***Original Research Article***

**Predictors of Food Insecurity in the Sundarbans: Multinomial Logit Approach Apropos the Food Insecurity Experience Scale**

**ABSTRACT**

Aims: This study examines socio-economic and demographic determinants of food insecurity in the Sundarbans region using a multinomial logistic regression model, aiming to identify key predictors of food insecurity levels and provide evidence-based recommendations for resilience and food security improvement in this ecologically fragile area.

Study Design: A cross-sectional analytical study employing multinomial logistic regression to assess categorical predictors of food insecurity.

Place and Duration of Study: Data were collected over six months (January 2024–December 2024 at regular time interval) across 11 blocks in South and North 24 Parganas, such as Gosaba, Basanti, Kakdwip, and Sagar.

Methodology: Structured interviews were conducted with 300 randomly selected respondents from a pool of individuals representing diverse livelihood groups. Socio-economic and environmental data were collected, including household income, cultivated land, education, indebtedness, and extension services participation. Food insecurity was categorized as food secure, moderately food insecure, and severely food insecure, and analyzed through multinomial logistic regression.

Results: The model demonstrated 80.9% overall predictive accuracy, correctly classifying 78.9% of food-secure households, 91.7% of moderately food-insecure households, and 39.5% of severely food-insecure households. Key protective factors included access to cultivated land, household education, and social capital, which mitigated food insecurity. In contrast, indebtedness and number of skipped meals increased food vulnerability. Agricultural extension services and formal in-kind transfers were effective interventions, particularly for severe food insecurity. Pseudo R-squared values (Nagelkerke: 0.663) confirmed the model’s explanatory strength. The odds ratio ([OR], 0.087; 95% CI 0.020 to 0.384 for ‘total cultivated land’ suggested a significant protective effect against food insecurity at the 1% significance level (p<0.001). One unit increase in cultivated land reduces the odds of food insecurity by approximately 91.3%, underscoring the importance of agricultural land access in enhancing food security.

Conclusion: Combating food insecurity in the Sundarbans requires integrated strategies enhancing land access, debt alleviation, education, social networks, and food assistance programs, offering actionable insights for equitable, sustainable food systems in vulnerable regions.

**KEYWORDS:** Cultivated Land, Food Insecurity, Multinomial Logistic Regression, Odds Ratio, Socio-Economic Determinants, Sundarbans, Vulnerability Assessment

**INTRODUCTION**

One of the most important issues facing the world today is food insecurity, which is characterised by irregular access to enough wholesome food that is safe and sufficient for an active and healthy life (FAO, 2023). Leading agencies including the World Food Programme (WFP), UNICEF, and the Food and Agriculture Organisation (FAO) recognise the four main components of food security—access, availability, utilisation, and stability—which together determine how well people are nourished and healthy (WFP, 2022). There are two categories of food insecurity: moderate and severe. Moderate insecurity is characterised by a decrease in the quantity and quality of food, whereas severe insecurity is characterised by circumstances in which people completely run out of food (FAO *et al.*, 2022). A number of methods are used around the world to quantify food insecurity, such as the Prevalence of Undernourishment (PoU), which assesses dietary energy deprivation, and the Food Insecurity Experience Scale (FIES), which records personal experiences of food-related hardships (FAO, 2023). Comparative evaluations of food security across countries are offered by composite indexes such as the Global Hunger Index (GHI) and Global Food Security Index (GFSI) (Von Grebmer *et al.*, 2023). Child mortality, stunting, wasting, and undernourishment are all assessed by the Global Hunger Index. India's GHI 2024 ranking of 105th out of 127 countries with a score of 27.3 for "serious hunger" reflects ongoing issues such as the country's 13.7% undernourished population, 35.5% stunting rate for children under five, and the highest rate of wasting in the world, 18.7% of children under five (von *Grebmer et al*., 2023). Similarly, in the Global Food Security Index (GFSI), India ranks 68th out of 113 countries, highlighting critical issues such as poverty, unequal distribution, and agricultural inefficiencies (EIU, 2023). By contrast, countries like Finland and Ireland rank highest in food security, while nations such as Sierra Leone and Haiti face severe challenges (EIU, 2023). India’s food insecurity is driven by rapid population growth, socio-economic disparities, climate change impacts, and water scarcity (Swaminathan, 2023). These national challenges are further intensified in the Sundarbans, an ecologically fragile yet densely populated coastal region of India (Danda, 2021). The Sundarbans exemplify the vulnerabilities faced by marginalized communities reliant on agriculture, fisheries, and forest-based livelihoods (Hazra *et al.*, 2022). Frequent extreme weather events, increasing sea levels, and soil salinity have significantly lowered agricultural output and harmed livelihoods, leading to recurring dangers of food shortages and instability in the region (Mukherjee *et al.*, 2023). Addressing food insecurity in the Sundarbans requires a nuanced understanding of its socio-economic determinants. Household income, education, landholding size, access to markets, and social capital are globally recognized as major contributors to food security (Sen & Dutta, 2020). Nevertheless, there are currently few region-specific assessments that are adapted to the particular ecological and socioeconomic vulnerabilities of the Sundarbans (Chowdhury & Ghosh, 2022). This study aims to bridge this gap by employing a multinomial logit model to analyze the socio-economic drivers of food insecurity in the Sundarbans. By examining a variety of socioeconomic factors, the study aims to give policymakers evidence-based suggestions that would enable focused interventions that improve resilience and lessen food insecurity among the agricultural and fishing communities in the area (Bera & Saha, 2021).

**METHODOLOGY**

The Sundarbans region was chosen as the research area due to its unparalleled ecological significance and pronounced socio-economic vulnerabilities, making it an ideal site for studying the dynamics of coastal resilience and food insecurity (Danda, 2021). Data for this study were collected across 11 administrative blocks in South and North 24 Parganas, covering key villages such as Gosaba, Basanti, Sagar, Kakdwip, Namkhana, Kultali, Patharpratima, Sandeshkhali, Minakhan, and Hijalganj (Mukherjee *et al.*, 2023). From this dataset, a random sample of 300 respondents was finalized for detailed analysis (Chowdhury & Ghosh, 2022). To rigorously examine the factors influencing food insecurity, the multinomial logit model was employed, as it is particularly adept at analyzing categorical dependent variables with multiple possible outcomes (Train, 2009). This analytical approach allowed the exploration of key predictors contributing to varying levels of household food insecurity in the Sundarbans (Bera & Saha, 2021). The multinomial logit model calculates the probability of a household falling into specific food insecurity categories based on a range of socio-economic and environmental factors, including income, educational attainment, type of livelihood, landholding size, and exposure to climate shocks (Hazra *et al.*, 2022). The multinomial logit model (MNL) Lal *et al*. (2025) extends the binomial logit model by allowing for multiple categorical outcomes instead of a binary dependent variable (Greene, 2018). In this study, the model analyzes the determinants of different livelihood strategies in the Sundarbans, where the dependent variable (e.g., food secure, moderately food insecure, and severely food insecure) represents different livelihood categories (e.g., agriculture, fishery, honey collection, or a cocombination of these) (Sen & Dutta, 2020). The reference category is typically agriculture, and all comparisons are made relative to this group (Gujarati & Porter, 2020). Mathematically, the MNL model estimates the probability of a household engaging in a particular livelihood strategy based on socio-economic and environmental predictors such as income, landholding size, education, social participation, indebtedness, and access to formal support systems (Maddala, 1983):

=1,2,….,J

where:

represents the probability of a household represents the probability of a household being in food insecurity category

X denotes the vector of independent variables

are the estimated coefficients, and

The base category (typically food-secure households) serves as the comparison group.

The model outputs **odds ratios (OR)** for each category relative to the base category.

**OR > 1** suggests a positive association (e.g., higher education increases food security).

**OR < 1** indicates a negative impact (e.g., indebtedness increases food insecurity).

**OR = 1** implies no effect.

Statistical significance is assessed using p-values (< 0.05 indicates a meaningful effect) and Wald statistics. Model fit is evaluated through the Likelihood Ratio (LR) Test, Pseudo R² (Nagelkerke R²). A well-fitting model should have a classification accuracy of >70%, correctly predicting livelihood choices. The multinomial logit model thus provides crucial insights into the socio-economic and behavioral determinants of livelihood strategies in the Sundarbans, guiding policymakers in designing targeted interventions to support sustainable income diversification and resilience among rural households.

**RESULTS AND DISCUSSION**

The findings of this study provide empirical insights into the fact socio-economic determinants of food insecurity in the Sundarbans.

**Table 1: Model Fit Statistics for Multinomial Logistic Regression Analysis**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Model** | **AIC** | **BIC** | **LL** | **χ2** | **df** | **Sig.** |
| Intercept Only | 561.666 | 569.067 | 557.666 | - | - | - |
| Final | 376.053 | 494.467 | 312.053 | 245.614 | 30 | <0.001 |

The statistics used in model fitting, such as AIC (Akaike Information Criterion), BIC (Bayesian Information Criterion), -2 Log Likelihood (-2LL), Chi-Square statistic, degrees of freedom (df), and p-value, serve as vital tools for assessing model quality and fit. Both AIC and BIC are measures of the relative quality of statistical models, estimating the information lost when a specific model represents the data-generating process. Lower AIC and BIC values indicate a better balance between model complexity and goodness of fit, with the model exhibiting the smallest values being generally preferred. The -2 Log Likelihood (-2LL) quantifies how well the model fits the data, where a lower value reflects a stronger fit, and it is often utilized in the calculation of the Chi-Square statistic for comparing nested models. The Chi-Square statistic, in this context, refers to a Likelihood Ratio Test that compares the full model to a simpler, nested model (such as an intercept-only model). A significant Chi-Square value, indicated by a low p-value (typically less than 0.05), suggests that the full model significantly outperforms the simpler model. The degrees of freedom (df) represent the number of independent pieces of information used in calculating the Chi-Square statistic, typically equal to the difference in the number of parameters between the two models. Finally, the p-value indicates the probability of obtaining a Chi-Square statistic as extreme as the one observed, assuming the simpler model is correct. A low p-value provides strong evidence against the simpler model, affirming that the full model offers a significantly better representation of the data. Together, these metrics collectively provide a robust framework for evaluating and comparing statistical models.

**Table 2.** **Evaluating Model Fit for Food Insecurity Determinants**

|  |  |  |  |
| --- | --- | --- | --- |
| **Test** | **Chi-Square** | **df** | **Sig.** |
| Pearson | 580.188 | 566 | 0.331 |
| Deviance | 312.053 | 566 | 1.000 |

The goodness-of-fit test results in table 2. presented in the table assess the adequacy of the multinomial logistic regression model in explaining food insecurity. The Pearson Chi-Square test (χ² = 580.188, df = 566, p = 0.331) and Deviance test (χ² = 312.053, df = 566, p = 1.000) indicate that the model's predicted probabilities align well with the observed data, as both tests yielded non-significant p-values (p > 0.05). These results suggest the model fits well and does not significantly deviate from the actual data distribution, validating its suitability for the analysis.

**Table 3. Pseudo R-Square Insights into Food Insecurity Predictors**

|  |  |
| --- | --- |
| **Measure** | **Value** |
| Cox and Snell | 0.560 |
| Nagelkerke | 0.663 |
| McFadden | 0.440 |

Pseudo-R-squared values—Cox and Snell, Nagelkerke, and McFadden (Table 3) offer distinct perspectives on the proportion of variance explained by multinomial logistic regression models. The Cox and Snell R-squared (0.560) adapts the linear regression concept but is limited in its ability to reach a maximum value of 1, indicating that 56.0% of the variance in the dependent variable is explained relative to its theoretical maximum. Nagelkerke R-squared (0.663) adjusts the Cox and Snell measure for interpretability, scaling it to achieve a maximum value of 1, showing that the model explains 66.3% of the variance—providing a more intuitive representation. McFadden R-squared (0.440), based on the likelihood ratio between the intercept-only and full models, is a conservative measure of goodness-of-fit; while its values tend to be lower, a score of 0.440 signifies that the model explains 44.0% of the variance relative to the baseline. Typically, McFadden values ranging from 0.2 to 0.4 are deemed acceptable in logistic regression contexts. Together, these measures reflect varying levels of explanatory power, with Nagelkerke R-squared presenting the most substantial contribution and McFadden R-squared offering a baseline comparison. These metrics underscore the robustness of the model in capturing key determinants of the dependent variable.

**Table 4: Parameter Estimates for Multinomial Logistic Regression Predicting Food Insecurity**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Variable** | **β** | **SE** | **Wald** | **Sig.** | **Exp(β)** | **95% CI for Exp(β)** |
| **(Food secure to Moderately food insecure)**  **(0 1)** |  |  |  |  |  |  |
| Intercept | -1.333 | 4.032 | 0.109 | 0.741 | - | - |
| Age | -0.009 | 0.030 | 0.093 | 0.760 | 0.991 | (0.935, 1.051) |
| Sex | -0.188 | 0.672 | 0.078 | 0.780 | 0.828 | (0.222, 3.093) |
| Total Income | <0.001 | <0.001 | 4.126 | 0.042\* | 1.000 | (1.000, 1.000) |
| Total Cultivated Land | -2.441 | 0.757 | 10.386 | 0.001\*\*\* | 0.087 | (0.020, 0.384) |
| Indebtedness | 1.156 | 0.469 | 6.068 | 0.014\* | 3.178 | (1.267, 7.974) |
| Social Participation | -0.023 | 0.140 | 0.026 | 0.871 | 0.978 | (0.744, 1.285) |
| Extension Participation | -0.165 | 0.087 | 3.588 | 0.058\* | 0.848 | (0.715, 1.006) |
| Formal In-kind Transfer | <0.001 | <0.001 | 11.275 | 0.001\*\*\* | 1.000 | (1.000, 1.000) |
| Skipped Meals/Year | 0.062 | 0.019 | 11.298 | 0.001\*\*\* | 1.064 | (1.026, 1.104) |
| Local Group Participation | 0.449 | 0.489 | 0.840 | 0.359 | 1.566 | (0.600, 4.088) |
| Help from Organizations | -0.513 | 0.521 | 0.968 | 0.325 | 0.599 | (0.216, 1.663) |
| Training Participation | -0.332 | 0.229 | 2.090 | 0.148 | 0.718 | (0.458, 1.125) |
| Interpersonal Cosmopolite | -0.515 | 0.161 | 10.254 | 0.001\*\*\* | 0.597 | (0.436, 0.819) |
| Household Education Years | -0.664 | 0.281 | 5.585 | 0.018\* | 0.515 | (0.297, 0.893) |
| Crops Last Season | 0.237 | 0.197 | 1.447 | 0.229 | 1.267 | (0.862, 1.863) |
| **(Food Secure to Food Insecure)**  **(0 2)** |  |  |  |  |  |  |
| Intercept | 12.463 | 4.815 | 6.699 | 0.010\* | - | - |
| Age | -0.032 | 0.039 | 0.659 | 0.417 | 0.969 | (0.897, 1.046) |
| Sex | 0.065 | 0.836 | 0.006 | 0.938 | 1.067 | (0.207, 5.492) |
| Total Income | <0.001 | <0.001 | 0.005 | 0.942 | 1.000 | (1.000, 1.000) |
| Total Cultivated Land | -1.078 | 0.939 | 1.319 | 0.251\* | 0.340 | (0.054, 2.142) |
| Indebtedness | 1.024 | 0.589 | 3.020 | 0.082 | 2.786 | (0.877, 8.845) |
| Social Participation | 0.234 | 0.172 | 1.854 | 0.173 | 1.264 | (0.902, 1.770) |
| Extension Participation | -0.322 | 0.108 | 8.837 | 0.003\*\* | 0.725 | (0.586, 0.896) |
| Formal In-kind Transfer | <0.001 | <0.001 | 7.301 | 0.007\*\* | 1.000 | (1.000, 1.000) |
| Skipped Meals/Year | -0.002 | 0.023 | 0.009 | 0.925 | 0.998 | (0.954, 1.043) |
| Local Group Participation | 0.230 | 0.628 | 0.134 | 0.714 | 1.259 | (0.368, 4.309) |
| Help from Organizations | -0.128 | 0.680 | 0.035 | 0.851 | 0.880 | (0.232, 3.338) |
| Training Participation | -0.381 | 0.291 | 1.710 | 0.191 | 0.683 | (0.386, 1.209) |
| Interpersonal Cosmopolite | -0.568 | 0.203 | 7.817 | 0.005\*\* | 0.567 | (0.381, 0.844) |
| Household Education Years | -0.852 | 0.440 | 3.738 | 0.053\* | 0.427 | (0.180, 1.012) |
| Crops Last Season | 0.182 | 0.255 | 0.512 | 0.474 | 1.200 | (0.728, 1.976) |

\*\*\* Indicates significant at 1% level of significance, in a two-tailed test, \*\* Indicates significant at 5% level of significance, in a two tailed test, \* Indicates significant at 10% level of significance, in a two-tailed test.

The multinomial logistic regression analysis highlights significant predictors of food insecurity (Table 4.) among households in the Sundarbans, reflecting complex socio-economic and environmental dynamics. Table 4 presents parameter estimates comparing food security categories: food-secure households (Category 0), moderately food insecure households (Category 1), and food insecure households (Category 2). The model demonstrated strong predictive accuracy, correctly classifying 80.9% of cases overall, with high accuracy for moderately food insecure households (91.7%) but lower for severely food insecure households (39.5%). Model fit indicators, including AIC (457.24) and BIC (511.76), underscore its robustness in capturing key determinants of food insecurity. In Category 0 to Category 1 (food secure to moderately food insecure): Total Income: A positive coefficient (<0.001) with a significance of p < 0.05 indicates that higher income slightly increases the likelihood of being in Category 1 compared to Category 0 3. Total Cultivated Land: A negative coefficient (-2.441) with a high significance (p < 0.001) suggests that more cultivated land significantly reduces the likelihood of moderate food insecurity (Category 1) compared to being food secure (Category 0). Indebtedness: A positive coefficient (1.156) with a significance of p < 0.05 implies that higher indebtedness increases the likelihood of being moderately food insecure (Category 1). Extension Participation: A negative coefficient (-0.165) with marginal significance (p < 0.10) suggests that participation in extension activities tends to reduce the likelihood of being in Category 1. Formal In-kind Transfer: A positive coefficient (<0.001) with a high significance (p < 0.001) indicates that receiving formal in-kind transfers increases the likelihood of being in Category 1. Skipped Meals/Year: A positive coefficient (0.062) with a high significance (p < 0.001) shows that more skipped meals per year significantly increase the likelihood of being moderately food insecure (Category 1). Interpersonal Cosmopolite: A negative coefficient (-0.515) with a high significance (p < 0.001) indicates that greater interpersonal connections significantly reduce the likelihood of being in Category 1. Household Education Years: A negative coefficient (-0.664) with a significance of p < 0.05 suggests that more years of household education reduce the likelihood of being moderately food insecure. In Category 0 to Category 2 (food secure vs. food insecure): Extension Participation: A negative coefficient (-0.322) with a significance of p < 0.01 indicates that participation in extension activities significantly reduces the likelihood of being in Category 2 compared to Category 0. Formal In-kind Transfer: A positive coefficient (<0.001) with a significance of p < 0.01 suggests that receiving formal in-kind transfers increases the likelihood of being in Category 2. Interpersonal Cosmopolite: A negative coefficient (-0.568) with a significance of p < 0.01 indicates that greater interpersonal connections significantly reduce the likelihood of being in Category 2. Household Education Years: A negative coefficient (-0.852) with marginal significance (p < 0.10) suggests that more years of household education tend to reduce the likelihood of being in Category 2. Indebtedness: A positive coefficient (1.024) with a significance of p < 0.10 implies that higher indebtedness increases the likelihood of being severely food insecure (Category 2). The forest plot (Fig. 1.) succinctly illustrates the odds ratios for variables influencing food insecurity among households, comparing food-secure (Category 0) to moderately food-insecure (Category 1) and severely food-insecure (Category 2). The odds ratios from the multinomial logistic regression model provide valuable insights into the likelihood of food insecurity based on various predictors. For instance, higher indebtedness significantly increases the probability of both moderate and severe food insecurity, with odds ratios of 3.178 (Category 0 to 1) and 2.786 (Category 0 to 2), respectively. Conversely, Total Cultivated Land (odds ratio: 0.087 for Category 0 to 1) and Interpersonal Cosmopolite (odds ratios: 0.597 for Category 0 to 1 and 0.567 for Category 0 to 2) show a protective effect by reducing the likelihood of food insecurity. These results illustrate how socio-economic and interpersonal factors influence food security, with higher odds ratios highlighting risks and lower values indicating mitigating factors, which can inform targeted interventions.

Significant predictors, such as Indebtedness, Total Cultivated Land, and Interpersonal Cosmopolite, reveal contrasting effects: while higher indebtedness increases food insecurity likelihood, larger cultivated landholdings and stronger interpersonal connections reduce the risk. Confidence intervals, shown as error bars, offer a sense of the reliability of these estimates, with non-overlapping intervals indicating stronger predictive certainty. This visualization highlights crucial socio-economic drivers of food insecurity, providing valuable insights for targeted interventions and informed policymaking.

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**Fig. 1. Visualizing the Drivers of Food Insecurity: Odds Ratios at a Glance**

**Table 5: Classification Accuracy of the Food Insecurity Predictive Model**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Observed** | **Predicted** |  |  | **Percent Correct** |
|  | Category 0 | Category 1 | Category 2 |  |
| Category 0 | 60 | 14 | 2 | 78.9% |
| Category 1 | 9 | 165 | 6 | 91.7% |
| Category 2 | 3 | 23 | 17 | 39.5% |
| Overall Percentage | 24.1% | 67.6% | 8.4% | 80.9% |

The multinomial logistic regression model demonstrated (Table 5.) an overall classification accuracy of 80.9%, effectively predicting 78.9% of food-secure households (Category 0), 91.7% of moderately food-insecure households (Category 1), and 39.5% of severely food-insecure households (Category 2). While the model performed well for food-secure and moderately food-insecure households, its lower accuracy for food-insecure households indicates the complexity of predicting this category, likely due to unaccounted factors. These results highlight the model's strong capability in identifying trends in food insecurity, with room for refinement in severe cases to improve predictive precision.

**Table 6: Summary of Significant Predictors of Food Insecurity in the Sundarbans**

|  |  |  |  |
| --- | --- | --- | --- |
| **Predictor** | **Effect on Category 1** | **Effect on Category 2** | **Interpretation** |
| Total Cultivated Land | Negative (\*\*\*) | Non-significant | Access to agricultural land significantly reduces  moderate food insecurity |
| Indebtedness | Positive (\*) | Positive (†) | Financial debt increases likelihood of food insecurity  at both levels |
| Extension  Participation | Negative (†) | Negative (\*\*) | Agricultural extension services protect against food  insecurity, especially severe cases |
| Formal In-kind  Transfer | Significant (\*\*\*) | Significant (\*\*) | Food assistance programs have significant impacts on  food security status |
| Skipped Meals/Year | Positive (\*\*\*) | Non-significant | Coping behavior strongly associated with moderate  food insecurity |
| Interpersonal  Cosmopolite | Negative (\*\*\*) | Negative (\*\*) | External connections and networks strongly protect  against food insecurity |
| Household  Education Years | Negative (\*) | Negative (†) | Education serves as a protective factor against food  insecurity |

\*\*\* Indicates significant at 1% level of significance, in a two-tailed test, \*\* Indicates significant at 5% level of significance, in a two tailed test, \* Indicates significant at 10% level of significance, in a two-tailed test.

Important factors affecting the degree of food insecurity in the Sundarbans are shown in Table 6. While access to farmed land has little influence on extreme food hardship, it dramatically lowers moderate food insecurity. While agricultural extension services guard against food insecurity, especially in extreme circumstances, debt raises risk on both fronts. While missing meals is significantly linked to just moderate food insecurity, formal in-kind transfers have a positive influence on food security across all categories. Household education years and social capital, as determined by interpersonal relationships, are important protective factors against moderate and severe food insecurity. To reduce food insecurity in the area, our findings highlight the necessity of focused interventions that address social networks, education, debt management, land access, and food assistance programs. The implications for food security span multiple dimensions, emphasizing the need for integrative approaches to ensure equitable access to food. Socio-economic factors like income levels, land access, education, and social networks significantly shape household resilience. Policies addressing poverty, inequality, and livelihood opportunities are crucial to reducing vulnerability. Climate and environmental changes, including extreme weather events and resource depletion, directly threaten agricultural productivity, highlighting the importance of sustainable farming practices and disaster preparedness. Behavioral aspects, such as coping strategies like skipping meals, reflect immediate responses to food insecurity but may result in long-term health consequences, requiring interventions that reduce reliance on such measures. Additionally, effective government policies, including food assistance programs, infrastructural development, and market access initiatives, play a pivotal role in building food systems that are stable and adaptable. Overall, addressing food security requires holistic solutions combining socio-economic development, environmental sustainability, and targeted policy interventions to ensure global food resilience.

**CONCLUSION**

The study provides crucial insights into the socio-economic determinants of food insecurity in the Sundarbans, emphasizing the importance of targeted interventions to enhance food security in this ecologically fragile region. Key findings reveal that factors such as access to cultivated land, household education, social capital, agricultural extension services, and formal in-kind transfers serve as protective mechanisms against food insecurity, while indebtedness and coping strategies like skipped meals exacerbate vulnerability. The multinomial logistic regression model demonstrates strong predictive accuracy, highlighting the interplay of socio-economic and environmental factors influencing food insecurity. These results underscore the urgent need for comprehensive policies that address systemic issues such as poverty, inequality, and resource management, while promoting sustainable agricultural practices and resilience-building programs. By integrating socio-economic development, climate adaptation strategies, and community-based interventions, policymakers can reduce food insecurity and foster long-term stability for vulnerable populations in the Sundarbans and beyond. This research contributes valuable evidence for designing effective measures to combat food insecurity, ensuring equitable and sustainable food systems in the face of growing environmental and socio-economic challenges.

**CONSENT**

All participants involved in the study provided informed consent prior to their inclusion. Participation was voluntary, and respondents were assured of their anonymity and confidentiality throughout the research process.

**ETHICAL APPROVAL**

This study was conducted in strict adherence to ethical research principles and received formal ethical clearance from [Name of Ethical Committee/Board]. The approval ensured that the study adhered to guidelines for the protection of human subjects, ensuring respect, safety, and confidentiality for all participants.

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