

Locally-informed risk maps for yellow fever: a modelling study in Ghana

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Abstract

Yellow fever (YF) outbreaks continue to occur in Africa and South America despite an effective vaccine. Knowing where and when certain areas are at greatest risk for YF could enable targeted allocation of resources for outbreak prevention and detection. While global risk maps of YF and other epidemic-prone pathogens exist, more granular models are needed for decision-makers. Therefore, we constructed a process for co-developing infectious disease risk maps with national experts and applied this process to model YF risk in Ghana. We collected local-level data on 14,534 patients tested for YF and eco-epidemiological covariates in Ghana from 2005–2024. We then created subnational risk maps for YF using ecological niche models that combined spatial epidemiological analysis and feedback from public health experts in Ghana. These risk maps can be used to inform targeted vaccination campaigns and diagnostic resource allocation. Our results demonstrate how local public health data can be combined with high-resolution earth observation data and expert feedback to create risk maps for infectious diseases such as YF that can directly inform subnational and national policy decisions.

Introduction

Yellow fever (YF) is a vaccine-preventable, mosquito-borne viral hemorrhagic fever. Multiple recent YF outbreaks have occurred in Africa and South America, raising concern for further resurgence. The Eliminate Yellow Fever Epidemics (EYE) strategy was launched by the World Health Organization (WHO) in 2017 with the goal of eliminating YF epidemics by 2026.¹ While the EYE strategy has increased YF immunization coverage, large outbreaks continue to occur due to gaps in vaccine-induced immunity.² Environmental change, urbanization, and human mobility also contribute to increasing YF risk over time.¹ Better understanding of where and when YF outbreaks are most likely to occur could enable targeted prevention strategies, including vaccination campaigns, community education, and vector control. Such targeted strategies will be increasingly important on a subnational level as the EYE strategy sunsets at the end of 2026, shifting the economic burden of implementation to countries and subnational jurisdictions.³

While risk maps can inform targeted interventions,^{4,5} maps must reflect the geographic scale of implementation to be useful for this purpose. Unfortunately, existing risk maps for YF and other mosquito-borne viruses have been primarily constructed at continental or global scales; a recent systematic review found no subnational risk maps for YF.⁶ Similarly, existing YF risk maps – designed more for burden estimation than local- or national-level decision-making – have included only limited local data or involvement of national experts. Novel data streams and methods provide the opportunity for a new generation of risk maps for arboviruses.⁷ Therefore, there is a need and an opportunity to develop subnational risk maps for arboviral diseases such as YF that incorporate local insight and granular data.

Ghana is one of 27 high-risk countries for YF as defined by the EYE strategy. Public health officials from the Ghana Health Service (GHS) consider subnational risk maps for YF to be potentially helpful for

planning future vaccination campaigns and optimizing diagnostic strategies.⁸ While risk maps for YF have previously been created,^{9–12} these maps lack the granularity, recent data, and local expertise needed for actionable insight in Ghana. The most recent global risk map for YF used only 25 cases from Ghana, primarily at the district level or higher.¹¹ Therefore, our aim was to co-develop subnational YF risk maps for Ghana using local data and a process that could be applied to other settings.

Given the need to better understand subnational YF risk in Ghana, our study had three main goals. First, we aimed to characterize the recent epidemiology of YF in Ghana using granular line-level surveillance case data. Second, we co-developed subnational risk maps for YF in Ghana using ecological niche models (ENMs). Lastly, we compared the predictive performance of these risk maps and obtained feedback from national public health experts to refine these maps for better decision-making.

Methods

Ethics statement

This research was determined to be exempt by UCLA IRB (IRB-25-1440) and approved by the Ghana Health Service Ethical Review Committee (GHSERC: 005/05/19).

Setting

The Republic of Ghana has 16 regions, which have been further divided into 261 administrative districts since October 2021 (Fig S1). Many public health decisions are made at the district level, which was the focus of our analysis. For the purposes of this study, we used the administrative boundaries from the 261 districts shared via the Ghana Statistical Service (Appendix). Because YF is a climate-sensitive mosquito-borne disease, we also analyzed the spatial epidemiology by ecological zones in Ghana. Districts were found to predominantly fit into five different ecological zones: Coastal Savanna, Wet Evergreen, Deciduous Forest, Transitional Zone, and Guinea Savanna (Appendix, Fig S2).¹³ The Guinea Savanna zone in the north of the country has a single rainy season, whereas the southern zones have bimodal rainy seasons, which influence vector dynamics and YF risk.^{13–16}

There are three main forms of YF vaccination in Ghana and other African countries: routine childhood vaccination, preventative mass vaccination campaigns (PMVCs), and reactive vaccination campaigns. The EYE strategy has aimed to achieve at least 50% YF vaccination coverage in endemic African countries, with 80% coverage being the recommended threshold for herd immunity.¹ Routine childhood vaccination for YF was implemented in 1992 in Ghana as part of the Expanded Programme on Immunization (EPI). The YF vaccine is normally given at 9 months after birth, or at 12 months if missed at the 9-month routine vaccination schedule. All travelers to Ghana are required to have proof of prior YF vaccination or medical exemption. From meetings with the Ghana Health Service, we learned that risk maps incorporating vaccination coverage could inform the planning of future vaccination campaigns.

In West Africa, initial testing for YF (after symptomatic presentation) is performed at national laboratories, and positive samples are then sent for confirmatory testing at the regional reference laboratory in Dakar, Senegal. In Ghana, initial YF testing is done via YF ELISA IgM at the National Public Health and Reference Laboratory (NPHRL) in Korle Bu. Confirmatory testing [plaque reduction neutralization testing (PRNT) and reverse transcriptase polymerase chain reaction (RT-PCR)] are done at the regional reference laboratory. Given the timing and resources involved in confirmatory testing, not all YF specimens undergo confirmatory testing, and multiple YF IgM positive cases in Ghana are sufficient to prompt an outbreak response.⁸ Because of resource constraints and delays in diagnostic testing⁸, risk maps could also inform where to target YF testing in Ghana.

Identifying yellow fever outbreaks and cases

We used multiple sources to identify YF cases in Ghana to include in our analysis. Line-level surveillance case data from the GHS were available from 2005–2024. Data from 2007 were unavailable; however, no YF cases were reported in Ghana during this year.¹⁶ The GHS data were obtained from querying the Epi Info and SORMAS databases for all individuals tested for YF. We compared these line level surveillance data with public health reports from a prior literature review.¹⁶

For our eco-epidemiological analysis, we included cases from the GHS that met the YF case definitions (suspected, probable, and confirmed) per the Integrated Disease Surveillance and Response (IDSR) third edition¹⁷, which are the operational definitions used for YF in Ghana (Appendix, Table S1). Suspected cases included all cases tested for YF in Ghana. The RT-PCR results and PRNT confirmatory results were only available from 2023 and 2024, so most IgM positive specimens were treated as probable cases (Appendix). Because probable/confirmed cases more likely represent true YF cases, we included these in our modelling analysis. Data were georeferenced and cleaned to match the current administrative boundaries (Appendix).

Spatial analysis and modelling framework

We developed two parallel spatial statistical analysis and modelling approaches (Fig. 1). In the first approach, we conducted an exploratory spatial analysis at the areal level. We cleaned and aggregated YF cases to the levels of district, region, and ecological zone to analyze

spatial areal level patterns (Appendix). We obtained annual district population from WorldPop (www.worldpop.org) and used annual district population to map YF incidence per district from 2005–2024. We then calculated local Moran's I to compare spatial autocorrelation/hotspots among confirmed/probable and suspected cases (Fig S3, S4).

For our second approach, we georeferenced the locations of confirmed/probable YF cases (Appendix). We then used the L function to compare clustering of cases and created a kernel density estimate, which

we used to adjust for sampling bias in the ENMs (Fig. S5, S6). We then used these case occurrence locations as the input for our ENMs. Machine learning methods have been most often used to develop risk maps of arboviral diseases such as YF that include point pattern occurrence data.⁶ Therefore, we selected three machine learning methods that have been previously used to develop YF risk maps: maximum entropy (Maxent), random forest (RF), and boosted regression trees (BRT).^{11,12,16} We then developed ENMs at 1 x 1 km resolution, the output which could be interpreted as suitability for YF occurrence.

The two parallel modelling approaches in the study are shown: (1) spatial areal level case data were analyzed to identify disease hotspots, and (2) point-pattern occurrence data and covariates were analyzed using ecological niche models/risk maps. Yellow fever case data are shown in blue, ecological covariates in green, and sociodemographic covariates in brown.

Covariate selection

Modelling the risk for YF requires understanding the regional eco-epidemiology. In Africa, YF is transmitted by *Aedes* mosquitoes circulates through the sylvatic, savannah, and urban cycles.¹⁸ While sporadic YF cases and outbreaks are most likely to begin via the sylvatic/savannah cycles in Ghana, the urban cycle driven by *Aedes aegypti* is most concerning for epidemics.¹⁶

Considering these ecological transmission cycles, we conducted a literature review to identify pertinent covariates that have been used in YF models and risk maps. This included a recent systematic review on the methods used to map *Aedes*-borne arbovirus risk.⁶ Key factors identified in previous studies for YF risk included temperature, precipitation, elevation, vegetation, immunization coverage, human population density, built environment, and distribution of vectors/non-human primates (NHPs).^{11,12,16,19–24} We created a causal conceptual framework to identify the key covariates to include in our model (Fig S7). From our framework we identified precipitation, temperature, vegetation, elevation, YF immunization coverage, built environment, and human population density as key potential drivers of YF human cases. Vectors and NHPs lacked comprehensive granular data in Ghana and were unobserved mediators in the framework, thus were not included in the models. We considered including global predictions on *Aedes aegypti* habitat suitability, which have been included in prior YF risk maps; however, these data are only available at a coarser spatial resolution and include few observations from Ghana. Additionally, removing this layer had minimal effect on prior global models.¹¹

Because ENMs predict environmental suitability by averaging spatial covariates and occurrences over time, it is inherently challenging to account for dynamic human interventions such as vaccination, which may change in response to outbreaks. Furthermore, recent frameworks for infectious disease risk mapping have emphasized that risk (the likelihood of disease) is a function of exposure to a hazard (pathogen/vector presence) and human vulnerability (i.e. vaccination status).^{25,26} Because of these factors and that YF vaccination data was only available at the district level in Ghana, we maintained YF

immunization coverage as a separate spatial component and included it in the final bivariate risk map. Therefore, the final risk map identified areas of overlap between high environmental suitability and low vaccination coverage as the areas at greatest risk for new YF outbreaks.

Covariate data

Spatial covariate data were collected from multiple sources as detailed in the Appendix (Table S2). High-resolution earth observation data were used for ecological covariates including bioclimatic variables (temperature, precipitation), elevation, and vegetation [measured as forest edge density and normalized difference vegetation index (NDVI)], as well as sociodemographic covariates including population density and built environment. We used correlation matrices and stepped pairwise selection to exclude members of covariate pairs with a correlation coefficient of $>|0.7|$ (Appendix). All of the covariates were standardized to a mean of 0 and variance of 1. The final selected covariates for the ENM included mean temperature of the coldest quarter, precipitation of the wettest quarter, NDVI, elevation, built-up area, and forest edge density. The maps of the covariates in Ghana are available in the Appendix (Fig S8).

To estimate annual YF vaccination coverage per district to include in the final risk map, we developed an age-structured cohort vaccination model (Appendix, Fig S9). This model included district-level data on routine infant immunization from the GHS and supplementary vaccination campaigns, building upon prior methods and estimates from 2000.²⁷ The model output was annual district-level YF immunization coverage in Ghana from 2000–2025. We used the most optimistic estimate of YF immunization coverage (assuming only unvaccinated populations are targeted in campaigns) in the final risk map. We categorized district vulnerability as high ($> 40\%$ unvaccinated), moderate ($20\text{--}40\%$ unvaccinated), and low ($< 20\%$ unvaccinated), based on EYE strategy thresholds.

Ecological niche models

We followed an ENM checklist for georeferencing occurrence data, processing covariates, calibrating/tuning models, and evaluating output (Table S3).²⁸ Full details of the modelling process are available in the Appendix. The final ENM included 130 unique occurrence locations from 2005–2024. Of these occurrences, 97 from 2005–2023 were used for training and 33 from 2024 were held out for testing. We compared three of the most popular machine learning algorithms for ENMs (Maxent, RF, and BRT), which have been previously individually used to model YF risk.^{11,12,16} To account for spatial autocorrelation, model calibration and tuning were done using 4-fold hierarchical checkerboard spatial block cross-validation on the training data. We used a grid search to compare hyperparameter scenarios and compared model performance based on the Continuous Boyce Index (CBI) and to break ties, the lowest average omission rate at the 10th percentile (OR10). The CBI is a threshold-independent metric for models that use presence-only occurrence data and is on a scale from -1 to 1 , with values close to 1 indicating strong positive correlation between occurrences and predicted suitability.²⁹ Final validation was done using out-of-sample prediction for 2024 (Appendix). The change of CBI values between cross-

validation and out-of-sample prediction were used to assess model overfitting and overall performance. A summary of model cross-validation and testing results is available in Table S4. Using the same testing data, we compared the predictive performance of our local model to the most recent global risk map for YF.¹¹

The Maxent version of the local model performed best, while the RF and BRT were prone to overfitting based on validation metrics and response curves. During the risk map co-development process, further described below, we learned that categorical risk maps with high, moderate, and low risk categories could be more useful for decision-makers. Therefore, the continuous ENM output of the best fitting Maxent model was transformed into a categorical risk map using the cutoff of the OR10 training presence threshold for the moderate-high threshold and the minimum training presence (MTP) threshold for the low-moderate threshold. This categorical map was then combined with district-level YF vaccination coverage estimates from 2025 to produce the final bivariate risk map.

Risk map co-development and feedback

We created a two-phase process of risk map co-development and feedback (Fig. 2). First, we co-developed the YF risk maps with disease surveillance officers at the GHS and researchers at the University of Ghana School of Public Health. This ensured that the public health officers who use and manage the YF surveillance data had input on the full development process (conceptualization, data collection/cleaning, covariate selection, spatial analysis/modelling, and risk map output). During this phase we held weekly meetings to collaborate on the risk maps and integrate recommendations. Examples of specific recommendations included (1) to use the GHS operational definitions for YF cases, (2) to use the administrative district boundaries from the Ghana Statistical Service, (3) to create high-resolution (1 km²), categorical versions of the maps, (4) to maintain consistent color palettes for environmental suitability across all maps, and (5) to use contrasting colors/layers for suitability and vaccination.

The timeline shows the process from risk map conceptualization to creation. The co-development phase is shown with the approximate proportion of activity during each step shown for the disease surveillance team (orange) and the modelling team (blue), which both consisted of staff from the Ghana Health Service and academic researchers. The final risk maps were shared with the leadership and public health decision-makers at the Ghana Health Service on August 13th, 2026.

For the second phase, we obtained feedback from public health officials in Ghana who were not directly involved in the risk map development process. We held a symposium in Accra, Ghana on August 13th, 2026, where we invited key public health leaders and decision-makers involved in YF prevention and control in Ghana. The participants included representatives from the Public Health Division; the Policy, Planning, Monitoring and Evaluation (PPME) Division; Disease Surveillance Department; EPI; and the NPHRL.

During this symposium, we used a two-step mixed-methods approach to obtain feedback from public health experts on the risk maps. In step 1, we presented the risk maps with a cross-sectional survey which included questions mapped to specific implementation outcomes. We used the implementation outcomes framework³⁰ and prior questions from the WHO Technical Advisory Group on Arboviruses to identify potential survey questions.¹¹ Because our primary goal was to evaluate risk map acceptability, which is a multi-faceted construct, we used the theoretical framework of acceptability to group the questions into more measurable acceptability outcomes.³¹ These outcomes included affective attitude (alignment of risk maps with expectations), ethicality (influence of development source), perceived effectiveness (operational relevance), self-efficacy (likelihood of adoption), and burden (barriers to use). The anonymous survey was administered using Qualtrics survey software (Qualtrics, Provo, UT). The survey questions and aggregated results are presented in the Appendix. Following the risk map presentation and survey, we engaged participants in a semi-structured feedback session to discuss the aggregated survey results.

Results

Yellow fever surveillance in Ghana

From 2005–2024 there were 14349 suspected, 154 probable, and 31 confirmed YF cases in Ghana. There were 15097 specimens collected for YF testing from these 14534 individuals. Of these tested individuals, 185 (1%) represented probable/confirmed YF cases. The median age of suspected cases was 10 years old (IQR 3–23) and of probable/confirmed cases was 12 (IQR 4–24) (Table 1). The majority of cases were male (57%) and lived in rural areas (64%). Overall, 32% of cases had reported prior YF vaccination, including 29% (53/185) of probable/confirmed cases. The median age of probable/confirmed cases with reported prior YF vaccination was 4 years old (IQR 2–9). Out of the 31 confirmed cases, five had a self-reported history of prior YF vaccination, including one patient who as RT-PCR positive (unknown vaccination date).

Table 1
Yellow fever cases in Ghana 2005–2024

Age (years)	Suspected (N = 14349)	Confirmed/Probable (N = 185)	Total (N = 14534)
0–14	8140 (56.7%)	97 (52.4%)	8237 (56.7%)
15–29	3343 (23.3%)	47 (25.4%)	3390 (23.3%)
30–44	1615 (11.3%)	25 (13.5%)	1640 (11.3%)
45–59	506 (3.5%)	7 (3.8%)	513 (3.5%)
60+	196 (1.4%)	5 (2.7%)	201 (1.4%)
Missing	549 (3.8%)	4 (2.2%)	553 (3.8%)
Sex			
Female	5656 (39.4%)	68 (36.8%)	5724 (39.4%)
Male	8125 (56.6%)	117 (63.2%)	8242 (56.7%)
Missing	568 (0.4%)	0 (0%)	568 (0.4%)
Residence			
Rural	9251 (64.5%)	95 (51.4%)	9346 (64.3%)
Urban	2631 (18.3%)	27 (14.6%)	2658 (18.3%)
Missing	2467 (17.2%)	63 (34.1%)	2530 (17.4%)
Prior YF vaccination (self-reported)			
No	9788 (68.2%)	132 (71.4%)	9920 (68.3%)
Yes	4561 (31.8%)	53 (28.6%)	4614 (31.7%)

District, regional, and ecological zone trends

The district-level incidence of YF cases from 2005–2024 are shown in Fig. 3. Both probable/confirmed and suspected YF incidence increased during the study period and tended to correlate at the district level. Incidence was highest in the northwest of the country (i.e. Savannah and Upper West regions). Hotspots and clusters were identified predominantly in the Savannah region (Fig S3-6), with most cases corresponding to the 2021–2022 outbreak that originated in the West Gonja district near Mole National Park.

The mapped district-level incidence of (a) probable/confirmed and (b) suspected YF cases in Ghana are depicted in 5-year intervals (2005–2009, 2010–2014, 2015–2019, 2020–2024). Districts that had zero

reported cases during these periods are shown in white.

Figure 4 and Fig. 5 depict the incidence of YF and changes in key YF determinants by ecological zone. Both YF incidence and testing were highest in the northern zones (Guinea Savanna and Transitional Zone) and increased over time. Vaccination coverage levels, temperature, and urbanization also increased over time. By 2025, YF vaccination coverage was estimated to exceed 80% in 148/261 (57%) of districts. Nevertheless, the greatest incidence of YF occurred in 2021 and 2024.

The line graphs depict the annual incidence (per 100,000 persons) of (a) confirmed/probable YF and (b) suspected YF, by ecological zone. The map in panel (c) shows the five ecological zones in Ghana, with colors corresponding to the lines in panels (a) and (b).

The line graphs show the annual (a) mean temperature of the coldest month (in degrees Celsius), (b) annual rainfall (in mm), (c) annual normalized difference vegetation index (NDVI) (standardized scale from 0 to 1, 1 = most vegetation), (d) YF immunization coverage (estimated proportion of population), and (e) built-up area (proportion of built/urban area), by ecological zone. Panel (f) depicts the ecological zones in Ghana.

Risk map output and testing

The continuous and categorical output from the best performing ENM is shown in Fig. 6. The optimal model had an average cross-validation training CBI of 0.87 and test CBI of 0.94. Full performance metrics are available in Table S4. Using the same 2024 testing data, the most recent global YF risk map from Lim et al. 2025 had a lower test CBI of 0.85 and also predicted the lowest environmental suitability near Mole National Park and the West Gonja district, which had the highest incidence of YF during the study period (Figure S10).

In the best performing ENM, there was positive association between YF environmental suitability with higher mean temperature of the coldest quarter, greater precipitation of the wettest quarter, more vegetation (NDVI and edge density), higher elevation, and greater built surface area. Based on variable permutation importance, the two most important factors were built surface area and mean temperature of the coldest quarter (Table S5). The model uncertainty is shown in Figure S11 and the response curves in Figure S12.

Figure 6. Ecological niche model for yellow fever in Ghana, 2005–2024

The ecological niche model (ENM) maps for yellow fever in Ghana are shown based on (a) mean continuous suitability and (b) categorical suitability.

The final bivariate risk map shared with public health officials in Ghana is shown in Fig. 7. The Western and Western North regions had the lowest estimated vaccination coverage, 68% and 71%, and moderate and high environmental suitability, respectively. The Savannah, Northern, and Oti regions had > 80% vaccination coverage and high environmental suitability. The predominant environmental suitability at

the district-level strongly predicted cases in the out-of-sample testing. Of the 30 districts that had YF cases in 2024, 28 (93%) had predominantly moderate to high environmental suitability. However, district-level vaccination coverage was less predictive; only 12 districts (40%) with cases had a vaccination coverage of less than 80%.

The (a) categorical environmental suitability map and (b) predicted vaccination coverage in 2025 were combined to create (c) the bivariate risk map for yellow fever in Ghana. This risk map was shared with public health decision-makers at the Ghana Health Service.

Feedback from public health decision-makers

The results from the survey are shown in Fig. 8. Of the 11 respondents, 10 (91%) had at least 10 years of public health experience, and 7 (64%) reported direct experience working with YF. There was a high proportion of respondents who agreed/strongly agreed that the risk map aligned with their expectations of YF risk (9/11) and was effective for informing targeted vaccination (10/11) and diagnostic testing (9/11). During the feedback session, the public health officials noted that externally generated maps from the EYE strategy had been developed in response to prior outbreaks for vaccination, but that locally-developed maps would be useful for proactive targeted vaccination. They also emphasized that local risk maps could be helpful for prioritizing which specimens to test for YF, since there is currently a limited supply of diagnostic reagents available in-country.

The Likert scale responses from public health experts are shown in the stacked bar plots with the percentage and number of respondents depicted.

A higher proportion of experts agreed/strongly agreed that they were confident in internally (7/8) and co-developed (8/10) risk maps than in externally generated maps (4/7). While there was agreement about adopting this type of risk map for their work (9/11), public health officials noted barriers such as technical understanding. During the feedback session, participants liked that the bivariate maps could help identify where to target vaccination efforts. However, they also noted the limitations of missing YF data due to surveillance gaps and how this may influence the risk maps.

Discussion

This study provides new insights into the epidemiology of YF in Ghana, the ability of subnational risk maps to improve public health policy decisions, and the process of model co-development and feedback with local experts. As this was (to our knowledge) the largest study of YF in an African country, including 14,534 patients, we identified key features of YF epidemiology such as greater incidence among children. Meanwhile, our local risk maps effectively identified areas for targeted vaccination and surveillance, and the co-development process made them more accurate and acceptable for public health decision-makers.

The majority of suspected and confirmed/probable YF cases in Ghana occurred among male children, particularly those living in rural areas. This differs from the epidemiology of YF outbreaks in South

America, which primarily have occurred among middle-age and older males in forested areas.³² This may be due to differing ecological transmission cycles and/or human behavior in Africa versus South America. For example, there has been recent urban transmission of YF in Africa unlike in South America. Additionally, young males in Ghana may be more exposed to the savannah/sylvatic cycle from working in pastoral settings,³³ and there could also be gaps in routine immunization for children in Ghana.

There were also instances of YF potentially occurring among previously vaccinated individuals in Ghana, which warrants further investigation. In 2014 the WHO changed the YF vaccination policy to a single dose for life.³⁴ However, there has been debate over the duration of immunity and how this may vary based on the setting (YF endemic vs non-endemic regions) and age at time of vaccination.^{34,35} For example, a study of Ghanaian and Malian children found waning of immunity in infants vaccinated at nine months of age, suggesting that booster doses for children may be needed.³⁶ In our study, the majority of YF cases with reported prior vaccination were also children. Thus, additional cohort studies and YF case investigations are necessary to understand whether YF vaccine failure is occurring in African settings.

While YF incidence decreased substantially in Ghana since the implementation of routine vaccination in 1992,¹⁶ recent outbreaks have occurred despite continued increases in vaccination and testing. Higher urbanization and temperature were the most significant predictive factors in our models, which was consistent with the most recent global YF risk map.¹¹ Urbanization and temperature – both of which are increasing in Ghana – are known to increase habitat suitability for *Aedes aegypti* and risk of YF transmission.²²

Through combining estimates of habitat suitability with vaccination coverage, we were able to identify areas for future targeted vaccination. While the northern regions in Ghana (i.e. Savannah and Upper West regions) are known YF hotspots and have relatively high vaccination coverage, we identified new areas that could be at risk for YF. In particular, the Western and Western North regions were predicted to have high suitability (although with greater uncertainty) and the lowest overall vaccination coverage. There have been fewer YF outbreaks and reactive vaccination campaigns in these regions, which could increase risk for future emergence. Public health officials agreed that these regions are concerning because of less surveillance in these areas, forest habitat for NHP hosts, and frequent cross-border travel. Additionally, these regions have been the epicenter of a recent mpox outbreak.³⁷ Therefore, these could be additional regions for targeted vaccination and increased surveillance.

In terms of diagnostic resource allocation for YF, we found that all regions had increasing trends in YF testing, which could reflect investment from the EYE strategy as well as greater awareness for YF. The Guinea Savanna ecological zone (which includes the Savannah and Upper West regions) had the highest incidence of YF cases and testing rates. These regions were also previously found to have some of the greatest diagnostic delays for YF due to specimen transportation.⁸ Additionally, we learned that there are

limited YF diagnostic tests/reagents available in-country and YF risk maps could help with prioritizing which specimens to test.

Through the process of co-developing YF risk maps, we learned multiple lessons. First, by collaborating with disease surveillance officers, we ensured that our risk maps included relevant operational data. Second, by receiving iterative feedback on the preliminary versions of the risk maps, our final output was more tailored for public health decision-makers. Furthermore, not only did the predictive performance of the local risk map improve compared to the global risk map, but also co-development likely made the local risk map more acceptable (and therefore more likely to be used) by country-level decision-makers than an externally generated map.

A limitation to our analysis is that the passive surveillance system for YF in Ghana may have missed YF cases and could be biased by access to healthcare/population density. We partially accounted for this in the ENM by using the kernel density estimate to make the occurrence and background points share the same spatial bias; however, this may not account for all forms of bias. As with previous YF risk maps, we used the location of residence or healthcare facility as a proxy for where YF infection occurred, but it is possible that infection occurred in a different location. This could have contributed to underprediction of risk in rural compared to urban areas. Risk may also have been underpredicted in coastal areas, which was observed on the out-of-sample testing, likely due to edge effects. High-resolution line-level data were also limited prior to 2005, meaning that while our maps reflected recent risk, they may miss areas of historical occurrence. We conducted a sensitivity analysis to include additional occurrences from 1969–2005 from our prior literature review¹⁶, which did not significantly affect the prediction but was limited by the availability of granular historical data (Appendix, Table S6-7, Fig S13-15). Human mobility also was not included in the modelling approach, and unvaccinated populations may move into areas with high suitability, increasing risk for YF. We observed that multiple recent YF cases were reported in areas with relatively high vaccination coverage estimates, which could reflect the need for better understanding mobility and higher-resolution vaccination coverage. Ultimately, predicting where the next YF outbreak will occur remains challenging, and risk maps are only one step in a larger decision-making process. Despite these limitations, we found that local data-driven risk maps are more accurate and acceptable for informing sub-national public health decision-making.

In summary, YF remains an ongoing public health threat. While global risk maps have been made for YF, these are less actionable on a sub-national level because of their broad scope and limited inclusion of local data or expert input. As the EYE strategy transitions, YF risk maps that are locally-informed could be key for identifying high-risk populations and targeting resources. Such local risk maps could also be useful for other emerging and re-emerging infectious diseases. However, to be effective, these tools need to be developed and implemented in close collaboration with national experts.

Declarations

Potential Conflicts of Interest

The authors declare no conflict of interest.

Author Contribution

Conceptualization: SDJ; Data curation: SDJ, NS, EK, RO, MY, SM, BA, PQ; Formal Analysis: SDJ, NS, MY, RO; Funding acquisition: SDJ; Methodology: SDJ, NS, MY, BA, RO; Writing – original draft: SDJ; Writing – review & editing: SDJ, NS, MY, AA, DWD, LS, FAB, EK, RO, BA, SM, PQ, JHKB, JOC, SKD

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Data Availability

The individual line-level human data from this study contain protected health information and are restricted from public sharing. These data may be made available upon request, subject to approval from the Ghana Health Service and from institutional review boards. The district aggregate data and modeling inputs are available at: <https://doi.org/10.6084/m9.figshare.33325002>

Code availability:

Analyses were performed using R version 4.5.2 using the following packages: pacman, tidyverse, patchwork, gt, sf, spdep, terra, ggplot2, ggspatial, cowplot, spatstat, sparr, raster, readxl, ggplot2, viridis, geodata, ENMeval, dismo, ecospat, caret, thematic, paletteer, SDMtune, biscale. The R scripts are available at: https://github.com/Judson-Lab/YF_Ghana_RiskMap

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Figures

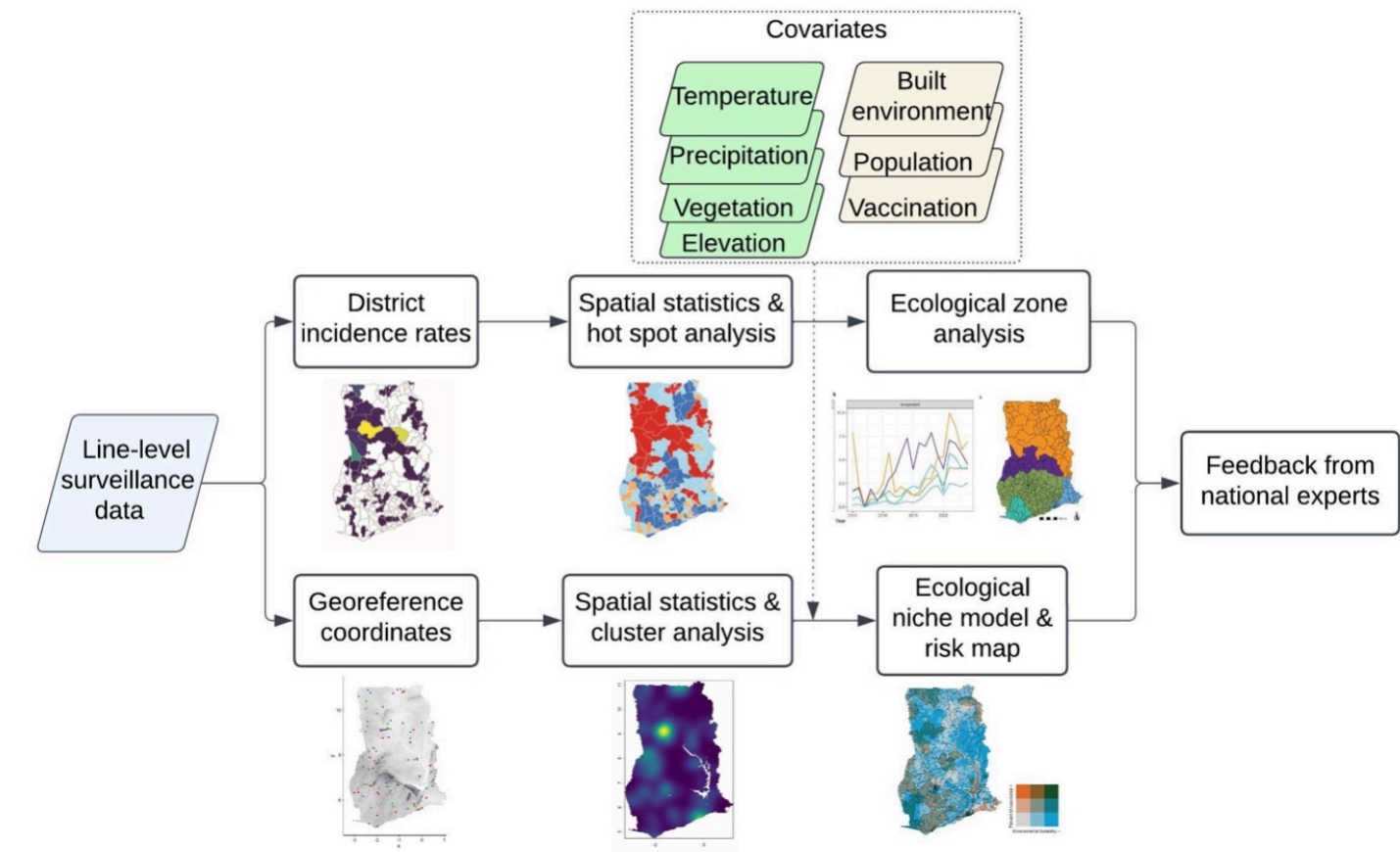


Figure 1

Flow diagram of modelling approaches for yellow fever risk maps.

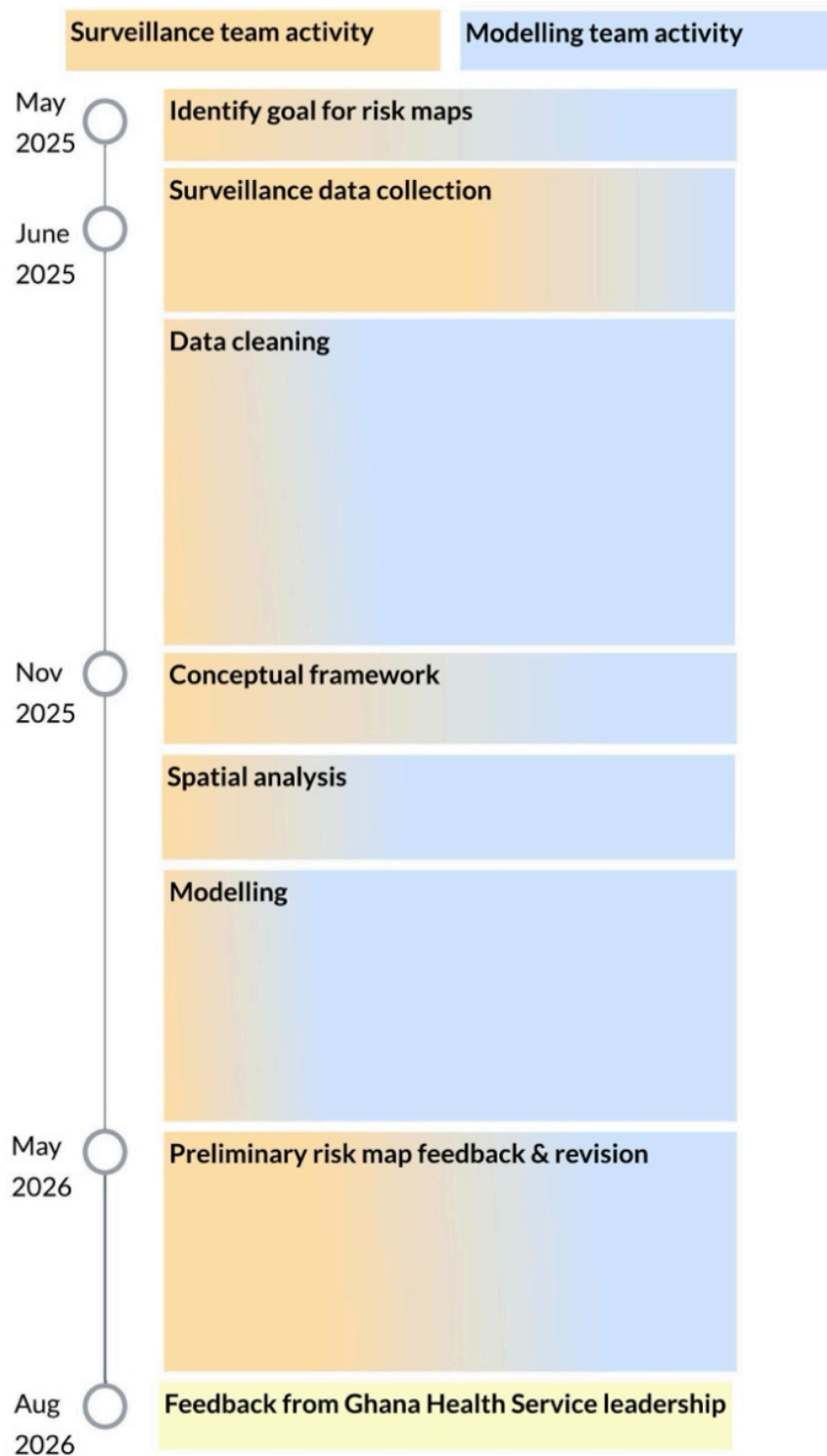


Figure 2

Timeline of risk map co-development process

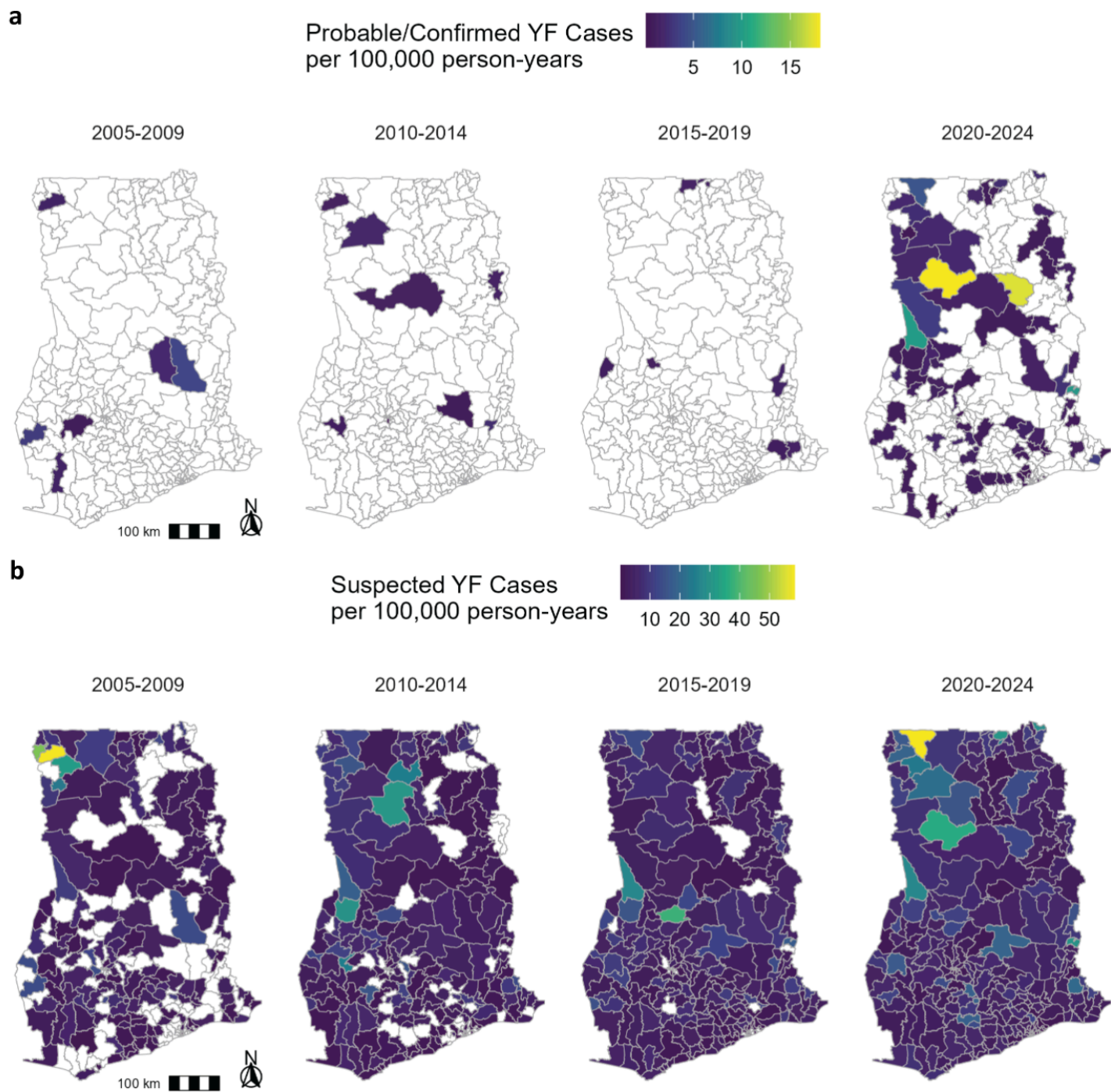


Figure 3

District-level incidence of yellow fever in Ghana, 2005-2024

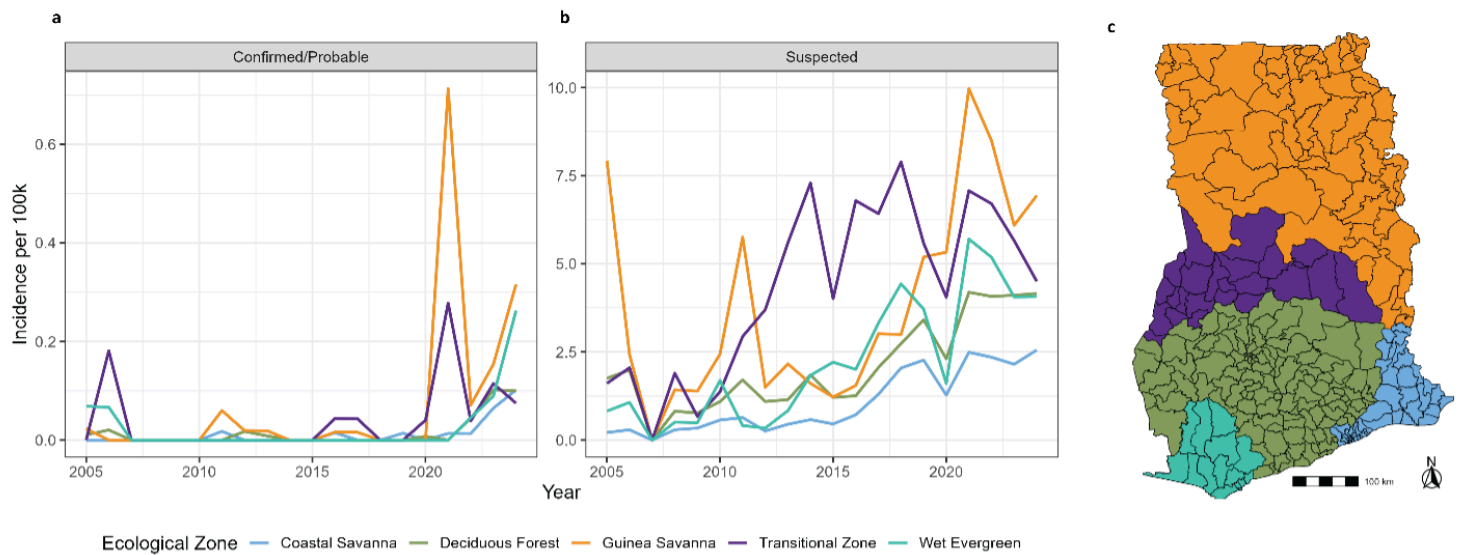


Figure 4

Annual incidence of YF by ecological zone in Ghana, 2005-2024.

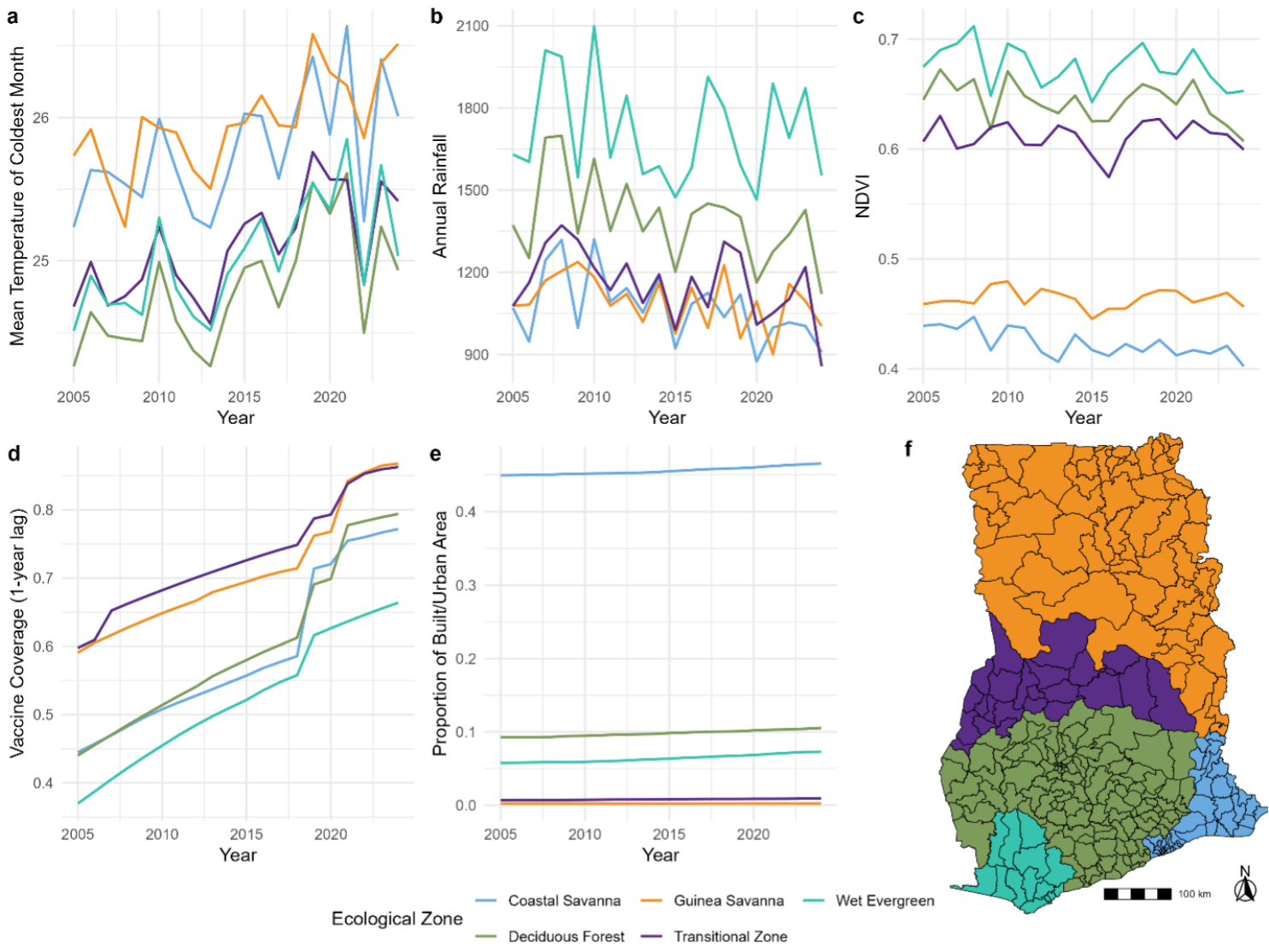


Figure 5

Annual covariates by ecological zone in Ghana, 2005-2024.

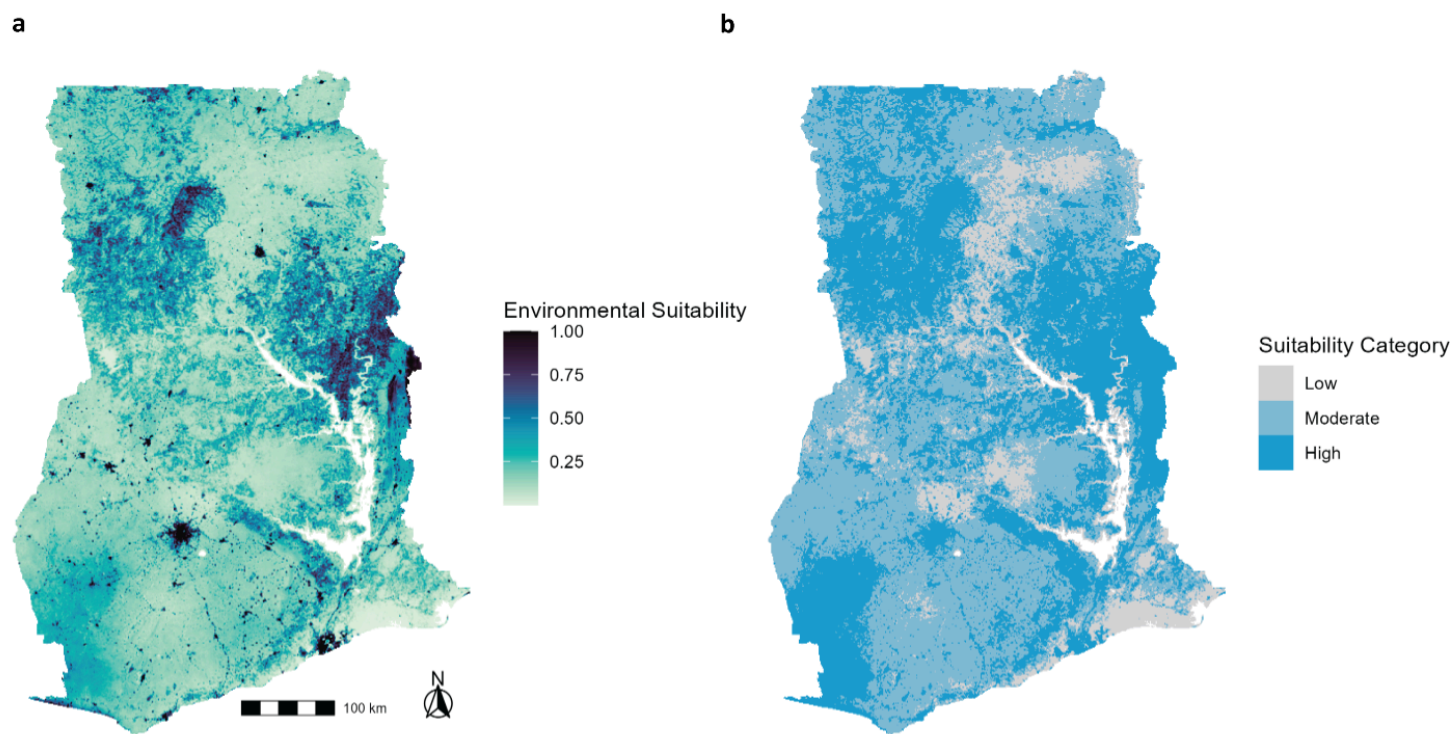


Figure 6

Ecological niche model for yellow fever in Ghana, 2005-2024

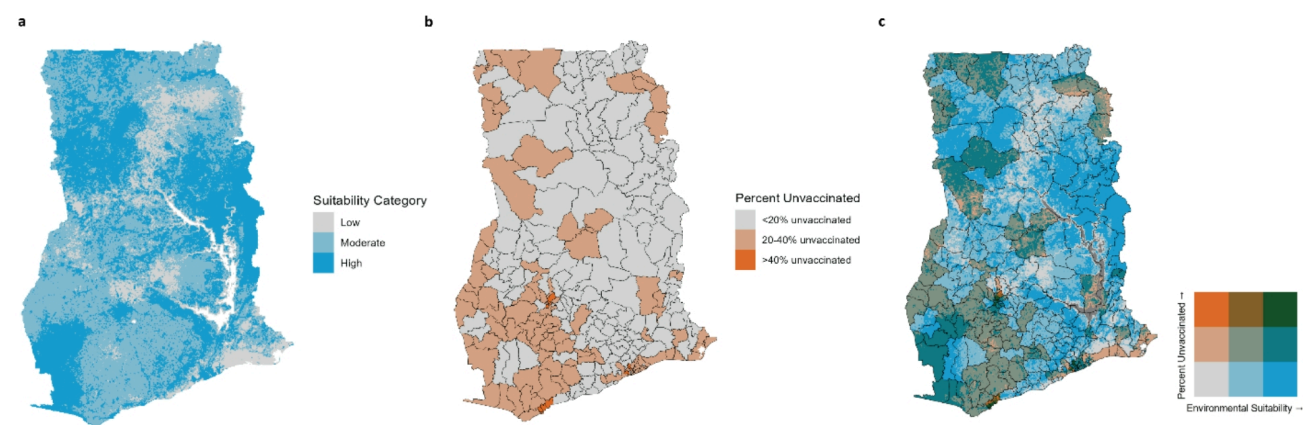


Figure 7

Risk map for yellow fever in Ghana

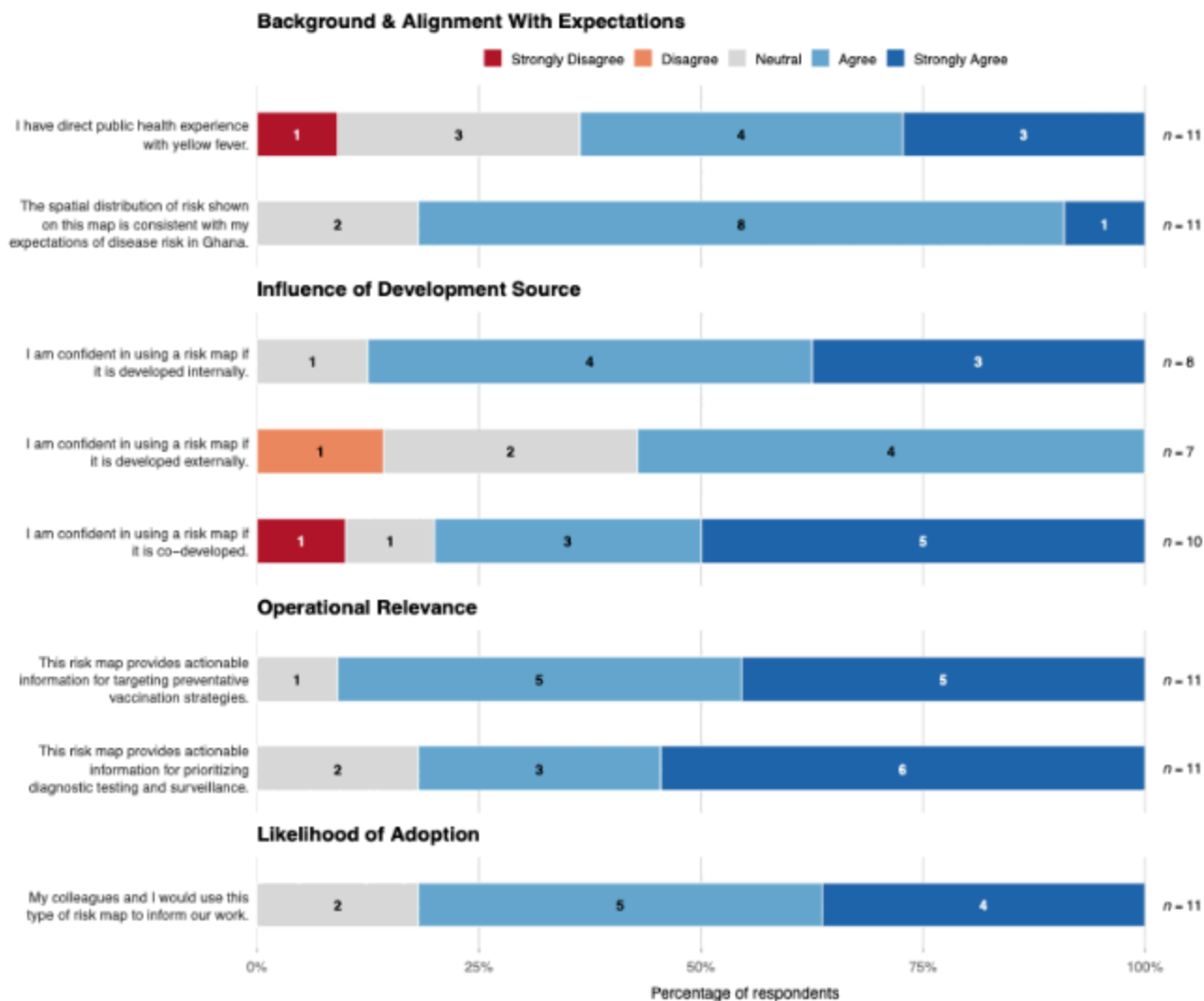


Figure 8

Survey responses regarding acceptability of yellow fever risk maps in Ghana

Supplementary Files

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- [Appendix9.9.26.docx](#)