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Exploring the Spatio-Temporal Dynamics of the Association between Climate Variables and Post-Harvest Loss of Cassava across Benue State, Nigeria

Tersugh Matthew Agera[1]*, Msugh Moses Kembe[1,2] & Ayeni Omini Abam[3]
[1]Center for Food Technology and Research (CEFTER), Makurdi, Benue State, Nigeria
[2]Rev. Fr. Moses Orshio Adasu University, Makurdi, Benue State, Nigeria
[3]Department of Statistics, Federal University of Lafia, Nasarawa State, Nigeria

Abstract

Nigeria is reckoned as one of the world's largest producers of cassava and contributes around 60 million tonnes annually. Despite its significance, post-harvest losses remain high within communities. This study investigated the spatio-temporal dynamics and influencing factors of PHLs across Benue State, Nigeria. By the integration of classical spatial statistics with Bayesian hierarchical modelling via the Integrated Nested Laplace Approximation (INLA), the study analyzed how cassava PHL evolved over time across locations. Results from the study showed a consistent weak negative spatial autocorrelation (Moran's I ≈ −0.31, p ≈0.055–0.063), indicating no strong clustering of PHL values but a mild dispersion pattern. The Local Moran's I (LISA) analysis revealed no statistically significant hotspots or outliers. It was observed that mean PHL values increased modestly from 29,968 in 2021 – 31,917 in 2024 and LGAs such as Ado, Ukum, and Ogbadibo recorded the highest losses, while Katsina-Ala, Obi, and Ado exhibited the strongest increasing trends. Temperature was identified as a small but credibsle positive predictor of PHL. Strong spatial random effects as highlighted in Ado (0.629), Ukum (0.541), and Kwande (−1.278) showed areas with significantly higher and lower losses, respectively, after controlling for climatic variables. By providing a comprehensive spatio-temporal analysis of cassava PHLs across Benue State, our study fills a critical knowledge gap in agriculture and spatial statistics. The findings from this study provide location specific intelligence and suggest that interventions should prioritize high-loss LGAs while adopting a mix of targeted and state wide-strategies.

Keywords: Cassava, Post-harvest loss, Spatio-temporal analysis, Bayesian modelling, INLA

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****Correspondences***
T. M. Agera ✉
tersughagera@bsum.edu.ng

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Introduction

Cassava (*Manihot esculenta* Crantz) is one of the major staple crop in sub-Saharan Africa and is a cornerstone for food security, a source for livelihoods for millions of smallholder farmers in the region [1, 2]. Nigeria is reckoned as one of the world's largest producers of cassava and contributes around 60 million tonnes annually [3]. Benue State, a sub-national entity in Nigeria is known for its fertile lands which support diverse crop production and is often called Nigeria's "Food Basket". Even though cassava production is dominated by smallholder farmers, Benue remains one of the leading producers of the crop [4]. Cassava supports household consumption as millions consume it as garri, fufu, flour, and chips, also it serves as a source of income generation as well as industrial uses and plays a pivotal role in rural economies and national food systems [5, 6].

Despite being a drought resistant crop, cassava faces substantial post-harvest losses (PHL) due to the physiology of it tubers, with high moisture content of about 60 %, rapid post-harvest physiological deterioration (PPD) begins within 24–48 h of harvest [7, 8]. Thus, prolonged storage without processing could accelerate microbial spoilage, vascular streaking, and tissue softening which render its tubers unmarketable or unfit for processing [9]. Studies have shown that PHLs of cassava in Nigeria can reach 20–55 % along the value chain [10], and estimates from Benue State range from 20–40 % or higher during processing and storage phases [11]. These losses compromise household as well as national food security, reduced farmer incomes, and general economic shortfalls along the cassava value chain leading to elevated levels of hunger and poverty [12].

The dynamics of PHLs are inherently influenced by Climatic factors. For instance, rising temperatures are known to increase PPD and microbial activity, while erratic rainfall and high humidity promote fungal growth [13]. Studies have indicated that increased tuber water content could lead to faster deterioration after harvest and shorten the in-ground storage window for cassava tubers, heightening spoilage rates due to climate variability [14]. The ability of shifting climatic patterns to influence the biological rate of tuber decay [15] and the physical difficulty of transporting harvested tubers across different locations significantly influence PHLs [11]. Notably, above average temperature and humidity values can to lead increase in physiological stress in roots, create a more stable environment for pest and diseases and reduce the efficacy of traditional processing methods like cassava fermentation or drying [16].

In a region like Benue State, the spatio-temporal analysis of climate-crop interactions is limited, especially for post-harvest loss. Most studies consider pre-harvest yield impacts, but fail to explore how inter-annual variations in temperature, rainfall, and humidity across local government areas interact to drive differential loss rates in the state. Understanding these dynamics is critical in the context of designing all-encompassing mitigation solutions to PHLs in the state. Our study seeks to fill a critical gap by exploring how state wide average climate stressors interact with LGA specific production dynamics to amplify losses over time by employing Bayesian spatio-temporal modelling approaches specifically, the Integrated Nested Laplace Approximation (INLA). The study will decouple the influence of state-wide climatic averages from localized spatial dependencies. This approach will allow for a detailed understanding of how broader environmental trends influence the geographical "hotspots" of cassava loss over time.

The objectives are to map spatial and temporal distribution of losses, calculate the Moran's I, analyse inter-annual patterns, and establish statistical relationships that can inform policy and extension services for reducing cassava PHL in a changing climate, obtain posterior mean for the spatial random effects, as well as temporal random effects and Hotspot analysis.

Materials and Methods

Research design

Our study will employ a Bayesian Spatio-temporal modelling framework to explore the dynamics between climate variables and the PHL of cassava utilizing a Gamma distribution to model losses. This Bayesian approach which works by incorporating prior information to produce posterior distributions will be retrospective, harnessing PHL as well as climate data between 2021 and 2024. The study will cover the 23 Local Government Areas (LGAs) of Benue State, Nigeria.

Data sources

Annual production in tonnes of cassava across the 23 LGAs of Benue State were obtained from the Benue Agricultural and Rural Development Agency (BNARDA) capturing the period of our study (2021-2024). Data beyond 2021 was not available and this informed our decision to limit our study to the four-year cycle.

PHL values: As is the case with most developing countries, PHL data measured along the agricultural supply chain is scarcely available. As a result, several international organizations and empirical studies estimate postharvest losses indirectly using production statistics and commodity-specific loss coefficients derived from empirical studies or expert assessments [17-20]. For cassava PHLs, loss percentages are established between 20-40 % in multiple regions across Nigeria including Benue State [11, 21].

Using the above percentages as proportions, our study simulated postharvest loss values using a beta distribution which is appropriate for modelling variables bounded between 0 and 1. The beta distribution was given as

$$p_{ct} \sim Beta(\alpha, \beta) \qquad (1)$$

Where: $p_{it} = Proportion\ of\ PHLs\ in\ location\ i\ at\ time\ t$

And specific PHL values obtained as;

$$L_{it} = p_{it} * D_{it} \qquad (2)$$

Where: $L_{it} = PHL\ values\ at\ location\ i\ in\ time\ t$ and $D_{it} = Total\ crop\ yield\ in\ location\ i\ at\ time\ t$

Climate variables: Data on state-wide monthly averages on rainfall (mm), temperature (ºC), and humidity (%) was obtained from the Nigerian Metrological Agency (NiMet) representing all the 23 LGAs of the state.

Exploratory data analysis

Exploratory descriptive analysis will involve creations of choropleth maps to show patterns of spatial variation across the 23 LGAs of Benue State, and temporal dynamics will be assessed through trend analysis. The above steps are important towards identifying underlying spatial heterogeneity and temporal variability before proceeding to formal modelling [22].

Global spatial autocorrelation

The global spatial autocorrelation measures the pattern of spatial distribution of variables and establishes map-wide trends of either clustered, dispersed or randomness of geographic features and associated data values [23]. To detect spatial dependence in cassava PHLs, we used the Moran's I statistic given as:

$$I = \frac{n}{\sum_{i \neq j} w_{ij}} \cdot \frac{\sum_i \sum_j w_{ij}(Y_i - \hat{Y})(Y_j - \hat{Y})}{\sum_i (Y_i - \hat{Y})^2} \qquad (3)$$

Where: n specifies the number of spatial units and w_{ij} the spatial weights while $\hat{Y}$ is the mean PHL. Moran's I statistic has been used as a standard diagnostic test for identifying spatial clustering and justifying using spatial explicit models [24].

Local spatial autocorrelation and hotspot detection

To identify localize spatial clustering, we computed the local indicators of spatial association (LISA) in order to categorise LGAs into high-high, low-low, and outlier categories. Furthermore, we employed the Getis–Ord G_i^* statistic to help detect significant hotspots and cold-spots. The enumerated steps are vital as recent risk mapping and environmental studies have employed them to capture spatial structure [25, 26].

Temporal trend analysis
We assessed cassava temporal trend using the Mann–Kendall test, with Sen's slope estimator for quantifying the extent of temporal change in losses. These tests were adopted due to their robustness to non-normality and missing data [27]. Autocorrelation (ACF) and partial autocorrelation (PACF) functions were further examined to identify temporal dependence structures, informing the specification of temporal random effects.

Bayesian spatio-temporal modeling framework
Our study specified a Bayesian hierarchical model within the Gamma framework to evaluate the association between climate variables and PHL of cassava while accounting for spatial and temporal dependence. PHL values followed the Gamma distribution given as:

$$Y_{it}|\mu_{it}, \phi \sim Gamma\left(shape = \phi, rate = \frac{\phi}{\mu_{it}}\right) \quad (4)$$

Where: $\mu_{it} > 0$ is the conditional mean of the distribution; $\phi > 0$ is the shape parameter controlling dispersion, with smaller ϕ indicating greater over-dispersion

In order to ensure positivity and link the mean μ_{it} to covariates and random effects, we used a log link function as specified below [28]:

$$\log(\mu_{it}) = \beta_0 + \sum_k \beta_k X_{it} + u_i + v_i + \delta_{it} \quad (5)$$

Where: β_k are regression coefficients, u_i represents spatial random effects, v_t denotes temporal random effects, and δ_{it}capturingthe spatio-temporal interaction. The Gamma model is appropriate for this data because they support positively skewed data and their flexibility in modelling complex dependence structures [29].

All models were assigned weakly informative priors, and the model was estimated using the Integrated Laplace Approximation (INLA) method.

Spatial random effects
Spatial random effects and spatial dependence are concepts used to describe how data points which are close in space correlate with neighbours than those far apart. In this study, we modelled spatial dependence using an intrinsic Conditional Autoregressive (ICAR) prior, a commonly used specification for areal data where spatial smoothing is induced through neighbourhood structure. The spatial random effect u_i defined conditionally as:

$$\mathrm{u_i}|u_{-i}^{*} \sim N\left(\frac{\sum_j w_{ij}u_j}{\sum_j w\_ij}, \frac{\delta_u^2}{\sum_j w_{ij}}\right) \quad (6)$$

Where: u_i denotes the vector of spatial effects which excludes area i, while w_{ij} are elements of the spatial weights matrix defining adjacency between areas, and δ_u^2 is the spatial variance parameter

The ICAR specifies that the conditional expectation of u_i is the average of its neighbouring values which enforces local spatial smoothing, while the conditional variance is inversely proportional to the number of neighbors. This structure induces strong spatial dependence and is particularly suitable for modelling spatially correlated residual variation in a real data.
But, the ICAR model uses an improper prior and its precision matrix is singular. To ensure identifiability, we imposed a sum-to-zero constraint $\sum u_i = 0$. This constraint anchors the spatial effects and allows for meaningful interpretation of relative spatial variation across LGAs.
The ICAR formulation has been widely applied in modern spatial epidemiology and environmental modelling due to its simplicity and effectiveness in capturing structured spatial heterogeneity [30, 31].

Temporal random effects
Temporal random effects account for unexplained variations overtime. They are modelled using first-order random walk (RW1) given as;

$$\mathrm{v_t} = v_{t-1} + \epsilon_t, \ \epsilon_t \sim N(0, \delta_u^2) \quad (7)$$

This approach captures gradual temporal evolution and is commonly applied in spatio-temporal Bayesian models [32].

Spatio-temporal interaction
The interaction term δ_{it} was included to capture localized deviations from global spatial and temporal trends. This component is particularly important for identifying region-specific responses to climate variability [33].

Model estimation
Model estimation was performed using Integrated Nested Laplace Approximation (INLA), a computationally efficient alternative to Markov Chain Monte Carlo methods for latent Gaussian models. INLA provides accurate posterior approximations with substantially reduced computational cost [34]. Recent studies demonstrate its effectiveness in large-scale spatio-temporal environmental modelling [35].

Posterior inference
Posterior mean summaries including means and 95 % credible intervals were obtained for all parameters. Posterior means of $u_i$were mapped to identify residual spatial patterns, while posterior means of v_t captured temporal evolution, and fixed effects β_k quantified climate–PHL relationships.

Model validation and diagnostics
Model performance was evaluated using the Deviance Information Criterion (DIC) and Watanabe–Akaike Information Criterion (WAIC). Posterior predictive checks were conducted to assess goodness-of-fit. Residual spatial autocorrelation was reassessed using Moran's I to confirm that spatial dependence had been adequately captured [24].
Limitations

Major limitations of this study include the relatively short period (2021-2024) under consideration; this was due to lack of data beyond 2021. Also, all climate variables included in the study were measured as state-wide averages which limit the study in making fine scale inferences about localities. The small number of spatial units (n=23, the larger the n, the better) reduced statistical power for detecting spatial autocorrelation. Future research should incorporate more granular data on storage infrastructure, socio-economic variables, and extension services.

Results and Discussions

Spatial distribution of cassava PHLs

Exploratory data checks showed that cassava PHLs were heterogeneous as seen in Fig. 1. There was no strong, continuous spatial clustering of loss patterns across localities. This lack of strong spatial clustering is a reflection that high PHLs are not strictly confined to one geographic zone but are scattered across localities and possibly driven by local factors (e.g., market access, storage infrastructure, road networks, or farmer practices).

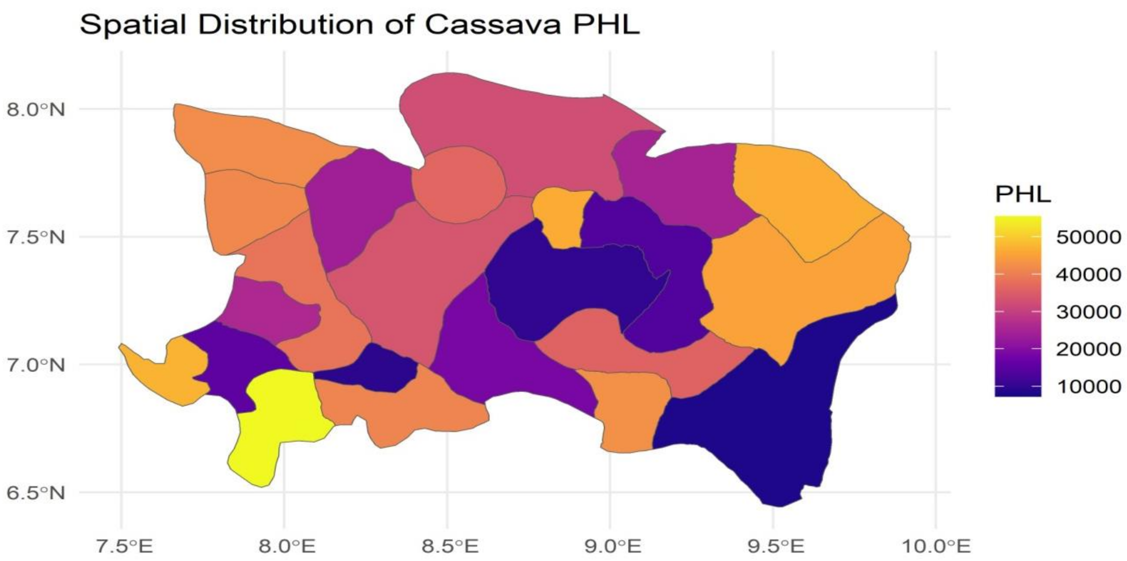

Figure 1: Spatial distribution of cassava post-harvest loss across Benue State, Nigeria (2021-2024)

Spatial autocorrelation

To perform further checks on the spatial nature of our data, we performed a Global Moran's I analysis as seen in (Table 1) and the result revealed a weak spatial autocorrelation of cassava PHLs across the 23 LGAs of Benue State during the period under study. The values of the Moran's I were between -0.3092 to -0.3169, with p-values between 0.0554 and 0.0630. We can infer that the values suggest a tendency toward spatial dispersion (a situation where neighbouring LGAs tend to have dissimilar PHL values), although the results were not statistically significant at the 5 % level of significance.

The Local Moran's I (LISA) analysis further supported the above findings as no individual LGA exhibited statistically significant clustering (High-High or Low-Low) or spatial outliers (High-Low or Low-High) in any year (all $p > 0.05$).

Table 1: Global Moran's I values (2021-2024) for cassava PHL in Benue State, Nigeria

Year	Moran's I	Expectation	p-value	Statistic (z)	N
2021	-0.3169	-0.0455	0.0554	-1.9158	23
2022	-0.3129	-0.0455	0.0591	-1.8874	23
2023	-0.3092	-0.0455	0.0630	-1.8592	23
2024	-0.3136	-0.0455	0.0580	-1.8956	23

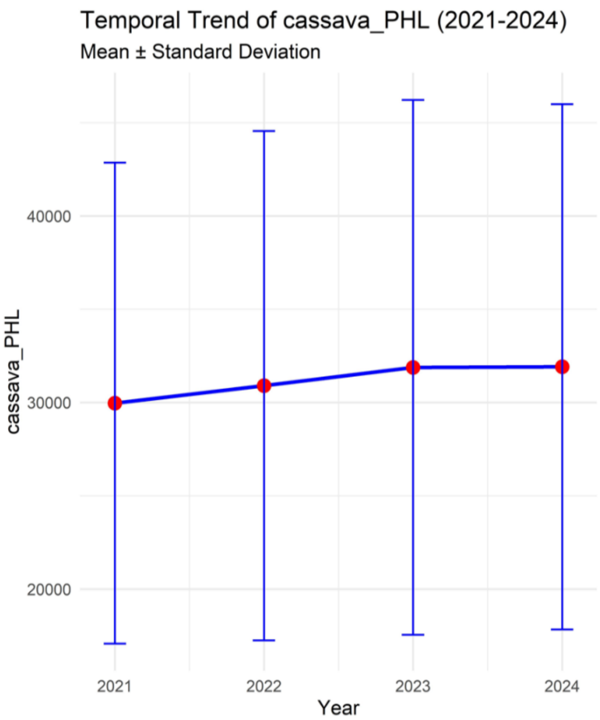

Figure 2: Temporal distribution of cassava post-harvest loss in Benue State, Nigeria (2021-2024)

Temporal trend analysis

Our descriptive temporal trend analysis shown in (Fig. 2) showed that cassava PHLs exhibited a modest but an upward trend in mean PHL values across the years under study. Mean cassava losses increased from 29,968 (tonnes) in 2021 to 31,917 (tonnes) in 2024 (see R code results) and variability remained high across years (SD ranging from 12,889 to 14,331) reflecting substantial heterogeneity among LGAs. Highest average PHLs were recorded in LGAs such as Ado (51,338), Ukum (46,907), and Ogbadibo (46,739), while Katsina Ala, Obi, and Ado recorded the strongest positive temporal trends (Pearso's r > 0.98). This means that the above LGAs demonstrated consistently worsening PHLs over the years under study.

Bayesian spatio-temporal modelling

We fitted three models to our data to enhance comparability and allow for choosing the model with the best fit. A baseline model, a temporal only model, and a spatio-temporal interaction model (see R code results). All series of Bayesian models were fitted using INLA with a Gamma family distribution. The full spatio-temporal interaction model (model 3) was fitted to include Besag ICAR spatial random effects, RW1 temporal random effects, and IID interaction effects, provided the best fit based on DIC and WAIC criteria.

Model fixed effects

Model fixed effects as shown in (Table 2) showed that standardized temperature had a small but statistically credible positive association with cassava PHLs (posterior mean = 0.024, 95 % CI: 0.000–0.048), while rainfall and humidity effects were negligible.

Table 2: Fixed Effects model for Bayesian estimation of the dynamics of climate on cassava PHLs across Benue State, Nigeria (2021-2024)

Variable	Mean	SD	2.5 % Quantile	50 % Quantile	97.5 % Quantile	Mode	KLD
(Intercept)	10.215	0.004	10.207	10.215	10.223	10.215	0.000
rainfall_std	0.004	0.006	-0.008	0.004	0.017	0.004	0.000
temp_std	0.024	0.012	0.000	0.024	0.048	0.024	0.001
humidity_std	0.003	0.009	-0.016	0.003	0.021	0.003	0.000

Posterior spatial random effects

The posterior spatial random effects represented in (Table 3) revealed strong and significant spatial heterogeneity. LGAs identified with the strongest negative spatial effects (lower-than-expected) average PHL values included Kwande (-1.278), Obi (-1.101), and Gboko (-0.975). On the other hand, Ado (0.629), Ukum (0.541), and Ogbadibo (0.537) showed strong positive spatial effects which indicates that these LGAs experienced persistently higher than average PHLs even after accounting for covariates.

Table 3: Posterior spatial random effects of cassava PHLs across Benue State, Nigeria (2021-2024)

LGA	ID	Effect	SD	2.5 %	97.5 %	Significant
Kwande	11	-1.2775	0.019	-1.3148	-1.2400	Yes
Obi	14	-1.1006	0.019	-1.1380	-1.0632	Yes
Gboko	5	-0.9751	0.019	-1.0125	-0.9377	Yes
Buruku	4	-0.7508	0.019	-0.7881	-0.7134	Yes
Okpokwu	18	-0.6383	0.019	-0.6757	-0.6009	Yes
Ado	1	0.6293	0.019	0.5920	0.6667	Yes
Ukum	21	0.5408	0.019	0.5035	0.5782	Yes
Ogbadibo	15	0.5371	0.019	0.4997	0.5745	Yes
Tarka	20	0.4979	0.019	0.4605	0.5353	Yes
Agatu	2	0.4488	0.019	0.4115	0.4862	Yes
Vandeikya	23	0.4448	0.019	0.4074	0.4821	Yes
Apa	3	0.4238	0.019	0.3864	0.4611	Yes
Katsina-Ala	9	0.4026	0.019	0.3652	0.4399	Yes
Konshisha	10	-0.3657	0.019	-0.4031	-0.3283	Yes
Oju	17	0.3461	0.019	0.3087	0.3834	Yes
Otukpo	19	0.3442	0.019	0.3068	0.3815	Yes
Makurdi	13	0.2817	0.019	0.2444	0.3191	Yes
Ushongo	22	0.2757	0.019	0.2383	0.3130	Yes
Gwer West	8	-0.2048	0.019	-0.2421	-0.1674	Yes
Gwer East	7	0.1892	0.019	0.1519	0.2265	Yes
Guma	6	0.1431	0.019	0.1057	0.1804	Yes
Ohimini	16	-0.0987	0.019	-0.1360	-0.0613	Yes
Logo	12	-0.0936	0.019	-0.1310	-0.0563	Yes

Table 4: Temporal random effects of cassava PHLs in Benue State, Nigeria (2021-2024)

Year	Effect	SD	2.5 %	97.5 %	Significant
1	0	0.0133	-0.0289	0.0289	No
2	0	0.0087	-0.0189	0.0189	No
3	0	0.0087	-0.0189	0.0189	No
4	0	0.0133	-0.0289	0.0289	No

Posterior temporal random effects

The posterior temporal random effects shown in (Table 4) were very small and not statistically credible (all credible intervals crossed zero), suggesting that after accounting for spatial structure and covariates, the overall temporal trend was modest.

This study presents one of the first spatio-temporal analyses of cassava post-harvest loss in Benue State, Nigeria's food basket. The consistent weak negative global Moran's I across four years suggest that cassava PHL does not exhibit strong spatial clustering. This implies that interventions may need to be broadly applied across the state's 23 LGAs rather than narrowly targeting specific communities as no substantial hotspots were identified. The absence of significant local clusters of PHLs further supports this conclusion.

The exhibition of modest temporal increase in mean PHL over the years under study is concerning considering cassava's critical role in food security and livelihoods. The identification of Ado, Katsina-Ala, and Obi as LGAs with both high average PHL and strong increasing trends is an indication that priority should be given to these areas for policy intervention. Factors responsible for the more than average PHL values and the continued positive trend in these LGAs may reflect specific or unique challenges related to infrastructure, storage facilities, or climate variability that were not fully captured by the included covariates.

The Bayesian spatio-temporal model demonstrated clear spatial structuring, with several LGAs showing strong positive or negative random effects. The significant positive spatial effect in Ado is particularly noteworthy, as this LGA consistently ranked highest in PHL. Such persistent spatial effects suggest underlying localized factors which may include lack of market access, processing technology, or pest/rodent pressure that may warrant further investigation.

The year-to-year variation was largely explained by the included predictors and spatial components as indicated by the weak temporal random effects after controlling for the spatial structure and climatic variables. The small positive effect observed for temperature aligns with existing literature on how increased temperatures can accelerate tuber deterioration and increase pest activity.

Conclusion

Our study successfully analysed the spatio-temporal trends as well as climate factors influencing postharvest loss of cassava across the 23 local government areas of Benue State, Nigeria, from 2021 to 2024. By the integration of spatial autocorrelation analysis, the evaluation of temporal trends, and Bayesian hierarchical spatio-temporal modelling with (INLA), our research provided valuable insights into the distribution and drivers of cassava PHL in Benue State, Nigeria's food basket.

This study recommends that cassava PHL interventions needs to be focused on high-risk LGAs such as Ado, Ukum, and Katsina-Ala while targeted intervention strategies should include improved storage technologies, processing facilities, and climate-smart post-harvest practices. The lack of strong spatial clustering is an indication that mixing targeted and state-wide interventions will be most effective in addressing cassava PHLs.

The adoption of Bayesian Spatio-temporal approaches in this study represents an advancement in the research framework that guides the practical application of Bayesian methods in bridging the gap between spatial statistics and agricultural post-harvest loss studies in Nigeria. Equally, our utilization of spatio-temporal methodologies instead of the conventional regression approaches has provided actionable, location-specific intelligence that can support evidence-based policies aimed at reducing cassava PHL, enhancing food security, and improving livelihoods in Benue State and similar cassava-producing regions across Africa.

Conflict of interest: Authors declare that there is no conflict of interest.

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