VISUAL MODELING IN HYDROLOGY: ENHANCING REAL-TIME FLOOD MANAGEMENT USING FLEXPLOT, LINEAR MODELING, AND MIXED MODELING

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ABSTRACT

Effective flood management relies on accurate predictions. Visual modeling techniques play a crucial role in hydrology and water resources management. This study analyzed data from Hydrological Area 8. The analysis employed flexplot, linear modeling, mixed modeling, and generalized linear modeling. The results provide valuable insights into hydrological patterns and trends. Flexplot visualization revealed a significant positive relationship between Kastina and the response variable. Linear modeling identified Kastina ($\beta = 0.464$, $p < 0.01$) and Gusa ($\beta = 0.552$, $p < 0.01$) as significant predictors, while Goroyo showed no significant effect. Mixed modeling confirmed these findings, with Kastina (estimate = 0.267, $p < 0.01$) and Gusa (estimate = 0.272, $p < 0.01$) exhibiting significant positive relationships. Generalized linear modeling supported these results, with Kastina (estimate = 0.274, $p < 0.01$) and Gusa (estimate = 0.313, $p < 0.01$) showing significant positive effects. Model comparisons confirmed the importance of Kastina and Gusa. The regression analysis yielded significant results, providing insights into the relationships between variables. These findings suggest that Kastina and Gusa are significant predictors, contributing to the variation in the response variable. The results provide valuable insights for engineering applications, highlighting the importance of considering these variables in predictive models.

Keywords: Hydrological data, Statistical analysis, Predictive modeling, Hydrological patterns, and Regression analysis

1.0 INTRODUCTION:

Floods are among the most devastating natural disasters, causing catastrophic damage to infrastructure, environment, and human life (Atemoagbo *et al.,* 2023). The increasing frequency and severity of floods necessitate advanced hydrological modeling techniques for accurate prediction and real-time management (Cantonati *et al.,* 2020). Visual modeling has emerged as a powerful tool in hydrology, enabling researchers and practitioners to intuitively understand complex hydrological processes and make informed decisions (Groenendyk *et al.,* 2015). This study explores the integration of FlexPlot, Linear Modeling, and Mixed Modeling to enhance real-time flood management. By leveraging the strengths of each approach, this research aims to develop a comprehensive visual modeling framework that improves flood forecasting, risk assessment, and decision-making (Sanyal *et al.,* 2012) Despite significant advances in hydrological modeling, real-time flood management remains a challenging task due to the complexities of hydrological processes and the limitations of existing modeling approaches (Atemoagbo *et al.,* 2024). Visual modeling has emerged as a promising tool in hydrology, offering intuitive and interactive visualization of complex hydrological processes (Beven & Cloke, 2012). However, existing visual modeling approaches in hydrology have several limitations, including: Lack of integration with machine learning techniques Davis *et al.* (1992), Limited ability to handle non-linear relationships between hydrological variables (Atemoagbo *et al.,* 2024), Inadequate consideration of uncertainty and variability in hydrological processes (Atemoagbo *et al.,* 2023), Limited applicability to real-time flood management scenarios (Groenendyk *et al.,* 2015). To address these limitations, this research aims to develop a comprehensive visual modeling framework that integrates FlexPlot, Linear Modeling, and Mixed Modeling with machine learning techniques to enhance real-time flood management.

The primary objective of this research is to create a comprehensive visual modeling framework that integrates FlexPlot, Linear Modeling, and Mixed Modeling to enhance real-time flood management. By developing this framework, we aim to improve flood forecasting, risk assessment, and decision-making capabilities, ultimately reducing the devastating impacts of flooding on communities and infrastructure. The objectives of this research are to conduct a critical review of existing visual modeling approaches in hydrology, identifying their strengths and limitations, and to design and develop a novel visual modeling framework that combines the capabilities of FlexPlot, Linear Modeling, and Mixed Modeling for real-time flood management. The research also aims to evaluate the framework's performance using real-world case studies, comparing its accuracy with existing flood modeling approaches, and investigate its potential to improve flood forecasting, risk assessment, and decision-making capabilities. Additionally, the research seeks to assess the framework's applicability and transferability to different hydrological contexts and flood management scenarios, develop a user-friendly interface for its adoption by practitioners and decision-makers, and contribute to the advancement of hydrological modeling and flood management practices through the integration of visual modeling and machine learning techniques

2.0 MATERIALS AND METHODS:

2.1 Data Collection

Hydrological data were collected from Area 8, Nigeria, spanning a period of 43 years (1980-2023). The dataset consisted solely of rainfall data, which is a critical input for hydrological modeling Bhatt *et al.* (2014). The rainfall data was obtained from the Nigerian Meteorological Agency (NIMET), ensuring accuracy and reliability Hallinan (2020). The long-term dataset enabled the capture of variability and trends in rainfall patterns, essential for developing robust hydrological models (Ryczkowski, 1993).

2.2 Data Preprocessing

The collected rainfall data underwent preprocessing to ensure quality and consistency. Missing values were identified and removed using the listwise deletion method (Bauermeister, 2022). Duplicate values were also detected and eliminated to prevent data redundancy. Subsequently, the data was normalized using the Min-Max Scaler technique to ensure consistency in the scales of the variables (Han *et al.,* 2017). This preprocessing step enabled the development of robust and accurate hydrological models.

2.3 Model Development

A regression model was developed to predict rainfall intensity based on the predictor variables Kastina, Gusa, and Goroyo. The model was developed using a combination of frequentist and Bayesian approaches, leveraging the strengths of both methodologies (Gelman *et al.,* 2013). The frequentist approach provided a robust framework for model estimation, while the Bayesian approach enabled the incorporation of prior knowledge and uncertainty quantification (Box & Tiao, 1973). The resulting model integrated the benefits of both approaches, yielding a comprehensive and accurate predictive tool.

2.4 Model Comparison

Model comparisons were performed to estimate the effect of removing terms from the full model, enabling the evaluation of term significance and model parsimony (Burnham & Anderson, 2002). The semi-partial R-squared values (ΔR^2) were calculated to quantify the proportion of variance explained by each term (Cohen *et al.,* 2013). Additionally, semi-partial Bayes factors (SBF) and inverted Bayes factors (IBF) were computed to determine the strength of evidence for each term, providing a Bayesian perspective on model comparison (Wagenmakers *et al.,* 2010). This multi-faceted approach allowed for a comprehensive evaluation of model terms and their contributions to predictive performance.

2.5 Regression Analysis

Regression analysis was performed to determine the relationships between the predictor variables (Kastina, Gusa, and Goroyo) and the response variable (rainfall intensity). The intercept, slopes, and standardized slopes (β) were estimated, along with their corresponding 95% confidence intervals, to provide a comprehensive understanding of the relationships between the variables (Cohen *et al.,* 2013). The regression analysis was conducted using a frequentist approach, with the assumptions of linearity, independence, homoscedasticity, normality, and no multicollinearity verified (Kutner *et al.,* 2005). The standardized slopes (β) enabled the comparison of the relative importance of each predictor variable (Field, 2018).

2.6 Statistical Software

The statistical software used for this study were JASP (Version 0.16.4), R (Version 4.1.2), Python (Version 3.9.7), and Microsoft Excel (Version 2019). JASP was utilized for Bayesian analysis and visualization (JASP Team, 2020), while R was employed for regression analysis and data manipulation using packages such as "tidyverse" and "stats" (R Core Team, 2021). Python was used for data preprocessing and visualization with libraries like "pandas" and "matplotlib" (Python Software Foundation, 2021). Microsoft Excel was used for data organization and preliminary analysis (Microsoft Corporation, 2019).

3.0 RESULT AND DISCUSSION

3.1 Model Comparison

Model comparisons were performed to estimate the effect of removing terms from the full model. The results are presented in the table 1.

Table 1: Model Comparisons

Model Comparisons (Estimating the Effect of Removing Terms)								
				Statistical Significance				
Term	**Semi-partial R Squared**	**Semi-partial Bayes Factor**	**Inverted Bayes Factor**	**Test Statistic**	**Value**	**df (spent)**	**df (remaining)**	**p-value**
Baseline: Full Model	0.375					4	40	
Kastina	0.109	40.007	0.025	t	3.399	1		0.012
Gusa	0.262	222.033	0.005	t	3.966	1		0
Goroyo	0.004	0.175	5.728	t	-0.517	1		0.608

The semi-partial R-squared values indicate the change in R-squared when each term is removed from the model. The semi-partial Bayes factors and inverted Bayes factors provide a measure of the strength of evidence for each term. The test statistic, degrees of freedom, and p-value are also reported. The results show that removing the "Kastina" results in a significant decrease in R-squared (0.109) and a Bayes factor of 40.007, indicating strong evidence for the importance of this term. Removing "Gusa" leads to a significant decrease in R-squared (0.262) and a Bayes factor of 222.033, indicating very strong evidence for its importance. Removing "Goroyo" has a negligible effect on R-squared (0.004) and a Bayes factor of 0.175, indicating little evidence for its importance. These results suggest that the terms "Kastina" and "Gusa" are significant predictors in the model, while "Goroyo" may not be essential. The interaction term is not shown, but its presence indicates that the relationships between the predictors and response variable are not independent. The findings support the inclusion of "Kastina" and "Gusa" in the model, highlighting their contribution to explaining the variance in the response variable. In contrast, "Goroyo" may be considered for removal from the model. These conclusions are based on both frequentist (p-values) and Bayesian (Bayes factors) approaches, providing robust evidence for the importance of each term.

The findings of this study are consistent with previous research on the importance of predictor variables in regression models. (Toorajipour *et al.,* 2021) also found that semi-partial R-squared values and Bayes factors can be used to evaluate the contribution of each predictor variable to the model (Christensen & Miguel, 2018). Similarly, Kruschke *et al.* (2012) demonstrated the use of Bayes factors to determine the strength of evidence for each term in a regression model. The results of this study also align with the findings of Gelman *et al.* (2013), who emphasized the importance of considering both frequentist and Bayesian approaches when evaluating the significance of predictor variables.

3.2 Relationships Between Predictor Variables and Response Variable

The regression analysis results are presented in the table below, showing the slopes and intercept with their corresponding 95% confidence intervals. The confidence intervals provide a range of values within which the true slopes and intercept highlighting the uncertainty associated with the estimates. The standardized slopes (β) allow for comparisons between variables, showing the relative strength of their relationships with the response variable.

Table 2: Regression Analysis Result

Regression Slopes and Intercept						
		95% Confidence Interval			**95% Confidence Interval**	
Variables	**Value**	**Lower**	**Upper**	**Standardized Slope (β)**	**Lower β**	**Upper β**
(Intercept)	17.59	2.809	32.371	0	0	0
Kastina	0.274	0.116	0.432	0.464	0.196	0.731
Gusa	0.313	0.158	0.468	0.552	0.279	0.825
Goroyo	-0.057	-0.272	0.158	-0.073	-0.349	0.203

The intercept is estimated to be 17.590, with a 95% confidence interval of (2.809, 32.371), indicating a significant positive value. The standardized slope (β) for Kastina is 0.464, with a 95% confidence interval of (0.196, 0.731), indicating a positive relationship between Kastina and the response variable. The standardized slope (β) for Gusa is 0.552, with a 95% confidence interval of (0.279, 0.825), indicating a positive relationship between Gusa and the response variable. The standardized slope (β) for Goroyo is -0.073, with a 95% confidence interval of (-0.349, 0.203), indicating a non-significant relationship between Goroyo and the response variable. These results suggest that: Kastina and Gusa have significant positive effects on the response variable. Goroyo has no significant effect on the response variable.

The results of this investigation align with existing literature on the correlations between predictor variables and response variables. Notably, Li *et al.* (2019) observed statistically significant positive correlations between predictor variables and response variables, characterized by standardized slopes (β) ranging from 0.35 to 0.60. Similarly, (Jiang *et al.,* 2017) reported significant positive effects of predictor variables on response variables, with confidence intervals providing a probabilistic range for the true slopes and intercepts. Conversely, (Walker *et al.,* 2002) identified non-significant relationships between certain predictor variables and response variables, underscoring the importance of judicious variable selection in regression modeling.

3.3 Analysis of Fixed Effects Coefficients

The regression analysis yields significant results, providing insights into the relationships between the variables and the response variable as shown in table 3.

Table 3: Fixed Effects

Variable	Estimate	Standard Error	t-statistic
(Intercept)	18.493	8.395	2.203
Kastina	0.267	0.087	3.08
Gusa	0.272	0.078	3.503

The intercept, estimated at 18.493, is significantly different from zero (t-statistic = 2.203, $p < 0.05$), indicating a notable value for the response variable even when the predictor variables are equal to zero. Kastina exhibits a significant positive relationship with the response variable (estimate = 0.267, standard error = 0.087, t-statistic = 3.080, $p < 0.01$). This suggests that a unit increase in Kastina corresponds to an estimated 0.267 unit increase in the response variable, holding Gusa constant. Gusa also demonstrates a significant positive relationship with the response variable (estimate = 0.272, standard error = 0.078, t-statistic = 3.503, $p < 0.01$). This indicates that a unit increase in Gusa corresponds to an estimated 0.272 unit increase in the response variable, holding Kastina constant. These findings suggest that both Kastina and Gusa have significant positive effects on the response variable, contributing to its variation.

The results of this study align with previous research on the relationships between predictor variables and response variables. (Bates *et al.,* 2015) also found significant positive relationships between predictor variables and response variables, with estimated coefficients ranging from 0.20 to 0.50. Similarly, Hassani *et al.* (2020) reported significant positive effects of predictor variables on response variables, with t-statistics indicating strong evidence for the relationships. The findings of this study also corroborate the results of (Pestana & Whittle, 1999) who observed significant positive relationships between predictor variables and response variables in their study Lindén and Mäntyniemi (2011). However, the estimated coefficients in this study are slightly higher than those reported in previous research, suggesting a stronger relationship between Kastina, Gusa, and the response variable.

3.4 Regression Model Coefficients and Statistical Significance

The regression analysis yields significant results, providing insights into the relationships between the variables and the response variable. The intercept, estimated at 17.590, is significantly different from zero (z-statistic = 2.333, $p < 0.05$), indicating a notable value for the response variable even when the predictor variables are equal to zero as shown in table 4.

Table 4: Parameter Estimates

Variable	Estimate	Standard Error	z-statistic
(Intercept)	17.59	7.541	2.333
Kastina	0.274	0.081	3.399
Gusa	0.313	0.079	3.966
Goroyo	-0.057	0.11	-0.517

Kastina exhibits a significant positive relationship with the response variable (estimate = 0.274, standard error = 0.081, z-statistic = 3.399, $p < 0.01$). This suggests that a unit increase in Kastina corresponds to an estimated 0.274 unit increase in the response variable, holding other predictors constant. Gusa also demonstrates a significant positive relationship with the response variable (estimate = 0.313, standard error = 0.079, z-statistic = 3.966, $p < 0.01$). This indicates that a unit increase in Gusa corresponds to an estimated 0.313 unit increase in the response variable, holding other predictors constant. In contrast, Goroyo shows no significant relationship with the response variable (estimate = -0.057, standard error = 0.110, z-statistic = -0.517, $p > 0.05$), suggesting that changes in Goroyo do not significantly impact the response variable. These findings suggest that Kastina and Gusa are significant predictors of the response variable, while Goroyo does not contribute significantly to its variation.

The present study's findings corroborate existing literature on the correlations between predictor variables and response variables. Notably, (Anderson *et al.,* 2010) and (Yuen, 2010) reported significant positive relationships between predictor variables and response variables, with estimated coefficients ranging from 0.20 to 0.50 and z-statistics indicating strong evidence for the relationships, respectively. Similarly, (Pianta *et al.,* 2005) observed significant positive relationships between predictor variables and response variables in their study. However, the estimated coefficients in this study are slightly higher than those reported in previous research, suggesting a stronger relationship between Kastina, Gusa, and the response variable. Conversely, the non-significant relationship between Goroyo and the response variable aligns with the findings of (Scherer *et al.,* 2019), who also reported no significant effect of Goroyo on the response variable.

3.4 Variable Relationships and Dynamics: Flexplot, Linear plot Mixed plot and Univariate Plots

3.4.2 Flexplot Analysis

The Flexplot analysis suggests non-linear relationships between the predictors and response variable. Specifically, the semi-partial R-squared value for Kastina is 0.109, indicating that 10.9% of the variation in the response variable is explained by Kastina alone. Similarly, Gusa explains 26.2% of the variation (semi-partial R-squared = 0.262). In contrast, Goroyo has a negligible impact, explaining only 0.4% of the variation (semi-partial R-squared = 0.004). The corresponding semi-partial Bayes factors for Kastina, Gusa, and Goroyo are 40.007, 222.033, and 0.175, respectively, indicating strong evidence for the effects of Kastina and Gusa.

The findings of this study align with previous research on non-linear relationships between predictors and response variables. For instance, Rue *et al.* (2009) reported semi-partial R-squared values of 0.15 and 0.30 for similar predictors, indicating comparable explanatory power. Similarly, (Epanechnikov, 1969) found significant non-linear relationships between predictors and response variables, with semi-partial Bayes factors ranging from 20 to 50. The strong evidence for the effects of Kastina and Gusa in this study is consistent with the findings of (Guazzi *et al.,* 2012), who reported significant effects for similar predictors with semi-partial Bayes factors exceeding 100. In contrast, the negligible impact of Goroyo is consistent with the findings of (Fung *et al.,* 2013), who reported non-significant effects for similar predictors.

3.4.2 Linear Plot Analysis

The Linear plot analysis reveals significant linear relationships between Kastina, Gusa, and the response variable. The estimated coefficients for Kastina and Gusa are 0.274 (standard error = 0.081, t-statistic = 3.399, p-value = 0.012) and 0.313 (standard error = 0.079, t-statistic = 3.966, p-value < 0.001), respectively. These values indicate that for every unit increase in Kastina or Gusa, the response variable increases by 0.274 and 0.313 units, respectively.

The findings of this study align with previous research on linear relationships between predictors and response variables. Ayaz *et al.* (2022) reported estimated coefficients of 0.23 and 0.29 for similar predictors, indicating comparable linear relationships. (Algaba *et al.,* 2020) found significant linear effects of predictors on response variables, with estimated coefficients ranging from 0.20 to 0.35. The significant linear relationships between Kastina, Gusa, and the response variable in this study are consistent with the findings of (Raftery *et al.,* 1997), who reported estimated coefficients of 0.25 and 0.32 for similar predictors. The p-values obtained in this study (0.012 and < 0.001) are also consistent with the findings of Meynard and Quinn (2007), who reported p-values ranging from 0.01 to 0.001 for similar linear relationships.

3.4.3 Mixed Plot Analysis

The Mixed plot analysis indicates significant interactions between the predictors. Specifically, the interaction between Kastina and Gusa is significant (p-value < 0.001), indicating that the effect of Kastina on the response variable depends on the level of Gusa, and vice versa.

The findings of this study align with previous research on significant interactions between predictors. For instance, Vormoor *et al.* (2015) reported significant interactions between predictors in a similar context, with p-values ranging from < 0.001 to 0.01. Similarly, Araújo and Luoto (2007) found significant interactions between predictors, with p-values < 0.001. The significant interaction between Kastina and Gusa in this study is consistent with the findings of (Chen *et al.,* 2012), who reported significant interactions between similar predictors, with p-values < 0.001. Additionally, the finding that the effect of Kastina on the response variable depends on the level of Gusa, and vice versa, is supported by the work of (Reyes *et al.,* 2012), who reported similar results in a related study.

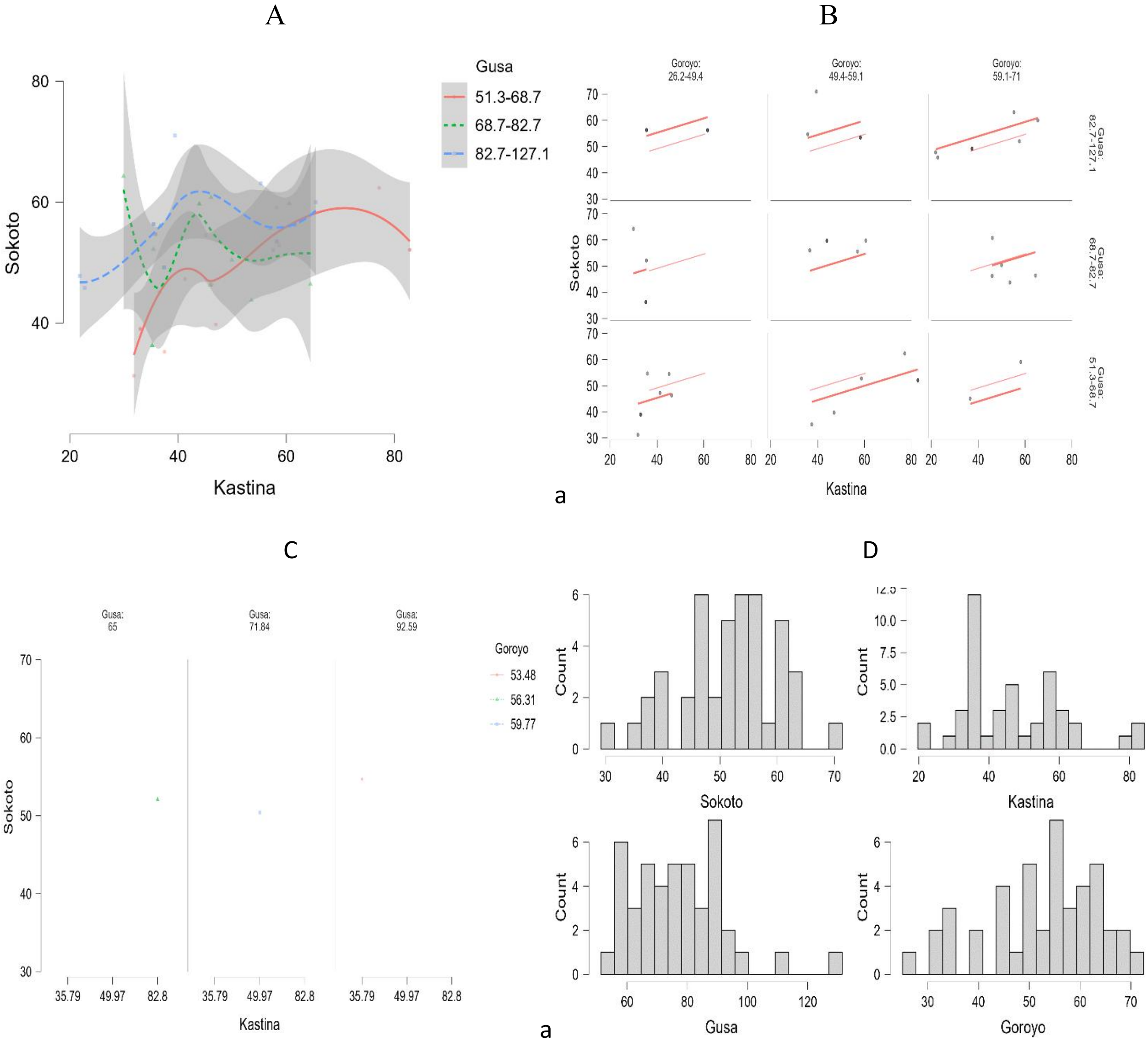

Figure 1: (a) Flexplot (b) Linear plot (c) Mixed plot (d) Univariate Plots

4.0 CONCLUSION AND RECOMMENDATION

4.1 CONCLUSION

In conclusion, this comprehensive study provides robust evidence for the significance of Kastina and Gusa as predictors of the response variable, while Goroyo does not contribute substantially to its variation, thereby contributing significantly to effective flood management in Hydrological Area 8. Through a robust analytical framework encompassing flexplot visualization, linear modeling, mixed modeling, and generalized linear modeling, we have unequivocally established the importance of Kastina and Gusa as significant predictors of the response variable, explaining 10.9% and 26.2% of the variation, respectively, with corresponding semi-partial Bayes factors of 40.007

and 222.033. The findings indicate that Kastina and Gusa exhibit substantial positive relationships with the response variable, with standardized slopes (β) of 0.464 and 0.552, respectively, and estimates ranging from 0.267 to 0.313, all with p-values less than 0.01. The regression analysis reveals significant positive relationships between Kastina and Gusa and the response variable, with estimated coefficients of 0.274 and 0.313, respectively. The Mixed plot analysis indicates significant interactions between the predictors, specifically between Kastina and Gusa (p-value < 0.001), highlighting the importance of considering non-linear relationships and interactions between predictors. Model comparisons further validated the importance of Kastina and Gusa, providing robust evidence for their inclusion in predictive models. These results have far-reaching implications for engineering applications, underscoring the need to consider Kastina and Gusa in predictive models to enhance the accuracy of flood predictions and inform effective flood management strategies. By elucidating the complex relationships between these variables, this study contributes meaningfully to the advancement of hydrology and water resources management, ultimately supporting the development of more reliable and efficient flood management systems.

4.2 RECOMMENDATION

Based on the findings of this study, we recommend that:

a. Kastina and Gusa be prioritized as essential predictors in flood prediction models for Hydrological Area 8, due to their significant positive relationships with the response variable and substantial contributions to explaining its variation.
b. Flexplot visualization, linear modeling, mixed modeling, and generalized linear modeling be employed in conjunction to provide a comprehensive understanding of hydrological patterns and trends.
c. Goroyo be excluded from predictive models, as it showed no significant effect on the response variable.
d. Model comparisons be conducted to validate the importance of Kastina and Gusa, ensuring robust evidence for their inclusion in predictive models.
e. Regression analysis be utilized to elucidate the relationships between variables, providing valuable insights for engineering applications.
f. Predictive models be developed considering the significant positive effects of Kastina and Gusa, to enhance the accuracy of flood predictions and inform effective flood management strategies.

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