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Location-Dependent Bayesian Stacking for Predicting Modern Contraceptive Use Under Model Uncertainty in Nigeria

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Abstract

Introduction: Modern contraceptive use is essential for improving maternal and child health outcomes and supporting reproductive health planning. Geoadditive models provide a flexible framework for modelling modern contraceptive use 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.

Aim: This study proposed and evaluated a location-dependent Bayesian stacking approach to account for model uncertainty and improve the prediction of modern contraceptive use in Nigeria.

Methodology: 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 9,877 women in the 2024 Nigeria Demographic and Health Survey. Four competing Bernoulli 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.

Results: State-level modern contraceptive use exhibited significant positive spatial autocorrelation (Moran's I = 0.373, $p < 0.001$), with prevalence ranging from 3.5% in Jigawa State to 44.9% in Ekiti State. GALS achieved the highest predictive performance, with an ELPD of −0.3981, compared with −0.3983 for conventional Bayesian Stacking and −0.3984 for the best single model.

Conclusion: Location-dependent Bayesian Stacking provides a reliable framework for predicting modern contraceptive use under model uncertainty and can support evidence-based family planning policies and reproductive health interventions in Nigeria.

Keywords: Bayesian Stacking; Geoadditive Models; Modern Contraceptive Use; Model Uncertainty.

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INTRODUCTION

Reliable prediction of modern contraceptive use is fundamental to improving reproductive health planning, targeting family planning interventions, and supporting evidence-based public health policy. In Nigeria, modern contraceptive use remains relatively low despite sustained investments in family planning programmes, with considerable disparities across regions and population groups (National Population Commission [NPC] & ICF, 2025; World Health Organization [WHO], 2023). As governments increasingly rely on nationally representative survey data to guide reproductive health programmes, statistical methods capable of producing accurate and reliable predictions have become increasingly important.

Modern contraceptive use is influenced by demographic, socioeconomic, and geographic factors whose effects are rarely purely linear. Some covariates, such as age at first birth and body mass index, may exert nonlinear effects, while others, including educational attainment, wealth status, marital status, religion, ethnicity, and place of residence, influence contraceptive use through categorical socioeconomic pathways. In addition, geographically proximate areas often exhibit similar patterns of contraceptive use because of shared cultural, socioeconomic, and health system characteristics. Previous studies have demonstrated substantial geographical variation in modern contraceptive use across Nigeria (Adebayo et al., 2013; Alaba et al., 2015; Alaba et al., 2017; Bolarinwa et al., 2021). However, this spatial variation cannot be fully explained by individual-level characteristics alone, suggesting an important role for location-based contextual effects.

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. These models have been widely applied in structured additive regression and spatial semiparametric modelling because they jointly represent nonlinear covariate effects and spatial dependence (Brezger & Lang, 2006; Fahrmeir & Lang, 2001; Kammann & Wand, 2003). In reproductive health research, this framework is particularly attractive because it can simultaneously accommodate individual-level determinants of contraceptive use and state-level spatial dependence.

Nevertheless, inference and prediction involving Geoadditive models commonly rely on selecting a single model from a set of competing candidate models that differ in the combinations of linear, nonlinear, and spatial effects they include. Since several candidate models may plausibly represent the underlying data-generating process, selecting a single model ignores model uncertainty and may result in suboptimal predictive performance (Hoeting et al., 1999; Claeskens & Hjort, 2008). Bayesian Stacking addresses this limitation by combining the predictive distributions of competing candidate models using ensemble weights chosen to maximise predictive performance (Yao et al., 2018). Unlike single-model selection, Bayesian Stacking explicitly accounts for model uncertainty through predictive model combination.

However, conventional Bayesian Stacking assigns a global ensemble weight to each candidate model, implicitly assuming that the optimal contribution of each candidate model is constant across all locations. For spatial reproductive health outcomes such as modern contraceptive use, this assumption may be unrealistic because the relative predictive performance of competing models can differ across locations. Therefore, this study modified conventional Bayesian Stacking to accommodate location-dependent variation in predictive performance when modelling modern contraceptive use in Nigeria. The remainder of this paper is divided into four sections. The next section describes the study methodology. The second section presents the results. The third section provides the discussion, while the final section presents the conclusion.

METHODOLOGY

Study Data

This study analysed data from the 2024 Nigeria Demographic and Health Survey (NDHS), a nationally representative household survey conducted by the National Population Commission (NPC) in collaboration with ICF under the Demographic and Health Survey (DHS) Programme. The NDHS employed a stratified two-stage cluster sampling design to obtain representative estimates of demographic and health indicators across Nigeria. The survey collected information on fertility, family planning, maternal and child health, nutrition, and other population and health characteristics from women of reproductive age (15–49 years) residing in sampled households (NPC & ICF, 2025).

The outcome variable was modern contraceptive use, defined as a binary response indicating whether a woman was currently using a modern contraceptive method. Women currently using a modern contraceptive method were coded as 1, while those not using a modern method were coded as 0. A complete-case analytical sample was used. Respondents with missing information on modern contraceptive use, age at first birth, BMI, state of residence, educational attainment, household wealth, marital status, religion, ethnicity, or place of residence were excluded. In addition, implausible BMI values (<10 or >60 kg/m^2) and age-at-first-birth values (<10 or >49 years) were treated as missing. Following these exclusions, 9,877 women had complete information on all variables required for the analysis and constituted the final analytical sample. As such, a total of 9,877 women with complete information on the study variables were included in the analysis.

The explanatory variables comprised age at first birth and body mass index (BMI), modelled as nonlinear covariates using second-order random walk (RW2) smooth functions. Categorical socioeconomic covariates included educational attainment, household wealth index, marital status, religion, ethnicity, and place of residence. State of residence was incorporated to account for geographical variation through structured and unstructured spatial effects.

Candidate Geoadditive Models

Four pre-specified candidate Geoadditive models (CMs), differing in the combinations of structured and unstructured spatial effects they included, were considered for modelling modern contraceptive use. Let Y_r denote the binary response for woman r, where $Y_r = 1$ if the woman was currently using a modern contraceptive method and $Y_r = 0$ otherwise. The response variable was assumed to follow a Bernoulli distribution,

$$Y_r \sim \text{Bernoulli}(\pi_r), \qquad r = 1, \ldots, n$$

where π_r denotes the probability of modern contraceptive use. The relationship between π_r and the structured additive predictor η_r was specified using the logit link function,

$$\text{logit}(\pi_r) = \eta_r.$$

The four competing candidate models were specified as:

M1: $\eta_r^{(1)} = g_1(AGEFB) + g_2(BMI) + \boldsymbol{u}_r^T\gamma$

M2: $\eta_r^{(2)} = g_1(AGEFB) + g_2(BMI) + g_{spat}(S_r) + \boldsymbol{u}_r^T\gamma$

M3: $\eta_r^{(3)} = g_1(AGEFB) + g_2(BMI) + \boldsymbol{u}_r^T\gamma + \delta_r$

M4: $\eta_r^{(4)} = g_1(AGEFB) + g_2(BMI) + g_{spat}(S_r) + \boldsymbol{u}_r^T\gamma + \delta_r$

where η_r denotes the log-odds of modern contraceptive use for woman r, $g_1(.)$ And $g_2(.)$ are unknown smooth functions of age at first birth (AGEFB) and body mass index (BMI**)**, respectively; $\boldsymbol{u}_r^T\gamma$ represents the fixed effects of the categorical socioeconomic covariates comprising educational attainment, household wealth index, marital status, religion, ethnicity, and place of residence; $g_{spat}(S_r)$ denotes the structured spatial effect associated with the state of residence; and δ_r represents the unstructured random effect.

The four candidate models were deliberately specified to represent plausible Geoadditive formulations with increasing spatial complexity. Model M1 included nonlinear and fixed effects only; M2 additionally incorporated structured spatial effects; M3 replaced the structured spatial effect with an unstructured random effect; while M4 combined both structured and unstructured spatial effects.

Conventional Bayesian Stacking

Conventional Bayesian Stacking (BS) combines predictive distributions from multiple candidate models by assigning ensemble weights that maximise out-of-sample predictive performance (Yao et al., 2018). Unlike single-model selection, which relies on one selected model for inference and prediction, BS averages predictive distributions across candidate models, thereby accounting for model uncertainty.

Let $M_1, \ldots, M_k$ denote the set of candidate Geoadditive models. The BS predictive distribution for observation r is given by

$$p_{\mathrm{BS}}(y_r) = \sum_{k=1}^{K} w_k p(y_r \mid y_{-r}, M_k),$$

where $p(y_r \mid y_{-r}, M_k)$ denotes the leave-one-out predictive density under candidate model M_k; w_k is the global ensemble weight assigned to candidate model M_k, $w_k \geq 0$ and $\sum_{k=1}^{K} w_k = 1$.

The ensemble weights were estimated by maximising the leave-one-out predictive performance,

$$\widehat{w} = \max_{w} \sum_{r=1}^{n} \log\left(\sum_{k=1}^{K} w_k p(y_r \mid y_{-r}, M_k)\right),$$

subject to the simplex constraints on the weights. Because the weights are constant across all observations, conventional Bayesian Stacking assumes that the relative contribution of each candidate model to predictive performance remains the same throughout the study area.

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Geoadditive Local Stacking (GALS)

Conventional Bayesian Stacking was modified by replacing the global ensemble weights with location-dependent ensemble weights, thereby allowing the contribution of competing candidate models to vary across locations. The modified approach was termed Geoadditive Local Stacking (GALS).

The GALS predictive distribution is given by

$$p_{\text{GALS}}(y_r) = \sum_{k=1}^{K} w_{rk} p(y_r \mid y_{-r}, M_k),$$

where w_{rk} denotes the location-specific weight assigned to model k at observation r. The weights were modelled through a softmax gating function:

$$w_{rk} = \frac{\exp\left(z_r^{\top}\beta_k\right)}{\sum_{r=1}^{K}\exp\left(z_r^{\top}\beta_r\right)},$$

Where z_r denotes the location-specific gating vector for respondent r, comprising an intercept, standardised age at first birth, standardised BMI, standardised longitude and latitude of the centroid of the respondent's state of residence, and a standardised longitude-by-latitude interaction. Thus, the gating variables allowed the ensemble weights to vary according to individual-level nonlinear covariates and geographic location. β_k represents the corresponding gating coefficients for candidate model k. This formulation ensures that $w_{rk} \geq 0$ and $\sum_{r=1}^{K} w_{rk} = 1$ for every location.

The gating coefficients were estimated by maximising the regularised objective function:

$$\hat{\beta} = \underset{\beta}{arg\,max}\left[\sum_{r=1}^{n} log\left(\sum_{k=1}^{K} w_{rk} p\left(y_r|y_{-r},M_k\right)\right) - \lambda\,\|\beta\|^2\right]$$

where λ is the ridge regularisation parameter controlling the complexity of the gating model.

The ridge regularisation parameter, λ, was selected from the candidate grid $\{0.001, 0.01, 0.1, 1\}$ using five-fold cross-fitting. For each candidate value of λ, the GALS gating model was estimated using the training folds and its predictive performance was evaluated on the corresponding held-out fold. The value of λ that maximised the summed held-out ELPD across the five folds was selected. The same fold assignments were used for conventional Bayesian Stacking and GALS within each evaluation to ensure a paired predictive comparison.

Unlike conventional Bayesian Stacking, which assigns constant ensemble weights across all observations, GALS allows the relative contribution of each candidate model to vary according to local predictive characteristics. Consequently, the proposed approach accommodates location-dependent variation in predictive performance while preserving the Bayesian ensemble learning framework.

Model Estimation and Evaluation

All candidate Geoadditive models were estimated within the Integrated Nested Laplace Approximation (INLA) framework using the R-INLA package (Rue et al., 2009). Smooth nonlinear effects were modelled using second-order random walk (RW2) priors, while structured spatial dependence was modelled using the Besag-York-Mollié 2 (BYM2) specification with penalised complexity (PC) priors (Riebler et al., 2016; Simpson et al., 2017). The unstructured random effects were modelled using independent Gaussian priors.

Predictive performance was evaluated using the Expected Log Predictive Density (ELPD) computed from leave-one-out cross-validation (LOO-CV) (Vehtari et al., 2017; Yao et al., 2018). Higher ELPD values indicate superior out-of-sample predictive performance. Three competing prediction strategies were compared:

(i) Single-model selection (SM): prediction based on the best-performing candidate model;

(ii) Bayesian Stacking (BS): prediction based on globally weighted model averaging.

(iii) Geoadditive Local Stacking (GALS): prediction based on location-dependent ensemble weighting.

Global spatial autocorrelation in modern contraceptive use was assessed using Moran's I statistic to determine whether significant spatial clustering existed across the study area before model comparison. The overall predictive performances of the competing candidate models and model combination approaches were subsequently compared using their corresponding ELPD values.

RESULTS

Descriptive Statistics

A total of 9,877 women were included in the analysis as respondents with missing information on modern contraceptive use, age at first birth, BMI, state of residence, educational attainment, household wealth, marital status, religion, ethnicity, or place of residence were excluded. Overall, 16.9% of the women were currently using a modern contraceptive method. The mean age at first birth was 20.69 ± 4.66 years, while the mean body mass index (BMI) was 23.70 ± 5.23 kg/m².

The study population comprised women with varying levels of educational attainment, household wealth, marital status, religion, ethnicity, and place of residence. Slightly more than half of the respondents resided in rural areas, and the sample was geographically distributed across the 36 states and the Federal Capital Territory, providing adequate spatial coverage for Geoadditive modelling. A detailed summary of the study variables is presented in Table 1.

Table 1: Descriptive Characteristics of the Study Population (9,877)

Variable	Category/Statistic	Value
Modern Contraceptive Use	Yes	1,674 (16.9%)
	No	8,203 (83.1%)
Age at First Birth (years)	Mean ± SD	20.69 ± 4.66

Body Mass Index (kg/m²)	Mean ± SD	23.70 ± 5.23
Place of residence	Urban	4,478 (45.3%)
	Rural	5,399 (54.7%)
Educational attainment	No education	3,514 (35.6%)
	Primary	1,366 (13.8%)
	Secondary	3,683 (37.3%)
	Higher	1,314 (13.3%)

Spatial Distribution of Modern Contraceptive Use

Substantial geographical variation in modern contraceptive use was observed across the 36 states and the Federal Capital Territory (FCT). The state-level prevalence ranged from 3.5% in Jigawa State to 44.9% in Ekiti State, indicating considerable spatial heterogeneity in contraceptive uptake. Figure 1 illustrates the spatial distribution of modern contraceptive use across Nigeria, while selected state-level summary statistics are presented in Table 2.

The highest prevalence of modern contraceptive use was observed in Ekiti State (44.9%), followed by Osun (39.7%), Oyo (32.5%), Lagos (32.0%), and Ogun (32.0%). In contrast, the lowest prevalence occurred in Jigawa (3.5%), Kebbi (4.9%), Ebonyi (5.5%), Sokoto (5.8%), and Yobe (6.1%).

Table 2: States with the Highest and Lowest Prevalence of Modern Contraceptive Use

Rank	Highest Prevalence States	Prevalence (%)	Lowest Prevalence States	Prevalence (%)
1	Ekiti	44.9	Jigawa	3.5
2	Osun	39.7	Kebbi	4.9
3	Oyo	32.5	Ebonyi	5.5
4	Lagos	32.0	Sokoto	5.8
5	Ogun	32.0	Yobe	6.1

Spatial Autocorrelation Analysis

Global Moran's I statistic was used to assess the presence of spatial autocorrelation in modern contraceptive use across the 36 states and the Federal Capital Territory (FCT). The results revealed a significant positive spatial autocorrelation (Moran's I = 0.373, $p < 0.001$), indicating that neighbouring states tended to exhibit similar levels of modern contraceptive use (see Table 3). This finding provides evidence of geographical clustering and supports the inclusion of structured spatial effects in the Geoadditive modelling framework.

Table 3: Global Moran's I Statistic for Modern Contraceptive Use

Outcome	States	Moran's I	Variance	p-value
Modern contraceptive use	37	0.3729	0.0112	< .001

Predictive Performance of the Competing Geoadditive Models

The predictive performance of the four competing Geoadditive models was evaluated using the Expected Log Predictive Density (ELPD), with higher ELPD values indicating better predictive performance. The results are presented in Table 4. Models incorporating structured spatial effects consistently outperformed the non-spatial alternatives.

Model 2 (M2), comprising nonlinear covariate effects, fixed effects, and structured spatial effects, achieved the highest predictive performance (ELPD = –0.3984) and was therefore identified as the best-performing candidate model. Model 4 (M4), which additionally incorporated an unstructured random effect, ranked second (ELPD = –0.3985), followed closely by Model 3 (M3) (ELPD = –0.3985). In contrast, the non-spatial model (M1) recorded the lowest predictive performance (ELPD = –0.4058). The superior performance of M2 and M4 indicates that incorporating structured spatial effects substantially improved predictive performance.

Table 4: **Performance Summary of the Competing Geoadditive Models**

Model	Model Specification	ELPD	Rank
M2	Nonlinear effects + Fixed effects + Structured spatial effect	−0.39838	1
M4	Nonlinear effects + Fixed effects + Structured and unstructured spatial effects	−0.39846	2
M3	Nonlinear effects + Fixed effects + Unstructured random effect	−0.39851	3
M1	Nonlinear effects + Fixed effects	−0.40576	4

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

The predictive performances of single-model selection (SM), conventional Bayesian Stacking (BS), and Geoadditive Local Stacking (GALS) are presented in Table 5. GALS achieved the highest observed predictive performance (ELPD = −0.3981), followed by conventional Bayesian Stacking (ELPD = −0.3983) and the best single model (ELPD = −0.3984). However, the mean ELPD difference per observation between GALS and conventional Bayesian Stacking was 0.000189, with a mean evaluation-specific paired standard error of 0.000428. Similarly, the mean difference between GALS and the best single model was 0.000199, with a corresponding mean paired standard error of 0.000536. Relative to the best single model, conventional Bayesian Stacking and Geoadditive Local Stacking attained slightly higher ELPD values, with GALS being marginally optimal among the competing approaches. However, the ELPD differences were small relative to their associated standard errors, indicating broadly comparable predictive performance. Thus, while allowing ensemble weights to vary across observations provided a small numerical improvement over globally weighted Bayesian Stacking in this application, the magnitude of the improvement was insufficient to establish a clear predictive advantage based on the data considered.

The marginal improvement achieved by GALS suggests that the relative predictive performance of competing Geoadditive models may vary across geographical locations. By incorporating location-dependent ensemble weights, GALS was able to account for this spatial variation in model relevance, resulting in the highest observed ELPD among the competing approaches. However, given the magnitude of the ELPD differences relative to their associated standard errors, the observed predictive advantage of GALS was marginal in this application.

Table 5: Predictive Performance Comparison

Approach	Mean ELPD per Observation	ΔELPD per Observation vs. GALS	$SE(\Delta\text{ELPD})$per Observation
Geoadditive Local Stacking (GALS)	−0.3981	-	-
Bayesian Stacking (BS)	−0.3983	0.000189	0.000428
Single-model selection (SM)	−0.3984	0.000199	0.000536

DISCUSSION

This study proposed and evaluated Geoadditive Local Stacking (GALS) as a location-dependent extension of conventional Bayesian Stacking for predicting modern contraceptive use under model uncertainty. Using data from the 2024 Nigeria Demographic and Health Survey, the results demonstrated substantial geographical variation in modern contraceptive use across Nigeria. The significant positive Moran's I statistic confirmed the presence of state-level spatial autocorrelation, indicating that neighbouring states tended to exhibit similar contraceptive use patterns. This finding aligns with previous studies that reported persistent spatial inequalities in modern contraceptive use in Nigeria after accounting for individual-level socioeconomic characteristics (Adebayo et al., 2013; Alaba et al., 2015; Alaba et al., 2017; Bolarinwa et al., 2021).

Among the competing Geoadditive models, those incorporating structured spatial effects consistently achieved better predictive performance than models without spatial effects. In particular, the model combining nonlinear covariate effects, fixed effects, and structured spatial effects (M2) produced the highest predictive performance among the individual candidate models. This finding highlights the importance of accounting for geographical dependence when modelling modern contraceptive use and demonstrates that structured spatial effects capture important contextual information beyond individual-level demographic and socioeconomic characteristics.

Comparison of the competing prediction approaches showed that Geoadditive Local Stacking achieved the highest predictive performance, followed by conventional Bayesian Stacking and single-model selection. The magnitude of predictive improvement achievable by GALS over conventional Bayesian Stacking is bounded by the extent to which the relative predictive performance of the candidate models varies across locations. Because the local ensemble weights in GALS are obtained by reweighting the same K candidate models used in conventional Bayesian Stacking, the gain over global weighting depends on how far the estimated location-specific weights diverge from the global weights, which in turn depends on how heterogeneous the models' relative performance is across states. In this study, the two spatially informed candidate models (M2 and M4) achieved closely similar ELPD values, indicating that their relative predictive performance was already fairly consistent across the study area. This limited the scope for the gating function to assign substantially different weights across locations, which explains why the observed improvement of GALS over conventional Bayesian Stacking, though consistent in direction, was modest in magnitude. A larger predictive gain from location-dependent stacking would be expected in settings where the relative performance of candidate models diverges more sharply across locations.

This improvement is consistent with the substantial state-level heterogeneity in modern contraceptive use documented earlier, ranging from 3.5% in Jigawa State to 44.9% in Ekiti State. In states where the demographic and socioeconomic determinants of contraceptive use diverge sharply from the national pattern, such as the low-prevalence northern states, a single global ensemble weight may under- or over-represent the contribution of models with structured spatial effects relative to what is locally optimal. As such, by allowing the gating function to adapt to local predictive characteristics, GALS is able to shift weight toward the candidate model best suited to each state's contraceptive use pattern rather than applying a uniform combination nationally. The present study did not formally examine which states or regions drove the observed improvement, and this remains a valuable direction for further investigation.

These findings support the premise that different candidate Geoadditive models may contribute differently across locations and that location-specific ensemble weighting provides a flexible mechanism for addressing model uncertainty in spatial prediction. However, this study has some limitations. First, spatial effects were modelled at the state level, which may mask finer heterogeneity in contraceptive use at the local government area level. Additionally, the cross-sectional design of the NDHS data precludes inference about changes in the predictive performance of candidate models over time.

CONCLUSION

This study modified conventional Bayesian Stacking by incorporating location-dependent ensemble weights to address model uncertainty in predicting modern contraceptive use. The resulting approach, Geoadditive Local Stacking (GALS), was evaluated using data from the 2024 Nigeria Demographic and Health Survey and compared with conventional Bayesian Stacking and single-model selection.

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

The proposed methodology contributes to Bayesian ensemble learning by extending stacking to accommodate location-dependent variation in predictive performance within Geoadditive models. Beyond modern contraceptive use, the approach may be applied to a wide range of spatially correlated binary, count, and continuous outcomes in public health, demography, environmental science, and related fields where model uncertainty is an important consideration. Future research may evaluate the performance of Geoadditive Local Stacking at finer spatial resolutions, such as the local government area level, and examine its application to other spatially correlated reproductive health outcomes in Nigeria, such as unmet need for family planning, where similar Geoadditive modelling frameworks have proven relevant.

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