

Background

Lassa fever remains a major public health threat in West Africa, with Nigeria experiencing recurrent outbreaks of varying intensity each year. Effective epidemic control depends on accurate epidemiological modeling; however, case data are compromised by under-reporting and inconsistent surveillance. Environmental drivers such as rainfall, temperature, and vegetation not only shape transmission dynamics but also influence the probability of case detection. Despite their importance, the role of these covariates in shaping reporting patterns remains poorly understood. Addressing this gap is essential for disentangling true transmission trends from surveillance artifacts and for guiding targeted interventions.

Objectives

The Objectives of the research are:

- Develop a scalable inference framework for epidemic modeling under noisy data.
- Quantify the extent of underreporting in Lassa fever surveillance.
- Capture the combined effects of climatic covariates on both transmission and reporting.

Methods

- A **Bayesian simulation-based inference (SBI)** framework was developed by extending the classical **SEIR (Susceptible–Exposed–Infectious–Recovered)** model with a covariate-conditioned, time-varying reporting function.
- The reporting function was parameterized by a neural network that maps weekly climatic covariates including **rainfall**, **mean temperature (bio1)**, **annual precipitation (bio12)**, and **vegetation index (NDVI)** to the probability of reported cases, thereby capturing seasonal and regional variation in surveillance performance.
- Joint posterior distributions of epidemiological parameters and reporting dynamics were estimated using **Sequential Neural Posterior Estimation (SNPE)** applied to **historical Lassa fever data** (Feb. 2015 - Oct. 2024) from the **Nigeria Centre for Disease Control**.

Results

Figure 1: The framework enables likelihood-free inference in the presence of latent, noisy, and partially observed surveillance data. The inferred reporting functions reveal distinct geographic and temporal patterns of reporting ($1 - \text{pr}(\text{underreporting})$), with surveillance performance varying seasonally and across regions.

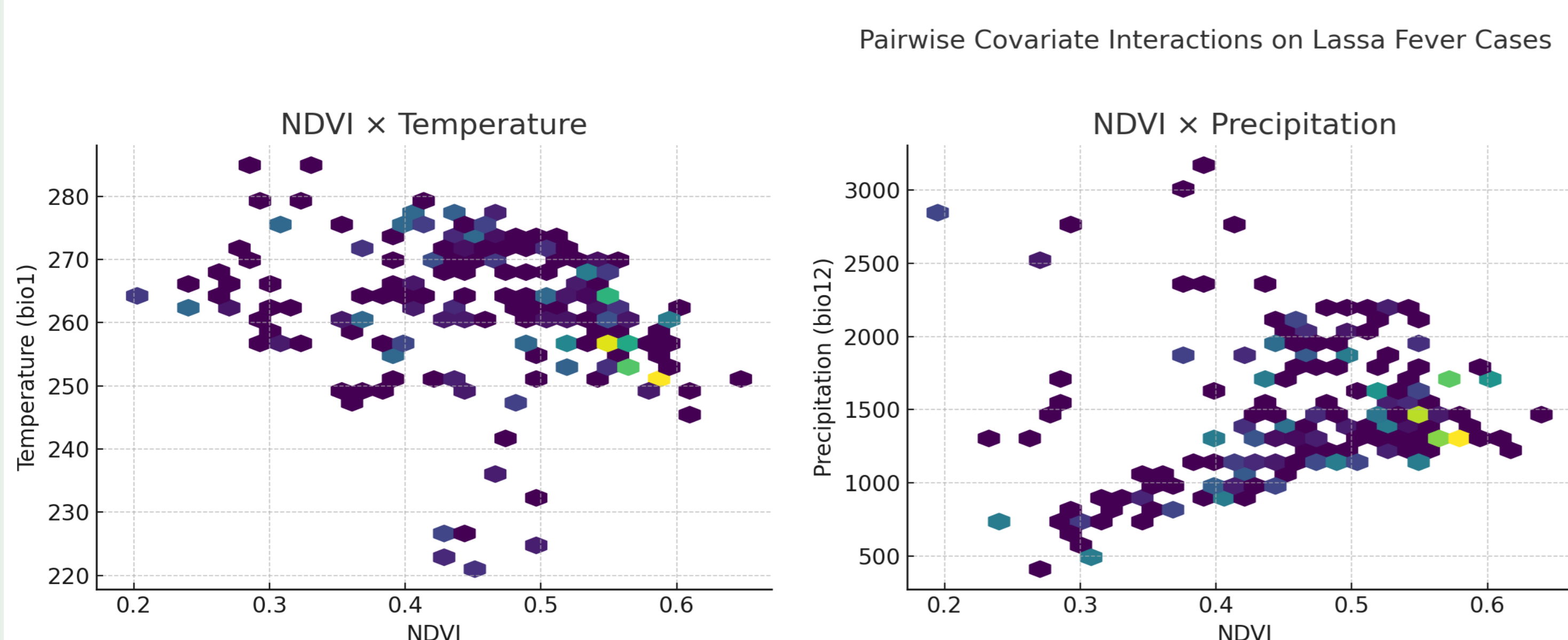
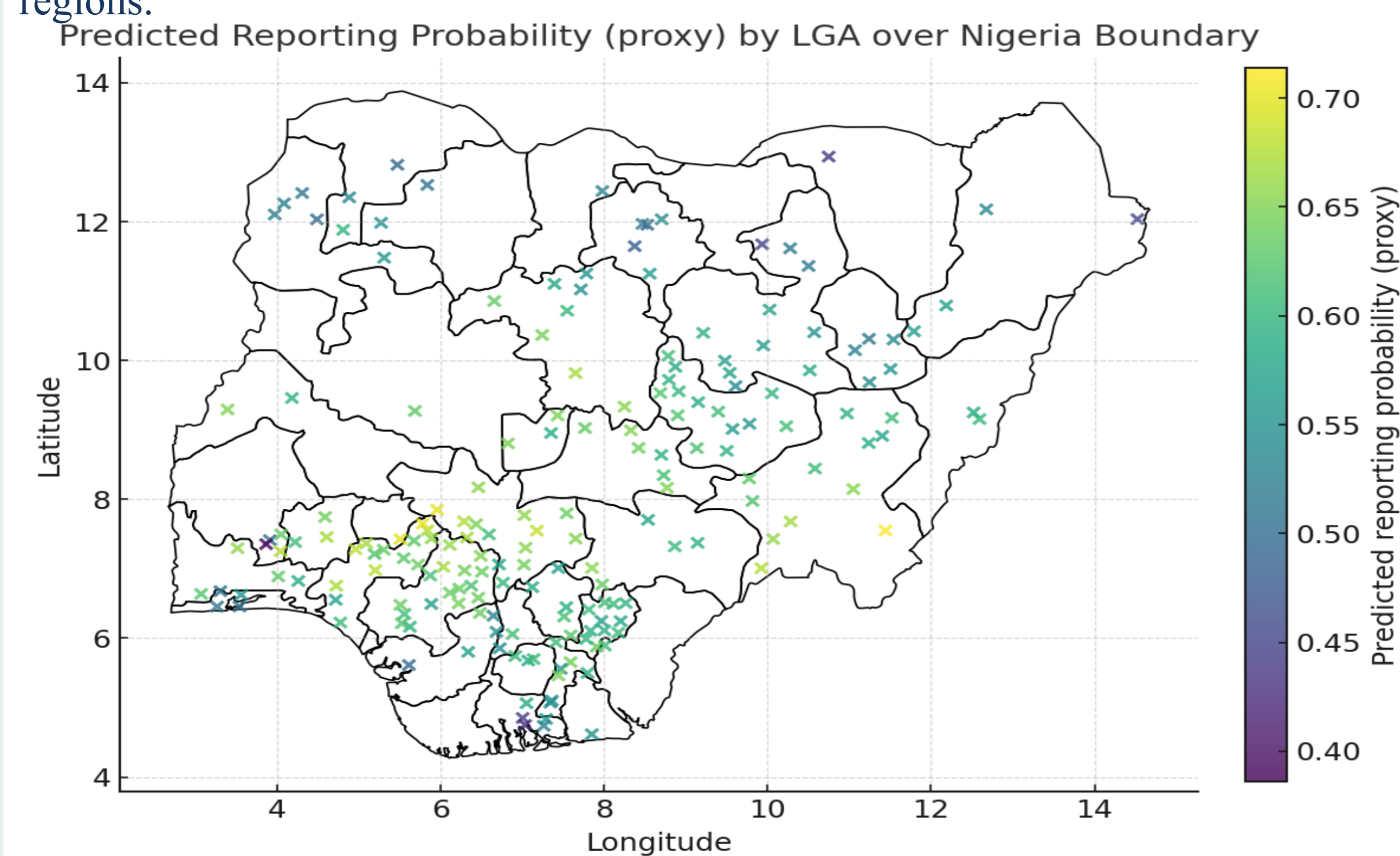


Figure 4: Pairwise covariate interaction on Lassa fever cases

Acknowledgement/Funding

This study is partially supported by the National Institutes of Health under Award Number U01AI151801 and D43TW012246. The funding body however had no role in the design of the study and collection, analysis, and interpretation of data and in writing the manuscript.

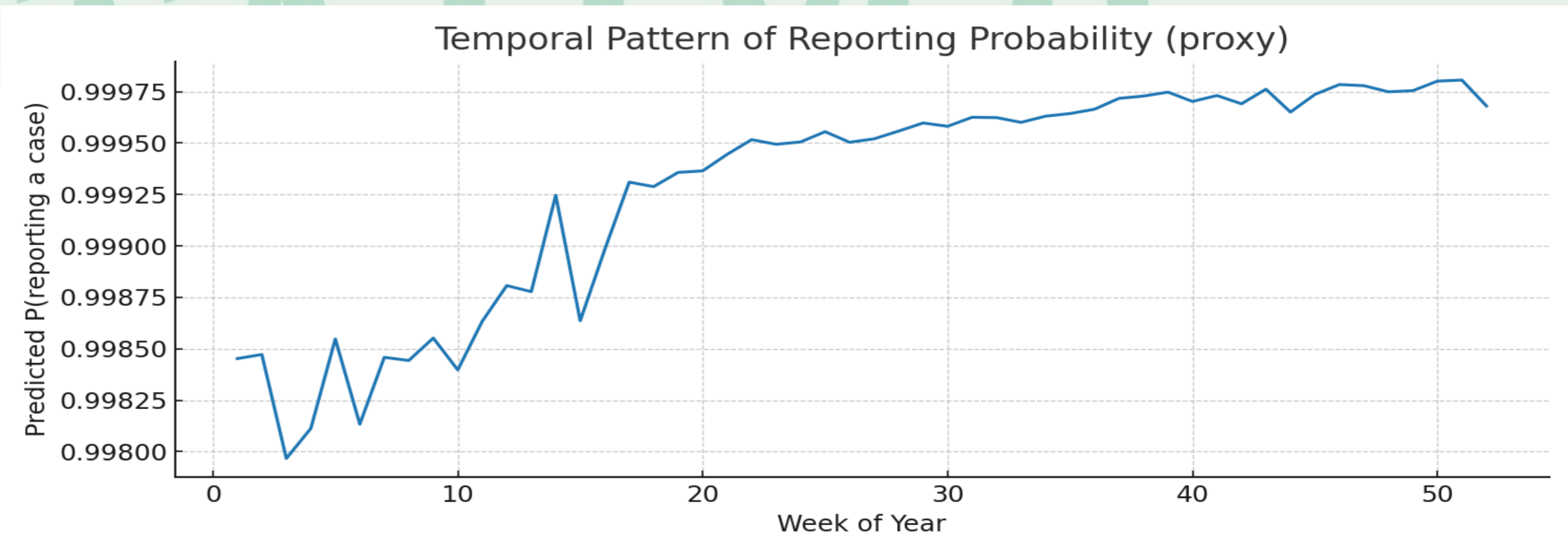


Figure 2: The inferred reporting functions reveal distinct geographic and temporal patterns of underreporting, with surveillance performance varying seasonally and across regions.

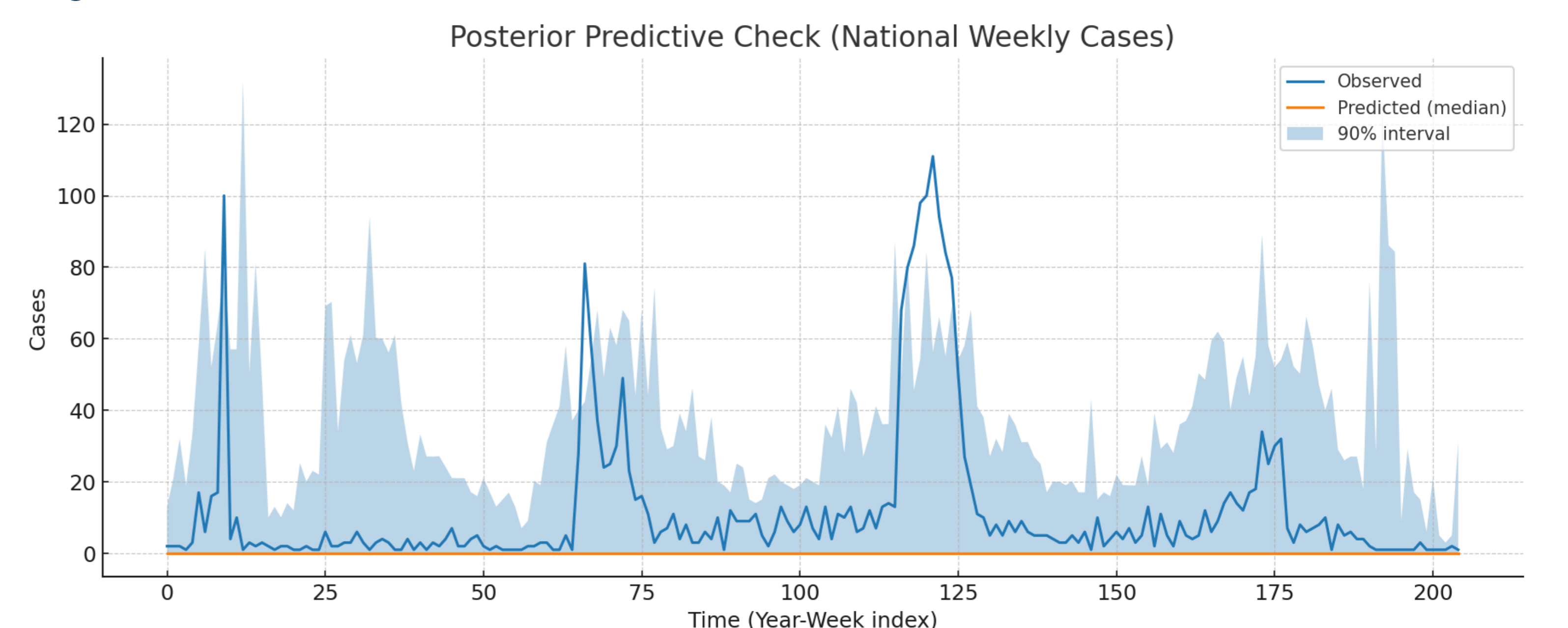


Figure 3: Posterior predictive checks demonstrate strong agreement between observed and simulated outbreak trajectories, supporting model validity.

Conclusion and Recommendation

This study demonstrate that integrating climatic covariates into a neural network–parameterized reporting function within a Bayesian simulation-based framework disentangles true transmission dynamics from reporting noise. This enables the inference of spatiotemporal patterns of under-reporting and the identification of regions where surveillance is weakest. The results highlight the dual value of environmental data: not only for improving transmission modeling but also for strengthening surveillance evaluation. These insights carry direct implications for epidemic forecasting, resource prioritization, and policy response to Lassa fever in Nigeria.

Future work will extend the model to incorporate socio-economic, demographic, health system, environmental, and ecological factors and will validate under-reporting estimates through surveillance audits and seroprevalence studies across Nigeria.