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Examining Variations in Sensitivity of Cereal Crop Yield to Climate Change Variables across the Regions in Northern Ghana using Multilevel and Bayesian Multilevel Modeling

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Abstract

The study applied both the multilevel and the Bayesian multilevel model approaches to investigate variations in the effects of climate variables on cereal crop yield in Northern Ghana with respect to the region of cultivation and year (time), and to compare the performance of the two models. Thirty-one years of data points on some climate variables and the annual yield of some selected cereal crops from the Meteorological Agency and the Ministry of Food and Agriculture of Ghana, respectively, were used. Results indicated significant variations in climate change impact across the regions and years of cultivation. Also, the study showed that the significant effect of humidity and sunshine ($p \leq 0.0001$ and $p = 0.0069$ respectively) on crop yield varies from one region to another, with humidity having the most variation. The study further revealed that the Bayesian Multilevel model performed better in its model scores and predictive ability. It concluded that there are variations in the impact of climate change on cereal crop yield in the regions in Northern Ghana and recommends that the climate characteristics of these regions should be taken into account in predicting future yield and adopting mitigation strategies.

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Keywords: Bayesian, Multilevel, Statistics, Multilevel Regression, Climate Change, Northern Ghana

Introduction

Agriculture, energy, and forestry are sectors that the Ghanaian economy depends heavily on. These sectors are climate sensitive (EPA, 2021). Consequently, any climatic anomaly tends to impact the economy, especially the vulnerable populations. The insufficient utilization of irrigation resources and a heavy reliance on adverse climatic conditions for successful harvests lead to considerable fluctuations in the standard of living of individuals.

Ghana is at significant socioeconomic risk from climate change, particularly in the northern sector, which has sporadic drought and flooding and a lengthy dry season lasting around seven months, followed by a shorter rainy season lasting roughly five months (Arndt et al., 2015). In addition to being the most agricultural region of Ghana, the northern sector is a major source of sorghum and millet and makes significant contributions to the production of rice and maize (MoFA-IFPRI, 2020; USDA/IPAD, 2024). It has a high proportion of farmers who grow food crops for subsistence. Floods, late rains before planting season, and ongoing droughts during planting season are examples of climate instability (Ahiamadia et al., 2024; Dumenu & Obeng, 2016). In addition to its other commercial use in sectors like the poultry and brewing industries (Gage et al., 2012), cereals (maize, rice, sorghum, and millet) constitute the main source of staples in Northern Ghana in particular and the nation overall (Darfour & Rosentrater, 2016). Therefore, doing this study in Northern Ghana is justified.

Additionally, climate change is having a worsening impact on food crop production (Anang & Amikuzuno, 2015). It is even having an impact on the United Nations Sustainable Development Goal Two, which aims to eradicate all forms of hunger, achieve food security, enhance nutrition, and advance sustainable agriculture by 2030 (Hwang & Kim, 2017; UNOSD, 2020). Because of this, every effort to sustain food production to feed the nation's growing population and economy, especially in the northern part of the country, is essential.

The effects of climate change on livelihoods and adaptation methods of rural communities in Ghana have been evaluated by several researchers (McCarthy et al., 2021; Yaro, 2013). Nevertheless, research on the differences in the impact of climate factors on cereal crop yield in Northern Ghana's various regions is scant or nonexistent. Additionally, the research area is hierarchical and structured, and its cereal crop yield data is insufficient, which makes the Multilevel and Bayesian Multilevel approaches the most appropriate (Flor et al., 2020; Gelman et al., 2013; Smid et al., 2020). Furthermore, no research has been found on the use of these models to

 ISSN: 1857-7881 (Print) e - ISSN 1857-7431

comprehend the circumstances in these areas. Also, the effects of climate change on crop yield may vary depending on local climate conditions (Mohammadi et al., 2023). Moreover, climate impacts in Ghana are observed to differ by region (Asante et al., 2024). However, there is no known study, to the best of the researchers' knowledge, on whether this varying impact of climate change occurs in the three regions of Northern Ghana, and on the sensitivity of the yield of the selected cereal crops. It is therefore necessary to look into how the selected cereals vary in their sensitivity to the effect of these three northern regions' climate variables. This raises the question of whether climate-dependent cereal crop output is sensitive to the time and location of cultivation and whether the effects of these factors vary by region. Thus, the study aimed to address these problems by identifying potential differences in cereal crop yields by time (year) and cultivation region, as well as by evaluating the differences in their susceptibility to climate change variables among Northern Ghanaian regions.

The study would explore the application of Bayesian Multilevel Modeling and Multilevel Modeling techniques to the problem-solving process and to suggest which of the two models fits the model the best. It also contributes to the body of knowledge that guides mitigation strategies for the effects of climate change in the studied region.

Climate change refers to alterations in climate resulting from human activities that modify the composition of the global atmosphere, in addition to natural climate variability observed over similar timeframes (UNFCCC, 2011).

According to Amikuzuno and Donkoh (2012), Northern Ghana's poverty is attributed to its susceptibility to climate change and other unfavorable climatic conditions, such as the lengthy dry season, recurrent intermittent droughts, and floods during the planting season. Temperatures and evapotranspiration have increased, while precipitation has marginally decreased, with the delayed commencement of the rainy season (USDA/GAIN, 2023). Amikuzuno and Donkoh (2012) noted that the yields of specific staple crops are influenced by the total quantity of rainfall during the planting season.

Multilevel modeling extends regression models, enabling the analysis of data with clustered or hierarchical structures (Cubillos et al., 2021; Roback & Legler, 2021). Its primary advantage lies in the ability to aggregate information across clusters, thereby enhancing the accuracy of model parameter estimates (McElreath, 2020). Dessie et al. (2020) iterated that hierarchical multivariate assumptions can be effectively handled using a multivariate multilevel model, which is not feasible with univariate models. Multilevel modeling has been utilized across various research domains, including public health (Diez-roux, 2000), child characteristics and

 ISSN: 1857-7881 (Print) e - ISSN 1857-7431

developmental factors (Smith & Shively, 2019), cross-cultural studies (Nezlek, 2010), and management (Molina-azorín et al., 2019), as well as numerous other fields and methodological concerns (Bolin et al., 2019; González-Romá & Hernández, 2023; Lin et al., 2019; Yamana, 2021).

Cubillos et al. (2021) noted that the application of multilevel models is constrained when confronted with limited data, resulting in erroneous estimates. In such instances, Bayesian estimation is frequently advocated as a substitute for frequentist estimates to address this issue. Research shows that Bayesian estimation performs well with complex models, small sample sizes, or significant missing data, and provides a clearer interpretation than frequentist estimates (Cubillos et al., 2021; Hox, 2019). Bayesian data analysis has gained prominence across various disciplines and is often favored over the conventional frequentist methodology, particularly in scenarios involving small sample sizes is due to Bayesian estimation's independence from the asymptotic properties of the data, allowing for interpretation and validation regardless of sample size (Kaplan, 2014; Smid et al., 2020). The Bayesian methodology facilitates the incorporation of a priori information through prior distributions of model parameters, which are subsequently conditioned on the data, proving particularly advantageous when expert knowledge is accessible. Furthermore, the adaptability of a Bayesian model allows for the explicit quantification of the uncertainty associated with the outcome's modeling. This adaptability can accommodate diminished sample sizes and may even encompass intricate frameworks such as multilevel modeling (Cubillos et al., 2021; Kaplan, 2014). Cubillos et al. (2021) determined that Bayesian multilevel models surpassed other models in predictive accuracy, as indicated by the leave-one-out information criterion. They compared the Bayesian technique with its frequentist counterpart and concluded that the Bayesian approach exhibited greater conservatism in its coefficient estimate.

Additional domains in which research utilizing Bayesian Multilevel Modeling has been conducted encompass comparative journalism studies and the calibration of process-based maize phenology (Adesina, 2021; Chan & Rauchfleisch, 2023; Viswanathan et al., 2022).

ISSN: 1857-7881 (Print) e - ISSN 1857-7431

Materials and Methods

Study Area

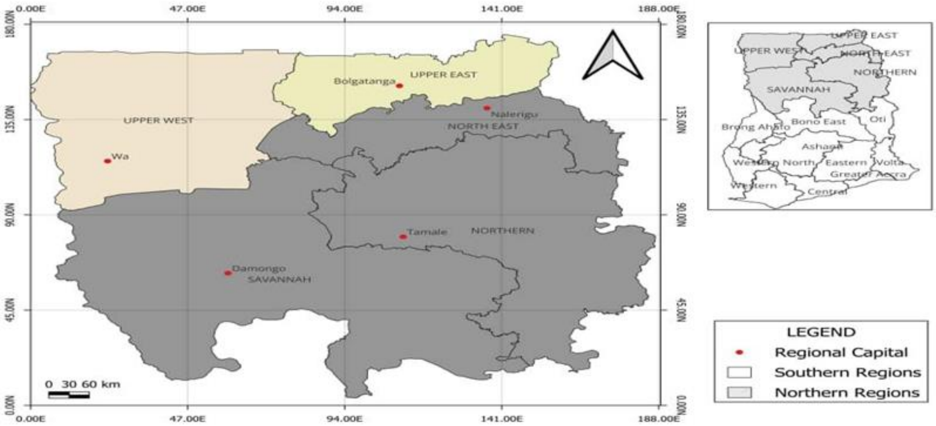

Figure 1. A Map of Northern Ghana (Insert: Map of Ghana)

Figure 1 shows the study area, which comprises Northern (Northern, Savanna, North East), Upper East, and Upper West regions, with the map of Ghana inserted. The area is one of the most agricultural parts of Ghana, with a high percentage of subsistence food crop farmers, covering about 36% of the nation's cereal (maize, rice, and sorghum) yield (MoFA, 2020). It is sensitive and vulnerable to climate change and unpredictable climatic variability, especially erratic rainfall.

Data Sources

The research utilized secondary data from state agencies responsible for its collection and management. Data on climate variables (rainfall, temperature, hours of sunshine, relative humidity, and wind speed) for Northern Ghana were obtained from seven weather stations (Bole, Salaga, Tamale, Wa, Yendi, Walewale, and Bawku) from 1992 to 2022, sourced from the Ghana Meteorological Agency (GMA). Annual cereal crop yield data were obtained from the Statistics, Research and Information Directorate (SRID) of Ghana's Ministry of Food and Agriculture (MoFA) for the period 1992 to 2022 in the research region.

Bayesian Data Modeling

Bayesian inference is the basis of the Bayesian perspective to data modeling. The Bayesian inference has its main characteristic as each parameter of a model is a random variable (Cubillos et al., 2021a; Gelman et al, 2013). This feature enables Bayesian models to comprehensively represent the inherent uncertainty in estimating a given parameter. In this case, Bayes'

 ISSN: 1857-7881 (Print) e - ISSN 1857-7431

theorem is used to model the probability of a parameter θ given a data set y as

$$p(\theta|y) = \frac{p(y|\theta)p(\theta)}{p(y)}, \tag{1}$$

The probability distribution of a parameter, $p(\theta|y)$, which represents the relative plausibility of different values of the parameter conditional on the data and the model (McElreath, 2020a; Ropero et al., 2019), can be estimated using this approach. The outcome of Bayesian analysis indicates that the probability distribution of a parameter, $p(\theta|y)$, known as the posterior distribution, is proportional to the product of the data's information (likelihood), $p(\theta|y)$, and the information accessible before the observation (prior), $p(\theta)$. The posterior distribution encompasses all the requisite information for conducting Bayesian inference.

Multilevel Regression Modeling

Multilevel modeling, also known as hierarchical linear or mixed-effects modeling, is a statistical method employed to evaluate data characterized by a hierarchical or nested structure (Roback & Legler, 2021). Data points are organized into clusters across many levels. Multilevel modeling facilitates the representation of variation across many hierarchical levels, encompassing both intra-group and inter-group variability. It is essential when basic linear regression assumptions are breached due to correlated data points or when the focus is on how group-level factors affect individual-level results (Dash, 2023). This model offers multiple advantages over conventional regression models, including enhanced inference from grouped data, a reduced number of parameters needed to represent groups, and the ability to estimate group effects, such as the regional impact on crop yield influenced by climate change (Smith & Shively, 2019).

In multilevel models, the intercept and coefficient are allowed to vary. The regression parameters delineating the overall associations between predictor and responder variables are identified, and the variances of the coefficients allowed to fluctuate among groups at elevated levels are also assessed. Typically, two multilevel models are examined: the random intercept model and the random coefficient model. The random intercept model, known as the unconditional means model, is typically the initial model applied in nearly all multilevel contexts. This model lacks predictors at both levels to evaluate the variation at each level, hence comparing intra-subject variability to inter-subject variability. Enhanced models will further elucidate the origins of both between-subject and within-subject variability. It can be specified using formulas at both tiers as

 ISSN: 1857-7881 (Print) e - ISSN 1857-7431

Level 1:

$$Y_{ij} = a_i + \varepsilon_{ij}, \quad \varepsilon_{ij} \sim N(0, \sigma^2) \tag{2}$$

Level 2:

$$a_i = a_0 + u_i, \qquad u_i \sim N(0, \sigma_u^2) \tag{3}$$

or as a composite model:

$$Y_{ij} = a_0 + u_i + \varepsilon_{ij} \tag{4}$$

Where a_i is the true mean response of all observations for subject i, and a_0 denotes the grand mean, which is the true mean of all observations throughout the whole population. The primary focus of the unconditional means model is the variance components, where σ^2 represents within-person variability and σ_u^2 denotes between-person variability. For a_i from (3), each subject's intercept is presumed to be a stochastic value drawn from a normal distribution centered a_0 with variance σ_u^2. Thus, it is referred to as the random intercepts model (Roback & Legler, 2021).

The relative levels of between-subject and within-subject variabilities can be compared through the intraclass correlation coefficient:

$$\hat{\rho} = \frac{Between\ subject\ variability}{Total\ variability} = \frac{\hat{\sigma}_u^2}{\hat{\sigma}_u^2 + \hat{\sigma}^2} \tag{5}$$

In a random coefficient model, the slope is allowed to vary across the groups. In certain instances, the random intercept alone may be inadequate to account for heterogeneity among the groups. Hence, a random slope model will be required where each group will have different slopes along with different intercepts (González-Romá & Hernández, 2023; Yamana, 2021).

It is formulated as:

$$y_{ij} = \beta_{0j} + \beta_{1j} x_{ij} + \varepsilon_{ij} \tag{6}$$

$$\beta_{1j} = \beta_1 + u_{1j} \tag{7}$$

$$\beta_{0j} = \beta_0 + u_{0j} \tag{8}$$

The composite model becomes;

$$y_{ij} = \underbrace{\beta_0 + \beta_1 x_{ij}}_{Fixed\ Part} + \underbrace{u_{1j} x_{ij} + u_{0j} + \varepsilon_{ij}}_{Random\ Part} \tag{9}$$

where $\varepsilon_{ij} \sim N(0, \sigma^2)$

Two random variables, u_{1j} and u_{0j}, for the slope and intercept, are introduced, respectively. The u_{ij} term, representing the disparity between the mean slope of the regression line and the slopes of various groups, accounts

 ISSN: 1857-7881 (Print) e - ISSN 1857-7431

for variations in slopes. The fixed part determines the overall regression line, while the variances and covariances of the slopes and intercepts are estimated for the random part. The slopes and intercepts are correlated. A positive covariance between these two indicates diverging regression lines, while a negative covariance suggests the lines are converging. A zero covariance suggests that there is no fixed pattern (Dash, 2023; Roback & Legler, 2021).
The statistical test employed is contingent upon the parameter being examined. Standard z-tests and t-tests may be employed for the fixed effect parameters. Likelihood ratio testing is, however, required to test for the random effects (Dash, 2023; Yamana, 2021).

Bayesian Multilevel Modeling

We try to predict an outcome y_i (crop yield) by a linear combination of an intercept α and a slope β that measures the impact of a predictor x_i (climate change variables) by

$$y_i \sim Normal(\mu_i, \sigma_e)$$
$$.\mu_i = \alpha + \beta x_1 \tag{10}$$

In Bayesian terms, (10) describes the likelihood of the model, which is the assumption made about the generative process from which the data is issued. It is assumed that the outcomes, y_i, are distributed normally around a mean μ_i with some error σ_e. By adding a varying intercept, (10) can be extended to the multilevel model as

$$y_i \sim Normal(\mu_i, \sigma_e)$$
$$\mu_i = \alpha_{ji} + \beta x_i \tag{11}$$
$$\alpha_j \sim Normal(\alpha, \sigma_\alpha)$$

Where α_{ij} indicates that each group j is given a unique intercept issued from a Gaussian distribution centered on α, the grand intercept, which implies that there might be different mean scores for each class (Nalborczyk et al., 2022a).

It can be seen from (11) that besides the residual standard deviation, σ_e, an additional variance component, σ_α, which is the standard deviation of the distribution of varying intercepts, is being estimated. The variation of the parameter α between groups j can be interpreted by considering the intra-class correlation (ICC);

$$\frac{\sigma_\alpha^2}{(\sigma_\alpha^2+\sigma_e^2)}, \tag{12}$$

which goes to 0 if the grouping conveys no information, and to 1 if all observations in a group are identical (Gelman & Hill, 2006). The next in the

 ISSN: 1857-7881 (Print) e - ISSN 1857-7431

Bayesian framework is the a priori distribution, which describes the population of intercepts and therefore models the dependency between these parameters. By adding a varying slope, which allowed to vary according to the group j, we have

$$\begin{gathered} y_i \sim Normal(\mu_i, \sigma_e) \\ \mu_i = \alpha_{ji} + \beta_{ji} x_i \\ \\ \alpha_j \sim Normal(\alpha, \sigma_\alpha) \\ \beta_j \sim Normal(\beta, \sigma_\beta), \end{gathered} \tag{13}$$

This indicates that the effects of the climate variables are allowed to differ from one region to another. The varying slopes are assigned a prior distribution centered on the grand β, and with a standard deviation σ_β.

Model Evaluation

The most common methods for model comparison are the Bayesian information criterion (BIC), the deviance information criterion (DIC), the Akaike information criterion (AIC), the widely applicable information criterion (WAIC), also referred to as the widely available information criterion or the Watanable-Akaike; which is an extension of the Akaike information criterion (AIC) that is more fully Bayesian than the deviance information criterion (DIC) (Watanabe, 2010), and the leave-one-out information criterion (LOOIC) (Cubillos et al., 2021; Vehtari & Gelman, 2016). This part of the study checks the prediction accuracy of the fitted model and will therefore use the LOOIC method, which estimates pointwise out-of-sample prediction accuracy using the log-likelihood evaluated at the posterior simulations of the parameter values. The Bayesian LOOIC predictive fit estimate is

$$LOOIC = \sum_{i=1}^{n} \quad p(y_i|y_{-i}) \tag{14}$$

Where $(y_i|y_{-i})$ is the leave-one-out predictive density obtained by fitting the data without the i^{th} data point? Lower LOOIC values denote better out-of-sample predictive accuracy performance (Cubillos et al., 2021).

Model Comparison

Model performance of the two models was assessed by comparing the values of their AIC, BIC, log-likelihood scores, WAIC, and LOOIC scores, depending on which is applicable. The smaller the value, the better the performance.

 ISSN: 1857-7881 (Print) e - ISSN 1857-7431

Statistical Software Employed

The study employed R version 4.3.3 software from the Comprehensive R Archive Network (CRAN) project, with its corresponding R packages. The brms package, which implements Bayesian multilevel models in R using the probabilistic programming language Stan, which was developed by Bürknr (2017), and its accompanying packages for the modeling processes were used.

Results and Discussions

Multilevel Regression Modeling

The study sought to test the hypothesis that there is no variation in the effects of climate change variables on cereal crop yield with time (year), and region of cultivation, using the available data. This investigates whether the relationship between crop yield and climate change is sensitive to time and region. A multilevel model fit to assess this assumption was generated (see Tables 1 and 2).

Table 1: Random Effects

Groups	Name	Variance	SD	Effect Prop
Year	(Intercept)	3.98E+11	630663	0.9532
Residual		1.95E+10	139757	0.0468

Table 2: Fixed Effects

	Estimate	Std. Error	df	t -value	Pr(>|t|)
(Intercept)	467240.75	114208.51	30.01	4.091	0.000297 ***

Table 1 provides estimates for the random effects in the form of variances and standard deviations (SD). It also provides the proportion of the random effect variance attributable to each random effect. It reveals that about 95% of the total variance of the random effects is attributed to the year effect. This makes time (year) an important factor that should be considered in fitting our model. This observation is further confirmed by the output on the fixed effect in Table 2, which provides the estimates. It provides a significant effect of time (years) on the yield at all levels of significance. This also confirms its significant effect on cereal crop yield; hence, the relationship between cereal crops and climate data is sensitive to time (years). This further confirms the fact that cereal crop yield and climate variables are dynamically related and should therefore be investigated by taking time (years) into account.

The study considered the year, region as the group, and the climate variables. It is shown in Table 3 that the year again accounts greatly for the variation, with a negative correlation between the year and region. It confirms the earlier conclusion that the relationship is sensitive to time.

 ISSN: 1857-7881 (Print) e - ISSN 1857-7431

Table 3: Random Effect

Groups	Name	Variance	SD	Corr
Year	(Intercept)	1.06719	1.03305	
	Region	0.00158	0.03975	-1.00
Residual		0.01235	0.11112	

Estimates of the fixed effect model are presented in Table 4. The region shows a significant difference at all levels of significance. This indicates that the effect of climate on crop yield is sensitive to the region of cultivation, with a negative relationship. That is, the differences in the effects of climate change on crop yield in these regions are not zero. It is also revealed from the table that humidity and sunshine indicate significant variations ($p \leq 0.0001$ and $p = 0.0069$, respectively) in their relationship with cereal crop yield in the regions. However, the other climate variables have not shown significance in the data as modeled.

Table 4: Fixed Effect

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.263063	0.188779	1.393	0.17323
Region	-0.130701	0.017825	-7.332	1.34e-09 ***
Temperature	0.009728	0.019633	0.495	0.62201
Rainfall	0.019374	0.018947	1.023	0.31049
Humidity	0.210892	0.018522	11.386	< 2e-16 ***
Windspeed	-0.021932	0.019699	-1.113	0.26985
Sunshine	0.053416	0.019096	2.797	0.00687 **
Model Diagnostics:				
AIC = 45.9	BIC = 73.7	$\alpha = 0.05$		

It can be seen from the results that the effect of climate change on cereal crop yield in Northern Ghana is influenced by time (year), the region within the North where it is cultivated, and also humidity and sunshine hours vary in their effects in the regions. Cereal crop yield is therefore sensitive to the aforementioned.

Bayesian Multilevel Modeling

The Bayesian Multilevel model approach generated Table 5. It contains the effects at the various levels, with the posterior mean as the 'Estimate' and the 'Est.Error' as the standard deviation of the posterior distribution. It also contains two-sided 95% credible intervals (L-95% CI and U-95% CI) established on quantiles, with Rhat, which provides information on the convergence of the algorithm and indicates that the chain has converged since the Rhat values are not significantly greater than 1.00 at each effect level on the table. From Table 5, the group-level effects are shown to be significant at the 95% credible interval, which is an indication that at the group level (region level), the year of cultivation has a significant influence on crop yield from the data. That is, the yield at the regions is influenced by the year of

 ISSN: 1857-7881 (Print) e - ISSN 1857-7431

cultivation. At the population level, however, it did not show significance in the interaction with year.

Table 5: Effect of Year on Cereal Crop Yield

Effects		Estimates	Est. Error	95% Cred Int		Rhat
Group-Level Effects	sd(Intercept)	1.02	0.14	0.79	1.33	1.02
Population-Level Effects	Intercept	-0.03	0.18	-0.40	0.34	1.03
Family Specific Parameters	Sigma	0.22	0.02	0.19	0.27	1.00

Each parameter is presented in Table 6 with the posterior mean as the 'Estimate' and the 'Est.Error' as the standard deviation of the posterior distribution. The table also contains two-sided 95% credible intervals (l-95% CI and u-95% CI) established on quantiles and Rhat, which provides information on the convergence of the algorithm. Rhat values of 1.00 for each variable in the tables (5 and 6) indicate that the chain has converged and we can work with the output. Again, from Table 6, the 'region' and 'wind speed' interactions have negative posterior means. 'Humidity' (0.21) has been shown to have a higher influence on crop yield than the others, with 'temperature'(0.01) showing the least influence. The table also shows 'region', 'hum', and 'suns', indicating statistical significance (credible intervals excluding zero), which implies that the region where the cereal crop is cultivated also influences the crop yield with regard to the available climate conditions. Humidity and sunshine are significant contributors to crop yield in each of the regions. Cereal crop yield has therefore been shown to be sensitive to these climate variables in Northern Ghana.

Table 6: Effect of Climate Variables on the Crop Yield in the Northern Regions

	Estimate	Est. Error	95% Cred. Int		Rhat
Group-Level Effects:~year (Number of levels: 31)					
sd(Intercept)	1.06	0.15	0.82	1.38	1.00
sd(region)	0.03	0.02	0.00	0.07	1.00
cor(Intercept,region)	-0.72	0.34	-0.99	0.37	1.00
Population-Level Effects:					
Intercept	0.26	0.19	-0.10	0.64	1.00
Region	-0.13	0.02	-0.17	-0.09	1.00
temperature	0.01	0.02	-0.03	0.05	1.00
rainfall	0.02	0.02	-0.03	0.06	1.00
Humidity	0.21	0.02	0.17	0.25	1.00
Windspeed	-0.02	0.02	-0.07	0.02	1.00
Sunshine	0.05	0.02	0.01	0.10	1.00
Family Specific Parameters:					
Sigma	0.12	0.01	0.10	0.15	1.00
Model Diagnostics:					
WAIC = -84.2	LOOIC = -74.4				

 ISSN: 1857-7881 (Print) e - ISSN 1857-7431

The results so far also confirm earlier works that observed that the effects of climate change on crop yield may vary depending on local climate conditions, and that their impacts in Ghana are observed to differ by region (Mohammadi et al., 2023; Asante et al., 2024).

Figure 2 shows the density (left) and trace (right) plots for the tail area of the distribution, which corresponds to the l-95% CI and u-95% CI in Table 6. It shows that the chains are stable.

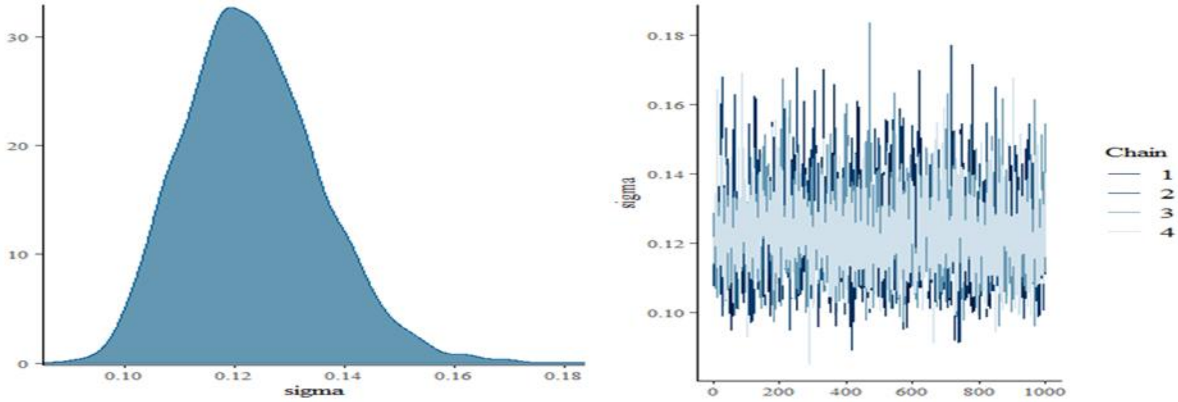

Figure 2: Density plot (Left) and Trace plot (Right)

Model Diagnostics

From Tables 5 and 6, the Rhat distributions contain values that are below 1.1, which is a good indication that the model converged. The trace plot in Figure 2 shows effective blending, which leads to the conclusion that the model has converged. The Bayesian Multilevel Model has MSE, RMSE, and MAE values of 0.0083, 0.0910, and 0.0623, respectively, which indicate a good predictive capacity and, for that matter, a good model fit. The plot of Figure 3 shows an even distribution of the residuals about the zero line over the period. It indicates a good fit of the model to the data, which implies that our prediction will be more accurate.

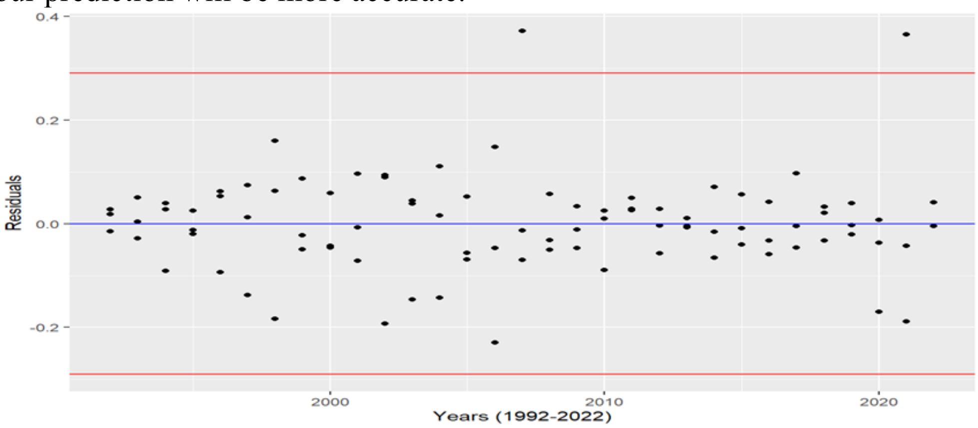

Figure 3: A plot of residuals for the period

 ISSN: 1857-7881 (Print) e - ISSN 1857-7431

Model Comparison

Both the Multilevel and Bayesian Multilevel Modeling generated the same model outputs and relationships. The Multilevel model generated model scores: AIC and BIC of 45.9 and 73.7, respectively. In the case of the Bayesian Multilevel Modeling, a WAIC of -84.2 and LOOIC of -74.4 indicate that the Bayesian Multilevel Modeling performs better in assessing and predicting the variations in sensitivity of cereal crop yield to climate change in the regions in Northern Ghana.

Conclusion

The study revealed that both the Bayesian Multilevel and Multilevel models performed well in assessing the variation in sensitivity of cereal crop yield to climate change in Northern Ghana. It also revealed that cereal crop yields in the study area have different sensitivities to their regions of cultivation. Whereas the other variables showed no significant difference, humidity and sunshine showed significant variations in their effects per region, with humidity contributing the highest variation in influence over crop yield. It further showed that the Bayesian Multilevel Modeling approach performed better in its model scores and predictive power. The study confirms earlier findings by earlier works that observed the varying impact of climate change on crop yield per local climate conditions and by region.

The study recommends that the climate characteristics of previous years and in the regions should be taken into account in predicting future yields and adopting mitigation strategies. Also, humidity and sunshine have significantly varying influences in the regions. Industry stakeholders can leverage this in their decision-making. Again, it recommends the use of Bayesian Multilevel modeling for prediction and also for understanding the variations in the sensitivity of cereal crop yield to climate change at the various levels and sectors of Northern Ghana. It further recommends that the study be extended to include other yield-influencing variables such as fertilizer use, vegetation cover, and also at the individual regional levels, or by considering the cereal crops separately.

Conflict of Interest: The authors reported no conflict of interest.

Data Availability: All data for this study are available from the authors upon reasonable request.

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References:

1. Adesina, O. S. (2021). Bayesian multilevel models for count data. *Journal of the Nigerian Society of Physical Sciences*, *3*(3), 224–233. https://doi.org/10.46481/jnsps.2021.168
2. Ahiamadia, D., Ramilan, T., & Tozer, P. R. (2024). Enhancing climate resilience in northern Ghana : A stochastic dominance analysis of risk-efficient climate-smart technologies for smallholder farmers. *Environmental Development*, *51*, 101031. https://doi.org/10.1016/j.envdev.2024.101031
3. Amikuzuno, J., & Donkoh, S. A. (2012). *Climate Variability and Yields of Major Staple Food Crops in Northern Ghana* (Vol. 20, Issue 2, pp. 349–360).
4. Anang, B. T., & Amikuzuno, J. (2015). Factors Influencing Pesticide Use in Smallholder Rice Production in Northern Ghana. *Agriculture, Forestry and Fisheries*, *4*(2), 77. https://doi.org/10.11648/j.aff.20150402.19
5. Arndt, C., Asante, F., & Thurlow, J. (2015). Implications of climate change for Ghana's economy. *Sustainability (Switzerland)*, *7*(6), 7214–7231. https://doi.org/10.3390/su7067214
6. Asante, S., Owusu, V., & Oppong, S. (2024). Marginal Impact of climate variability on crop yields in Ghana. *Scientific African*, *25*(April), e02314. https://doi.org/10.1016/j.sciaf.2024.e02314
7. Bolin, J. H., Finch, W. H., & Stenger, R. (2019). Estimation of Random Coefficient Multilevel Models in the Context of Small Numbers of Level 2 Clusters. *Educational and Psychological Measurement*, *79*(2), 217–248. https://doi.org/10.1177/0013164418773494
8. Chan, C. H., & Rauchfleisch, A. (2023). Bayesian Multilevel Modeling and Its Application in Comparative Journalism Studies. *International Journal of Communication*, *17*(111), 3700–3721.
9. Cubillos, M., Wulff, J. N., & Wøhlk, S. (2021). A multilevel Bayesian framework for predicting municipal waste generation rates. *Waste Management*, *127*, 90–100. https://doi.org/10.1016/j.wasman.2021.04.011
10. Darfour, B., & Rosentrater, K. A. (2016). Maize in Ghana: An overview of cultivation to processing. *2016 American Society of Agricultural and Biological Engineers Annual International Meeting, ASABE 2016*, 1–16. https://doi.org/10.13031/aim.20162460492
11. Dash, S. K. (2023). *A brief introduction to Multilevel Modelling*. Analytic Vidhya. https://www.analyticsvidhya.com/blog/2022/01/a-brief-introduction-to-multilevel-modelling/

 ISSN: 1857-7881 (Print) e - ISSN 1857-7431

12. Dessie, Z. G., Zewotir, T., Mwambi, H., & North, D. (2020). *Multivariate multilevel modeling of quality of life dynamics of HIV infected patients*. *2*, 1–14.
13. Diez-roux, A. V. (2000). Multilevel Analysis in Public Health Research. *Annu. Rev. Public Health.*
14. Dumenu, W. K., & Obeng, E. A. (2016). Climate change and rural communities in Ghana: Social vulnerability, impacts, adaptations and policy implications. *Environmental Science and Policy*, *55*(February 2018), 208–217. https://doi.org/10.1016/j.envsci.2015.10.010
15. EPA. (2021). *Ghana ' s Third Biennial Update Report to United Nations Framework Convention on Climate Change*.
16. Flor, M., Weiß, M., Selhorst, T., Müller-Graf, C., & Greiner, M. (2020). Comparison of Bayesian and frequentist methods for prevalence estimation under misclassification. *BMC Public Health*, *20*(1), 1–10. https://doi.org/10.1186/s12889-020-09177-4
17. Gage, D., Bangnikon, J., Abeka-Afari, H., Hanif, C., Addaquay, J., Antwi, V., & Hale, A. (2012). The Market for Maize, rice, Soy, and WarehouSing in Northern Ghana. *ASABE*, *January*.
18. Gelman, A., Carlin, J.B., Stern, H.S., Dunson, D.B., Vehtari, A., Rubin, D. B. (2013). *Bayesian Data Analysis*. Chapman & Hall, Boca Raton, FL.
19. Gelman, A., & Hill, J. (2006). *Data Analysis Using Regression and Multilevel/Hierarchical Models*. Andrew Gelman Jennifer Hill.
20. González-Romá, V., & Hernández, A. (2023). Conducting and Evaluating Multilevel Studies : Recommendations, Resources , and a Checklist. *Sage*, *26*(4), 629–654. https://doi.org/10.1177/10944281211060712
21. Hox, J. J. (2019). Bayesian Multilevel Modeling. *Wiley StatsRef: Statistics Reference Online*, 1–7. https://doi.org/10.1002/9781118445112.stat08140
22. John B. Nezlek. (2010). Multilevel Modeling and Cross-Cultural Research. In *Cross-Cultural Research Methods in Psychology*.
23. Kaplan, D. (2014). *Bayesian Statistics for the Social Sciences* (Second Edi). Guilford Press.
24. Ladislas Nalborczyk, Cédric Batailler, Hélène Loevenbruck, Anne Vilain, & Paul-Christian Bürkner. (2022). *An Introduction to Bayesian Multilevel Models Using brms: A Case Study of Gender Effects on Vowel Variability in Standard Indonesian*.
25. Lin, X., Chowdhury, A., Wang, X., & Terejanu, G. (2019). Approximate computational approaches for Bayesian sensor placement in high dimensions. *Information Fusion*, *46*, 193–205. https://doi.org/10.1016/j.inffus.2018.06.006

 ISSN: 1857-7881 (Print) e - ISSN 1857-7431

26. Maccarthy, D. S., Adam, M., Freduah, B. S., Fosu-Mensah, B. Y., Ampim, P. A. Y., Ly, M., Traore, P. S., & Adiku, S. G. K. (2021). Climate change impact and variability on cereal productivity among smallholder farmers under future production systems in west africa. *Sustainability (Switzerland)*, *13*(9). https://doi.org/10.3390/su13095191
27. McElreath, R. (2020). *Statistical Rethinking: A Bayesian Course with Examples in R and Stan*. CRC Press, Boca Raton, FL. https://doi.org/doi.org/10.1201/9780429029608
28. MoFA. (2020). *Cereal Production Figures from 1992*.
29. MoFA-IFPRI. (2020). Ghana's Maize Market. *International Food Policy Research Institute (IFPRI) in Ghana*, *1*, 1–4.
30. Mohammadi, S., Rydgren, K., Bakkestuen, V., & Gillespie, M. A. K. (2023). Impacts of recent climate change on crop yield can depend on local conditions in climatically diverse regions of Norway. *Scientific Reports*, *0855*, 1–12. https://doi.org/10.1038/s41598-023-30813-7
31. Molina-azorín, J. F., Pereira-moliner, J., López-gamero, M. D., Pertusa-ortega, E. M., & Tarí, J. J. (2019). Multilevel research: Foundations and opportunities in management. *BRQ Bus. Res. Q*. https://doi.org/10.1016/j.brq.2019.03.004
32. Nalborczyk, L., Batailler, C., Loevenbruck, H., Vilain, A., & Bürkner, P. C. (2019). An introduction to Bayesian multilevel models using brms: A case study of gender effects on vowel variability in standard Indonesian. *Journal of Speech, Language, and Hearing Research*, *62*(5), 1225–1242. https://doi.org/10.1044/2018_JSLHR-S-18-0006
33. Paul-Christian Bürkner. (2017). brms : An R Package for Bayesian Multilevel Models. *Journal of Statistical Software*, *80*(1). https://doi.org/10.18637/jss.v080.i01
34. Roback, P., & Legler, J. (2021). *Beyond Multiple Linear Regression: Applied Generalized Linear Models and Multilevel Models in R* (First). CRC Press.
35. Ropero, R. F., Rumí, R., & Aguilera, P. A. (2019). Bayesian networks for evaluating climate change influence in olive crops in Andalusia, Spain. *Natural Resource Modeling*, *32*(1), 1–18. https://doi.org/10.1111/nrm.12169
36. Smid, S. C., McNeish, D., Miočević, M., & van de Schoot, R. (2020). Bayesian Versus Frequentist Estimation for Structural Equation Models in Small Sample Contexts: A Systematic Review. *Structural Equation Modeling*, *27*(1), 131–161. https://doi.org/10.1080/10705511.2019.1577140

 ISSN: 1857-7881 (Print) e - ISSN 1857-7431

37. Smith, T., & Shively, G. (2019). Multilevel analysis of individual , household , and community factors influencing child growth in Nepal. *BMC Pediatrics*, 1–14.
38. UNFCCC. (2011). Climate change science - the status of climate change science today. *United Nations Framework Convention on Climate Change*, *February 2011*, 1–7. https://unfccc.int/files/press/backgrounders/application/pdf/press_factsh_science.pdf
39. USDA/GAIN. (2023). *Ghana Climate change report*. http://africa.cimafoundation.org/documents/869
40. USDA/IPAD. (2024). *USDA/IPAD Country Summary*. https://ipad.fas.usda.gov/countrysummary/default.aspx?id=GH
41. Vehtari, A., & Gelman, A. (2016). *Practical Bayesian model evaluation using leave-one-out cross-validation and WAIC ∗*. *September*, 1–28.
42. Viswanathan, M., Scheidegger, A., Streck, T., Gayler, S., & Weber, T. K. D. (2022). Bayesian multi-level calibration of a process-based maize phenology model. *Ecological Modelling*, *474*(May), 110154. https://doi.org/10.1016/j.ecolmodel.2022.110154
43. Watanabe, S. (2010). Asymptotic equivalence of Bayes cross validation and widely applicable information criterion in singular learning theory. *Journal of Machine Learning Research*, *11*, 3571–3594.
44. Yamana, H. (2021). Introduction to Multilevel Analysis. *Annals of Clinical Epidemiology*, *3*(1), 5–9.
45. Yaro, J. A. (2013). The perception of and adaptation to climate variability/change in Ghana by small-scale and commercial farmers. *Regional Environmental Change*, *13*(6), 1259–1272. https://doi.org/10.1007/s10113-013-0443-5