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Location-Dependent Bayesian Stacking for Nigerian Household Wealth Prediction Under Model Uncertainty

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Abstract

Reliable prediction of household wealth is essential for monitoring socioeconomic inequality and supporting evidence-based economic planning. Geoadditive models provide a flexible framework for modelling household wealth by incorporating linear, nonlinear, and spatial effects. However, prediction commonly relies on selecting a single model, which ignores model uncertainty, or on conventional Bayesian Stacking with global ensemble weights, which may not adequately capture location-specific predictive performance. This study proposed and evaluated a location-dependent Bayesian stacking approach to account for model uncertainty and improve the spatial prediction of household wealth in Nigeria. Conventional Bayesian Stacking was modified by incorporating location-dependent ensemble weights, resulting in Geoadditive Local Stacking (GALS). The proposed approach was evaluated using data from 39,050 respondents in the 2024 Nigeria Demographic and Health Survey. Four competing Gaussian Geoadditive models incorporating socioeconomic and spatial effects were fitted, and predictive performance was compared with conventional Bayesian Stacking and single-model selection using expected log predictive density (ELPD), with higher ELPD indicating better predictive performance. State-level household wealth exhibited strong positive spatial autocorrelation (Moran's I = 0.703, $p < 0.001$), with mean wealth scores ranging from −1.077 in Kebbi State to 1.316 in Lagos State. GALS achieved the highest predictive performance, with a mean ELPD of −0.8350, compared with −0.8355 for conventional Bayesian Stacking and −0.8373 for the best single model. Location-dependent Bayesian Stacking provides a reliable framework for household wealth prediction under model uncertainty and can support evidence-based socioeconomic planning and policy in Nigeria.

Keywords: Bayesian stacking; geoadditive models; household wealth; model uncertainty.

1. Introduction

Reliable prediction of household wealth is fundamental to monitoring socioeconomic inequality, targeting public interventions, and supporting evidence-based economic planning (Demoze *et al.*, 2026; Elmelech, 2026; Corley *et al.*, 2026). In Nigeria, persistent wealth disparities remain a major policy concern, with inequality concentrated across regions and socioeconomic groups (Oxfam, 2024; World Bank, n.d.). As governments increasingly rely on spatially referenced household survey data to guide policy decisions, statistical methods capable of producing accurate and reliable predictions have become increasingly important (Newhouse, 2024; Dong *et al.*, 2026).

Household wealth is influenced by demographic, socioeconomic, and geographic factors whose effects are rarely purely linear (Meng *et al.*, 2025; Asongu & Simo-Kengne, 2026). Some covariates, such as age, may exert nonlinear influences, while others, such as education, employment status, and place of residence, may act through categorical socioeconomic pathways (Howe *et al.*, 2008). In addition, geographically proximate areas often exhibit similar welfare patterns because of shared environmental, infrastructural, and contextual conditions (Jung *et al.*, 2025). Evidence from spatial inequality research in sub-Saharan Africa has shown that regional disparities are often substantial and are not fully explained by household endowments alone, suggesting an important role for location-based contextual effects (Shifa & Leibbrandt, 2024; Sulemana *et al.*, 2019).

Geoadditive models provide a flexible framework for representing such complexity by combining linear covariate effects, smooth nonlinear functions, and spatial random effects within a single predictor (Alaba *et al.*, 2017). These models have been widely used in structured additive regression and spatial semiparametric modelling because they allow the joint representation of nonlinear covariate effects and spatial dependence (Brezger & Lang, 2006; Fahrmeir & Lang, 2001; Kammann & Wand, 2003). In household wealth research, this framework is particularly attractive because it can accommodate both individual-level socioeconomic covariates and state-level spatial dependence (Kammann & Wand, 2003).

Nevertheless, applied analyses often involve multiple plausible geoadditive specifications, and selecting a single best model introduces model uncertainty that may compromise predictive performance (Hoeting *et al.*, 1999). Bayesian stacking offers an attractive alternative to single-model selection by combining predictive distributions from multiple models using weights chosen to optimise predictive accuracy (Yao *et al.*, 2018). The stacking framework proposed by Yao *et al.* (2018) is specifically designed for predictive aggregation in settings where the true data-generating process may not be among the candidate models.

However, conventional stacking assigns a global ensemble weight to each candidate model, implicitly assuming that the best model combination is the same for all locations. For spatial socioeconomic data, this assumption may be too restrictive because the relative predictive performance of candidate models can vary across locations. This study, therefore, aimed to modify conventional Bayesian stacking to account for location-dependent predictive behaviour in household wealth prediction.

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2. Materials and Methods

2.1. Study Data

This study employed data from the 2024 Nigeria Demographic and Health Survey (NDHS), a nationally representative household survey conducted under the Demographic and Health Surveys Programme. The survey employed a stratified two-stage cluster design to collect demographic, socioeconomic, and health-related information across the 36 states of Nigeria and the Federal Capital Territory. Sampling weights were incorporated in the analysis to account for the complex survey design and support nationally representative inference. DHS wealth measurement and construction have been widely documented in the survey literature (Rutstein, 2008; Rutstein & Johnson, 2004).

The analysis was based on the Individual Recode dataset comprising 39,050 women aged 15–49 years. The response variable was the household wealth score. Unlike wealth quintiles, which classify households into ordered categories, the continuous wealth score preserves underlying socioeconomic variation and is more suitable for Gaussian geoadditive modelling and predictive comparison.

Explanatory variables were selected based on socioeconomic relevance and prior use in household welfare studies. These included age, educational attainment, employment status, place of residence, marital status, religion, and ethnicity. Age was modelled nonlinearly, while the remaining covariates were treated as fixed effects. State of residence was incorporated to account for spatial dependence through structured and unstructured spatial random effects.

2.2. Candidate Geoadditive Models

Geoadditive models allow the response to depend on linear covariates, nonlinear smooth effects, and spatial random effects within a unified predictor. Let y_i denote the household wealth score for the i-th respondent. The general geoadditive predictor is written as:

$$\boldsymbol{\eta_i} = \boldsymbol{\beta_0} + \boldsymbol{x}_i^{\top}\boldsymbol{\beta} + \boldsymbol{f}\left(\text{age}_{\boldsymbol{i}}\right) + \boldsymbol{s}(\text{state}_{\boldsymbol{i}}) \quad (1),$$

where β_0 is the intercept, $\boldsymbol{x_i}$ denotes the socioeconomic covariates, $f(\cdot)$ is a smooth nonlinear effect of age, and $s(\cdot)$ is the spatial effect associated with the state of residence. Geoadditive and structured additive models of this type are standard in spatial semiparametric modelling (Fahrmeir & Lang, 2001; Kammann & Wand, 2003).

The nonlinear effect of age was modelled using a second-order random walk (RW2) prior. Spatial dependence was represented using either an independent and identically distributed (IID) random effect or the Besag–York–Mollié 2 (BYM2) model, which captures structured and unstructured spatial variation (Riebler ***et al.***, 2016).

Four competing Gaussian geoadditive models were specified under the model-uncertainty framework:

Model 1 (M1): Non-Spatial Geoadditive Model

$$y_i = \beta_0 + x_i^\top \beta + f(\text{age}_i) + \varepsilon_i \tag{2}$$

This model includes fixed effects and a nonlinear age effect, but no spatial component.

Model 2 (M2): Linear Age with Structured Spatial Effects

$$y_i = \beta_0 + x_i^\top \beta + \beta_a \text{age}_i + s_{\text{BYM2}}(\text{state}_i) + \varepsilon_i \tag{3}$$

This model assumes a linear effect of age and structured spatial dependence.

Model 3 (M3): Nonlinear Age with Unstructured Spatial Effects

$$y_i = \beta_0 + x_i^\top \beta + f(\text{age}_i) + u(\text{state}_i) + \varepsilon_i \tag{4}$$

where $u(\text{state}_i)$ represents unstructured spatial heterogeneity.

Model 4 (M4): Full Geoadditive Model

$$y_i = \beta_0 + x_i^\top \beta + f(\text{age}_i) + s_{\text{BYM2}}(\text{state}_i) + \varepsilon_i \tag{5}$$

This is the most flexible specification, combining nonlinear age effects with structured spatial dependence. These models represent plausible alternative representations of the nonlinear and spatial structure underlying household wealth and therefore constitute the candidate model set under model uncertainty.

2.3. Conventional Bayesian Stacking

Model uncertainty arises when several plausible models explain the data reasonably well, making single-model selection potentially unstable for prediction. Bayesian stacking attempts to address this problem by combining predictive distributions from multiple models using weights that maximise out-of-sample predictive performance (Yao *et al.*, 2018).

Suppose K competing geoadditive models are available, with leave-one-out predictive density $p_k(y_i \mid y_{-i})$ for model k and observation i. Conventional stacking forms the combined predictive density

$$\boldsymbol{p}_{\text{BS}}(\boldsymbol{y_i} \mid \boldsymbol{y_{-i}}) = \sum_{\boldsymbol{k=1}}^{\boldsymbol{K}} \boldsymbol{w_k}\, \boldsymbol{p}(\mid \boldsymbol{y_{-i}}, \boldsymbol{M_k}) \tag{6},$$

where $w_k \geq 0$ and $\sum_{k=1}^{K} w_k = 1$; y_{-i} denotes all observations except observation i; $i = 1, \dots, n$ indexes the repondents; M_k is the kth candidate model.

The stacking weights are obtained by maximising leave-one-out predictive performance:

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$$\max_{\boldsymbol{w}} \sum_{i=1}^{n} \log\left(\sum_{k=1}^{K} \boldsymbol{w_k}\, \boldsymbol{p}(\boldsymbol{y_i} \mid \boldsymbol{y_{-i}}, \boldsymbol{M_k})\right) \quad (7),$$

subject to the simplex constraints on w. LOO-CV is the standard basis for this criterion and is closely linked to predictive performance assessment in Bayesian modelling (Vehtari *et al.*, 2017).

Although conventional stacking accounts for model uncertainty, it assigns a single global weight to each model. As a result, every location receives the same ensemble weight. In spatial socioeconomic settings, this may be restrictive because the best predictive model can vary across regions.

2.4. Geoadditive Local Stacking (GALS)

To address the limitations of global weighting, this study proposes Geoadditive Local Stacking (GALS), in which ensemble weights vary across locations. For the i-th observation, the stacked predictive density is:

$$\boldsymbol{p}_{\mathrm{GALS}}(\boldsymbol{y_i} \mid \boldsymbol{y_{-i}}) = \sum_{k=1}^{K} \boldsymbol{w_{ik}}\, \boldsymbol{p_k}(\boldsymbol{y_i} \mid \boldsymbol{y_{-i}}, \boldsymbol{M_k}) \quad (8),$$

where w_{ik} denotes the location-specific weight assigned to model k at observation i. The weights were modelled through a multinomial logistic gating function:

$$\boldsymbol{w_{ik}} = \frac{\exp(\boldsymbol{z_i^{\top}\beta_k})}{\sum_{l=1}^{K} \exp(\boldsymbol{z_i^{\top}\beta_l})} \quad (9),$$

where z_i denotes the location-specific gating variables; β_k denotes the gating coefficient for model k. This softmax parameterisation ensures that $w_k \geq 0$ and $\sum_{k=1}^{K} w_k = 1$ for every location.

The coefficients were estimated by maximising the regularised optimisation:

$$\hat{\beta} = arg\,\max_{\beta}\left[\sum_{i=1}^{n} log\left(\sum_{k=1}^{K} w_{ik} p(y_i|y_{-i}, M_k)\right) - \lambda||\beta||^2\right] \quad (10),$$

where λ denotes the regularisation parameter; M_k denotes the k-th candidate model.

Allowing ensemble weights to vary across locations enables GALS to adapt to local predictive heterogeneity by assigning greater weight to models that perform better in different locations.

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2.5. Model Evaluation

Predictive performance was assessed using the Expected Log-Predictive Density (ELPD), a standard measure for Bayesian predictive evaluation (Vehtari *et al.*, 2017). ELPD is computed from leave-one-out cross-validation (LOO-CV). For a fitted model, ELPD is defined as:

$$\text{ELPD} = \sum_{i=1}^{n} \log p\,(y_i \mid y_{-i}) \tag{11}$$

and the mean ELPD per observation is

$$\text{Mean ELPD} = \frac{1}{n}\sum_{i=1}^{n} \log p\,(y_i \mid y_{-i}) \tag{12}.$$

Higher ELPD values indicate better predictive performance. Predictive performance was compared across three approaches: Single Model (SM), selecting the candidate model with the best predictive performance; conventional Bayesian Stacking (BS), using global ensemble weights; and Geoadditive Local Stacking (GALS), the proposed location-dependent stacking framework.

Prior to model fitting, exploratory spatial analysis was conducted to assess spatial dependence in household wealth across the 36 states and the Federal Capital Territory. Global spatial autocorrelation was evaluated using Moran's I, defined as:

$$I = \frac{N}{S_0}\frac{\sum_i \sum_j w_{ij}\,(y_i - \bar{y})(y_j - \bar{y})}{\sum_i (y_i - \bar{y})^2} \tag{13},$$

where w_{ij} is the spatial neighbourhood weight between locations i and j, N is the number of locations, and S_0 is the sum of all spatial weights. A statistically significant positive Moran's I indicates clustering of similar wealth values across neighbouring states (Moran, 1950).

3. Results and Discussions

3.1. Descriptive Statistics

A total of 39,050 respondents from the 2024 NDHS were included in the analysis. Household wealth varied substantially across socioeconomic groups. Table 1 summarises the distribution of wealth by employment status, place of residence, and educational attainment.

Employed respondents had a higher mean wealth score (0.075 ± 0.963) than unemployed respondents (−0.282 ± 0.972). Urban residents also recorded much higher wealth (0.519 ± 0.819) than rural residents (−0.631 ± 0.788), reflecting pronounced urban-rural socioeconomic differences. Wealth increased steadily with educational attainment: women with no formal education had the lowest mean wealth score (−0.877 ± 0.594), while those with higher education had the highest mean wealth score (1.023 ± 0.693). These descriptive findings suggest that employment, education, and place of residence are important determinants of household wealth and justify their inclusion in the geoadditive models.

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Table 1. Descriptive Statistics of Household Wealth by Selected Socioeconomic Characteristics

Variable	Category	N	Mean wealth score	SD
Employment	Yes	23,044	0.075	0.963
	No	16,006	−0.282	0.972
Residence	Urban	18,920	0.519	0.819
	Rural	20,130	−0.631	0.788
Education	No education	12,139	−0.877	0.594
	Primary	4,382	−0.285	0.758
	Secondary	16,777	0.287	0.803
	Higher	5,752	1.023	0.693

3.2. Spatial Distribution of Household Wealth

Household wealth varied markedly across Nigeria's states and the Federal Capital Territory, indicating substantial geographical inequality. Mean state-level wealth scores ranged from −1.077 in Kebbi State to 1.316 in Lagos State, a difference of approximately 2.39 wealth-score units (see Table 2).

States in the southern region generally recorded higher household wealth than those in the northern region. Lagos had the highest mean wealth score (1.316), followed by the Federal Capital Territory (0.908), Edo (0.832), Anambra (0.776), and Ogun (0.769). In contrast, Kebbi (−1.077), Jigawa (−0.993), Sokoto (−0.809), Yobe (−0.754), and Borno (−0.742) had the lowest mean wealth scores. These results demonstrate strong spatial heterogeneity in household wealth and suggest that neighbouring states tend to share similar socioeconomic conditions.

Table 2. States with the Highest and Lowest Mean Household Wealth Scores

Rank	Highest wealth states	Mean wealth	Lowest wealth states	Mean wealth
1	Lagos	1.316	Kebbi	−1.077
2	FCT	0.908	Jigawa	−0.993
3	Edo	0.832	Sokoto	−0.809
4	Anambra	0.776	Yobe	−0.754
5	Ogun	0.769	Borno	−0.742

3.3. Spatial Autocorrelation Analysis

Global Moran's I indicated strong positive spatial autocorrelation in household wealth across the 36 states and the Federal Capital Territory. The estimated Moran's I was 0.703 ($p < .001$), well above the expected value under spatial randomness (−0.028). This indicates that states with similar wealth levels tended to cluster geographically rather than being randomly distributed (see Table 3).

The observed spatial dependence supports the inclusion of structured spatial effects in the geoadditive models and provides empirical justification for the location-dependent weighting strategy in GALS. Spatial clustering implies that model suitability may vary across regions, which is precisely the kind of heterogeneity GALS is designed to capture (Moran, 1950; Riebler *et al.*, 2016).

In addition, the strong positive Moran's I confirmed that household wealth was spatially clustered, with neighbouring states exhibiting similar welfare levels. This finding is consistent with prior spatial modelling work and supports the use of geoadditive formulations in which both nonlinear covariate effects and spatial dependence are represented explicitly (Fahrmeir & Lang, 2001; Kammann & Wand, 2003; Moran, 1950).

Table 3. Moran's I Test for Spatial Autocorrelation in Household Wealth

Outcome	States	Moran's I	Variance	p-value
Household wealth	37	0.703	0.0118	< .001

3.4. Predictive Performance of the Competing Geoadditive Models

The predictive performance of the four candidate geoadditive models was evaluated using mean ELPD. Models incorporating spatial effects consistently outperformed the non-spatial specification, indicating that spatial structure contributed meaningfully to household wealth prediction.

Across the analyses, the spatial models M3 and M4 dominated the best single-model selection results. M3 was selected as the best-performing model in 55.6% of the analyses, while M4 was optimal in 44.4%. In contrast, the non-spatial model M1 and the linear-age spatial model M2 were not selected as the best model in any analysis. This pattern shows that spatial dependence was important, but no single model was uniformly best across all settings, indicating model uncertainty (see Table 4).

The comparison of the candidate geoadditive models further highlighted the importance of spatial structure. The fact that the best-performing single model alternated between M3 and M4 suggests that no single specification dominated uniformly. This is a clear indication of model uncertainty. Conventional stacking addresses this by averaging predictive distributions, but it still assumes that model contributions remain constant across all locations. In the present setting, this assumption may be too restrictive because the predictive suitability of competing geoadditive models can vary across locations.

Table 4. Performance Summary of the Competing Geoadditive Models

Model	Description	Percentage Selected as Best (%)
M1	Fixed effects + RW2(age)	0.0
M2	Fixed effects + linear age + BYM2	0.0
M3	Fixed effects + RW2(age) + IID spatial	55.6
M4	Fixed effects + RW2(age) + BYM2 spatial	44.4

3.5. Comparison of Single-Model Selection, Bayesian Stacking, and GALS

The predictive performance of the best single model, conventional Bayesian stacking, and GALS was compared using mean ELPD per observation. GALS achieved the highest predictive performance, with a mean ELPD of −0.8350, compared with −0.8355 for conventional Bayesian stacking and −0.8373 for the best single model (see Table 5). This implies that GALS had a better predictive performance, with progressive gains over conventional Bayesian Stacking and the best single model. This suggests that the proposed location-dependent weighting scheme provided a predictive gain. The improvement is substantively meaningful because it indicates that GALS captured local predictive heterogeneity that global stacking could not fully exploit.

The superior performance of GALS can be explained by local predictive heterogeneity and spatially varying model suitability. In other words, the model that predicts best in one region may not be the best in another. GALS adapts to this by allowing observation-specific ensemble weights, so the contribution of each candidate model can vary with location. This provides a principled way to combine models when predictive structure is not spatially uniform. The result is a more flexible ensemble that preserves the advantages of Bayesian stacking while better matching the realities of geographically structured socioeconomic data (Yao *et al.*, 2018).

Table 5. Predictive Performance Comparison

Method	Mean ELPD per Observation
Best Single Model	−0.8373
Bayesian Stacking	−0.8355
Geoadditive Local Stacking (GALS)	−0.8350

From a methodological perspective, this study extends conventional Bayesian stacking by introducing observation-specific ensemble weights for geoadditive models. Unlike standard stacking, which assumes constant model contributions across all observations, the proposed approach allows model contributions to vary spatially, thereby improving predictive performance under model uncertainty. This is especially relevant in settings where the data-generating process is heterogeneous across space and where local prediction is the main objective.

The findings have practical implications for socioeconomic planning and spatial policy analysis. Improved prediction of household wealth can help identify disadvantaged regions more accurately and support more targeted interventions. More broadly, GALS may be useful in other spatial and demographic applications where local predictive behaviour differs across geographical units.

4. Conclusion

This study modified conventional Bayesian stacking by replacing global ensemble weights with location-dependent ensemble weights to address model uncertainty in spatial household wealth prediction. The resulting approach, Geoadditive Local Stacking (GALS), was evaluated using nationally representative data from the 2024 NDHS and compared with conventional Bayesian stacking and single-model selection.

The results demonstrated strong spatial variation in household wealth across Nigeria and confirmed significant positive spatial autocorrelation. Models incorporating spatial effects consistently outperformed the non-spatial model, underscoring the importance of accounting for geographical dependence. GALS achieved the highest predictive performance among the competing approaches, indicating that location-dependent ensemble weighting can improve prediction under model uncertainty.

The proposed approach contributes to Bayesian ensemble learning by extending stacking to accommodate spatially varying predictive behaviour in geoadditive models. Beyond household wealth prediction, the approach may be applied in social, demographic, environmental, and public health studies where predictive relationships vary across space.

While the study offers valuable insights, it is limited by the empirical evaluation being based on a single nationally representative dataset. Future research may assess the generalisability of GALS across different countries, outcomes, and spatial resolutions. Overall, the study demonstrates that incorporating location-dependent ensemble weights into Bayesian stacking provides a flexible and effective framework for spatial prediction in the presence of model uncertainty.

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