.005$), however, the smooth effect was reduced to a linear relationship with COPD illnesses in Kampala City.

The spatial smooth term was highly significant and statistically significant(edf = 3.99, $p = < 0.001$) with the COPD illnesses, highlighting the significant geographic variability in COPD illnesses across Kampala City.

The interaction between month and spatial location was not statistically significant (edf = 2.80, $p = 0.174$), suggesting that the seasonal effects on COPD illnesses were relatively consistent across geographic areas.

Similarly, the interaction between month and year was not statistically significant (edf = 0.75, $p = 0.296$), indicating a relatively stable seasonal pattern over the study period.

The relationships in Fig. 5also revealed that COPD illnesses peak seasonally between May and August. Temporal trends revealed a steady increase in COPD burden, especially in 2022 onwards, with prominent peaks in the early months of 2022 and 2023, again in mid-2024.(interaction between month and year).

Figure 5 further illustrates spatial patterns, especially in the central and Makindye divisions, compared to other areas of Kampala City. The spatial-seasonal interaction also indicated that seasonal COPD burden varied by location, with high cases reported in May, June, July, and August, especially in Makindye Division (Fig. 7)

6.4.3.2 The ST-GAM smooth effects plots for COPD, asthma, and pneumonia in Kampala city

Discussion

This study employed a spatiotemporal Generalised Additive Model to assess how climate and air quality variables, spatial location, and time influence respiratory disease patterns in Kampala City. The results showed that the spatial and temporal distribution of asthma, COPD, and pneumonia varied significantly across divisions. Makindye division, for example, exhibited persistent clustering of asthma and COPD illnesses. This area is characterized by dense settlement, limited green space, and frequent traffic congestion, all of which are known to increase exposure to both air pollution and heat stress. Kawempe and Central divisions, on the other hand, consistently showed higher pneumonia cases. These divisions include some of the most socioeconomically disadvantaged neighbourhoods, where informal housing is common and access to quality health services is limited, reflecting both environmental exposures and socio-structural vulnerabilities.[15, 19]

The ST-GAM results revealed that COPD patterns were largely affected by spatial and seasonal factors, rather than climatic variables. This, however, contrasts with studies from Europe, where COPD has shown strong associations with temperature and pollution over time[19]

The predictive model excluded climate variables, suggesting entrenched local environmental exposures such as household air pollution and unregulated urban emissions may play a more dominant role. This is consistent with previous reports indicating that urban slums and informal settlements in Kampala are disproportionately affected by indoor air pollution due to biomass use[8, 9]. The spatial clustering of COPD in central and Makindye divisions further supports this, as these areas combine high population density, traffic congestion, and poor ventilation, all of which are known for elevating chronic respiratory disease risks[2, 20]. It also supports the WHO 2025 report on air quality, advocacy for precision public health, where interventions are not only tailored to diseases but also to the places and communities where they are most needed.

On the other hand, asthma exhibited a significant sensitivity to PM_{2.5}, confirming the pollutant's well-established role as an asthma trigger[21, 22]. The nonlinear and statistically significant effect of PM_{2.5} in the asthma model supports findings from urban studies in both high and low-income settings, which have linked fine particulate exposure to increased asthma exacerbations and hospital admissions[23, 24]. The spatial burden of asthma was highest in the Central and Nakawa divisions, areas with more vehicular emissions and commercial activities. This aligns with Thaker, Smith [5], who noted that rapid urbanization and poor transport planning contribute to concentrated zones of ambient air pollution, particularly harmful to individuals with pre-existing respiratory conditions.

Pneumonia showed a significant nonlinear association with precipitation, suggesting that wet conditions can encourage the spread of respiratory pathogens. This may be due to factors like mold growth, indoor crowding, and damp environments [25, 26]. These findings reflect what other studies in East Africa have also observed, where pneumonia illnesses tend to rise during the rainy season, likely because of cooler temperatures and higher humidity during that time[11]. The ST-GAM model revealed that Kawempe and Central divisions, areas known for high population densities and inadequate sanitation infrastructure, were pneumonia hotspots, which is consistent with evidence linking structural deprivation to increased respiratory disease transmission[3, 17].

Across all models, the longitude-latitude spline was highly significant, indicating the importance of localised spatial factors[15, 16]. These spatial dependencies underscore the need for place-based policy interventions, such as division-level air quality monitoring, infrastructure upgrades, and targeted health services.

Temporally, both asthma and pneumonia displayed seasonal variation, with partial effects peaking in the wet months(May-July), consistent with prior studies that documented climate-related surges in respiratory illnesses during periods of high humidity and precipitation[27, 28]. In contrast, COPD exhibited a relatively stable seasonal pattern, with the most prominent increase in disease burden occurring in mid-2022 to 2023, possibly due to cumulative exposure or seasonal shifts in air quality. The interaction term between month and year was significant for asthma and pneumonia,

suggesting interannual variability in seasonal peaks, potentially influenced by changing weather patterns consistent with climate change projections for the region.[7, 12].

Importantly, the spatial seasonality interaction was not statistically significant across models, indicating that while disease rates varied by division and month, the seasonal patterns were broadly consistent across space. These findings support the potential for uniform seasonal forecasting of respiratory risk, which could aid citywide preparedness and hospital resource allocation.

The study had strengths that included the use of flexible and robust analytical approaches, especially GAM and their spatio-temporal extensions, which enabled the detection of complex, non-linear relationships between climatic variables, air quality, and respiratory disease outcomes across both space and time. Moreover, the integration of the multiple data sources provided a comprehensive representation of real-world environmental exposures. Further strengths were the application of spatial and temporal smoothing techniques that allowed the identification of localised disease hotspots, seasonal patterns, and long-term trends, thereby generating evidence to support targeted and climate-responsible public health interventions in high-risk divisions of Kampala.

The study, however, had limitations that included reliance on aggregated, division-level data, which restricted adjustment for individual-level confounders such as age, sex, comorbidities, etc and increased the potential for ecological fallacy. It also focused on PM_{2.5} to the exclusion of other important pollutants such as nitrogen dioxide, ozone, and Sulphur dioxide, which may have led to an underestimation of the total air pollution burden. Additionally, potential misclassification of residence due to high commuter inflows into Kampala may affect the accuracy of spatial attribution and limit the generalizability of the findings beyond the study setting. The use of routinely collected surveillance data may also introduce reporting inconsistencies and underreporting across facilities.

Conclusion

This study examined the spatio-temporal influence of climate variability and ambient air pollution on the morbidity of COPD, asthma, and pneumonia across the five divisions of Kampala City from 2021 to 2024. The findings demonstrate complex, non-linear, and disease-specific associations between environmental exposures and respiratory morbidity. With PM_{2.5} emerged as the most consistent and statistically significant, potentially modifiable determinant across all outcomes. PM_{2.5} demonstrated important nonlinear relationships, particularly for asthma morbidity, while spatial and seasonal effects consistently shaped respiratory disease distribution across Kampala. Pronounced spatial heterogeneity was identified, with central, Kawempe, and Nakawa divisions constituting persistent high burden clusters, alongside temporal patterns indicating fluctuating and, in some cases, increasing disease trends. Collectively, these results provide empirical support for the application of flexible spatio-temporal modelling frameworks in environmental epidemiology and highlight the need for targeted, climate-responsive public health and environmental interventions, particularly in informal and underserved urban communities in low- and middle-income settings.

Declarations

Ethical consideration

Ethical standards were adhered to during the conduct of this study. Approval to conduct the study was received from the Uganda National Council of Science and Technology through the Makerere University School of Public Health, Higher Degree Research and Ethics Committee-MakSPH-REC-556. Permissions to use the data were also obtained from different offices and authorities. i.e., Ministry of Health, Health Information System Program Uganda, Kampala Capital City Authority. Informed consent to participate was not required because the study utilized routinely collected secondary

data that were aggregated and de-identified before analysis. All methods were carried out in accordance with relevant guidelines and regulations and the principles of the Declaration of Helsinki.

Competing interest:

No competing interest

Clinical Trial number

Not applicable

Funding:

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Author Contribution

FA– Conceptualized the manuscript, developed methods, conducted analysis, and wrote the final draft. PMN, SM, CNK, and EI supported the analysis, interpretation of results, and report writing. SK, LA, NMT, TA, and SH provided methodological guidance and critically reviewed the manuscript for intellectual content. CN provided overall supervision and critically reviewed the manuscript for scientific rigor. All authors read and approved the final version of the manuscript.

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Data Availability

Data are available from the corresponding author upon reasonable request and with permission from the Ministry of Health, HISP Uganda, and KCCA.

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Figures

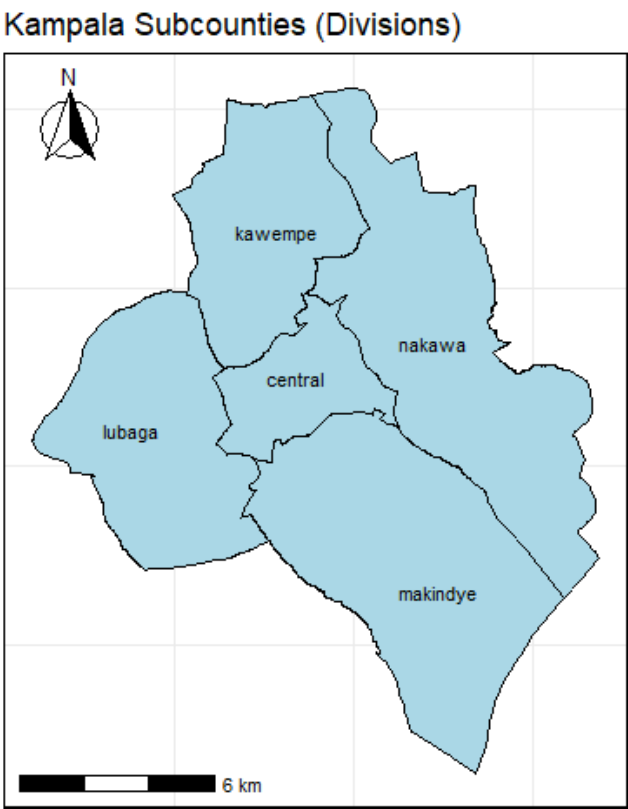


Figure 1

The map of the five divisions of Kampala city

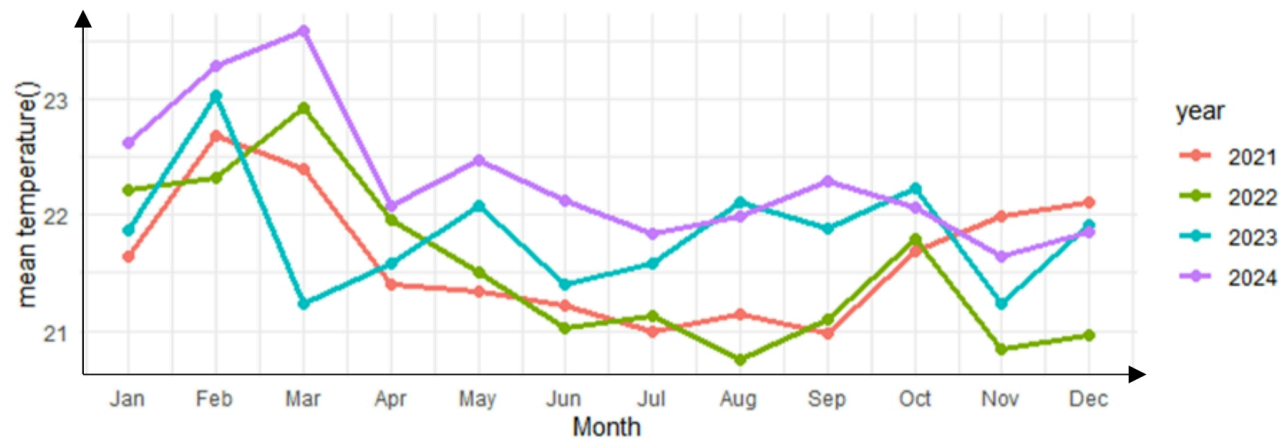


Figure 2

The monthly Average temperature trends in Kampala City from January to December over four years (2021-2024)

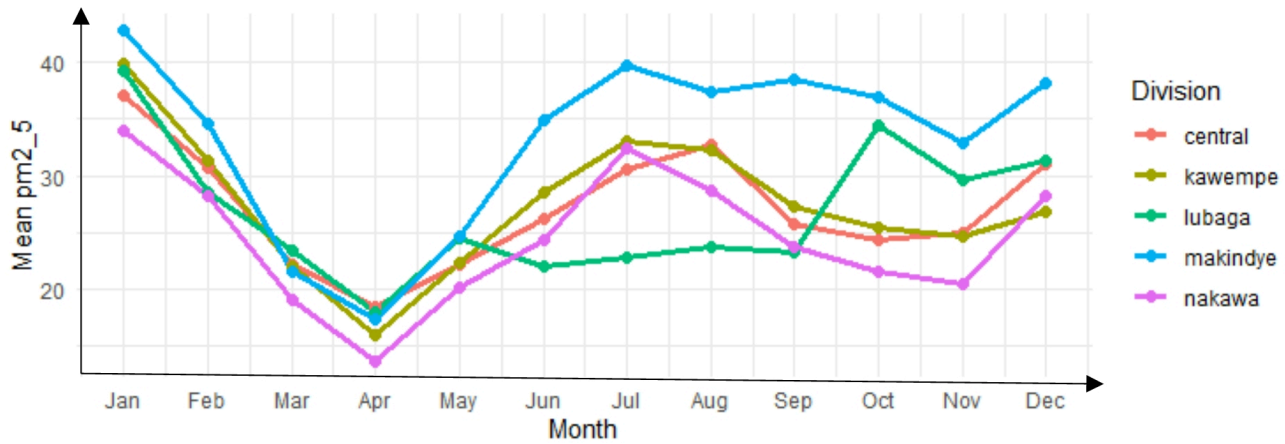


Figure 3

The monthly average particulate matter (PM2.5) across the five divisions of Kampala

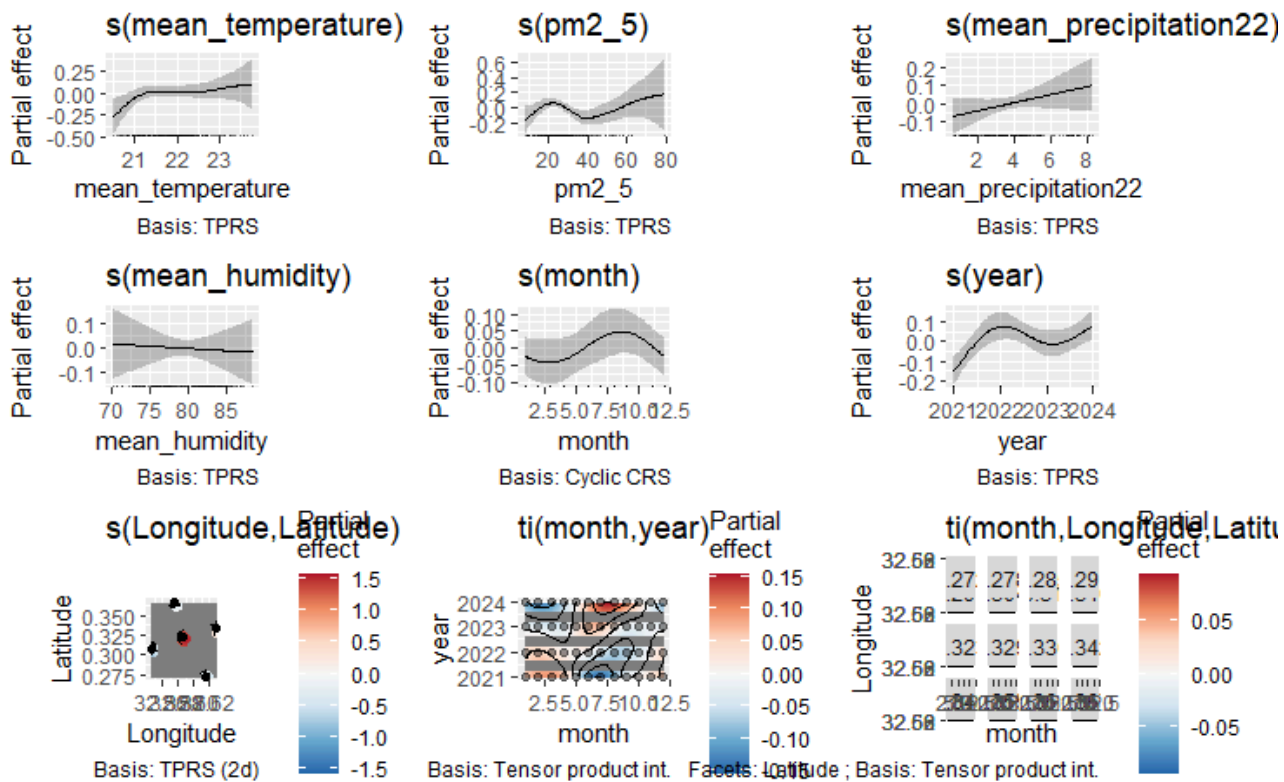


Figure 4

Asthma smoothed effects of covariates and tensor products. The y-axis denotes the effect size of variables, x-axis denotes observed data points. The shaded areas indicate the 95% confidence interval

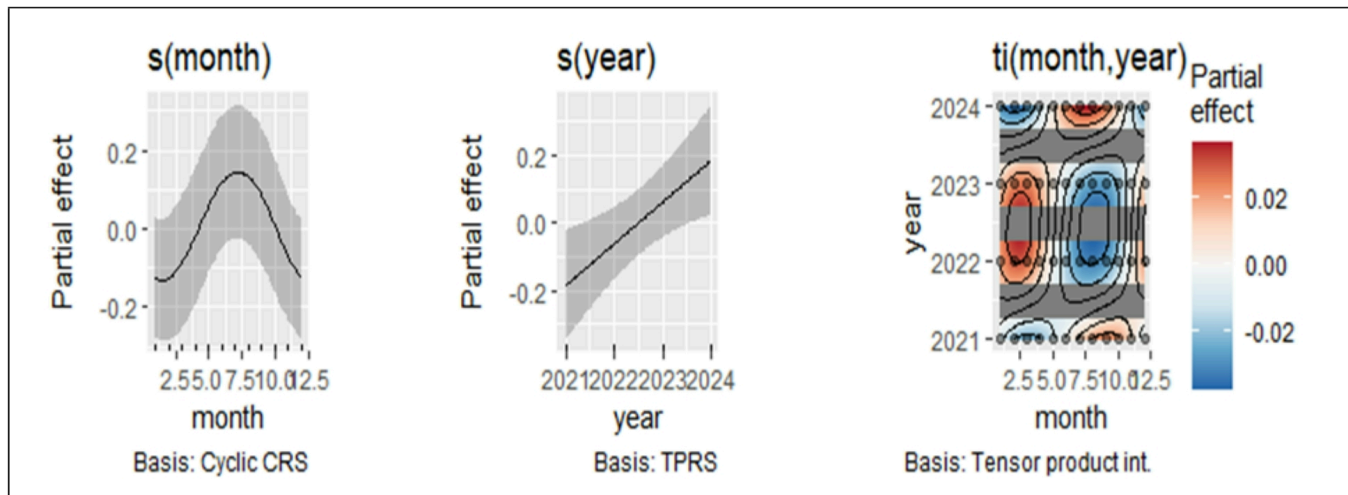


Figure 5

COPD smoothed effects of covariates and tensor products. The y-axis denotes the effect size of variables, x-axis denotes observed data points. The shaded areas indicate the 95% confidence interval

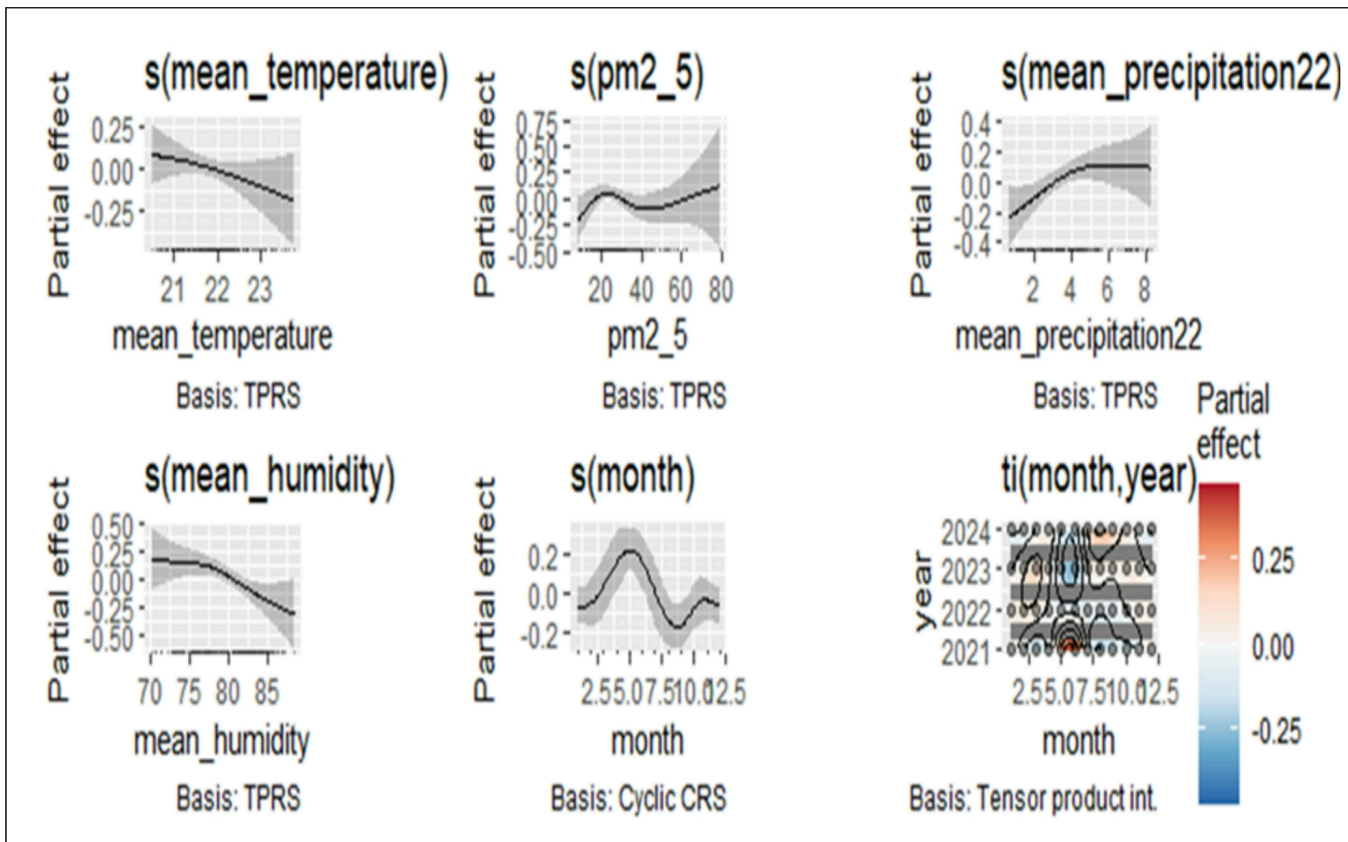


Figure 6

Pneumonia smoothed effects of covariates and tensor products. The y-axis denotes the effect size of variables, x-axis denotes observed data points. The shaded areas indicate the 95% confidence interval

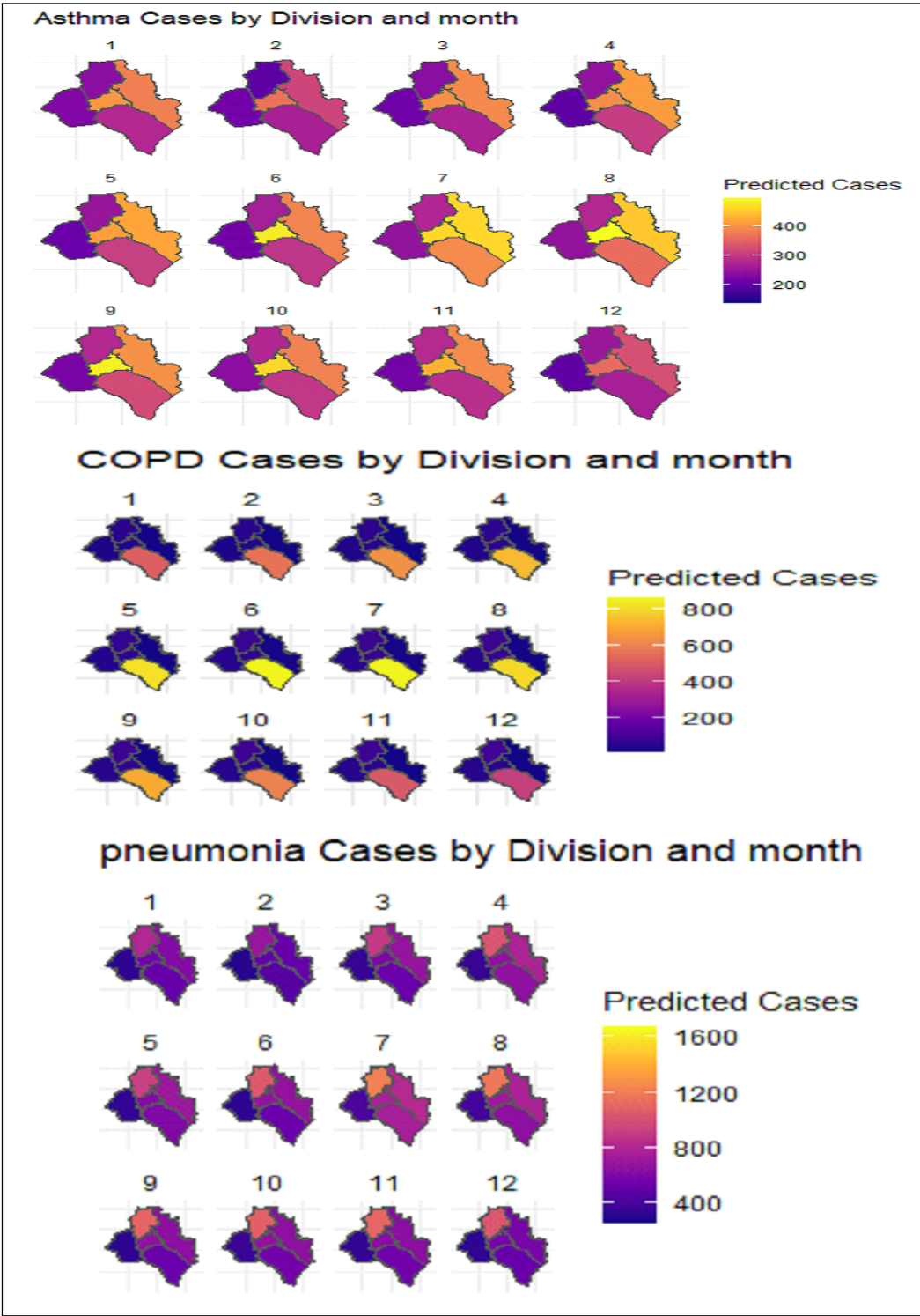


Figure 7

Maps showing the effect of monthly respiratory diseases in the different divisions of Kampala City, Uganda, 2021-2024