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Village-Level Spatial and Multidimensional Analysis of Undernutrition among Tribal Children (7–59 Months) in Gujarat, India

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ABSTRACT

Background: Child undernutrition remains a major public health challenge in India, particularly among tribal populations. This study assessed spatial patterns and multidimensional determinants of undernutrition among children aged 7–59 months in Garbada Taluka of Dahod district, Gujarat. **Methods**: A cross-sectional household survey (n=645) was conducted in all 34 villages of Garbada Taluka of Dahod District. Anthropometric indicators were measured using WHO standards. A Village-Level Vulnerability Index (VLVI) was developed using sanitation, maternal education, household wealth, and remoteness. Spatial analyses included Global Moran's I, Local Indicators of Spatial Association (LISA), Geographically Weighted Regression (GWR), and mapping of VLVI scores. **Results:** Moran's, I indicated weak spatial autocorrelation (I = 0.113, p=0.084). LISA identified one hotspot and two cold spots. VLVI maps showed higher undernutrition prevalence in high-vulnerability villages. VLVI correlated positively with undernutrition (ρ=0.32, p=0.065). GWR highlighted maternal education, sanitation, and remoteness as significant local drivers. **Conclusions:** Undernutrition in tribal children exhibits localized clustering and multidimensional vulnerability. VLVI mapping provides evidence for geographically targeted interventions focusing on sanitation, maternal literacy, and village-level disparities.

Keywords: Child undernutrition; Tribal populations; Spatial analysis; Village-Level Vulnerability Index (VLVI); Geographically Weighted Regression (GWR); India

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Introduction

Child undernutrition continues to represent a critical global health and development challenge, undermining progress towards Sustainable Development Goal 2 (Zero Hunger). Despite significant investments, an estimated 149 million children under five remain stunted, and 45 million suffer from wasting worldwide[1]. The burden is disproportionately high in low and middle-income countries (LMICs), where food insecurity, poverty, and structural inequities intersect to perpetuate malnutrition[2].

Recent advances in geospatial analysis have highlighted the heterogeneous distribution of child undernutrition across countries and regions. Studies in Ethiopia and South Asia have applied Moran's I, Local Indicators of Spatial Association (LISA), and spatial regression models to identify hotspots of stunting, wasting, and underweight, linking them with sanitation, maternal education, and environmental conditions[3–5]. Long-term analyses from India further demonstrate clustering of child growth failure associated with sanitation and socio-demographic factors[6]. Additional studies in Ethiopia have detected coexisting forms of undernutrition using spatial scan statistics[7] and explored advanced geostatistical prediction of anemia risk[8].

Systematic reviews confirm the value of spatial methods—including clustering, Bayesian geostatistical models, and spatial regression—for uncovering geographic disparities in child health and guiding targeted interventions[9,1] . These approaches underscore the importance of village-level or area-specific analyses to avoid masking within-district inequalities.

Parallel to geospatial approaches, research has increasingly emphasized multidimensional vulnerability as a determinant of child malnutrition. Composite indices such as the Multidimensional Vulnerability Index (MVI) and the Livelihood Vulnerability Index (LVI) integrate socioeconomic, environmental, and health-related factors—including education, sanitation, food access, and remoteness—to capture overlapping risks[11, 12]. Applications in LMICs, from flood-prone communities in Indonesia to rural and tribal areas in India, show that household and community vulnerability scores strongly predict malnutrition and food insecurity[13, 14]. Furthermore, climate variability and agricultural dependence have been identified as amplifiers of nutrition insecurity, reducing dietary diversity and weakening resilience in agrarian LMIC populations[15].

Yet, in India—home to one of the world's largest concentrations of tribal populations—village-level spatial and multidimensional analyses of child undernutrition remain limited. National surveys such as NFHS provide district-level estimates, but often obscure micro-level clustering in marginalized tribal communities. Dahod district in Gujarat, an Aspirational District with a predominantly Bhil and Patelia tribal population, continues to report some of the highest undernutrition rates nationally[16].

This study addresses these gaps by applying spatial and multidimensional methods to examine child undernutrition in Garbada Taluka of Dahod district, Gujarat, India. Using geo-tagged household survey data from 645 children aged 7–59 months, we constructed a Village-Level Vulnerability Index (VLVI)—adapted from the LVI-IPCC framework—capturing sanitation, maternal education, household wealth, and geographic remoteness. We then employed Moran's I, LISA, and Geographically Weighted Regression (GWR) to identify spatial clustering and local determinants of undernutrition. By combining spatial epidemiology with a multidimensional vulnerability index, this study provides novel evidence to inform geographically targeted interventions for tribal populations in India and contributes to global discussions on resilience and equity in nutrition security.

Methodology

Study Area: The study was conducted in Garbada Taluka of Dahod district, Gujarat, India, an Aspirational District recognized by the Government of India for its persistent developmental challenges. Dahod has a predominantly tribal population, largely from the Bhil and Patelia communities, and is characterized by high poverty, low literacy, poor access to health services, and dependence on rain-fed maize cultivation. According to the National Family Health Survey-5 (NFHS-5), Dahod continues to report child undernutrition rates (stunting and underweight) above state and national averages[16]. Despite this burden, village-level spatial studies remain scarce, making Garbada a critical setting for assessing localized nutrition vulnerabilities.

Study Design and Sample Size: A cross-sectional household survey was carried out in 2023, covering all 34 villages of Garbada Taluka. The study population consisted of children aged 7–59 months.

The sample size was estimated using Cochran's formula[17] for large populations:

$$n_0 = \frac{Z^2 pq}{\epsilon^2}$$

where $Z = 1.96$ (95% confidence level), $p = 0.5$(assumed heterogeneity), $q = 1 - p$, and $e = 0.04$(margin of error). The minimum required sample size was 601 households. To account for non-response, a total of 645 households were surveyed.

Sampling and Household Selection: To ensure unbiased representation, randomized household points were generated within the study area polygon using spatial sampling tools in R (version 4.2.1)[18]. A minimum distance of 50 meters between points was imposed to prevent clustering. These randomized points were overlaid on a high-resolution satellite image of the study area to guide fieldwork.

During data collection, the household nearest to each randomized point was selected for interview. This approach minimized sampling bias and ensured spatial dispersion across villages.

Data Collection: Geographic coordinates of surveyed households were recorded using the GPS Essentials[19] and Google Earth[20] mobile applications. To improve positional accuracy, the study area was divided into a 25 × 25 m grid system. Household survey data and coordinates were recorded in Epicollect[21], a mobile-based data collection platform.

Anthropometric measurements were collected following WHO guidelines, and z-scores were computed for weight-for-age (WAZ), height-for-age (HAZ), and weight-for-height (WHZ) using WHO growth standards[22].

Village-Level Vulnerability Index (VLVI): A Village-Level Vulnerability Index (VLVI) was developed to capture multidimensional risk factors associated with child undernutrition. The VLVI was conceptually adapted from the Livelihood Vulnerability Index (LVI–IPCC framework), which integrates domains of exposure, sensitivity, and adaptive capacity[11, 12].

For this study, four locally relevant domains were included:

1. Sanitation – access to improved sanitation.
2. Maternal education – years of maternal schooling.
3. Household wealth – asset ownership and landholding.
4. Remoteness – distance from health centers and markets.

Indicators were normalized on a 0–1 scale and aggregated with equal weights to produce a composite VLVI score for each village. Villages were then categorized into low, medium, and high vulnerability terciles. Similar adaptations of the LVI-IPCC framework have been reported in LMIC contexts[13].

Statistical and Spatial Analysis: All analyses were performed in R (version 4.2.1) [18].

- Descriptive statistics were generated using the tidy verse and dplyr packages.
- Global Moran's I was used (spdep) to assess overall spatial autocorrelation of undernutrition indicators.
- Local Indicators of Spatial Association (LISA) were applied (spdep, spatialreg) to identify village-level hotspots and outliers.
- Geographically Weighted Regression (GWR) was conducted (GW model) to examine spatially varying associations between undernutrition and vulnerability factors.
- Visualizations and maps were created in R using ggplot 2 and tmap.
- A significance threshold of $p < 0.05$ was applied.

Result

The results are presented thematically, beginning with the socio-demographic profile of surveyed households, followed by spatial and statistical test results on undernutrition patterns, village-level vulnerability classifications, spatial clustering maps, and finally the associations between vulnerability domains and child nutrition indicators.

Socio-demographic Profile of the Study Population: The study covered 645 households across 34 villages in Garbada Taluka of Dahod district. As shown in Table 1, the vast majority of participants belonged to Scheduled Tribes (97%), with minimal representation from Scheduled Castes (2%) and Other Backward Classes (1%). Within the tribal population, the Bhil Community (56.4%) and Patelia community (40.9%) predominated, reflecting the distinct demographic profile of the region. Most households had medium-sized families (6–10 members, 63.6%), and the predominant housing type was mixed construction (61.9%). Land ownership was nearly universal (94%), and 88% of households reported livestock ownership. Together, these indicators emphasize the tribal and agrarian context of the study area.

Table- 1: Socio-demographic profile of surveyed households in Garbada Taluka (n = 645)

Indicator	Category	No.	%
Social Group	Scheduled Tribes (ST)	628	97.3
	Bhil	364	56.4
	Patelia	264	40.9
	Scheduled Castes (SC)	11	1.7
	Other Backward Classes (OBC)	6	0.9
Family Size	Small (3–5 members)	119	18.4
	Medium (6–10 members)	410	63.6
	Large (11–15 members)	87	13.5
	Very Large (16+ members)	29	4.5
Type of House	Kutcha	33	5.1
	Mixed	399	61.9
	Pakka	213	33.0
Land Ownership	No Land	14	2.1
	Owned (Single)	606	94.0
	Partnership	25	3.9
Livestock Ownership	Yes	568	88.1
	No	77	11.9

Notes: *This table summarizes the distribution of surveyed households by social group, family size, type of housing, land ownership, and livestock ownership. Percentages are based on the total of 645 households.*

Spatial and Statistical Analysis: The spatial and statistical tests are summarized in Table 2. Global Moran's I indicated a weak positive spatial autocorrelation (I = 0.113, p = 0.084), suggesting that the distribution of undernutrition across villages showed slight clustering but without strong statistical significance. Local Indicators of Spatial Association (LISA) identified one High-High cluster and two Low-Low clusters ($p < 0.10$), demonstrating the presence of localized clustering of undernutrition.

No significant association was observed between the Village-Level Vulnerability Index (VLVI) and LISA cluster types (χ^2=2.83, df=4, p=0.586). Similarly, the ANOVA results (F=1.85, p=0.174) indicated no significant difference in undernutrition prevalence across VLVI categories. A moderate positive correlation was noted between VLVI scores and undernutrition prevalence (ρ=0.32, p=0.065), which was close to statistical significance, suggesting a trend of higher undernutrition in more vulnerable villages.

Table-2: Summary of Spatial and Statistical Test Results on Undernutrition among Children (7–59 months) in Garbada Taluka, Dahod District

Test Type	Statistic / Correlation	p-value	Interpretation
Global Moran's I	0.113	0.084	Weak positive spatial autocorrelation
LISA Cluster Types	1 High-High, 2 Low-Low	<0.10	Local clustering identified
𝔑2 (VLVI × LISA)	χ^2 = 2.83, df = 4	0.586	No significant association
ANOVA (by VLVI)	F = 1.85	0.174	No significant difference
Spearman Correlation	ρ = 0.32	0.065	Moderate, nearly significant

Geographically Weighted Regression (GWR) Analysis: The results of the Geographically Weighted Regression (GWR) are presented in Table 3. Sanitation score showed a positive association (coefficients: 1.12–1.32), indicating that poorer sanitation was consistently linked with higher undernutrition. Maternal education displayed the strongest positive relationship (coefficients: 3.57–4.00), underscoring that lower education levels of mothers contributed significantly to undernutrition. Wealth score demonstrated a protective effect (coefficients: –0.68 to –0.50), with better household wealth associated with reduced prevalence of undernutrition. Remoteness also exhibited a moderate positive effect (coefficients: 2.61–2.84), suggesting that children from more geographically distant villages were more vulnerable to undernutrition. However, the overall model fit was modest (Pseudo R^2=0.095), indicating that while these factors contributed locally, other unmeasured determinants may also influence nutritional outcomes. However, the overall model fit was modest (Pseudo R^2=0.095), indicating that while these factors contributed locally, other unmeasured determinants may also influence nutritional outcomes

Table-3: Results of Geographically Weighted Regression (GWR) for Determinants of Undernutrition among Children (7–59 months) in Garbada Taluka, Dahod District

Variable	Coefficient Range	Direction of Effect	Interpretation
Sanitation Score	1.12 – 1.32	Positive	Poorer sanitation → higher undernutrition
Education Score	3.57 – 4.00	Strong Positive	Lower maternal education → higher undernutrition
Wealth Score	–0.68 – –0.50	Negative (Protective)	Better wealth → lower undernutrition
Remoteness Score	2.61 – 2.84	Moderate Positive	Remote villages → more vulnerable to undernutrition
Overall GWR Fit	**Pseudo R^2 = 0.095**		GWR explains ~9.5% variation; limited but locally informative

The Moran's I scatter plot (Figure 1) illustrates the relationship between the prevalence of underweight children and its spatial lag across villages. The positive slope of the regression line indicates a weak but positive spatial autocorrelation, consistent with the calculated Moran's I value of 0.113 (p = 0.084). This suggests that villages with higher prevalence of underweight children tended to be located near villages with similarly high prevalence, although the clustering was not statistically significant at the 5% level.

Figure-1: Moran's : Scatterplot for Undernutrition

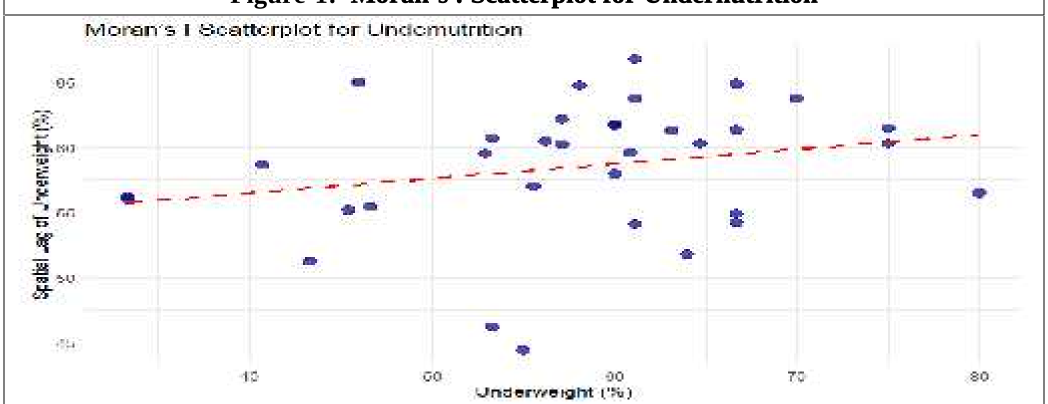

Figure-1: Moran's I Scatterplot for Undernutrition among Children (7–59 months) in Garbada Taluka, Dahod District: *The scatterplot plots village-level underweight prevalence (%) on the x-axis against the spatial lag of underweight prevalence (%) on the y-axis. The red dashed line represents the global trend of Moran's I, while the vertical and horizontal dashed lines indicate the mean values, dividing the plot into quadrants corresponding to different clustering types (High-High, Low-Low, High-Low, and Low-High).*

The Moran's I scatter plot (Figure 1) illustrates the relationship between the prevalence of underweight children and its spatial lag across villages. The positive slope of the regression line indicates a weak but positive spatial autocorrelation, consistent with the calculated Moran's I value of 0.113 (p=0.084). This suggests that villages with higher prevalence of underweight children tended to be located near villages with similarly high prevalence, although the clustering was not statistically significant at the 5% level.

LISA Analysis of Undernutrition Patterns: The LISA cluster analysis identified statistically significant local patterns of undernutrition (Figure 2). One village, Sahada, emerged as a High-High cluster (hotspot), indicating a concentration of high undernutrition surrounded by similarly high-prevalence villages. In contrast, Ambli and Abhlod were classified as Low-Low clusters (coldspots), suggesting comparatively lower undernutrition prevalence in these villages and their neighbours. The remaining villages did not show statistically significant clustering, indicating a heterogeneous distribution of undernutrition across the study area.

Figure-2: LISA Cluster Map of Undernutrition among Children (7–59 months) in Garbada Taluka, Dahod District

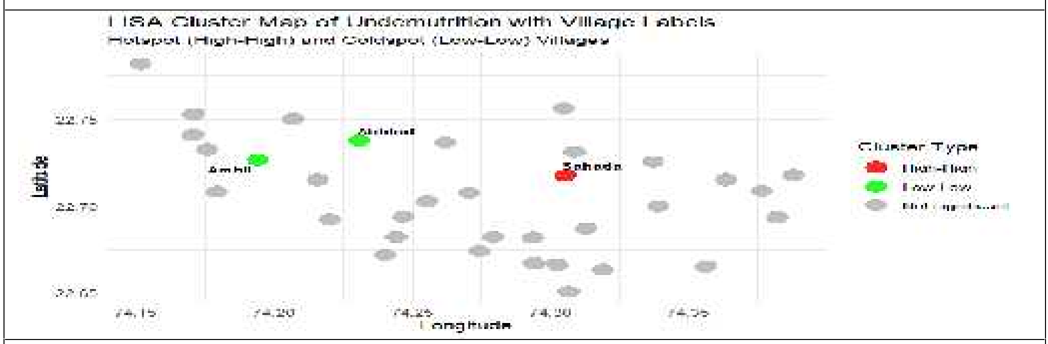

Figure-2: LISA Cluster Map of Undernutrition among Children (7–59 months) in Garbada Taluka, Dahod District ***I:*** *The map displays village-level clustering of undernutrition using Local Indicators of Spatial Association (LISA). Villages marked in red indicate hotspots (High-High clusters), green indicates cold spots (Low-Low clusters), and grey denotes villages without significant clustering.*

Village-Level Vulnerability and Undernutrition: The bubble map (Figure 3) illustrates the spatial distribution of undernutrition alongside the Village-Level Vulnerability Index (VLVI) classifications. Villages with higher VLVI scores (red, high vulnerability) generally corresponded to larger bubble sizes, indicating higher prevalence of underweight children. In contrast, villages with low VLVI (green) tended to have smaller bubble sizes, reflecting comparatively lower prevalence of undernutrition. However, this relationship was not consistent across all villages, and statistical testing showed no significant association between VLVI categories and undernutrition prevalence (ANOVA, F =1.85, p=0.174). These results highlight the complex and heterogeneous nature of vulnerability and nutritional outcomes across the study area.

Figure-3: Spatial Distribution of Village-Level Vulnerability and Undernutrition among Children (7–59 months) in Garbada Taluka, Dahod District

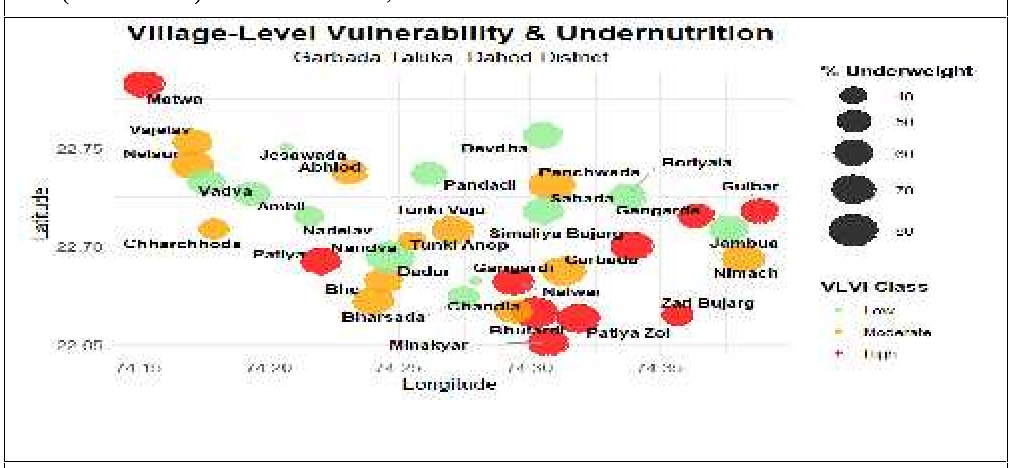

Figure-3: Spatial Distribution of Village-Level Vulnerability and Undernutrition among Children (7–59 months) in Garbada Taluka, Dahod District: *Bubble size shows percentage of underweight children, while color indicates VLVI class (green = low, orange = moderate, red = high). Larger bubbles in high-vulnerability villages reflect higher undernutrition, though patterns vary across the area.*

Discussion

This study provides village-level insights into the spatial and multidimensional determinants of child undernutrition in Garbada Taluka of Dahod district, Gujarat. Although global spatial autocorrelation showed only weak clustering, the identification of a hotspot and cold spots through LISA emphasizes the micro-geographic variability of undernutrition. Similar patterns of localized clustering have been documented in other Indian contexts, where sanitation, maternal education, and socioeconomic disadvantage drive disparities in child nutrition outcomes[23]. These findings confirm that aggregated district-level estimates can mask small-area inequalities, making village-level analysis critical in tribal regions.

The Village-Level Vulnerability Index (VLVI) developed in this study integrated sanitation, maternal education, wealth, and remoteness, offering a multidimensional perspective on risk. Although associations were not statistically strong, the observed trend of higher undernutrition in more vulnerable villages aligns with recent work applying composite indices in India and other LMICs[24]. Such approaches recognize that undernutrition stems from overlapping social, infrastructural, and environmental constraints rather than economic status alone. Notably, villages such as Sahada appeared as undernutrition hotspots in the LISA analysis but were classified as lower vulnerability in the VLVI. This divergence underscores both the utility and the limits of composite indices: while VLVI captures structural vulnerability through sanitation, maternal education, wealth, and remoteness, outcome clustering may also be shaped by unmeasured factors such as cultural food practices, seasonal shocks, or local health service dynamics. The role of maternal literacy and sanitation in shaping undernutrition patterns in this study is consistent with earlier findings that education and WASH conditions are among the most influential determinants of child growth outcomes[25].

The protective effect of household wealth observed here further reinforces evidence that poverty reduction strategies can complement nutrition-specific interventions. However, the relatively low explanatory power of the GWR model suggests that other unmeasured factors—such as seasonal food insecurity, dietary diversity, migration, and health service access—may also shape outcomes. Similar limitations have been reported in advanced geostatistical analyses of child undernutrition, which point to the need for integrated, mixed-method approaches[26].

Our findings have important implications for nutrition policy and program design in India. The identification of village-level clustering through VLVI underscores the need for interventions tailored at micro-geographies, particularly within tribal and hard-to-reach populations. This resonates with national initiatives such as Poshan 2.0, which emphasize convergence of food, health, and sanitation strategies to address undernutrition in a holistic manner. Village-level evidence can prevent dilution of resources at district scales and ensure that programmatic attention reaches households facing the greatest vulnerability. Comparisons with other LMICs highlight that such micro-level clustering is not unique to India. In Ethiopia, SaT Scan-based analyses detected coexisting forms of undernutrition, revealing pockets of high burden despite national improvements[7]. In Bangladesh, household- and maternal-level predictors were strongly associated with children's dietary outcomes[4]. Likewise, climate-linked vulnerabilities in Indonesia have been shown to undermine child nutrition through pathways of food insecurity[13]. These converging patterns suggest that fine-grained geospatial methods are increasingly relevant for LMIC nutrition research.

Recent contributions highlight the policy relevance of such spatial and multidimensional approaches. For example, Bhadra et al.[26] and Vishwakarma et al.[23] stress the value of combining spatial clustering with socioeconomic indicators to design region-specific interventions. Nambiar et al.[24] extend this logic to the Parliamentary Constituency level, showing how political-administrative boundaries can serve as a basis for targeted programs. For tribal populations, where geographic remoteness and social marginalization compound risks, this evidence underscores the urgency of deploying granular, context-specific strategies under national frameworks such as Poshan Abhiyaan and the Aspirational Districts Programme.

Overall, this study contributes to the growing body of research demonstrating that spatial epidemiology, when combined with multidimensional indices, provides actionable insights for addressing child undernutrition. By identifying vulnerable villages and highlighting sanitation and maternal literacy as consistent drivers, the findings offer a replicable framework for other tribal districts facing similar challenges.

Conclusion

This study highlights the presence of localized clustering and multidimensional vulnerability influencing child undernutrition in a tribal setting. Maternal education, sanitation, and remoteness emerged as consistent local determinants, while household wealth exerted a protective effect. The findings underscore the need for geographically targeted interventions that address structural and social determinants of undernutrition.

Future Scope: Future research should integrate longitudinal data, dietary diversity, and resilience frameworks to better capture the multifactorial nature of child undernutrition. Linking spatial vulnerability indices with climate variability and food security assessments could provide more comprehensive evidence for policy translation in tribal and rural contexts.

Ethical Approval: Ethical clearance for this study was obtained from the Institutional Ethics Committee for Human Research (IECHR), Faculty of Family and Community Sciences, The Maharaja Sayajirao University of Baroda (Approval No: IECHR/FCSc/2020/68).

Consent to Participate: Written informed consent was obtained from all participants prior to data collection.

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Data Availability: The data supporting the findings of this study were collected through a primary household survey in Garbada Taluka, Dahod District, Gujarat. Due to confidentiality and ethical restrictions, the dataset is not publicly available. De-identified data may be shared by the corresponding author upon reasonable request.

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