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RESEARCH ARTICLE

REVISED New title: Re-evaluating environmental associations with meningitis risk across Africa

[version 2; peer review: 2 approved, 1 approved with reservations]
Previously titled: "Updating the meningitis belt: associations between environmental factors and epidemic meningitis risk across Africa"

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Abstract

Background

Previous analytical work, defining the distribution of meningitis epidemics in Africa is over 20 years old, with climate change representing an ongoing issue. We aim to update this analysis and determine if the meningitis belt geography and associated environmental risk factors have changed in the last two decades.

Methods

Epidemic bacterial meningitis data from 2003–2022 were provided by WHO-AFRO. Districts across Africa were coded 1 if they experienced a meningitis outbreak and 0 if not. Monthly means of windspeed, rainfall, dust, and humidity were processed into climatic profiles using k-means clustering. We undertook logistic regression with meningitis epidemic history as the dependent variable and k-means clusters of rainfall, dust, humidity, and windspeed, alongside land-cover type as independent variables. A sensitivity analysis was conducted, excluding the Democratic Republic of Congo (DRC), due to limited laboratory confirmation of cases.

Open Peer Review

Approval Status ? ✓ ✓

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version 2 (revision) 13 Feb 2026		✓ view	✓ view
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Any reports and responses or comments on the article can be found at the end of the article.

Results

Rainfall, dust, windspeed and humidity demonstrated the strongest statistical association with outbreaks and were included in our final model. With a probability cut-off >0.4, our model had specificity and sensitivity of 82.07% and 82.22%, respectively, in identifying districts having experienced a meningitis epidemic. The Sahelian region had the highest risk of meningitis outbreaks (probability >0.8), consistent with previous findings. The inclusion/exclusion of the DRC had a significant impact on our model. In the full model the Republic of the Congo, Gabon, and Angola had a moderate risk of meningitis (probability >0.4), suggesting a possible expansion of the belt. However, when the DRC was excluded, no countries surrounding the meningitis belt were at risk for outbreaks, highlighting the importance of laboratory testing and case confirmation.

Conclusions

The apparent extension of risk beyond the belt possibly reflects surveillance limitations rather than alterations in disease ecology. Where possible, laboratory confirmation should be used to support surveillance of suspected meningitis outbreaks and cases.

Plain language summary

Bacterial meningitis is a significant public health issue within sub-Saharan Africa, where outbreaks show a distinct seasonal pattern. Cases peak within the dry season, characterised by low humidity and high dust levels. Most cases occur within 26 countries spanning Senegal to Ethiopia, known as the meningitis belt. In this study, we evaluated the statistical association between history of meningitis outbreaks across Africa and climatic factors including rainfall, dust, humidity, wind speed and land cover type. We aimed to see if there had been any changes in at-risk regions of meningitis in line with climate change.

This study revealed that the central and western part of the Sahelian region of Africa, with lower rainfall and humidity, had the highest risk of meningitis outbreaks. This includes countries such as Burkina Faso, Chad, Gambia, Niger and Nigeria. Several countries bordering the meningitis belt had a moderate outbreak risk, suggesting a potential expansion. However, when we excluded outbreaks from the Democratic Republic of Congo due to poor case confirmation, no countries surrounding the meningitis belt were at risk for outbreaks. It is important to improve diagnostic capacity within meningitis outbreaks, to accurately assess disease risk across the continent.

Keywords

Bacterial meningitis, meningococcal meningitis, infectious disease epidemiology, epidemiology, climate change, public health

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REVISED **Amendments from Version 1**

In line with reviewer comments, we have made several changes to this manuscript. Within the introductory section we have first re-examined the literature and added details on recent outbreak reports and vaccination coverage studies. Both the introductory and discussion sections have been revised to reflect the extended temporal window, the use of higher-resolution environmental datasets, methodological comparability with Molesworth *et al.*, and the inclusion of wind speed as a novel variable. Furthermore, the study title has been changed to reflect the study's scope and focus as suggested.

We have updated the methodology section to include detailed information regarding backwards stepwise analysis to reach the final model, including multicollinearity diagnostics and the decision rules used for variable exclusion. Within the methodology section we have included parameter details for clusters, including number of clusters chosen, number of starts and convergence criteria. Alongside this our extended data includes random seeds and elbow plots for all variables, allowing for improved reproducibility. We have rerun the k-means clustering analysis increasing both the number of random starts and iterations from the default settings. In addition, district level outbreak weighting was subsequently adjusted to optimise sensitivity and specificity. We have also rerun the analysis and updated the model to include windspeed as a variable within the final model.

Finally, we have also carried out an additional sensitivity analysis which only considered outbreaks that occurred prior to the introduction of MenAfriVac on a country level. Furthermore, within our discussion we examine how the inclusion of vaccination coverage and socio-demographic variables might alter the observed associations.

Any further responses from the reviewers can be found at the end of the article

Introduction

The African meningitis belt, which spans from Senegal, through to Ethiopia and Eritrea has a high seasonal incidence of bacterial meningitis (WHO, 2025). The meningitis belt was first defined in 1963 by Lapeyssonie, as an area within sub-Saharan Africa including 11 countries with a high incidence of meningitis epidemics with approximately 300–1100 mm of annual rainfall (Lapeyssonnie & World Health Organisation, 1963). It was found that meningitis outbreaks largely occured during the hotter dry season within sub-Saharan Africa, indicative of a correlation with seasonal weather patterns (Lapeyssonnie & World Health Organisation, 1963). In 1971, an extension of the meningitis belt towards East Africa was proposed to include regions of Rwanda, Burundi, Uganda, Tanzania and Kenya based on observation of epidemics from 1911–1965 (Mpairwe & Matovu, 1971). In 1987, Greenwood furthered this work to include areas of 17 countries, excluding the Democratic Republic of Congo (DRC) (Greenwood, 1987). The meningitis belt currently spans 26 countries in sub-Saharan Africa. Globally, in 2019, approximately 50% of all meningitis cases in children under 5 years occurred within the meningitis belt (GBD 2019 Meningitis Antimicrobial Resistance Collaborators, 2023).

Seasonality and climate variability have a key influence on the spatiotemporal distribution of bacterial meningitis across Africa. This influence is predominantly seen in meningitis cases caused by Neisseria meningitidis (Greenwood, 1999). Within the dry season (December to April), driven by the onset of the Harmattan winds and increased dust concentration, disease incidence can reach 800 cases per 100,000 people (Mohammed *et al.*, 2017). Bacterial meningitis incidence decreases and epidemics end with the beginning of the wet season characterized by pre-monsoon rainfall (Agier *et al.*, 2013). Major bacterial meningitis outbreaks occur between every 5–12 years across the belt, where incidence can reach 1000 cases per 100,000 people (Mohammed *et al.*, 2017).

Several climatic models have been able to highlight the spatiotemporal relationship between meningitis cases, and meteorological weather events (Chen *et al.*, 2023; Tall *et al.*, 2022). A global generalized linear regression model found that increased temperature variability was significantly associated with higher meningitis risk (Chen *et al.*, 2023). A modelling study across Burkina Faso found a significant association between meningitis incidence and both relative humidity and temperature (Tall *et al.*, 2022). Several additional studies within the meningitis belt have concluded that humidity, dust, wind speed and rainfall are associated with meningitis epidemics (Agier *et al.*, 2013; Besancenot *et al.*, 1997; Sultan *et al.*, 2005; Thomson *et al.*, 2006; Yaka *et al.*, 2008). However, these studies are often limited in their geographical scope to either one or a subset of countries within the meningitis belt. The specific mechanism is not known, but seasonal climatic factors may aid in the promotion of bacterial transmission and progression from carriage to invasive disease (Mueller & Gessner, 2010). Work linking environmental factors and meningitis have been used successfully to support awareness, preparedness and response actions for meningitis outbreaks (Dione *et al.*, 2022).

A 2002 study by Molesworth *et al.*, investigated the spatial distribution of meningitis epidemics in Africa by conducting a systematic review of district-level meningitis outbreaks in Africa between 1980 and 1999. This determined that in addition to those countries within the meningitis belt at the time Guinea-Bissau, Guinea, Côte d'Ivoire, Togo, the Central African Republic and Eritrea had a high epidemic burden (Molesworth *et al.*, 2002). In 2003 this study was used to

develop a logistic regression model investigating the relationship between epidemic location and environmental variables to locate districts within Africa with increased risk of meningitis epidemics. Zonal profiles of climatic variables were developed for use within the model. Absolute humidity and land-cover type were best able to predict meningitis epidemics, with dust and rainfall profiles also being independently associated with epidemic location (Molesworth *et al.*, 2003). The association with dust is thought to be in line with the increase in dust following the Sahelian droughts of the 1970s and 1980s (Palmgren, 2009). The model also demonstrated that climatic zones without distinctive seasonal changes including desert and forest areas are less likely to have epidemics as contrasted to regions with wet and dry seasons (Molesworth *et al.*, 2003). A later evaluation of this risk model, examining meningitis outbreaks from 2000–2004 indicated that meningitis epidemics may be extending southwards within Togo, the Central African Republic, Cameroon, and Côte d'Ivoire (Savory *et al.*, 2006). The authors concluded that the southwards extension of the meningitis belt was consistent with regional deforestation and desertification. It was suggested that alterations in land usage, combined with climatic factors, potentially led to a humidity reduction combined with an increase in dust, favouring epidemic conditions.

Our work will present an update on the associations between environmental variables and meningitis epidemic risk across Africa. Despite the changing epidemiology of bacterial meningitis since 2002 due to the introduction of Haemophilus influenzae type b, pneumococcal and particularly meningococcal vaccines, environmental risk factors for outbreaks remain consistent and relevant within the context of widespread vaccination. Historically, across the African meningitis belt, most bacterial meningitis outbreaks have been caused by meningococcal group A, previously responsible for 80–85% of all outbreaks (WHO, 2025). Following the introduction of MenAfriVac from 2010 onwards, with initial campaigns taking place in Niger, Burkina Faso and Mali, there has been a significant reduction of meningococcal outbreaks within vaccinated countries (Bender *et al.*, 2023). It has been estimated that across the belt, the introduction of MenAfriVac led to a 57% decrease in the overall incidence of suspected meningitis cases, with this reaching a 91% reduction in Chad (Trotter *et al.*, 2017). By 2019 approximately 350 million people aged between 1–29 years within the meningitis belt had received a MenAfriVac dose as part of these campaigns (Bender *et al.*, 2023). In respect to routine immunisation, eight countries within the meningitis belt, mostly located in the Western Sahel, had a coverage of >60% as of 2021, with Burkina Faso having the highest routine immunisation coverage of 87.3% (Bender *et al.*, 2023).

However, whilst outbreaks of group A meningococcal (NmA) epidemics have decreased as a result there have been persistent outbreaks due to other meningococcal groups (NmW, NmX and NmC) as well as pneumococcal meningitis since 2013 (Franklin *et al.*, 2021; Ibarz-Pavón *et al.*, 2011; Sidikou *et al.*, 2016; Trotter *et al.*, 2017). Furthermore, there have been several recent meningitis outbreaks across Togo, Nigeria and Niger since 2020, all of which have been caused by non-NmA bacterial pathogens or serotypes. Following on from the most recent meningococcal group C outbreak (NmC) in Nigeria, the country introduced the novel Men5CV vaccine, effective against serogroups A, C, W, X, and Y. From between 25th and 28th March 2024 a rollout of Men5CV across Nigeria, led to the vaccination of over one million individuals aged 1–29 (Ukoaka *et al.*, 2024). Although routine vaccination campaigns have altered the epidemiology of bacterial meningitis across the African continent, outbreaks still occur periodically, driven by both environmental and biological drivers.

It is important to understand the evolving impact of climate change on meningitis incidence, given that more than half of known human pathogenic diseases can be exacerbated by climate change (Mora *et al.*, 2022). With 20 years having passed since the publication of Molesworth *et al.*'s logistic regression model, we aim to understand if the geography of the meningitis belt and risk factors associated with meningitis have changed. This paper serves to extend the temporal window of environmental associations with meningitis risk across the whole African continent by 20 years. By using 20 years of monthly meteorological data, our study focuses on climate dynamics, as opposed to shorter-term weather assessments. This puts our study ahead of Savory *et al.*'s 2006 paper, which only examined four years of data. Our longer-term analysis enables the isolation and identification of climatic trends amidst the natural variability of weather. Furthermore, since Molesworth *et al.*'s and Savory *et al.*'s publications, there have been significant advancements in the resolution of environmental meaning that updating previous work should serve to create a more reliable risk model. By repeating the methods used by Molesworth *et al.*, with new data, we are conducting a longitudinal epidemiological evaluation to look for a signal of change, before then going on to investigate the relationship between climate and meningitis further. This allows us to draw conclusions based on data without confounding our findings by changing methodology. Furthermore, most epidemiological studies of meningitis incidence across Africa, including Tall *et al.*, focus on either one or a subset of belt countries. By focusing on the impact of bacterial meningitis across Africa, we can account for the differential effects of climatic factors across the continent, rather than examining localized atmospheric changes. Finally, this paper serves as an advancement to both Molesworth and Savory's papers in that we reevaluated the environmental variables used within the final statistical model, considering the additional impact of both windspeed and

temperature. This analysis is highly relevant to understanding the effect of climate on meningitis incidence in the context of a changing climate (Cliff *et al.*, 2025).

Methods

Epidemiological data source

The World Health Organisation Regional Office for Africa (WHO-AFRO) provided us with data regarding meningitis epidemics reported to their enhanced meningitis surveillance system from 2003 through to 2022 (Lingani *et al.*, 2015). In accordance with guidelines from the World Health Organisation (WHO) an epidemic was defined as any district reaching the epidemic threshold of 10 suspected meningitis cases per 100,000 population per week or with a seasonal cumulative incidence of 100 suspected meningitis cases per 100,000 population (Trotter *et al.*, 2015).

The enhanced meningitis surveillance system reports disease data from 24 countries across sub-Saharan Africa which are at high risk of meningitis outbreaks (Extended data). This includes countries both inside and adjacent to the current meningitis belt. Whilst this excludes countries in North Africa that have been previously identified as high-risk, there have been limited outbreaks in that region during the study period (Mazamay *et al.*, 2021). Outbreak metadata included the week, year, country and administrative level 2 district (ADMN2) of each meningitis epidemic as well as population size and number of cases.

As both pathogen and serotype data on individual outbreaks were unavailable, we did not examine the impact of vaccination as part of our main investigation, instead undertaking a sensitivity analysis excluding outbreaks that occurred after the introduction of MenAfriVac. For all countries across the meningitis belt, we used the date of MenAfriVac introduction from Bender *et al.* and set districts with outbreaks only occurring after vaccine introduction to zero. This allows us to understand how the introduction of MenAfriVac by country affects the association between climatic variables and bacterial meningitis incidence.

We did not consider vaccination as an independent variable within the model in part due to the static nature of the logistic regression model. Additionally, many outbreaks would have occurred before meningococcal and pneumococcal vaccinations were introduced, and the risk of epidemics from other serogroups/serotypes remains.

Assigning outbreaks to ADMN2 districts

Meningitis epidemics were assigned to their respective ADMN2 districts using a district level shapefile of the whole continent of Africa. This was carried out using Stata/SE 18 with the shapefile being obtained from the Database of Global Administrative Areas (GADM). ADMN2 districts were used in all countries where available, apart from in Libya, Western Sahara and Comoros, where only ADMN1 level subdivisions exist. The GADM shapefile used within this study reflects ADMN2 district boundaries as of 2022.

However, district boundaries frequently change over time, making it more difficult to accurately assign older outbreaks to current administrative units. To address spatial mismatches and uncertainty with reported outbreak districts, we used an older WHO-provided ADMN2 shapefile of Africa to map historical epidemics to the 2022 GADM districts using R version 4.3.1.

For outbreaks that could only be assigned to a district with the older WHO shapefile we calculated spatial overlaps between the WHO and GADM ADMN2 shapefiles, to ensure temporal alignment. Districts with at least 50% spatial overlap were initially used to assign meningitis epidemics to ADMN2 districts within the GADM shapefile. To increase the number of epidemics, we were able to assign the process was repeated using a 30% overlap threshold. Alongside this, we carried out a short sensitivity analysis, changing the overlap thresholds to 60% and 40% to ensure that statistical modelling results demonstrate robustness to boundary uncertainty. All ADMN2 districts in the GADM continental shapefile were then assigned a binary value of either 1 or 0, representative of whether they had ever had a meningitis epidemic from 2003–2022.

Environmental data sources and variables

Publicly available environmental data with uniform latitude-longitude grid-based coverage was used in this analysis. Variables used were originally derived from the interpolation of climatic anomalies across global weather station networks (Table 1). All environmental data used was on a monthly level. When selecting environmental variables for inclusion, we both utilised variables identified in Molesworth *et al.*'s original analysis and examined the wider scientific literature for environmental variables with a known association with meningitis incidence.

Table 1. Characteristics of environmental variables to be included within risk modelling. We have included a comparison between resolution of environmental data used within this analysis to that used by Molesworth *et al.*

Variable	Time period	Resolution of grid squares	Units	Data source	Molesworth resolution
Average daily dew point temperature	2002–2020	0.1° x 0.1°	Degrees Kelvin (K)	Copernicus Climate Change Service, 2020	0.5° x 0.5°
Average daily surface pressure	2002–2020	0.1° x 0.1°	Hectopascals (hPa)	Copernicus Climate Change Service, 2020	0.5° x 0.5°
Average daily rainfall	2002–2022	5km	Monthly atmospheric precipitation (mm)	CHIRPS- (Funk *et al.*, 2015)	0.5° x 0.5°
Average daily aerosol index (dust)	2002–2022 (excluding 2014–2016 due to data availability)	1.0° x 1.0°	Aerosol concentrations (unitless measure)	Copernicus Climate Change Service, 2019	1.0° x 1.0°
Land-cover type	2020	300m	Categorical variable numbered from 10-220	European Space Agency Climate Change Institute- (Lamarche *et al.*, 2017)	1 km
Average monthly wind speed	2002–2022	4km	Wind speed (m/s)	Copernicus Climate Change Service- Hersbach *et al.* (2023)	Variable not included in Molesworth's 2003 analysis
Average monthly temperature	2003–2022	1.0° x 1.0°	Average temperature (K)	Goddard Earth Sciences Data and Information Services Center (2013)	Variable not included in Molesworth's 2003 analysis

From Molesworth's original analysis we examined the impact of specific humidity (g/m^3), aerosol optical depth (unitless measure), rainfall (mm), and land coverage (categorical land cover class) on meningitis epidemics. We additionally examined the impact of temperature (K) and windspeed (m/s) as these variables are also known to have an association with meningitis epidemics across Africa. Details regarding the derivation of specific humidity, selection of environmental data sources and raster aggregation can be found within the extended data.

Processing of climatic data

For consistency with the methodology used in Molesworth *et al.*'s analysis, we followed the same approach in processing climatic data. This involved processing temporal environmental data into static variables that capture seasonal patterns, which could then be included in a logistic regression model. Monthly means of each temporal environmental variable were converted into a single composite surface representing seasonal profiles. This transformation was applied to rainfall, wind speed, specific humidity, temperature and aerosol optical depth (AOD) data as these variables have a known seasonal component and are expected to change over time. We presumed that land cover category would remain static over the 2003–2022 study period. The workflow, mirrors that implemented by the ADDAPIX software within Molesworth *et al.*'s 2003 analysis (Griguolo & Santacroce, 1996) (Figure 1).

As an initial step we decreased the data dimensionality of each temporal variable due to the size of the raster data set which would necessitate a high level of computing power. This was achieved using principle component analysis in R 4.3.1 to decrease both the data dimensions and the number of raster layers to be analysed, whilst retaining 95% of the seasonal information retained within the raster data. Following this the K means algorithm was then used to divide each seasonal variable raster into distinct clusters based on data similarity. This is achieved through the K-means algorithm's ability to

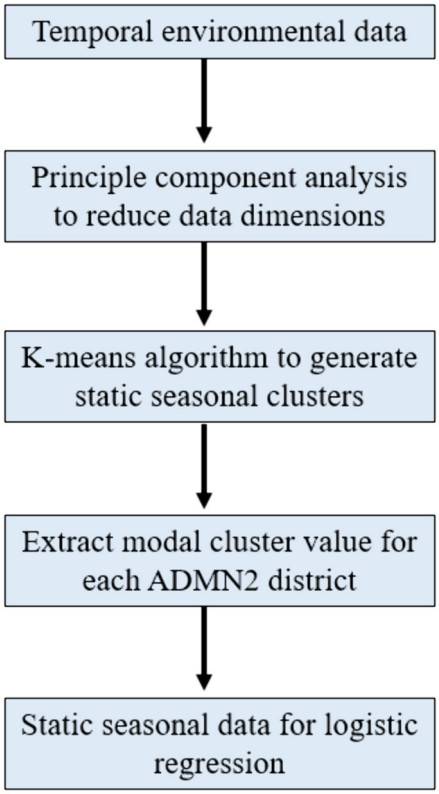


Figure 1. Workflow of environmental data processing for inclusion within static logistic regression model.

assign data points to clusters whilst continuously updating the clusters' respective mean values, allowing the algorithm to minimize the intracluster variance. For all temporal climate variables (windspeed, humidity, rainfall, temperature and dust) the optimal number of clusters to use in within the k-means clustering algorithm was selected based on the elbow method, plotting total within-cluster sum of squares (SSE) for k = 5–15. We also validated the subjectivity of the elbow method by using silhouette scores for each variable. For all temporal variables, both the elbow curve and silhouette score results can be found in the extended data (Govender & Sivakumar, 2020; Griguolo & Santacroce, 1996; Umargono *et al.*, 2020). The extended data contains information of the fixed random seeds for all variables used, as well as elbow curves for reproducibility. K-means clustering was initialised using the k-means package algorithm with 25 random starts (nstart = 25) to ensure stability. The algorithm iterated until convergence with a maximum of 300 iterations. Cluster results were validated through an initial visual check against Koppen Geiger and Schultz climate zonal maps alongside Molesworth *et al.*'s environmental clustering results (Beck *et al.*, 2018). Figure 2 demonstrates the results of our environmental clustering profiles for temperature, windspeed, rainfall, AOD and specific humidity.

Finally, for each of the 6350 ADMN2 districts within the GADM shapefile of Africa, the extract () function from the raster package in R, identified the most common cluster value within each district for all processed environmental variables (Hijmans *et al.*, 2025). This value was then assigned to each ADMN2 district as its representative cluster. For the landcover data, the extract function was used to determine the most common landcover type within each ADMN2 district in the GADM shapefile. This processing was carried out at the native resolution of each environmental dataset, except for when raster aggregation had occurred, as specified in the supporting information.

For all variables any environmental clusters with less than 50 districts were assigned to their nearest neighbour cluster using a cluster dendrogram to prevent complete separation and inflated significance. This led to a total of 5 windspeed clusters, 6 rainfall clusters, 8 specific humidity clusters, 9 AOD clusters and 10 temperature clusters across the African continent. These k-mean cluster profiles of each variable could then be used as dependent variables within our logistic regression model. This allows for consistency with Molesworth *et al.*'s analysis, with logistic regression allowing for direct comparison between risk maps. By using logistic regression we can examine the impact of environmental risk factors across the whole of the meningitis belt and its surrounding area.

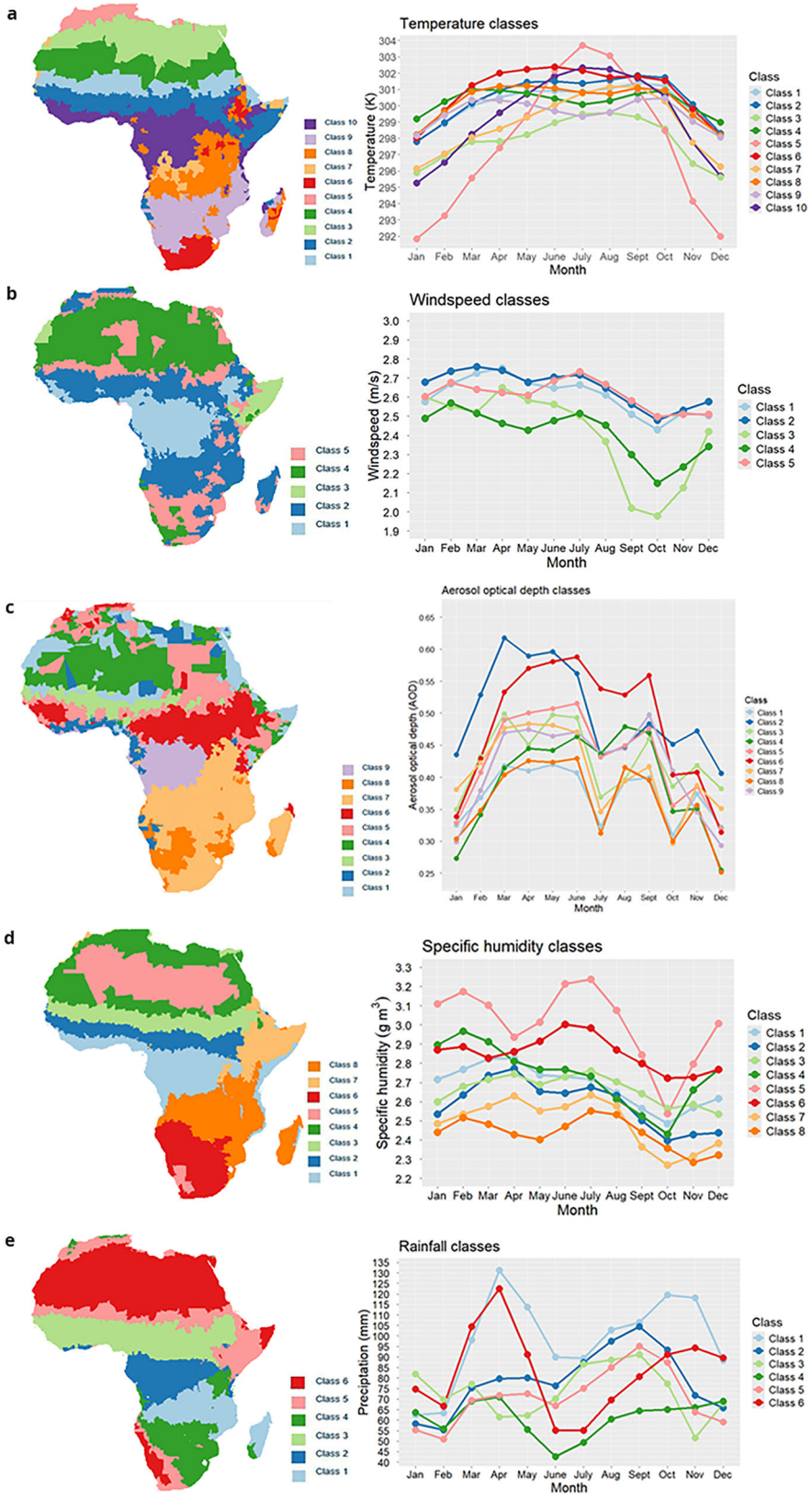


Figure 2. Seasonal cluster profiles of climate (right panel) alongside the relative assigned district classes (left panel). Variables presented were used within the final model: temperature (**a**), windspeed (**b**), aerosol optical depth (AOD) (**c**), specific humidity (**d**) and rainfall (**e**).

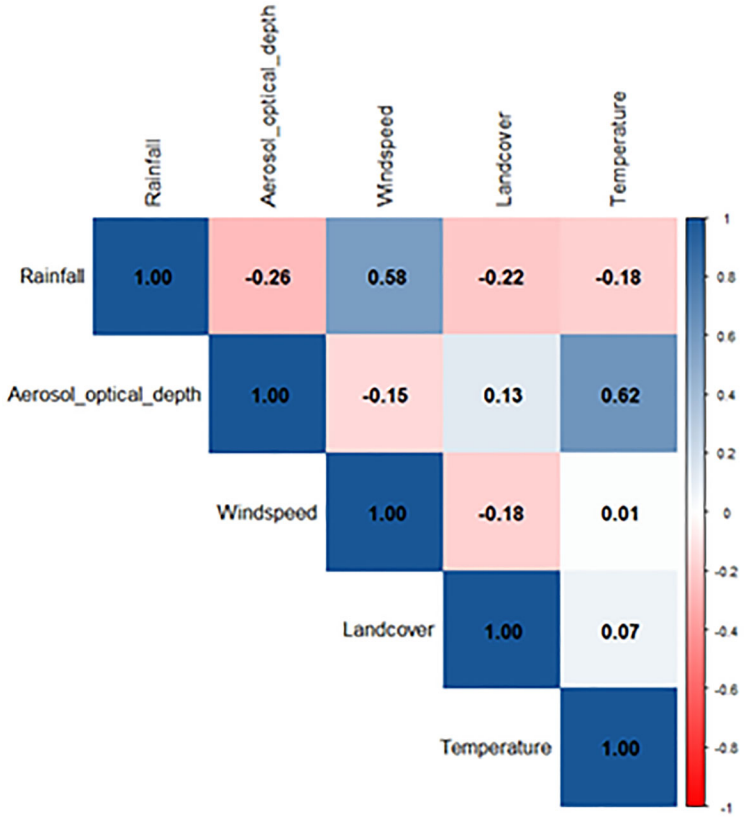


Figure 3. Pearson's correlation coefficient between climatic variables used within logistic regression (−1 to 1).

Model specification and epidemic weighting

Within our study, the dependent variable was district history of meningitis epidemic, whilst the independent variables were k-means clusters of rainfall, aerosol optical depth, specific humidity and wind speed, and average land cover class. Using a cut off value of >0.6 in our Pearson's correlation coefficient we excluded temperature from our logistic regression model and retained atmospheric dust . With the removal of temperature from the initial model, the variance inflation factor for all variables was under 2.0. (Figure 3).

We ran the model weighting for inverse district size, population density and growth and fertility rate. We balanced the class weights for districts with/without epidemics by ensuring that resulting model sensitivity and specificity are both maximized. This was carried out due to the large imbalance between ADMN2 districts with/without an epidemic. Area averages were also based on a cosine of latitude weighting due to our use of regular longitude/latitude gridded data. We also conducted a sensitivity analysis, running the logistic regression model without the Democratic Republic of Congo (DRC), due to the country's very limited laboratory confirmation of suspected cases (Mazamay *et al.*, 2020).

Risk analysis

Backwards stepwise logistical regression was used to identify the risk of meningitis outbreak within a district in Africa and the relative environmental associations across the whole dataset. For environmental variables, we used a threshold significance level of <0.05 when identifying statistically significant associations. The probability of each district ever having had an epidemic was predicted through the model, before being grouped into risk categories and then mapped. The model was tested by checking specificity and sensitivity, examining collinearity through the Variance inflation factor, as well as utilising McFadden's Pseudo-R2 Interpretation for goodness of fit (Hardin & Hilbe, 2007). Finally, a receiver-operator characteristics (ROC) curve was used to examine the model's capability to discriminate between true positives and false positives across all possible thresholds. The logistic regression model's ability to predict outbreaks was verified using mean validation, splitting the data into "train" and "test" sections. Although Molesworth et al, used a 60:40 split for train and test data, we initially selected a 80:20 split as we had a much smaller proportion of ADMN2 districts effected by bacterial meningitis epidemics. We validated our results using a 60:40 split to allow for an equitable comparison with Molesworth's work. Models were recreated with the train data 10 times and then used to predict epidemic risk within the

test data. Mean sensitivity and specificity of the validation data were compared against that of the backward stepwise model formed from the whole data set. R code used to run this analysis can be found within the following GitHub repository (https://github.com/molly-cliff/Meningitis-belt-location).

Results

Epidemic overview and geographic distribution

Between 2003 and 2022 there were 1069 reported district level epidemics each with at least 10 suspected cases per 100,000 population per week. Within the same period 14 district-level annual outbreaks were recorded each with a seasonal cumulative incidence of at least 100 suspected meningitis cases per 100,000 population. 55 epidemics were dropped from the final dataset as we were unable to assign them to an appropriate ADMN2 district in either the WHO or GADM shapefile. After considering duplicate districts (with more than one epidemic) 523 districts had experienced at least one outbreak of bacterial meningitis during the study period. This represents 8.2% of all 6350 districts in Africa within our dataset (Figure 4).

Regional trends and repeated outbreaks

The majority of bacterial meningitis epidemics within Africa, occurred within the Central Sahel region, with Burkina Faso, Chad and Niger having over 50% of their ADMN2 districts affected by an outbreak. Additionally, within this region, Nigeria had over 200 districts affected by a meningitis outbreak. However, across the most western and eastern parts of the Sahel, Mauritania and Sudan both reported zero outbreaks with Mali also reporting a low number of affected districts. Across the remainder of the meningitis belt Togo, Ghana, The Gambia, and Ethiopia were also affected by meningitis outbreaks. Whilst the north of the Democratic Republic of Congo was thought to be the region of the country within the meningitis belt, between 2003 and 2022 outbreaks occurred throughout the country. Within our study period, 51% of all districts within the DRC experienced a meningitis outbreak. If districts in DRC are excluded then there were 442 ever-affected epidemic districts in our dataset.

Figure 5 presents a temporal analysis of districts within Africa that have repeatedly reported epidemics of bacterial meningitis. Whilst most districts within the meningitis belt are reporting less than 5 outbreaks within the 19 year reporting period, a small number of districts are reporting regularly repeating outbreaks. At least one ADMN2 district within each of Niger, the DRC, Central African Republic, Chad, Burkina Faso, Côte d'Ivoire and Benin have reported at least 5 outbreaks from 2003–2022. Table 2 contains climatic class information for the 20 districts with the largest attack rate based on suspected cases counts.

In the post-vaccination era, the Democratic Republic of Congo (DRC) has reported over 10 districts within meningitis outbreaks each year from 2011 onwards, highlighting a change in reporting practice. This is notable as it surpasses the typical reporting regions such as the Sahelian countries like Burkina Faso, Chad, and Nigeria, known for many large outbreaks. Burkina Faso, DRC and Nigeria all reported over 100 outbreaks of bacterial meningitis from 2003–2022 with DRC and Nigeria reporting 228 and 316 outbreaks respectively.

Environmental predictors of meningitis epidemics

All climatic variables were independently associated with the location of epidemics. We initially carried out backwards stepwise regression to decide whether any climatic variables could be removed from the final model. The step function which we used to carry backwards stepwise regression decides the removal of variables based on changes in the

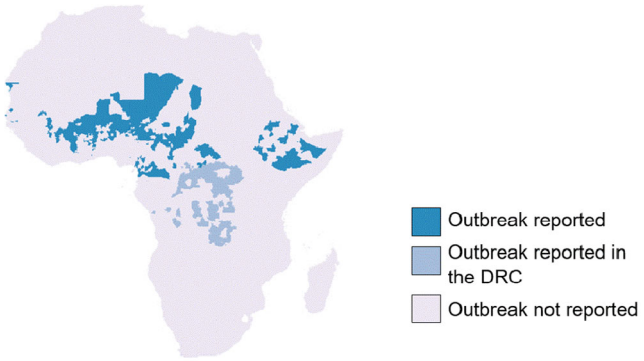


Figure 4. Map of Africa showing the location of meningitis epidemics reported to WHO-AFRO between 2003–2022.

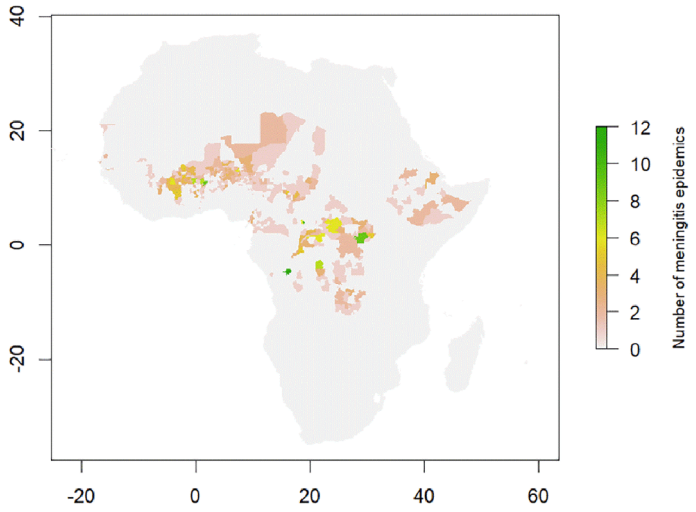


Figure 5. Map of number of bacterial meningitis epidemics per ADMN2 districts across reporting countries (2003–2022).

Table 2. Climatic classes of each of the ADMN2 districts reporting the 20 largest outbreak weeks of bacterial meningitis.

Country	ADMN2 District	Suspected cases per 100,000 population	Rainfall class	Humidity class	Aerosol optical depth class	Windspeed class
Democratic Republic of the Congo	Manono	1063.56	Class 1	Class 8	Class 7	Class 1
Democratic Republic of the Congo	Mweka	408.97	Class 2	Class 1	Class 10	Class 1
Democratic Republic of the Congo	Banalia	404.08	Class 2	Class 1	Class 6	Class 1
Cameroon	Moutourwa	380.99	Class 3	Class 3	Class 5	Class 2
Democratic Republic of the Congo	Djugu	291.67	Class 2	Class 1	Class 7	Class 1
Nigeria	Aleiro	238.38	Class 3	Class 3	Class 3	Class 2
Burkina Faso	Bazèga	237.26	Class 3	Class 3	Class 3	Class 2
Nigeria	Buji	229.05	Class 3	Class 3	Class 3	Class 2
Niger	Niamey	218.91	Class 5	Class 3	Class 3	Class 5
Nigeria	Jama'are	216.39	Class 3	Class 3	Class 3	Class 2
Nigeria	Taura	190.17	Class 3	Class 3	Class 1	Class 2
Burkina Faso	Kompienga	174.75	Class 3	Class 2	Class 3	Class 5
Burkina Faso	Loroum	173.09	Class 5	Class 3	Class 3	Class 5
Burkina Faso	Kourwéogo	167.41	Class 3	Class 3	Class 3	Class 2
Burkina Faso	Koulpélogo	147.60	Class 3	Class 2	Class 3	Class 2
Democratic Republic of the Congo	Kinshasa	142.24	Class 2	Class 1	Class 10	Class 1

Table 2. *Continued*

Country	ADMN2 District	Suspected cases per 100,000 population	Rainfall class	Humidity class	Aerosol optical depth class	Windspeed class
Democratic Republic of the Congo	Mambasa	136.27	Class 2	Class 1	Class 6	Class 1
Cameroon	Ngoumou	132.06	Class 2	Class 1	Class 2	Class 1
Nigeria	Danja	129.59	Class 3	Class 3	Class 3	Class 2
Burkina Faso	Boulkiemdé	128.79	Class 3	Class 3	Class 3	Class 2

Watanabe-Akaike Information Criterion, aiming to create a more parsimonious model. Of all environmental variables considered, removal of landcover was the only change that led to decrease in WAIC, leading to its removal from the final model. We then examined collinearity between variables, using the variance inflation factor. All variance inflation factor (VIF) values were below 2.0, indicative of limited collinearity between variables. Finally, we used the likelihood ratio test to evaluate the contribution of each remaining predictor, comparing nested models with and without remaining predictors. A statistically significant change in model fit was defined as $p < 0.05$. Alongside this we compared the area under the receiver operating characteristic curve (AUC) between nested models to see which model predictors lead to a notable AUC decrease (>0.05) upon their removal.

Comparative details of model specificity and sensitivity, including the landcover cluster variable can be found within the extended data. Despite the sensitivity and specificity of the model, including landcover remaining relatively close to that of the final model, eliminating the variable allowed for a more parsimonious model.

Following this methodology, rainfall, aerosol optical depth, windspeed and humidity were used as independent variables within the final model. Weighting for district size, population density, and fertility rate did not improve the model performance and was therefore discarded. In manually balancing the class weighting for the response variable through ensuring that the resulting model sensitivity and specificity are both optimised, a weighting of 0.842 for districts with an epidemic against a weighting of 0.158 for districts without an epidemic was most appropriate.

Model performance

Our final backwards stepwise model including the DRC, is outlined in Table 3 in relation to its estimated coefficients, 95% confidence intervals, and variable contribution. Reference clusters were chosen in order to balance standard error across the logistic regression model. We aimed to avoid the risk of inflated standard errors which would undermine model precision, instead choosing clusters based on the dependent variable distribution.

Table 3. Logistic regression results regarding the association between meningitis outbreaks and climatic clusters. Variables selected in backwards stepwise regression for final model were rainfall, aerosol optical depth, windspeed and specific humidity.

Variable (Class)	Experienced an epidemic (n)	Did not experience an epidemic	Odds ratio	95% CI Lower	95% CI Upper	p-value
Rainfall - Class 1	12	545	3.779	0.998	14.311	0.0504
Rainfall- Class 2 (Reference)	58	813	1	Reference	Reference	Reference
Rainfall - Class 3	369	1312	1.196	0.604	2.368	0.607
Rainfall -Class 4	0	1057	0.006	0.0004	0.0004	0.104
Rainfall - Class 5	77	1400	0.392	0.168	0.915	0.0303
Rainfall - Class 6	7	700	0.047	0.012	0.187	<0.0001
Aerosol -Class 1	60	505	3.895	1.612	9.411	0.0025
Aerosol - Class 2 (Reference)	15	600	1	Reference	Reference	Reference
Aerosol - Class 3	231	242	6.258	2.631	14.886	<0.0001

Table 3. *Continued*

Variable (Class)	Experienced an epidemic (n)	Did not experience an epidemic	Odds ratio	95% CI Lower	95% CI Upper	p-value
Aerosol - Class 4	6	307	2.9	0.767	10.961	0.1166
Aerosol - Class 5	75	1179	1.645	0.714	3.787	0.2421
Aerosol - Class 6	70	1204	1.913	0.856	4.277	0.1141
Aerosol - Class 7	20	1406	0.294	0.095	0.908	0.0335
Aerosol - Class 8	0	103	0.783	0.028	22.175	0.8858
Aerosol - Class 9	46	281	4.902	2.092	11.485	0.0003
Humidity - Class 1	88	1268	0.075	0.037	0.153	<0.0001
Humidity - Class 2	114	424	0.369	0.216	0.631	0.0003
Humidity - Class 3 (Reference)	273	930	1	Reference	Reference	Reference
Humidity - Class 4	6	1382	0.062	0.023	0.166	<0.0001
Humidity - Class 5	3	92	2.616	0.439	15.584	0.291
Humidity - Class 6	0	242	0.248	0.01	5.995	0.3906
Humidity - Class 7	23	562	0.193	0.086	0.432	<0.0001
Humidity - Class 8	16	927	0.076	0.021	0.274	0.0001
Wind Speed - Class 1 (Reference)	103	950	1	Reference	Reference	Reference
Wind Speed - Class 2	309	3122	0.359	0.212	0.61	0.0001
Wind Speed - Class 3	2	109	0.381	0.073	1.979	0.2509
Wind Speed - Class 4	12	590	0.156	0.055	0.448	0.0005
Wind Speed - Class 5	96	1056	0.347	0.155	0.776	0.01

Epidemic risk mapping across Africa

In reference to our risk map and table (Figure 6, Table 4), the central and western part of the Sahelian region of Africa, with lower rainfall, specific humidity and an extended dry season had the highest risk of meningitis outbreaks (probability >0.8), mirroring Molesworth *et al.*'s observations. Burkina Faso, Cameroon, Chad, Gambia, Mali, Niger, Nigeria, Senegal, South Sudan and Sudan all had at least 25% of their districts with a high risk (probability >0.6), of meningitis outbreaks. This region remained at the highest risk for outbreaks even at the lower bound of the 95% confidence interval. Countries to the south of the Sahel, with a shorter and less extreme dry season had a moderate risk of meningitis outbreaks (probability 0.4–0.59). In contrast to Molesworth *et al.*, several countries to the south were identified to have a moderate risk of meningitis outbreaks. Republic of the Congo, Gabon, and Angola all had at least 15% of their districts with a moderate risk of meningitis outbreaks. Notably Gabon and the Republic of Congo had 68.75% and 29.73% districts with a moderate risk of outbreak. In addition to this Algeria had 108 of its southernmost districts with a moderate risk of outbreaks. These are all countries border the current meningitis belt. Whilst this may suggest an expansion of the meningitis belt more work should be undertaken to verify the reported meningitis outbreaks, specifically with respect to laboratory confirmation of *Neisseria meningitidis.*

Logistic regression model sensitivity and specificity

We used a receiver operator curve to understand our model's performance regarding sensitivity and specificity independent of a single probability cutoff (Figure 7). The area under the curve represents the model's ability to distinguish between true positives and false positives across all possible classification thresholds. With an area under the curve (AUC) of 0.908, the epidemic risk assigned was higher for districts with epidemics than for those without in 90.8% of ADMN2 districts. In using a probability cutoff value of >0.4 for predicting epidemic experience, the model had a specificity and sensitivity of 82.07% and 82.22%, respectively; these statistics were confirmed in the validation process (Table 5). Here, specificity and sensitivity refer to the model's ability to correctly identify ADMN2 districts that have

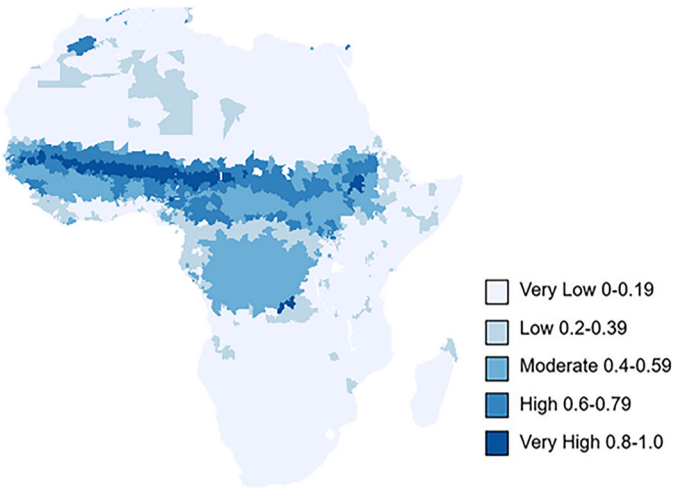


Figure 6. Risk map of meningitis outbreaks across Africa, based on our final logistic regression results. The key represents the probability of ADMN2 district having experienced a meningitis outbreak based on environmental cluster data from 2003–2022. The extended information contains 95% CI risk maps of the probability of ADMN2 district having experienced a meningitis outbreak.

Table 4. Number of districts within each risk category for all countries across Africa. The key represents the probability of ADMN2 district having experienced a meningitis outbreak based environmental cluster data from 2003–2022.

Country	Very Low 0.0–0.19	Low 0.2–0.39	Moderate 0.4–0.59	High 0.6–0.79	Very High 0.8–1.0
Algeria	1324	20	108	0	0
Angola	121	16	26	0	0
Benin	46	3	22	5	2
Botswana	30	0	0	0	0
Burkina Faso	0	0	11	12	22
Burundi	130	0	0	0	0
Cameroon	2	24	9	19	4
Central African Republic	0	17	24	10	0
Chad	9	1	17	24	2
Côte d'Ivoire	16	7	10	0	0
Democratic Republic of the Congo	42	50	144	2	2
Djibouti	17	3	0	0	0
Egypt	337	0	1	2	0
Equatorial Guinea	29	0	3	0	0
Eritrea	34	12	3	1	0
Ethiopia	18	20	33	4	3
Gabon	7	18	11	1	0
Gambia	0	9	8	20	0
Ghana	180	20	30	30	0
Guinea	7	4	17	66	3
Guinea-Bissau	3	0	34	0	0
Kenya	261	37	0	0	0
Lesotho	10	0	0	0	0
Liberia	10	52	3	0	0

Table 4. *Continued*

Country	Very Low 0.0–0.19	Low 0.2–0.39	Moderate 0.4–0.59	High 0.6–0.79	Very High 0.8–1.0
Libya	22	0	0	0	0
Madagascar	20	2	0	0	0
Malawi	243	0	0	0	0
Mali	8	1	10	20	11
Mauritania	18	6	13	7	0
Morocco	42	9	0	3	0
Mozambique	122	6	0	0	0
Namibia	107	0	0	0	0
Niger	6	1	1	24	4
Nigeria	159	101	154	162	193
Republic of the Congo	3	111	33	1	0
Rwanda	30	0	0	0	0
Senegal	0	13	19	11	2
Sierra Leone	4	9	0	1	0
Somalia	65	9	0	0	0
South Africa	52	0	0	0	0
South Sudan	1	1	27	16	0
Sudan	32	4	24	19	0
Tanzania	168	8	0	0	0
Togo	18	3	7	12	0
Tunisia	114	121	1	1	0
Uganda	127	23	7	6	0
Western Sahara	4	0	0	0	0
Zambia	115	0	0	0	0
Zimbabwe	91	0	0	0	0
Total	**4203**	**672**	**810**	**420**	**245**

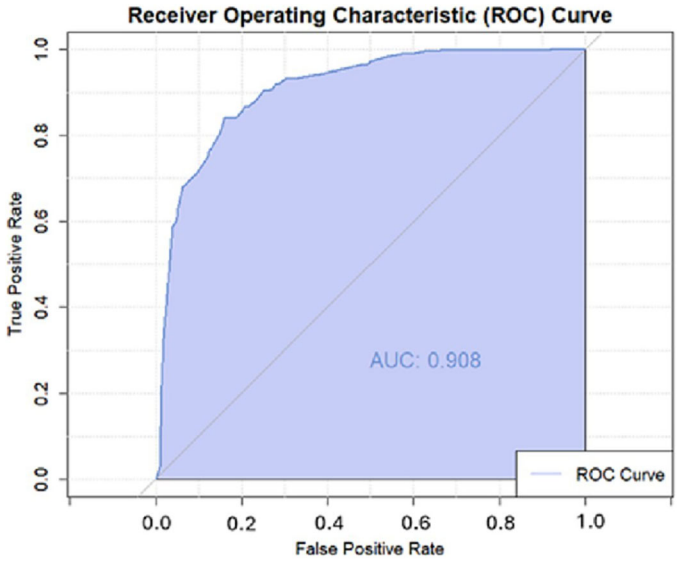


Figure 7. Receiver Operating Characteristic Curve for climatic logistic regression.

Table 5. Results of sensitivity and specificity of final model for full dataset and mean validation. Final model included cluster profiles of rainfall, aerosol optical depth, and specific humidity, with the mean validation using a 80%/20% and 60%/40% train and test split.

Epidemic experience	**Model Predicted**		
Never	4782	1045	5827
Ever	93	430	523
Total districts	4875	1475	6350
Model	**Specificity % (95% CI)**		**Sensitivity % (95% CI)**
Final (100%)	82.07		82.22%
Mean validation (20%)	81.66(80.13-84.27)		82.21(80.141-84.28)
Mean validation (40%)	82.03(81.71-82.35)		82.38 (80.64-84.11)

never/ever been affected by a meningitis epidemic, as in true negatives and true positives. As a comparison, Molesworth *et al.*, achieved a relative specificity and sensitivity of 67% and 83% within their full model using a cut-off value of >0.4. When the intersection overlap thresholds were adjusted to 60% and 40% as opposed to the previously used 50% and 30%, the AUC remained at 0.908, as only four district outbreaks were affected by the small boundary changes.

Sensitivity analysis: Exclusion of DRC

The results of the logistic regression model without DRC can be found in the extended data. These results include a full model table, risk category table (Extended data), ROC curve (Extended data) and sensitivity and specificity table. Overall, removing the DRC improved model fit with a sensitivity of 87.33% and specificity of 87.66 %, when using a probability cutoff value of >0.4 for predicting epidemic experience. This represents a 5% increase in both model sensitivity and specificity. This can also be seen in the ROC curve with an improved AUC of 0.932.

Within this model, the proportion of districts with a high probability of meningitis outbreaks remained largely comparable to our full model. The proportion of ADMN2 districts with a high risk of meningitis (probability >0.66) was 6.6% which is comparable to 6.0% ADMN of districts in this risk category in our full model. Burkina Faso, Cameroon, Chad, Gambia, Mali, Niger, Nigeria, Senegal, South Sudan and Sudan all had at least 25% of their districts with a high risk of meningitis outbreaks. Notably, Burkina Faso and Niger had 76% and 78% respectively of their ADMN2 districts within this risk category and Nigeria had 355 districts classified as at least high risk.

The key difference within the sensitivity analysis is that a large number of ADMN districts that would have been categorized as moderate risk (probability 0.4–0.59) within the full model are now low risk (probability 0.2–0.39). Within this model, no country on the periphery of the meningitis belt had any districts with at least a moderate risk of meningitis outbreak (probability 0.4–0.59). Republic of the Congo, Gabon, and Angola which were all at risk of meningitis outbreaks within the full model, had no districts with a moderate risk of meningitis outbreaks.

Sensitivity analysis: Exclusion of post-MenAfriVac outbreaks

When removing outbreaks that occurred post the introduction of MenAfriVac across Africa, we were left with 308 districts ever affected by a meningitis outbreak. This led to reduced model sensitivity (74.2%), compounded by higher specificity (93.6%), with an AUC of 0.929 using a 0.4 ROC cut-off. Further details of this analysis, alongside a risk map of the subsetted outbreak model can be found within the extended data. When only considering pre-MenAfriVac epidemics the region at risk for meningitis outbreaks within our risk map had contracted. Regions of countries previously identified as being at risk of meningitis epidemics, including parts of Ethiopia, Eritrea, Ghana, Togo and the Democratic Republic of the Congo, no longer had a demonstrable outbreak risk.

Discussion

Key findings

This study examines the spatial patterns of meningitis epidemics across the African continent from 2003–2022 in relation to environmental variables. We determined that rainfall, specific humidity, windspeed, and aerosol optical depth were key predictors in identifying outbreak location. Our model surpasses Molesworth *et al.*'s in environmental raster resolution and has equal if not improved statistical specificity and sensitivity. Our environmental logistic regression model has significantly improved specificity, at 82.1% as opposed to Molesworth *et al.*'s 67.0%. Through maintaining methodological comparison with Molesworth et al's original work we have conducted a longitudinal epidemiological

evaluation of climatic effects on meningitis incidence without introducing confounding factors through methodological changes. Our study extends the temporal window of Molesworth's previous analysis by an additional 20 years. As a comparison Savory's analysis only extended the analysis by only four years, examining 71 meningitis epidemics whereas our analysis includes 523 outbreaks, representing a substantially richer dataset. Additionally, we considered the impact of wind speed on bacterial meningitis epidemics a variable not examined in either Molesworth's or Savory's work. Finally, with 20 years having passed since the Molesworth and Savory's publications we have been able to take advantage of the considerable increase in spatial and temporal resolution of environmental data.

Our study reaffirmed the key influence of climate on meningitis outbreak risk, across the belt. As in Molesworth *et al.*'s work, districts/regions of Africa with distinct wet and dry seasons were more likely to have meningitis outbreaks. This is highlighted within our specific humidity clustering, where Clusters 2 and 3 which had consistently low humidity from January to March, within the meningitis dry season had the most outbreaks. While there is some variation in aerosol optical depth preceding an outbreak, Cluster 2 which had the highest wind speed within the typical meningitis dry season had the majority of outbreaks. All environmental variables exhibited seasonal clustering within or around the meningitis belt, emphasizing the climatic influence on meningitis epidemics. Importantly, our full model highlighted a potential expansion of the meningitis belt as a result of a changing climate. Republic of the Congo, Gabon and Angola all had at least 15% of their districts with a moderate risk (probability 0.4–0.59) of meningitis outbreaks. Within our study period, Angola experienced several meningitis outbreaks, indicative of a potential expansion of the region at risk (Savory *et al.*, 2006). More recently, in 2023 Angola experienced a significant increase in suspected meningitis incidence, reporting over 68,000 cases. This is also supported by Savory *et al.*, who when evaluating Molesworth's environmental data with a 100-mile southwards expansion of risk region were able to improve the pre-existing environmental model sensitivity from 84% to 88% (Savory *et al.*, 2006). However, our sensitivity analysis, excluding data from the Democratic Republic of the Congo (DRC), demonstrated the model's vulnerability to inconsistent case reporting. Within the DRC very few suspected cases are tested for laboratory confirmation (Mazamay *et al.*, 2020). Across rural ADMN2 districts in Africa, suspected bacterial meningitis are infrequently confirmed as a result of limited access to laboratory and hospital diagnostic facilities (Mazamay *et al.*, 2020).

Published literature, describing both the structure and performance of the meningitis surveillance system utilized across the DRC, remains limited. This ultimately makes it difficult to assess surveillance system discrepancies, reporting biases and spatial misclassification. However, a 2021 bacterial meningitis outbreak within the country highlights several systemic weaknesses within routine surveillance, likely to influence spatial risk estimates (Bita Fouda *et al.*, 2024). Within this outbreak, only 213 cerebrospinal fluid specimens were laboratory tested from over 2500 reported cases. Of the samples tested, 57 (26.7%) were confirmed as bacterial meningitis. To contrast, approximately 800 cases were tested with a rapid malaria diagnostic test, of which 77 tested positive, leading to a 5-week delay in epidemic detection. During this period, samples were tested for Ebola virus, shigellosis and salmonellosis at the National Institute for Biomedical Research (INRB) laboratory in Kinshasa (Bita Fouda *et al.*, 2024). Such ongoing testing for other pathogens during the meningitis epidemic suggests that limitations in meningitis testing were likely due to a lack of reagents, experience, or appropriate training. Across the DRC this warrants an investigation into reporting practices as well as pathogen-wide laboratory testing.

When we excluded the DRC from our logistic regression model, there was a notable increase in sensitivity and specificity by approximately 5%. However, within this model, no countries adjacent to the existing meningitis belt had a demonstrated risk of outbreaks, highlighting the importance of data quality and its impact on perceived risk patterns. In line with the Defeating Meningitis by 2030 Roadmap, developing reliable and affordable diagnostic tests for bacterial meningitis, could improve case ascertainment within resource-limited settings (Cliff *et al.*, 2024). Improved surveillance of meningitis outbreaks across Africa is vital to validate the potential expansion of high-risk areas and deepen our comprehension.

Limitations and future research

There are some limitations regarding our modelling approach, the most pertinent being our choice to only use environmental predictors. These provide necessary but not sufficient conditions for an outbreak. A number of risk factors including vaccination rates, population level immunity, migration levels and physical contact rate have a key role within the dynamics of bacterial meningitis outbreaks across Africa (Agier *et al.*, 2017; Trotter *et al.*, 2017). Increasing vaccination rates and population immunity would likely decrease meningitis risk. Similarly, lower regional levels of physical contact between individuals would also decrease bacterial meningitis risk, with lower risk also being found in less urbanized areas. Higher levels of migration may also compound the increasing risk of bacterial meningitis outbreaks. Whilst not being able to include these variables within a static logistic regression model may overstate the importance of environmental factors, it is unlikely that these socioeconomic variables would be available on a continental level at an

appropriate resolution for inclusion within the model. Furthermore, data regarding either meningococcal or pneumococcal vaccination rates would likely be coarse and heterogenous within its coverage.

Additionally, while used static land cover as a risk factor within our model, further work could consider this as a temporal variable due to the impact of deforestation and desertification on outbreak risk (Tollefson, 2020; Yang *et al.*, 2022). As in Molesworth *et al.*'s analysis, whilst we received epidemic reports from enhanced disease surveillance countries, other countries outside this region may have unreported meningitis outbreaks. Through combining local data into ADMN2/ADMN1 statistics there is the potential for some discrepancy between regions where patients develop bacterial meningitis and the location of health facilities reporting cases, leading to a loss of data specificity (Molesworth *et al.*, 2003). The use of k-means clustering and PCA simplifies the data being used, potentially compromising the predictive power of the logistic regression model, if key variations in the data are not captured. We avoided particularly sparse categories by ensuring at least 50 districts were in each cluster but some categories inevitably described more districts than others. In the future we will explore different methods that do not involve k-means clustering, but found it useful here to repeat the methods used previously to explore any signals for changing geographic risk.

Within our analysis we excluded vaccination coverage as a risk factor within our primary model, as it will not have an impact on environmental risk factors for meningitis across Africa. Although vaccination will serve to decrease the risk of epidemics in vaccinated areas it will not affect unvaccinated regions and is independent of environmental/climatic variables. MenAfriVac, offering protection against group A meningococcus, was introduced in mass campaigns across the belt from 2010 onwards, followed by introduction into the essential programme of immunisation (EPI) (Djingarey *et al.*, 2015). Most countries have also introduced pneumococcal conjugate vaccines into EPI over a similar time period. To account for how the introduction of both pneumococcal and meningococcal vaccines during our study period has reshaped the epidemiology of bacterial meningitis, we conducted a sensitivity analysis only considering outbreaks that had occurred before the introduction of MenAfriVac. Details of this can be found within the extended data, with the resulting risk map showing a decrease in the area at risk of meningitis epidemics. This suggests that several outbreaks that occurred across the belt were likely caused by non-serogroup A meningococci or other meningitis-causing bacteria.

Lastly, although we used a 20-year time period as such length is typical in climate analyses, we assumed that climatic conditions were static across the reporting period. This may not be the case. Nicholson *et al.*, have determined that there has been a decrease in precipitation levels preceding the typical dry season across the Sahel (Nicholson *et al.*, 2018). Within this region temperatures are also rising 1.5 times faster than the global average (Office of the High Commissioner for Human Rights, 2025). Ghanaian focus group discussion has highlighted participants' experience of an expanding dry season which now stretches from February to June, with air temperatures rising to 48°C (Codjoe & Nabie, 2014). It has also been suggested that there has been a global increase in the severity and intensity of sand and dust storms including the Harmattan winds over Africa in recent decades (Li *et al.*, 2025), contributing to Sahelian drought persistence and increasing the risk of meningitis outbreaks. These findings reinforce the need for more sophisticated spatial-temporal modelling to anticipate how climate change may reshape meningitis epidemiology.

Conclusion

Our study highlights that the environmental risk factors for meningitis epidemics have largely remained unchanged across a 40-year period, aligning with previous findings by Molesworth *et al.* Whilst our logistic regression model suggests a potential expansion of the meningitis belt, this signal is highly sensitive to the quality of surveillance data. The inclusion of the DRC, where we know that few cases are laboratory confirmed had a significant impact on the model. Whilst Republic of the Congo, Gabon, and Angola had a moderate risk of meningitis (probability 0.4–0.59) within our full model, no countries surrounding the meningitis belt had a demonstrated risk of meningitis within the sensitivity analysis that excluded DRC. It is essential to improve epidemic reporting and diagnostic capacity within meningitis outbreaks, to accurately assess disease risk across the continent.

Data availability

Underlying data

Figshare: Updating the meningitis belt: associations between environmental factors and epidemic meningitis risk across Africa- Supporting data https://doi.org/10.6084/m9.figshare.29900975 (Cliff, 2025a).

This project contains the following underlying data:

Figure2_rainfall.xlsx, Figure2_dust.xlsx, Figure2_temperature.xlsx, Figure2_windspeed.xlsx and Figure2_humidity.xlsx- Files containing the climatic variable averages for k mean clustering technique across months. These files are used in plotting the graphs within Figure 2

ADMN2_outbreak_details.xlsx- File containing the ADMN district locations of meningitis epidemic history in Africa from 2003–2022. This file was used to generate the plot in Figure 4

outbreak_counts.xlsx- File containing the number of outbreaks in ADMN districts across Africa from 2003–2022. This file was used to generate the plot in Figure 5

Cluster_epidemic_analysis.xlsx- File containing the final k means cluster values for each of the ADMN2 districts used within the final logistic regression model. This file was used to generate Table 3, Table 4 and Table 5, as well as the relevant sensitivity analysis within the Extended data

Model_epidemic_prediction.xlsx- File containing results of the logistic regression model, and has both the predicted risk and category used within our final predictive risk map. This file was used to generate Figure 6 and supports the results of our full model's sensitivity and specificity

Data are available under the terms of the Creative Commons Attribution 4.0 International license (CC-BY 4.0).

The raw data on meningitis epidemics by ADMN district was provided by WHO AFRO via co-authors Andre Bita, Anderson Latt and Clement Lingani. These data are not publicly available in the format used in this publication. To access this data an application would need to be made via Clement Lingani who can be contacted at linganic@who.int. A range of publicly available meningitis surveillance data are available via the Power BI WHO meningitis data dashboard

Extended data

Figshare: Updating the meningitis belt: associations between environmental factors and epidemic meningitis risk across Africa- Extended data and additional information

https://doi.org/10.6084/m9.figshare.29786375.v1 (Cliff, 2025b)

This project contains the following underlying data:

Extended data.pdf- This pdf file contains the results of the sensitivity analysis carried out within this paper, where we ran the logistic regression model without the Democratic Republic of Congo, due to the country's limited laboratory confirmation. Alongside this the risk map of our sensitivity analysis only examining pre-MenAfriVac vacciantions can be found within this data. This pdf file also contains information regarding weighting strategies, data aggregation and the specific humidity calculation used, which are not required to follow study design and analysis of the results, but are instead supplementary.

Data are available under the terms of the Creative Commons Attribution 4.0 International license (CC-BY 4.0).

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References

Agier L, Deroubaix A, Martiny N, *et al.*: **Seasonality of meningitis in Africa and climate forcing: aerosols stand out.** *J R Soc Interface.* 2013; **10**(79): 20120814.
PubMed Abstract | Publisher Full Text | Free Full Text

Agier L, Martiny N, Thiongane O, *et al.*: **Towards understanding the epidemiology of *Neisseria meningitidis* in the African meningitis belt: a multi-disciplinary overview.** *Int J Infect Dis.* 2017; **54**: 103–112.
PubMed Abstract | Publisher Full Text

Beck HE, Zimmermann NE, McVicar TR, *et al.*: **Present and future Köppen-Geiger climate classification maps at 1–km resolution.** *Sci Data.* 2018; **5**(1): 180214.
PubMed Abstract | Publisher Full Text | Free Full Text

Bender RG, Shen J, Aravkin A, *et al.*: **Meningococcal A conjugate vaccine coverage in the meningitis belt of Africa from 2010 to 2021: a modelling study.** *EClinicalMedicine.* 2023; **56**: 101797.
PubMed Abstract | Publisher Full Text | Free Full Text

Besancenot JP, Boko M, Oke PC: **Weather conditions and cerebrospinal meningitis in Benin (gulf of Guinea, West Africa).** *Eur J Epidemiol.* 1997; **13**(7): 807–815.
PubMed Abstract | Publisher Full Text

Bita Fouda AA, Latt A, Sinayoko A, *et al.*: **The bacterial meningitis epidemic in Banalia in the Democratic Republic of Congo in 2021.** *Vaccines (Basel).* 2024; **12**(5): 461.
PubMed Abstract | Publisher Full Text | Free Full Text

Chen J, Jiao Z, Liang Z, *et al.*: **Association between temperature variability and global meningitis incidence.** *Environ Int.* 2023; **171**: 107649.
PubMed Abstract | **Publisher Full Text**

Cliff M: Updating the meningitis belt: associations between environmental factors and epidemic meningitis risk across Africa- Supporting data. *figshare.* Dataset. 2025a.
Reference Source

Cliff M: **Updating the meningitis belt: associations between environmental factors and epidemic meningitis risk across Africa-extended data and additional information.** *figshare.* Journal contribution. 2025b.
Reference Source

Cliff M, Jahn S, Bita A, *et al.*: **Re-examining the meningitis belt: associations between environmental factors and epidemic meningitis risk across Africa.** *medRxiv.* 2025; 2025.02.25.25322867.
Publisher Full Text

Cliff M, Welaga P, Mohammed N, *et al.*: **Strategies for controlling pneumococcal disease and outbreaks during humanitarian emergencies.** *Nat Med.* 2024; **30**(6): 1515–1516.
PubMed Abstract | **Publisher Full Text**

Codjoe SNA, Nabie VA: **Climate change and cerebrospinal meningitis in the Ghanaian meningitis belt.** *Int J Environ Res Public Health.* 2014; **11**(7): 6923–6939.
PubMed Abstract | **Publisher Full Text** | **Free Full Text**

Copernicus Climate Change Service: **Agrometeorological indicators from 1979 to present derived from reanalysis.** Copernicus Climate Change Service (C3S) Climate Data Store (CDS). 2020.
Publisher Full Text

Copernicus Climate Change Service: **Aerosol properties gridded data from 1995 to present derived from satellite observation.** Copernicus Climate Change Service (C3S) Climate Data Store (CDS). 2019.
Publisher Full Text

Dione C, Talib J, Bwaka AM, *et al.*: **Improved sub-seasonal forecasts to support preparedness action for meningitis outbreak in Africa.** *Clim Serv.* 2022; **28**: 100326.
PubMed Abstract | **Publisher Full Text** | **Free Full Text**

Djingarey MH, Diomandé FVK, Barry R, *et al.*: **Introduction and rollout of a new group A meningococcal conjugate vaccine (PsA-TT) in African meningitis belt countries, 2010–2014.** *Clin Infect Dis.* 2015; **61 Suppl 5**(Suppl 5): S434–S441.
PubMed Abstract | **Publisher Full Text** | **Free Full Text**

Franklin K, Kwambana-Adams B, Lessa FC, *et al.*: **Pneumococcal meningitis outbreaks in Africa, 2000–2018: systematic literature review and meningitis surveillance database analyses.** *J Infect Dis.* 2021; **224**(12 Suppl 2): S174–S183.
PubMed Abstract | **Publisher Full Text** | **Free Full Text**

Funk C, Peterson P, Landsfeld M, *et al.*: **The climate hazards infrared precipitation with stations--a new environmental record for monitoring extremes.** *Sci Data.* 2015; **2**(1): 150066.
PubMed Abstract | **Publisher Full Text** | **Free Full Text**

Gavi: **In world first, Nigeria introduces new 5-in-1 vaccine against meningitis**. Accessed: 6 January 2026; 2025.
Reference Source

GBD 2019 Meningitis Antimicrobial Resistance Collaborators: **Global, regional, and national burden of meningitis and its aetiologies, 1990–2019: a systematic analysis for the Global Burden of Disease Study 2019.** *Lancet Neurol.* 2023; **22**(8): 685–711.
PubMed Abstract | **Publisher Full Text** | **Free Full Text**

GES DISC Dataset: AIRS/Aqua L3 Monthly Standard Physical Retrieval (AIRS+AMSU) 1 degree x 1 degree V006 (AIRX3STM 006). (accessed 2026-01-29).
Reference Source

Govender P, Sivakumar V: **Application of *k*-means and hierarchical clustering techniques for analysis of air pollution: a review (1980–2019).** *Atmos Pollut Res.* 2020; **11**(1): 40–56.
Publisher Full Text

Greenwood B: **Manson Lecture: meningococcal meningitis in Africa.** *Trans R Soc Trop Med Hyg.* 1999; **93**(4): 341–353.
PubMed Abstract | **Publisher Full Text**

Greenwood BM: **The epidemiology of acute bacterial meningitis in tropical Africa**. In: Williams, J.D. and Burnie, J.P. (eds.) *Bacterial meningitis.* London: Academic Press, 1987; 61–92.

Griguolo S, Santacroce P: **Analysing, classifying and displaying time series of images pixel-by-pixel: the package ADDAPIX**. FAO Agrometeorology Series Working Paper (FAO). 1996; (13), (Accessed: 1 July 2025).
Reference Source

Hardin JW, Hilbe JM: **Generalized linear models and extensions, second edition.** Stata Press, 2007.
Reference Source

Hersbach H, *et al.*: **ERA5 hourly data on single levels from 1940 to present.** Copernicus Climate Change Service (C3S) Climate Data Store (CDS). 2023.
Publisher Full Text

Hijmans RJ, van Etten J, Sumner M, *et al.*: **raster: Geographic data analysis and modeling**. 2025; (Accessed: 1 July 2025).
Reference Source

Ibarz-Pavón AB, Morais L, Sigaúque B, *et al.*: **Epidemiology, molecular characterization and antibiotic resistance of *Neisseria meningitidis* from patients ≤15 years in Manhiça, rural Mozambique.** *PLoS One.* 2011; **6**(6): e19717.
PubMed Abstract | **Publisher Full Text** | **Free Full Text**

Lamarche C, Santoro M, Bontemps S, *et al.*: **Compilation and validation of SAR and optical data products for a complete and global map of Inland/Ocean water tailored to the climate modeling community.** *Remote Sens.* 2017; **9**(1): 36.
Publisher Full Text

Lapeyssonnie L, World Health Organization: **La méningite cérébro-spinale en Afrique.** *Bulletin of the World Health Organization.* 1963; **28**(Suppl): 3–39. (Accessed: 4 June 2025).
Reference Source

Li T, Cohen AJ, Krzyzanowski M, *et al.*: **Sand and dust storms: a growing global health threat calls for international health studies to support policy action.** *Lancet Planet Health.* 2025; **9**(1): e34–e40.
PubMed Abstract | **Publisher Full Text** | **Free Full Text**

Lingani C, Bergeron-Caron C, Stuart JM, *et al.*: **Meningococcal meningitis surveillance in the African meningitis belt, 2004–2013.** *Clin Infect Dis.* 2015; **61 Suppl 5**(Suppl 5): S410–S415.
PubMed Abstract | **Publisher Full Text** | **Free Full Text**

Mazamay S, Broutin H, Bompangue D, *et al.*: **The environmental drivers of bacterial meningitis epidemics in the Democratic Republic of Congo, central Africa.** *PLoS Negl Trop Dis.* 2020; **14**(10): e0008634.
PubMed Abstract | **Publisher Full Text** | **Free Full Text**

Mazamay S, Guégan JF, Diallo N, *et al.*: **An overview of bacterial meningitis epidemics in Africa from 1928 to 2018 with a focus on epidemics "outside-the-belt".** *BMC Infect Dis.* 2021; **21**(1): 1027.
PubMed Abstract | **Publisher Full Text** | **Free Full Text**

Mohammed I, Iliyasu G, Habib AG: **Emergence and control of epidemic meningococcal meningitis in sub-Saharan Africa.** *Pathog Glob Health.* 2017; **111**(1): 1–6.
PubMed Abstract | **Publisher Full Text** | **Free Full Text**

Molesworth AM, Cuevas LE, Connor SJ, *et al.*: **Environmental risk and meningitis epidemics in Africa.** *Emerg Infect Dis.* 2003; **9**(10): 1287–93.
PubMed Abstract | **Publisher Full Text** | **Free Full Text**

Molesworth AM, Thomson MC, Connor SJ, *et al.*: **Where is the meningitis belt? Defining an area at risk of epidemic meningitis in Africa.** *Trans R Soc Trop Med Hyg.* 2002; **96**(3): 242–249.
PubMed Abstract | **Publisher Full Text**

Mora C, McKenzie T, Gaw IM, *et al.*: **Over half of known human pathogenic diseases can be aggravated by climate change.** *Nat Clim Chang.* 2022; **12**(9): 869–875.
PubMed Abstract | **Publisher Full Text** | **Free Full Text**

Mpairwe Y, Matovu HL: **Cerebrospinal meningitis in East Africa 1911–1965.** *Trans R Soc Trop Med Hyg.* 1971; **65**(1): 70–77.
PubMed Abstract | **Publisher Full Text**

Mueller JE, Gessner BD: **A hypothetical explanatory model for meningococcal meningitis in the African meningitis belt.** *Int J Infect Dis.* 2010; **14**(7): e553–559.
PubMed Abstract | **Publisher Full Text**

Nicholson SE, Funk C, Fink AH: **Rainfall over the African continent from the 19th through the 21st century.** *Glob Planet Change.* 2018; **165**: 114–127.
Publisher Full Text

Office of the High Commissioner for Human Rights (OHCHR): **Report: How climate change affects the human rights of Sahel region migrants**. 2025; (Accessed: 20 June 2025).
Reference Source

Palmgren H: **Meningococcal disease and climate.** *Glob Health Action.* 2009; **2**(1): 2061.
PubMed Abstract | **Publisher Full Text** | **Free Full Text**

Savory EC, Cuevas LE, Yassin MA, *et al.*: **Evaluation of the meningitis epidemics risk model in Africa.** *Epidemiol Infect.* 2006; **134**(5): 1047–1051.
PubMed Abstract | **Publisher Full Text** | **Free Full Text**

Sidikou F, Zaneidou M, Alkassoum I, *et al.*: **Emergence of epidemic *Neisseria meningitidis* serogroup C in Niger, 2015: an analysis of national surveillance data.** *Lancet Infect Dis.* 2016; **16**(11): 1288–1294.
PubMed Abstract | **Publisher Full Text** | **Free Full Text**

Sultan B, Labadi K, Guégan JF, *et al.*: **Climate drives the meningitis epidemics onset in West Africa.** *PLoS Med.* 2005; **2**(1): e6.
PubMed Abstract | **Publisher Full Text** | **Free Full Text**

Tall H, Yameogo I, Novak R: **Impact of climate factors in modeling and predicting the transmission of meningitis in Africa: the case of Burkina Faso.** *Arch Clin Med Case Rep.* 2022; **06**(06): 715–724.
Publisher Full Text

Thomson MC, Molesworth AM, Djingarey MH, *et al.*: **Potential of environmental models to predict meningitis epidemics in Africa.** *Trop Med Int Health.* 2006; **11**(6): 781–788.
PubMed Abstract | Publisher Full Text

Tollefson J: **Why deforestation and extinctions make pandemics more likely.** *Nature.* 2020; **584**(7820): 175–176.
PubMed Abstract | Publisher Full Text

Trotter CL, Cibrelus L, Fernandez K, *et al.*: **Response thresholds for epidemic meningitis in sub-Saharan Africa following the introduction of MenAfriVac®.** *Vaccine.* 2015; **33**(46): 6212–6217.
PubMed Abstract | Publisher Full Text

Trotter CL, Lingani C, Fernandez K, *et al.*: **Impact of MenAfriVac in nine countries of the African meningitis belt, 2010-15: an analysis of surveillance data.** *Lancet Infect Dis.* 2017; **17**(8): 867–872.
PubMed Abstract | Publisher Full Text

Ukoaka BM, Okesanya OJ, Daniel FM, *et al.*: **A perspective on the novel pentavalent Men5CV (NmCV-5) meningitis vaccine and Nigeria's pioneering rollout campaign.** *Infez Med.* 2024; **32**(3): 323–9.
PubMed Abstract | Publisher Full Text | Free Full Text

Umargono E, Suseno JE, Gunawan SKV: **K-means clustering optimization using the elbow method and early centroid determination based on mean and median formula.** In: *The 2nd International Seminar on Science and Technology (ISSTEC 2019),* Atlantis Press, 2020; 121–129.
Publisher Full Text

World Health Organization: **Pneumococcal meningitis – Togo**. 2023; (Accessed: 6 January 2026).
Reference Source

World Health Organization: **In world first, Nigeria introduces new 5-in-1 vaccine against meningitis**. 2024; (Accessed: 6 January 2026).
Reference Source

World Health Organization: **Meningococcal meningitis**. Regional Office for Africa, 2025; (Accessed: 4 June 2025).
Reference Source

Yaka P, Sultan B, Broutin H, *et al.*: **Relationships between climate and year-to-year variability in meningitis outbreaks: a case study in Burkina Faso and Niger.** *Int J Health Geogr.* 2008; **7**(1): 34.
PubMed Abstract | Publisher Full Text | Free Full Text

Yang Z, Gao X, Lei J, *et al.*: **Analysis of spatiotemporal changes and driving factors of desertification in the Africa Sahel.** *CATENA.* 2022; **213**: 106213.
Publisher Full Text

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Version 2

Reviewer Report 20 May 2026

https://doi.org/10.21956/wellcomeopenres.28522.r147683

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✓ **Junjun Chen**
Johns Hopkins University, Baltimore, USA

The authors have satisfactorily addressed my previous concerns. The methodology is now well-documented. I approve this revised version.

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Biomedical engineering, public health data science, environmental epidemiology, and AI-driven modeling of disease risk.

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard.

Reviewer Report 12 March 2026

https://doi.org/10.21956/wellcomeopenres.28522.r147684

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✓ **Tiantian Li**
Chinese Center for Disease Control and Prevention, Beijing, China

Reviewer Report
The revised manuscript has satisfactorily addressed the main concerns raised in the previous review round. The authors have improved the transparency and robustness of the analysis by expanding the methodological description of the clustering procedure (including initialization, random seeds, and convergence criteria), providing additional sensitivity analyses (e.g., pre-

MenAfriVac outbreaks and district boundary thresholds), and revising the discussion to better contextualize vaccination coverage and surveillance limitations. The revised title more accurately reflects the scope of the study, and the inclusion of uncertainty information in the extended data improves the interpretability of the risk estimates.
I have only two minor suggestions that may help further improve clarity.

First, the manuscript should clarify which variables were ultimately retained in the final regression model. The Discussion notes that rainfall, specific humidity, wind speed, and aerosol optical depth were key predictors, whereas Table 5 appears to include cluster profiles of rainfall, aerosol optical depth, and specific humidity only. Clarifying whether wind speed was included in the final model would improve consistency across sections.

Second, the manuscript notes that variables with Pearson correlation coefficients >0.6 were excluded to reduce collinearity, leading to the removal of temperature while retaining aerosol optical depth. A brief clarification or supporting reference for the chosen correlation threshold and variable selection approach would further improve transparency.

Overall, the revisions have strengthened the manuscript and improved its reproducibility and interpretation. I consider the manuscript suitable for indexing.

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Mainly engaged in research on environment and health, with a focus on the impacts of climate change, air pollution, and other environmental factors on population health, including the environmental drivers of infectious disease transmission.

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard.

Version 1

Reviewer Report 19 November 2025

https://doi.org/10.21956/wellcomeopenres.27291.r134964

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?

Tiantian Li
Chinese Center for Disease Control and Prevention, Beijing, China

Reviewer:
This study utilizes WHO-AFRO meningitis surveillance data from 2003–2022, combined with multiple environmental covariates including rainfall, specific humidity, aerosol optical depth

(AOD), wind speed, and land-cover type, to evaluate environmental determinants of epidemic meningitis risk across Africa. Using K-means clustering and logistic regression, the authors identify rainfall, humidity, and aerosol concentration as the strongest predictors. When data from the Democratic Republic of the Congo (DRC) are included, the model suggests a potential south-western expansion of high-risk areas; however, after excluding the DRC, the results align closely with Molesworth et al. (2003), showing no spatial expansion. The study represents a substantial methodological advance over previous work in terms of temporal coverage, data resolution, and model reproducibility, providing valuable evidence on climate–meningitis relationships. Nevertheless, several aspects concerning the study's framing, variable selection, model comparability, and interpretation require further refinement.

Major comments

1. The current title, "Updating the meningitis belt," implies that the research re-defines the spatial boundaries of the belt. Yet, after excluding the DRC, the distribution of high-risk areas remains largely consistent with Molesworth et al. (2003), without any confirmed expansion. This could mislead readers regarding the novelty of the findings. The authors are encouraged to reconsider the title and reposition the study focus. If no new belt boundary has been empirically defined, alternative titles such as "Re-evaluating environmental associations with meningitis risk across Africa" or "Revalidation of environmental determinants of meningitis outbreaks" would more accurately reflect the study's scope.
2. The introduction cites Chen et al. (2023), who demonstrated a significant association between temperature variability and meningitis incidence, yet temperature was not included in the present model. The authors should clarify whether this omission was due to multicollinearity, data availability, or model stability. Given temperature's central role in dry-season transmission mechanisms, its exclusion requires explicit justification based on statistical or theoretical grounds.
3. The authors deliberately modeled only environmental variables to avoid immunological confounding. However, since the large-scale introduction of MenAfriVac after 2010 has profoundly altered meningitis epidemiology, omitting vaccination coverage, population immunity, migration, and urbanization may overstate the role of environmental predictors. The discussion should explicitly acknowledge this limitation and speculate how inclusion of immunization or socio-demographic variables might alter the observed associations.
4. The DRC substantially affects spatial risk estimates, yet the explanation provided—"limited laboratory confirmation"—is insufficient. The authors should explore surveillance system discrepancies, reporting biases, and potential spatial misclassification (case reporting site vs infection origin). The Methods section should also specify how spatial mismatches and uncertainty were addressed (e.g., overlap thresholds, interpolation precision, temporal alignment).
5. The paper's main contribution lies in: (i) extending the temporal window by 20 years; (ii) using substantially higher-resolution environmental datasets; (iii) maintaining methodological comparability with Molesworth et al. to enable longitudinal evaluation; and (iv) introducing wind-speed as a new variable. These advances should be systematically emphasized in the Introduction and Discussion, with explicit comparisons to Molesworth (2003), Savory (2006), and Tall (2022) to highlight methodological and policy-relevant innovations.
6. Wind speed and land-cover were excluded from the final model, yet both are ecologically relevant—especially wind speed, which is closely linked to aerosol dispersion during the dry season. The authors should provide detailed information on stepwise-selection criteria (e.g., significance thresholds), multicollinearity diagnostics (e.g., VIF values), and decision rules for exclusion. Supplementary material should include model performance comparisons with and without these variables to improve transparency and reproducibility.

7.The Methods section notes the use of iterative modeling and the elbow method to determine the optimal number of clusters, but the corresponding plots or justification are not presented. The authors should include the elbow curve or other validation metrics (e.g., silhouette scores) in the appendix or methods figure to enhance traceability of data processing.
8. The study uses an 80/20 training-validation split, whereas Molesworth et al. (2003) employed a 60/40 split. The higher AUC (0.908 vs 0.82) may partly reflect this difference rather than a true improvement in model performance. The authors should justify their choice of partition ratio and, ideally, replicate the analysis using a 60/40 split for direct comparability.

Minor comments
9. Only the final retained variables' cluster maps are shown, while those of excluded variables (wind speed, land-cover) are omitted. Please provide clustering outputs for all variables in the Supplementary Materials to clarify the full environmental data-processing workflow.
10. Periods are missing at the end of the sections *"Logistic regression model sensitivity and specificity," "Key findings,"* and *"Limitations and future research."*
11. In Figure 2(b), the label should read "specific humidity (g/m^3)" rather than "specific humidity (g/m3)." All figures and tables should use standardized SI units and consistent typographical formatting.

Is the work clearly and accurately presented and does it cite the current literature?
Partly

Is the study design appropriate and is the work technically sound?
Partly

Are sufficient details of methods and analysis provided to allow replication by others?
Partly

If applicable, is the statistical analysis and its interpretation appropriate?
Partly

Are all the source data underlying the results available to ensure full reproducibility?
Partly

Are the conclusions drawn adequately supported by the results?
Partly

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Mainly engaged in research on environment and health, with a focus on the impacts of climate change, air pollution, and other environmental factors on population health, including the environmental drivers of infectious disease transmission.

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard, however I have significant reservations, as outlined above.

Author Response 21 Jan 2026

Molly Cliff

We would like to thank the reviewer for both taking the time to review this manuscript and for the insightful comments contained within the review. In this response we display the reviewer's comments in normal text and our response in italics

Major comments

1. The current title, "Updating the meningitis belt," implies that the research re-defines the spatial boundaries of the belt. Yet, after excluding the DRC, the distribution of high-risk areas remains largely consistent with Molesworth et al. (2003), without any confirmed expansion. This could mislead readers regarding the novelty of the findings. The authors are encouraged to reconsider the title and reposition the study focus. If no new belt boundary has been empirically defined, alternative titles such as "Re-evaluating environmental associations with meningitis risk across Africa" or "Revalidation of environmental determinants of meningitis outbreaks" would more accurately reflect the study's scope.
The study title has been changed to reflect the study's scope and focus as suggested.

2. The introduction cites Chen et al. (2023), who demonstrated a significant association between temperature variability and meningitis incidence, yet temperature was not included in the present model. The authors should clarify whether this omission was due to multicollinearity, data availability, or model stability. Given temperature's central role in dry-season transmission mechanisms, its exclusion requires explicit justification based on statistical or theoretical grounds.
Within our paper we have rerun the analysis and reconsidered the role of temperature. Temperature was excluded from the final model due to collinearity with other factors as and our decision to prioritise Aerosol Optical Depth within the analysis.

3. The authors deliberately modelled only environmental variables to avoid immunological confounding. However, since the large-scale introduction of MenAfriVac after 2010 has profoundly altered meningitis epidemiology, omitting vaccination coverage, population immunity, migration, and urbanization may overstate the role of environmental predictors. The discussion should explicitly acknowledge this limitation and speculate how inclusion of immunization or socio-demographic variables might alter the observed associations.
We have updated our analysis to include a sensitivity analysis which only considered outbreaks that occurred prior to the introduction of MenAfriVac on a country level. Details of this analysis can be found in both the results section of the manuscript as well as the extended data. Furthermore, within our discussion we examine how the inclusion of vaccination coverage and socio-demographic variables might alter the observed associations. One of the key challenges of analysing both vaccination coverage and socio-demographic variables is the availability of such data. It is unlikely that such data would be available of continental level at an appropriate resolution for inclusion within the model.

4. The DRC substantially affects spatial risk estimates, yet the explanation provided—"limited laboratory confirmation"—is insufficient. The authors should explore surveillance system discrepancies, reporting biases, and potential spatial misclassification (case reporting site vs infection origin). The Methods section should also specify how spatial mismatches and uncertainty were addressed (e.g., overlap thresholds, interpolation precision, temporal alignment).
Unfortunately, there is limited information and literature regarding surveillance system discrepancies, reporting biases, and spatial misclassification for meningitis outbreaks in the DRC. We have tried to address this information gap by describing a 2021 outbreak of meningitis within the DRC that highlights issues regarding national surveillance and outbreak reporting If the reviewer is aware of data sources or literature that could provide insight into surveillance system discrepancies, reporting biases, and potential spatial misclassification within the DRC we would welcome this guidance as we could then explore these issues further within future analyses. Further to this our methods section already describes the handling of spatial uncertainty, including spatial overlap between WHO and GADM ADMN2 shapefiles to address district boundary changes as well as overlap thresholds. As this model is a static outbreak analysis with districts marked as 1/0 if they had ever experienced an outbreak within a 20-year period, temporal uncertainty remains limited. We have clarified the methodology to emphasise these points further.

5. The paper's main contribution lies in: (i) extending the temporal window by 20 years; (ii) using substantially higher-resolution environmental datasets; (iii) maintaining methodological comparability with Molesworth et al. to enable longitudinal evaluation; and (iv) introducing wind-speed as a new variable. These advances should be systematically emphasized in the Introduction and Discussion, with explicit comparisons to Molesworth (2003), Savory (2006), and Tall (2022) to highlight methodological and policy-relevant innovations. *Thank you for this suggestion.*
Both the introduction and discussion have been revised to reflect the contributions of this paper. We have emphasised the extended temporal window, the use of higher-resolution environmental datasets, methodological comparability with Molesworth et al., and the inclusion of wind speed as a novel variable. Furthermore, we have made explicit comparisons to Molesworth (2003), Savory (2006), and Tall (2022) in both the introduction and the discussion to highlight methodological advancements of this analysis alongside policy-relevant innovations.

6. Wind speed and land-cover were excluded from the final model, yet both are ecologically relevant—especially wind speed, which is closely linked to aerosol dispersion during the dry season. The authors should provide detailed information on stepwise-selection criteria (e.g., significance thresholds), multicollinearity diagnostics (e.g., VIF values), and decision rules for exclusion. Supplementary material should include model performance comparisons with and without these variables to improve transparency and reproducibility.
We have updated the methodology section to include detailed information regarding backwards stepwise analysis to reach the final model, including multicollinearity diagnostics and the decision rules used for variable exclusion. We have also rerun the analysis and updated the model to include windspeed as a variable within the final model. Alongside this we have updated the extended information section to include model performance comparisons with and without

landcover, highlighting our decision to opt for a more parsimonious model as well as to improve transparency and reproducibility.

7. The Methods section notes the use of iterative modeling and the elbow method to determine the optimal number of clusters, but the corresponding plots or justification are not presented. The authors should include the elbow curve or other validation metrics (e.g., silhouette scores) in the appendix or methods figure to enhance traceability of data processing.
We have updated the methodology section of our paper to include parameter details for clusters, including number of clusters chosen, number of starts and convergence criteria. Alongside this our extended data includes random seeds and elbow plots for all variables, allowing for improved reproducibility. We have rerun the k-means clustering analysis increasing both the number of random starts and iterations from the default settings. In addition, district level outbreak weighting was subsequently adjusted to optimise sensitivity and specificity.

8. The study uses an 80/20 training-validation split, whereas Molesworth et al. (2003) employed a 60/40 split. The higher AUC (0.908 vs 0.82) may partly reflect this difference rather than a true improvement in model performance. The authors should justify their choice of partition ratio and, ideally, replicate the analysis using a 60/40 split for direct comparability.
Within the methods section we have clarified that we initially chose an 80/20 split as we had a smaller number of outbreaks affected districts as compared to Molesworth et al. (2003). To allow for comparability we have also replicated the analysis using a 60/40 split and found that model sensitivity and specificity remain similar to the results of the 80/20 split

Minor comments
9. Only the final retained variables' cluster maps are shown, while those of excluded variables (wind speed, land-cover) are omitted. Please provide clustering outputs for all variables in the Supplementary Materials to clarify the full environmental data-processing workflow.
Within the methods section we have provided clustering outputs for all temporal variables. As we used static values for landcover, no clustering was carried out on this variable with the static categorical values being used within our model.

10. Periods are missing at the end of the sections "Logistic regression model sensitivity and specificity," "Key findings," and "Limitations and future research."
This has now been corrected

11. In Figure 2(b), the label should read "specific humidity (g/m^3)" rather than "specific humidity (g/m3)." All figures and tables should use standardized SI units and consistent typographical formatting. *This has now been updated*

Competing Interests: No competing interests were disclosed.

Reviewer Report 11 November 2025

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Junjun Chen
Johns Hopkins University, Baltimore, USA

Summary
The authors present an updated environmental risk map of epidemic bacterial meningitis in Africa (2003 to 2022) using WHO-AFRO surveillance and modern environmental datasets. Monthly climate variables, rainfall, aerosol optical depth (dust), specific humidity, and windspeed, were reduced into seasonal profiles using PCA and k-means clustering, while land cover was treated as static. Logistic regression linked district-level epidemic history (ever vs never) to these climate profiles and land cover types.

After stepwise selection, the final model retained rainfall, dust, and humidity as key predictors, achieving an AUC of 0.908 with roughly 81% specificity and 84% sensitivity ($p > 0.4$). Excluding the DRC improved AUC to 0.944 and increased specificity by about 11%. The resulting risk map recovered the canonical Sahelian belt as the highest-risk zone, while the moderate risk signal seen in peripheral countries (Republic of Congo, Gabon, Liberia, Angola) disappeared once the DRC was excluded, highlighting how data quality and laboratory confirmation critically shape risk interpretation. The authors appropriately emphasize improved diagnostics and surveillance capacity under the WHO “Defeating Meningitis by 2030” roadmap.

This is a strong and timely study that (1) reaffirms the robustness of Sahel-linked climatic drivers of meningitis, (2) demonstrates excellent predictive performance, and (3) responsibly examines the appearance of “belt expansion” through a well-designed sensitivity analysis that attributes it to surveillance bias rather than ecological change. Addressing several methodological and reporting refinements, especially spatial dependence, uncertainty communication, and clustering reproducibility, would further enhance both the scientific rigor and the operational utility of this work.

I am genuinely excited for this paper’s indexing. It is an important and impactful contribution to climate-epidemiological modeling and public-health policy in sub-Saharan Africa.

Strengths
This manuscript sets a clear comparative objective against the classic Molesworth model, allowing time-consistent inference while leveraging modern, high-resolution environmental data. The authors provide transparent performance metrics and a particularly insightful DRC sensitivity analysis that directly addresses surveillance quality. Moreover, the policy relevance is substantial: the findings have clear implications for early-warning systems, surveillance strengthening, and resource allocation across the meningitis belt.

Suggestions

1. Uncertainty communication

Only point probabilities are mapped. For policy-relevant interpretation, users need a sense of uncertainty, especially in peripheral or moderate-risk regions. Consider adding uncertainty layers (eg, standard errors or 95% CIs of predicted probabilities) and/or regional calibration plots to convey confidence in model outputs.

2. Clustering reproducibility

Clarify the k-means clustering setup and reproducibility parameters. While the workflow is outlined, exact specifications, such as the number of clusters per variable, selection criteria (elbow, silhouette, or SSE), initialization method, number of starts, stopping rule, and random seeds, should be reported. This transparency would greatly improve reproducibility.

3. District mapping sensitivity

Potential misclassification may arise when mapping historical outbreaks to 2022 GADM boundaries using 50%/30% overlap thresholds. A short sensitivity analysis varying these thresholds (eg, 40% and 60%) and reporting stability in coefficients or AUC would demonstrate robustness to boundary uncertainty.

4. Data reproducibility

Because the WHO-AFRO outbreak data are not publicly accessible, full replication is currently limited. To improve transparency, consider releasing an anonymized proxy dataset (eg, district-level binary outcomes by country with masked IDs) or a deterministic script that reconstructs the analysis dataset from a standard WHO extract format. This would allow authorized users to fully reproduce the results.

5. Vaccination and immunity context

The exclusion of vaccination variables is reasonable to isolate environmental effects, but a brief sensitivity discussion on whether including simple covariates, such as MenAfriVac rollout year or PCV introduction by country, affects calibration or association strength would strengthen the interpretation.

6. Recurrent-epidemic districts

It would be valuable to include a table of the top 20 districts with recurrent epidemics, along with their corresponding climate classes. This addition would enhance practical relevance for outbreak preparedness programs and country-level health planners.

Is the work clearly and accurately presented and does it cite the current literature?

Yes

Is the study design appropriate and is the work technically sound?

Yes

Are sufficient details of methods and analysis provided to allow replication by others?

Yes

If applicable, is the statistical analysis and its interpretation appropriate?

Yes

Are all the source data underlying the results available to ensure full reproducibility?
Yes

Are the conclusions drawn adequately supported by the results?
Yes

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Biomedical engineering, public health data science, environmental epidemiology, and AI-driven modeling of disease risk.

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard, however I have significant reservations, as outlined above.

Author Response 21 Jan 2026

Molly Cliff

We would like to thank the reviewer for both taking the time to review this manuscript and for the insightful comments contained within the review. In this response we display the reviewer's comments in normal text and our response in italics

1. **Uncertainty communication**
   Only point probabilities are mapped. For policy-relevant interpretation, users need a sense of uncertainty, especially in peripheral or moderate-risk regions. Consider adding uncertainty layers (eg, standard errors or 95% CIs of predicted probabilities) and/or regional calibration plots to convey confidence in model outputs.

To enhance policy relevant interpretation we have added in risk maps with 95% CI have been added into the extended data, to convey confidence in model outputs.

2. Clustering reproducibility
Clarify the k-means clustering setup and reproducibility parameters. While the workflow is outlined, exact specifications, such as the number of clusters per variable, selection criteria (elbow, silhouette, or SSE), initialization method, number of starts, stopping rule, and random seeds, should be reported. This transparency would greatly improve reproducibility. *We have updated the methodology section of our paper to include parameter details for clusters, including number of clusters chosen, number of starts and convergence criteria. Alongside this our extended data includes random seeds and elbow plots for all variables, allowing for improved reproducibility. We have updated the k-means clustering analysis, increasing both the number of random starts and iterations from the default settings. Furthermore, district level outbreak weighting was adjusted to optimise sensitivity and specificity.*

1. **District mapping sensitivity**
   Potential misclassification may arise when mapping historical outbreaks to 2022 GADM boundaries using 50%/30% overlap thresholds. A short sensitivity analysis

varying these thresholds (eg, 40% and 60%) and reporting stability in coefficients or AUC would demonstrate robustness to boundary uncertainty.

Within our methodology and results section, we have defined a sensitivity analysis that we undertook varying the overlap threshold of historical outbreaks to 40% and 60%. Within this analysis the AUC remained at 0.908, as only four district outbreaks were affected by the small boundary changes.

1. **Data reproducibility**
   Because the WHO-AFRO outbreak data are not publicly accessible, full replication is currently limited. To improve transparency, consider releasing an anonymized proxy dataset (eg, district-level binary outcomes by country with masked IDs) or a deterministic script that reconstructs the analysis dataset from a standard WHO extract format. This would allow authorized users to fully reproduce the results.

Unfortunately, it remains difficult to release an anonymized proxy version of the raw data, as the spatial identifiers within such a dataset would make it possible to identify the dates and locations of outbreaks. Furthermore, the outbreak dataset from WHO-AFRO is subject to explicit data usage and redistribution restrictions, preventing its release. To maximise reproducibility of results all datasets apart from the raw epidemiological surveillance data which is subject to data sharing restrictions from the World Health Organisation are publicly available. All processed datasets are available as part of the underlying data. Figshare: Updating the meningitis belt: associations between environmental factors and epidemic meningitis risk across Africa- Supporting data https://doi.org/10.6084/m9.figshare.29900975 Furthermore, within the manuscript we have documented all processing steps applied to the epidemiological data and made the R code publicly available on GitHub.

5. Vaccination and immunity context

The exclusion of vaccination variables is reasonable to isolate environmental effects, but a brief sensitivity discussion on whether including simple covariates, such as MenAfriVac rollout year or PCV introduction by country, affects calibration or association strength would strengthen the interpretation.

We have updated our analysis to include a sensitivity analysis which only considered outbreaks that occurred prior to the introduction of MenAfriVac on a country level. Details of this analysis can be found in both the results section of the manuscript as well as the extended data. Furthermore, within our discussion we examine how the inclusion of vaccination coverage and socio-demographic variables might alter the observed associations.

6. Recurrent-epidemic districts

It would be valuable to include a table of the top 20 districts with recurrent epidemics, along with their corresponding climate classes. This addition would enhance practical relevance for outbreak preparedness programs and country-level health planners.

The results section has now been updated to include a table of the top 20 districts with recurrent epidemics, along with their corresponding climate classes

Competing Interests: No competing interests were disclosed.

Reviewer Report 30 September 2025

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MUHAMMAD UMAR AHSAN
D.G Khan Medical College, Punjab, Pakistan

1. Is the work clearly and accurately presented, and does it cite the current literature? **Partly**
   Some important recent outbreak reports, WHO updates, and vaccination coverage studies are under-cited.
2. Is the study design appropriate and is the work technically sound? **Partly**
   The decision to exclude vaccination coverage and socio-demographic variables may oversimplify the model. Interpretation of a possible south-westerly expansion may reflect a data artifact.
3. Are sufficient details of methods and analysis provided to allow replication by others? **Partly**
   Parameter details for clustering (e.g., exact number of clusters chosen, initialization, random seed, convergence criteria) are not fully described.
4. If applicable, is the statistical analysis and its interpretation appropriate? **I cannot comment**. A qualified statistician is required.
5. Are all the source data underlying the results available to ensure full reproducibility? **No**
   The environmental source data are open, but the epidemiological data and processed datasets are not accessible, which prevents full reproducibility.
6. Are the conclusions drawn adequately supported by the results? **Partly**
   Conclusions are partly supported by the results. The findings regarding rainfall, dust (AOD), and humidity as key environmental drivers, as well as the persistence of the Sahel as the primary high-risk zone, are demonstrated. However, the assertion of a south-westerly expansion of the meningitis belt (into Congo, Gabon, Liberia, and Angola) is less robust.

Is the work clearly and accurately presented and does it cite the current literature?
Partly

Is the study design appropriate and is the work technically sound?
Partly

Are sufficient details of methods and analysis provided to allow replication by others?
Partly

If applicable, is the statistical analysis and its interpretation appropriate?
I cannot comment. A qualified statistician is required.

Are all the source data underlying the results available to ensure full reproducibility?
No

Are the conclusions drawn adequately supported by the results?
Partly

Competing Interests: No competing interests were disclosed.

Reviewer Expertise: Consequences of climate change on health.

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard, however I have significant reservations, as outlined above.

Author Response 21 Jan 2026

Molly Cliff

We would like to thank the reviewer for both taking the time to review this manuscript and for the insightful comments contained within the review. In this response we display the reviewer's comments in normal text and our response in italics

1. Is the work clearly and accurately presented, and does it cite the current literature? **Partly**
   Some important recent outbreak reports, WHO updates, and vaccination coverage studies are under-cited.

We have updated the manuscript introduction to include details on the introduction of both MenA and Men5CV vaccines across the meningitis belt, citing key studies which also examine vaccination coverage. Additionally, we have included further details of recent bacterial meningitis outbreaks into the paper's introduction. If the reviewer still feels that we have under cited the literature, we would appreciate details of specific studies or reports that should be included.

1. Is the study design appropriate and is the work technically sound? **Partly**
   The decision to exclude vaccination coverage and socio-demographic variables may oversimplify the model. Interpretation of a possible south-westerly expansion may reflect a data artifact.

We have updated our analysis to include a sensitivity analysis which only considered outbreaks that occurred prior to the introduction of MenAfriVac on a country level. Details of this analysis can be found in both the results section of the manuscript as well as the extended data. Furthermore, within our discussion we examine how the inclusion of vaccination coverage and socio-demographic variables might alter the observed associations. One of the key challenges of analysing both vaccination coverage and socio-demographic variables is the availability of such data. It is unlikely that such data would be available of continental level at an appropriate resolution for inclusion within the model. Regarding the reviewer's comment that a possible south-westerly expansion may reflect a data artefact, we emphasize that this this a key point of the paper. Our analysis highlights that the possible expansion of the meningitis belt region is likely driven by unconfirmed cases of suspected meningitis in the ***Democratic Republic of the Congo (DRC). Within this paper we argue that the apparent extension of the belt into the Republic of Congo, Gabon and Angola does not represent a climate driven shift in the meningitis belt but is instead likely an artefact of reporting practices in the DRC,*** *with far fewer laboratory confirmed cases relative to neighbouring regions.*

1. Are sufficient details of methods and analysis provided to allow replication by others? **Partly**
   Parameter details for clustering (e.g., exact number of clusters chosen, initialization, random seed, convergence criteria) are not fully described.

We have updated the methodology section of our paper to include parameter details for clusters,

including number of clusters chosen, number of starts and convergence criteria. Alongside this our extended data includes random seeds and elbow plots for all variables, allowing for improved reproducibility. We have rerun the k-means clustering analysis increasing both the number of random starts and iterations from the default settings. In addition, district level outbreak weighting was subsequently adjusted to optimise sensitivity and specificity.

1. If applicable, is the statistical analysis and its interpretation appropriate? **I cannot comment**. A qualified statistician is required.
2. Are all the source data underlying the results available to ensure full reproducibility? **No**
   The environmental source data are open, but the epidemiological data and processed datasets are not accessible, which prevents full reproducibility.

All datasets apart from the raw epidemiological surveillance data which is subject to data sharing restrictions from the World Health Organisation are publicly available. All processed datasets are available as part of the underlying data. Figshare: Updating the meningitis belt: associations between environmental factors and epidemic meningitis risk across Africa- Supporting data 10.6084/m9.figshare.29900975). Furthermore, within the manuscript we have documented all processing steps applied to the epidemiological data and made the R code publicly available on GitHub.

1. Are the conclusions drawn adequately supported by the results? **Partly**
   Conclusions are partly supported by the results. The findings regarding rainfall, dust (AOD), and humidity as key environmental drivers, as well as the persistence of the Sahel as the primary high-risk zone, are demonstrated. However, the assertion of a south-westerly expansion of the meningitis belt (into Congo, Gabon, Liberia, and Angola) is less robust.

Regarding the south-westerly expansion of the meningitis belt, as mentioned above this paper argues that this is likely an artefact of reporting practices within the Democratic of Congo. ***Within the paper conclusion we advocate for the improvement of*** *epidemic reporting and diagnostic capacity within meningitis outbreaks, to accurately assess disease risk across the continent.*

Competing Interests: No competing interests were disclosed.