

Original Research

Spatial Analysis of Environmental Vulnerability Among Tribal Households in Garbada Taluka, Dahod District, Gujarat, India

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Abstract: Tribal households in western India remain highly exposed to environmental and infrastructural challenges that influence their livelihood and food security. Assessing vulnerability at multiple scales is essential for targeted adaptation planning. This study aimed to develop a composite Environmental Vulnerability Index (EVI) for tribal households in Garbada Taluka, Dahod district, Gujarat, and to examine spatial disparities at both the village and household levels. Primary data from 645 households were analysed. Crop diversity was calculated using the Shannon Index, and a composite EVI was constructed from four indicators: landholding size, crop diversity, water sufficiency, and sanitation access. Households were classified into low, medium, and high vulnerability categories. Statistical analyses (descriptive statistics, correlations, regression) were combined with GIS-based spatial mapping to examine patterns across villages and within communities. Descriptive results showed that two-thirds of households fell into the medium vulnerability category, with smaller proportions classified as low or high. Regression analysis confirmed that landholding size was a significant predictor of household income. Spatial mapping identified Matwa, Zari Bujarg, and Garbada as high-vulnerability clusters, while villages such as Jesawada, Ambli, and Devda demonstrated relatively lower vulnerability. Household-level mapping revealed intra-village disparities, with highly vulnerable households present even in resilient villages. The dual-scale EVI analysis highlights both village-level hotspots and household-level variations in vulnerability. These findings have policy relevance for climate adaptation, agricultural diversification, and WASH interventions under tribal development schemes.

Future research should integrate direct nutrition indicators with environmental vulnerability frameworks to strengthen the linkages with food and nutrition security.

1. INTRODUCTION

Tribal populations in India continue to experience high levels of vulnerability due to intersecting social, economic, and environmental challenges. Limited landholding, reliance on rainfed agriculture, and inadequate access to safe water and sanitation contribute to fragile livelihoods. These conditions create cycles of poverty and environmental stress, leaving households with fewer opportunities to adapt to changing conditions.

Dahod district in eastern Gujarat is one of the predominantly tribal regions of the state. The livelihood of households in this area is largely dependent on agriculture, with maize serving as the primary crop. Agricultural practices, however, are characterized by small, fragmented landholdings and limited crop diversity. At the same time, household amenities such as water supply and sanitation remain inadequate in many villages. Together, these factors shape patterns of environmental vulnerability and influence household well-being. Previous studies have highlighted persistent poverty and livelihood challenges among tribal households in Gujarat (Shah & Kumar 2008), and newer analyses continue to emphasize the structural disadvantages faced by tribal populations across India's agrarian regions (Mathew 2024; Sharma & Mohan 2024). According to the District Census Handbook: Dahod (Census of India 2011), Garbada Taluka and other parts of the district remain heavily tribal in composition, with low literacy levels and poor household amenities. The Aspirational Districts Dashboard (NITI Aayog 2023) further indicates that Dahod continues to lag behind state averages in key indicators related to health, nutrition, and education, reflecting persistent human-development challenges in tribal regions.

Recent assessments emphasize the importance of integrated approaches to vulnerability analysis. Empirical studies from tribal regions across India demonstrate that climate variability, limited livelihood diversification, and constrained adaptive capacity jointly shape household-level vulnerability (Kumar et al. 2023). The Climate Vulnerability Assessment for Adaptation Planning (DST 2021) underscores the role of GIS-based methods in identifying hotspots of risk across India, while the Gujarat State Action Plan on Climate Change and Health (2022–27) (Government of Gujarat 2024) highlights Dahod as a district facing multiple stressors related to environment and health conditions. Institutional studies also underline the gendered and intergenerational

dimensions of vulnerability: the M.S. Swaminathan Research Foundation (MSSRF 2024) reports disproportionate impacts of climate change on women and children across India's agro-ecological zones, while the Council on Energy, Environment and Water (CEEW 2025) emphasizes the role of institutional capacity and climate-resilient agriculture in enhancing adaptive responses among smallholder and tribal communities. Complementary reviews (Mohanty 2024) argue for multidisciplinary approaches linking sustainability, rural livelihoods, and tribal well-being to policy frameworks for inclusive development. Studies have shown that maize–legume intercropping systems can enhance resource use efficiency, soil fertility, and overall sustainability in smallholder farms (Dwivedi et al. 2016).

Against this backdrop, the present study was undertaken in Garbada Taluka of Dahod district, Gujarat, with the objective of developing an Environmental Vulnerability Index (EVI) at the household level. While national- and district-level environmental vulnerability assessments exist, they largely rely on aggregated indicators that mask household-level and intra-village disparities, particularly in tribal regions. Empirical studies using primary household data combined with GIS to assess environmental vulnerability at micro scales remain limited. This study addresses this gap by developing a household-level Environmental Vulnerability Index (EVI) and applying a dual-scale spatial analysis to identify both village-level hotspots and intra-village heterogeneity in Garbada Taluka. Using primary survey data, the EVI was constructed from land size, crop diversity, and WASH indicators, and spatial analysis was applied to examine household- and village-level patterns of vulnerability. By highlighting these patterns, the paper aims to provide an evidence base for local planning and to strengthen resilience among tribal households.

2. MATERIALS AND METHODS

2.1. Study Area

The research was carried out in Garbada Taluka of Dahod District, Gujarat, India, one of the nine talukas of Dahod. The district has a predominantly tribal population and has been recognized as an Aspirational District by the Government of India due to persistent developmental challenges in education, health, agriculture, and infrastructure (NITI Aayog 2023). Garbada was selected as the study site because of its diverse topography—comprising hilly, plain, and medium regions—which provides a natural setting to examine geographical variations in agricultural practices and household vulnerability. Agriculture, particularly maize cultivation, is the primary livelihood activity in this region. The study was conducted between February 2023 and July 2023.

2.2. Study Design and Sample

A cross-sectional household survey was conducted among 645 households in Garbada Taluka. Households were selected using random GPS points generated in ArcGIS 10.5, enforcing a minimum 50 m spacing to reduce clustering and spatial bias. This spatial randomization approach followed the GIS-based household selection method described by Mathenge et al. (2023). Random points were overlaid on high-resolution satellite imagery and village boundary layers, then matched to actual household locations during field visits using GPS-enabled Android devices. This procedure ensured uniform geographic coverage and minimized enumerator bias.

2.3. Data Collection

Primary data were collected through structured interviews and household-level observations using a pretested questionnaire. The tool included the following modules:

1. **Household characteristics:** family size, number of children, annual income, and landholding (acres).
2. **Agriculture:** production data for maize, rice, wheat, and soybean.
3. **Water and sanitation:** household access to sufficient water supply and toilet facilities (MSSRF 2024).
4. **Geolocation:** latitude and longitude of each household recorded using handheld GPS devices.

Ethical clearance was obtained from the Department of Foods and Nutrition, Faculty of Family and Community Sciences, The Maharaja Sayajirao University of Baroda.

2.4 Variables and Indicators

2.4.1 Crop Diversity:

Crop diversification was measured using the Shannon Diversity Index (H') and the Simpson Diversity Index (D) (Magurran 2004). Both indices were computed from production data of maize, rice, wheat, and soybean. While both indices were examined descriptively, the Shannon index was chosen for regression and EVI construction because it captures both crop richness and evenness in diversified farming systems (Sibhatu, Krishna & Qaim 2015).

2.4.2 WASH Indicators:

Water sufficiency (yes/no) and toilet access (yes/no) were included as essential indicators of environmental health (DST 2021).

2.4.3 Household Income:

Annual self-reported earnings were recorded and validated through cross-verification of agricultural output and market prices (Shukla, Abraham & Parekh 2025).

2.4.4 Landholding Size:

The total cultivated land (in acres) was measured and used to classify households into small, medium, and large categories following the 33rd percentile cut-offs (Government of Gujarat 2024).

2.5 Environmental Vulnerability Index (EVI)

An Environmental Vulnerability Index (EVI) was constructed at the household level using four indicators: landholding size, crop diversity, water sufficiency, and toilet facility. Each variable was coded as binary (0 = not vulnerable, 1 = vulnerable).

$$EVI_i = \sum_{j=1}^4 X_{ij} \quad \dots(1)$$

Where:

Specifically:

- X_{i1} = 1 if landholding \leq 33rd percentile (small landholding); else 0
- X_{i2} = 1 if Shannon diversity \leq 33rd percentile (low crop diversity); else 0
- X_{i3} = 1 if the household lacked sufficient water; else 0
- X_{i4} = 1 if the household lacked a toilet facility; else 0

Thus, EVI_i ranged from 0 (no vulnerability) to 4 (highest vulnerability).

Households were categorized as:

1. Low vulnerability: scores 0–1
2. Medium vulnerability: scores 2–3
3. High vulnerability: score 4

This composite-index approach aligns with contemporary frameworks that integrate multiple environmental and socio-economic stressors into a single standardized measure of vulnerability. Similar additive or weighted-index methods have been recently applied in social and ecological contexts for micro-level vulnerability assessment, adapted here to the household scale (Smits & Huisman 2024). Equal weighting was adopted to maintain transparency and reduce subjectivity in the absence of empirically derived weights, a common approach in exploratory household-level vulnerability assessments. While binary coding improves

interpretability and comparability across indicators, it may result in some loss of information from underlying continuous variables, which is acknowledged as a limitation of the present study.

For village-level thematic maps, continuous indicator values were classified using percentile-based thresholds, where values ≤ 33 rd percentile represent low, 34–66th percentile represent medium, and ≥ 67 th percentile represent high levels of vulnerability or deprivation.

2.6 Data analysis

2.6.1 Statistical analysis

All quantitative analyses were performed using R software (version 4.3.3). Descriptive statistics (means, medians, and percentages) were computed to summarize household- and village-level indicators. Spearman's rank correlation was used to examine associations among key variables, including landholding size, crop diversity, water sufficiency, toilet access, and household income. To identify determinants of household income, a linear regression model was estimated with log-transformed income as the dependent variable. Household and village-level Environmental Vulnerability Index (EVI) scores were summarized to highlight patterns of vulnerability across the study area. The combined use of R for statistical analysis and ArcGIS 10.5 for spatial visualization ensured robust analytical rigor and reproducibility.

2.6.2 Spatial analysis

Household coordinates and village boundary shapefiles were imported into ArcGIS 10.5 for spatial visualization. Five thematic maps were generated to illustrate spatial variability in key indicators:

1. Household-level EVI classification,
2. Village-level mean EVI,
3. Village-level crop diversity (Shannon index),
4. Village-level percentage of households with sufficient water, and
5. Village-level percentage of households with toilet facilities.

3. RESULTS AND DISCUSSION

The findings of the study are presented at both the household and village levels to capture individual and spatial patterns of vulnerability. The results include descriptive statistics of households, correlation and regression analyses to assess key determinants of income and vulnerability, and the construction of an Environmental Vulnerability Index (EVI). Spatial analysis using ArcGIS further illustrates inter-village

variation in crop diversity, water sufficiency, sanitation, and EVI distribution. Together, these findings provide a comprehensive picture of environmental vulnerability among tribal households in Garbada Taluka.

The results are presented below, with interpretation provided alongside to place the findings in the context of existing literature.

3.1. Household characteristics

The surveyed households had an average landholding size of 3.25 acres, with a median of 4 acres (Table 1). Household size averaged 6.2 members, with a median of 2 children. Annual household income averaged ₹159,855, though the range was wide (₹10,000–100,000), reflecting heterogeneity in livelihoods. About 68% of households reported sufficient water availability, while 62% had a toilet facility. Crop diversity was modest, with a mean Shannon index of 1.12 and a Simpson index of 0.62, confirming the dominance of maize cultivation. Such dependence on maize as a staple crop under rainfall variability has been previously documented in Dahod (Chawra et al. 2024). Poverty and livelihood vulnerability tied to land access among Gujarat's tribal communities have also been emphasized by Shah (2008).

Table 1: Descriptive statistics of surveyed households (n=645)

Variable	Mean / %	Median	Min–Max
Landholding size (acres)	3.25	4.0	0-15
Household size	6.2	7.0	2-15
Children in household	2.1	2.0	0-6
Annual income (₹)	159,855	140,000	10,000-100,000
% with sufficient water	68%	-	-
% with toilet facility	62%	-	-
Shannon diversity (mean)	1.12	-	0-1.79
Simpson diversity (mean)	0.62	-	0-0.80

While crop diversity reflects agricultural resilience, its relationship with household resources and infrastructure was further explored through correlation and regression analysis

Spearman's correlation analysis (Table 2) showed a weak but significant positive relationship between landholding and income ($\rho = 0.079$, $p = 0.046$), suggesting that larger farms provided some income advantage. A significant correlation was also observed between water sufficiency and toilet access ($\rho = 0.086$, $p = 0.030$),

reflecting the link between household infrastructure and sanitation. Crop diversity, however, showed no significant association with either income or water sufficiency, highlighting the persistence of maize monocropping. These findings are consistent with national assessments that highlight landholding as a stronger determinant of household resilience compared to diversification (DST 2021; Smits & Huisman 2024).

Table 2: Spearman correlations between key indicators

Variables	rho (ρ)	p-value
Landholding vs Income	0.079	0.046*
Crop diversity vs Income	0.069	0.079
Crop diversity vs Water	- 0.024	0.548
Landholding vs Water	- 0.019	0.639
Toilet vs Water	0.086	0.030*

* $p < 0.05$; ns = not significant

3.2 Determinants of household income

Regression analysis confirmed that landholding size was the only significant predictor of household income ($\beta = 0.032$, $p = 0.028$), after adjusting for crop diversity, water sufficiency, and sanitation (Table 3). The adjusted R^2 was only 0.009, indicating that agricultural and infrastructure variables explained less than 1% of income variation. This highlights the complexity of tribal livelihoods, where income depends on multiple non-farm and environmental factors. Similar weak explanatory power of agricultural determinants has been observed in Central India's vulnerability studies (Smits & Huisman 2024) and in Gujarat's State Action Plan on Climate Change and Health (Government of Gujarat 2024). The very low adjusted R^2 (0.009) suggests that agricultural and WASH-related variables alone are insufficient to explain household income variation in tribal settings. In districts such as Dahod, household incomes are widely reported to depend on diversified livelihood strategies, including non-farm employment and seasonal migration, which were beyond the scope of the present study. The regression results should therefore be interpreted as indicative associations rather than strong predictors of income, and future research may benefit from incorporating migration, wage labour, and social protection variables. Although crop diversity is widely linked to resilience and nutrition outcomes in the literature, it did not show a statistically significant association with household income in the present analysis.

Table 3: Regression results: Determinants of log household income

Predictor	Estimate	Std. Error	t-value	p-value
Intercept	11.616	0.080	145.6	<0.001
Landholding (acres)	0.032	0.014	2.20	0.028 *
Crop diversity (Shannon)	0.052	0.071	0.73	0.465
Water sufficiency	0.061	0.046	1.34	0.181
Toilet facility	0.043	0.046	0.94	0.346

*Model fit: Adjusted $R^2 = 0.009$; $F(4, 640) = 2.43$, $p = 0.046$ ($p < 0.05$)

3.3 Spatial analysis of vulnerability

To complement the statistical findings, spatial analysis was undertaken to capture the geographic variation in agricultural practices, WASH infrastructure, and environmental vulnerability across Garbada Taluka. Mapping key indicators at both the village and household levels helps to visualize disparities that may not be fully apparent in tabular summaries. This approach highlights clusters of high vulnerability and provides a basis for identifying priority areas for intervention. Fig 1–5 present the spatial distribution of crop diversity, sanitation, water sufficiency, and composite Environmental Vulnerability Index (EVI).

3.3.1 Crop diversity and environmental indicator

Crop diversity, measured using the Shannon Index, was lowest in Matwa, Zari Bujarg, and Garbada (red), reflecting maize-dominated monocropping, while Ambli, Jesawada, and Devda showed relatively higher diversity (green) (Fig. 1). Low Shannon scores indicate limited crop diversification, which is associated with higher vulnerability to climatic shocks and lower dietary diversity, essential for child health. Similar rainfall-driven monocropping patterns have been observed in Dahod (Chawra et al. 2024). At the nutrition level, studies show that agricultural diversification, as captured through the Shannon Index, is positively associated with household dietary adequacy (Smits & Huisman, 2024). The map illustrates the spatial distribution of crop diversity across villages. Villages shaded red represent low crop diversity (dominated by maize monocropping), yellow indicates medium diversity, and green denotes high diversity with more balanced cultivation of cereals, pulses, and oilseeds. High-diversity villages (e.g., Ambli, Jesawada, Devda) reflect more resilient farming systems, while low-diversity clusters (e.g., Matwa, Zari Bujarg, Garbada) highlight areas vulnerable to climatic shocks and dietary monotony.

Sanitation access was poorest in Matwa, Vajelav, and Zari Bujarg, where fewer than 40% of households reported a toilet, whereas Jesawada and Bharsada performed better (Fig.2). Poor sanitation is a well-documented determinant of undernutrition: NITI Aayog (2024) and Pickering et al. (2019) report that toilet access reduces the odds of stunting by 16–39%. This map presents the spatial distribution of sanitation coverage across villages. Villages shaded red represent very low coverage, orange indicates low coverage, yellow shows medium coverage, and green represents high coverage. Very low coverage is concentrated in Matwa, Vajelav, and Zari Bujarg, while comparatively better access is observed in Jesawada, Bharsada, and Ambli. The clustering of red and orange zones across central and southern Garbada indicates critical sanitation deficits, which are strongly linked to child undernutrition through higher exposure to diarrhoeal and parasitic infections.

Water sufficiency was particularly low in Garbada, Zari Bujarg, and Matwa (<40%), while Patiya, Bhe, and Devda demonstrated better access (Fig. 3). These results align with evidence from Maternal & Child Nutrition showing that children in households with sufficient water were significantly more likely to meet minimum dietary diversity standards (Gao et al. 2022). This map shows the distribution of household water sufficiency across villages. Villages shaded red represent very low access, orange indicates low access, yellow shows medium access, and green denotes high access. Very low sufficiency is concentrated in Matwa, Zari Bujarg, Garbada, and Boriyala, while Patiya, Bhe, Jesawada, and Devda exhibit higher sufficiency. The clustering of water-deficit villages in the central and southern parts of Garbada reflects underlying infrastructural and resource constraints. Research from rural India, including Uttarakhand, also highlights that improved water and sanitation access reduces stunting by lowering exposure to diarrhoeal and parasitic infections (Nair, Augustine & Konapur, 2017).

To integrate these multiple dimensions—land, diversity, water, and sanitation—into a single measure, a composite Environmental Vulnerability Index (EVI) was constructed.

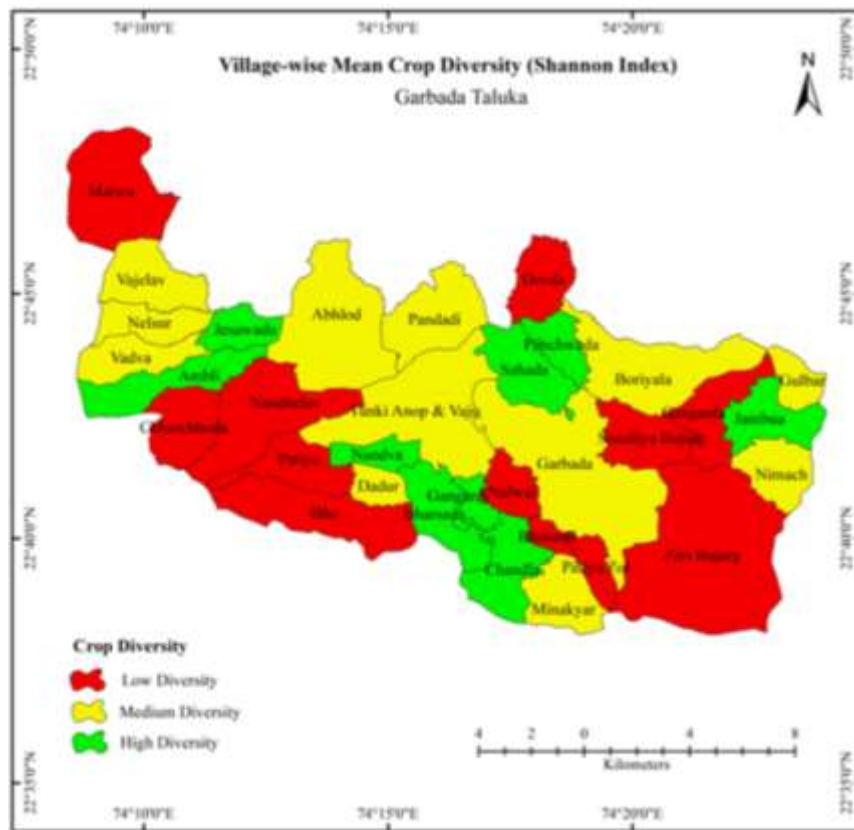


Fig. 1: Village-wise mean crop diversity (Shannon Index) in Garbada Taluka

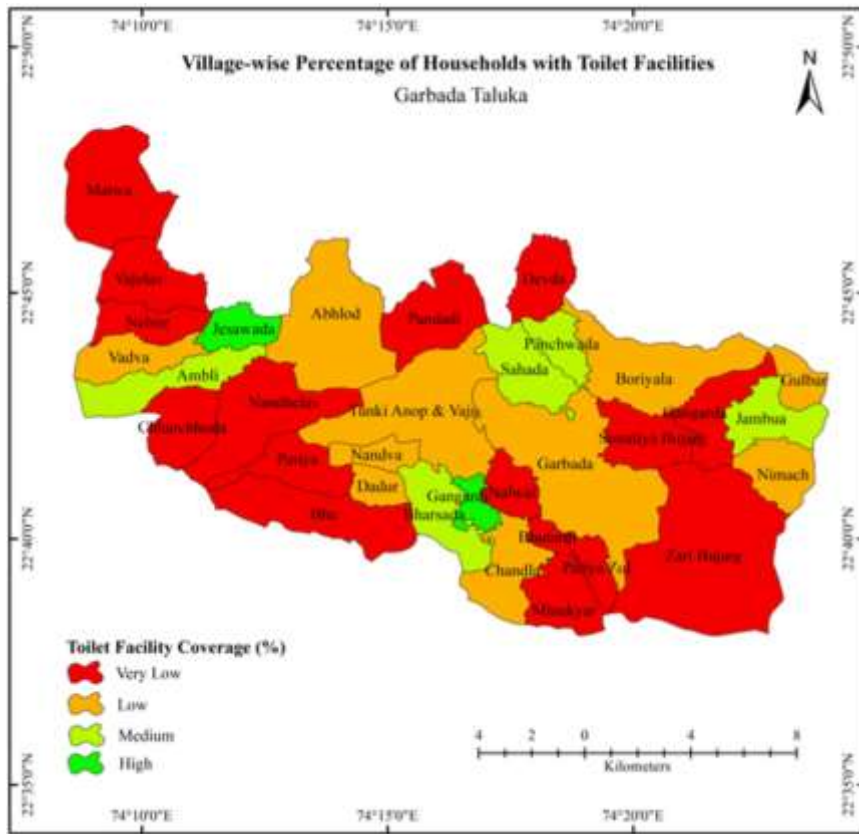


Fig. 2: Village-wise percentage of households with toilet facilities in Garbada Taluka

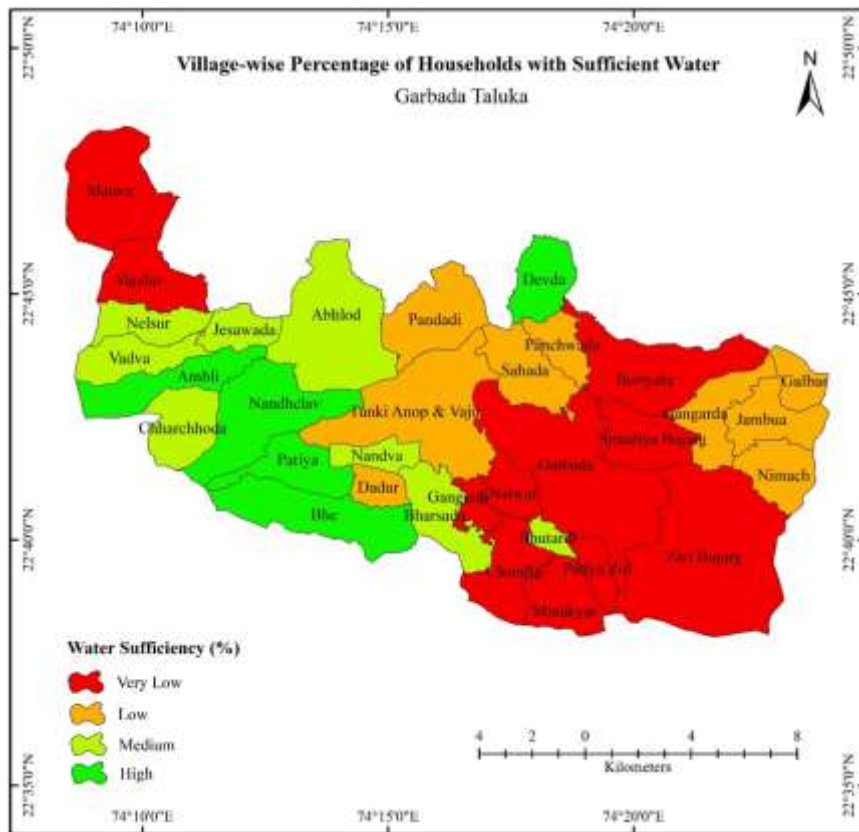


Fig. 3: Village-wise percentage of households with sufficient water in Garbada Taluka

3.3.2. Environmental Vulnerability Index (EVI)

The household-level EVI revealed that 53.8% of households were classified as medium vulnerability, 41.4% as low, and 4.8% as high (Table 4). The dominance of medium vulnerability suggests that while extreme conditions are rare, most households face sustained risks due to small landholdings, low crop diversity, and limited WASH infrastructure. These results align with the national Climate Vulnerability Assessment (DST 2020), which found medium vulnerability to be prevalent across large parts of India, and with hotspot analyses of regional disparities (Ravichandran et al. 2023).

Table 4: Distribution of Environmental Vulnerability Index (EVI) classes

EVI Class	Criteria (score)	No. of households
Low	0–1	267
Medium	2–3	347
High	4	31

While the EVI summary provides a quantitative distribution of vulnerability, spatial mapping allows these patterns to be visualized across villages.

3.3.3 Village level spatial patterns

Figures 1–4 provide an overview of village-level environmental indicators across Garbada Taluka. These maps highlight variations in crop diversity, sanitation, water sufficiency, and the aggregated Environmental Vulnerability Index (EVI). Together, they illustrate the uneven distribution of resources and resilience among villages. For instance, villages such as Matwa, Zari Bujarg, Garbada, and Simaliya Bujarg consistently emerged as high-vulnerability clusters (Fig. 4), marked by low crop diversity, poor sanitation, and inadequate water sufficiency. In contrast, villages like Jesawada, Ambli, and Devda displayed relatively higher resilience with more diversified production systems and better infrastructure. These spatial patterns are consistent with broader state-level assessments, such as the Gujarat SAPCC (2024), which identified Dahod district as a climate- and environment-sensitive region.

Although village-level patterns highlight clusters of vulnerability, households within the same village often differ substantially. Household-level mapping helps capture these intra-village disparities.

3.3.4 Household-Level Spatial Patterns

At the micro scale, (Fig. 5) shows household-level EVI. Even within medium-vulnerability villages such as Sahada and Pandadi, households were heterogeneous—some resilient, others highly vulnerable. This intra-village disparity is often masked in aggregated data and underscores the value of household-scale mapping (Raj & Sofi 2023).

Comparing village- and household-level results helps to assess whether vulnerability patterns are consistent across scales, or if finer variations are masked in aggregated data. Household-level EVI provides a quantitative basis for capturing intra-village variability, as individual households are assigned numeric vulnerability scores ranging from 0 to 4. The observed co-existence of highly vulnerable and relatively resilient households within the same village reflects uneven access to land, water, sanitation, and agricultural resources at the household scale. Such intra-village heterogeneity highlights the limitation of relying solely on village-level averages and reinforces the importance of household-scale analysis for targeted planning and intervention.

3.3.5 Consistency Across Scales

A comparison of the village-level (Fig. 4) and household-level (Fig. 5) Environmental Vulnerability Index (EVI) demonstrates both consistency and complementarity in the findings. At the aggregate scale, villages such as Matwa, Zari Bujarg, Garbada, and Vajelav were consistently classified as highly vulnerable. This pattern was reinforced at the micro scale, where a large share of households in these villages was mapped under the high vulnerability category. At the same time, household-level mapping revealed intra-village disparities that were not visible in the aggregate analysis, with even resilient villages such as Jesawada and Ambli containing a few high-vulnerability households.

Such dual-scale findings align with earlier research on environmental conditions and health outcomes. For instance, household environmental conditions have been shown to directly affect morbidity in India (Brahmanandam and Nagarajan 2021), while behavioural interventions such as waste segregation in Delhi demonstrate how socioeconomic factors shape vulnerability at the micro level ((Kaur & Kaur 2024). These insights reinforce the importance of combining both village- and household-level analyses, as undertaken in this study. This map shows the average environmental vulnerability of households aggregated at the village level. Villages shaded green represent low vulnerability, yellow indicates medium vulnerability, and red denotes high

vulnerability. High EVI values are concentrated in Zari Bujarg, Garbada, Simaliya Bujarg, and Nandhelav, while Jesawada, Ambli, Devda, and Gulbar show relatively lower vulnerability. The map highlights regional clustering of vulnerability, with southern and central villages facing greater environmental stress compared to western and northern areas.

At the district and state level, composite indices have been widely applied for climate vulnerability assessment. The Council on Energy, Environment and Water (Mohanty & Wadhawan 2021) produced a district-level vulnerability atlas of India, and the Department of Science and Technology’s Climate Vulnerability Assessment for Adaptation Planning in India (DST 2021) combined environmental, economic, and social indicators to guide adaptation strategies. The clustering of high-vulnerability villages in Garbada corresponds to similar spatial disparities documented in western and central India.

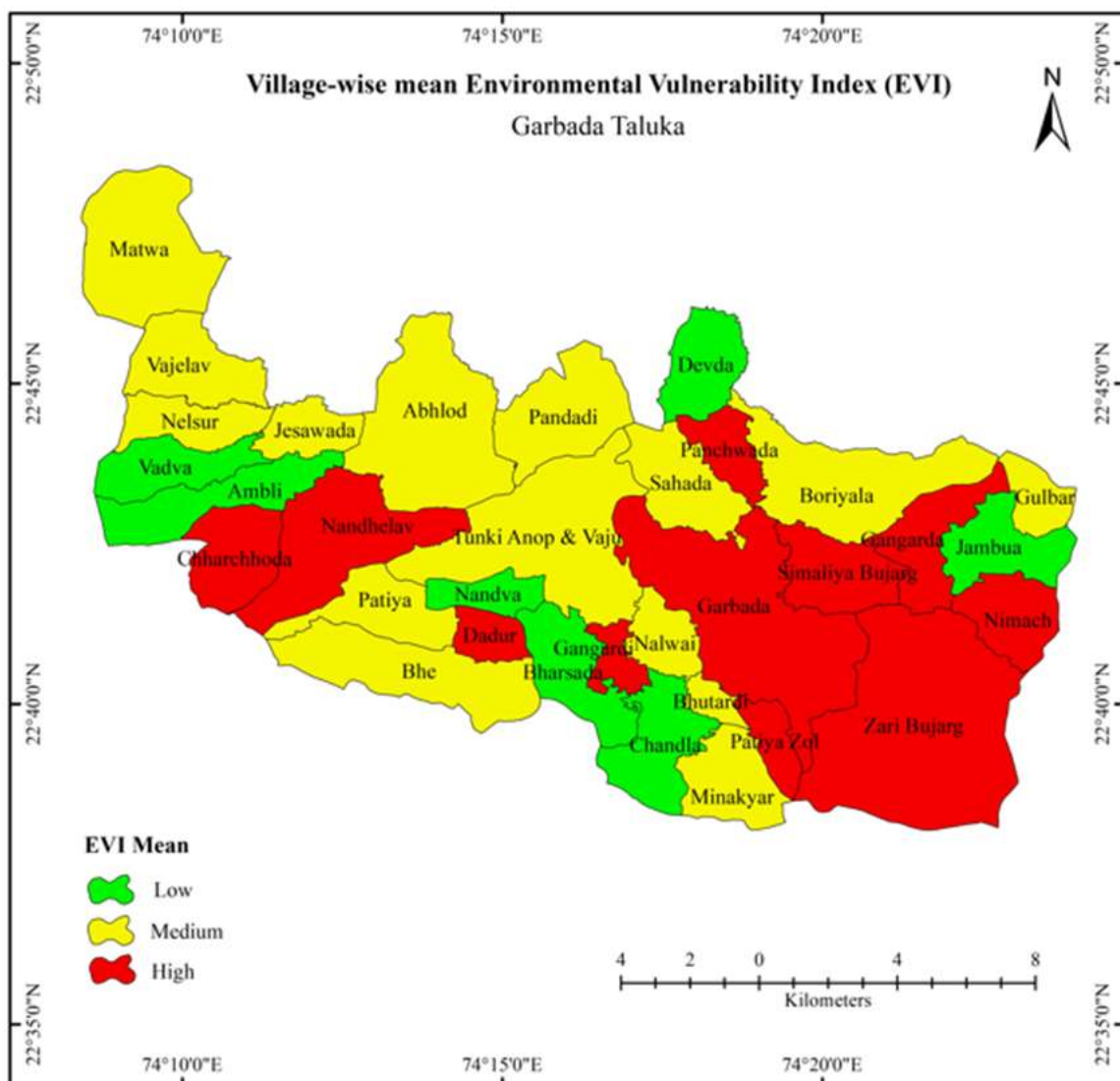


Fig.4: Village-wise mean Environmental Vulnerability Index (EVI) in Garbada Taluka

At the regional scale, studies using the Climate Vulnerability Index have highlighted significant variation in exposure and adaptive capacity across Indian states (Singh et al. 2021). Evidence from tribal areas in Central India shows that livelihood vulnerability is strongly mediated by crop diversity, landholding, and water access (Smits & Huisman 2024), while household-level vulnerability in the Western Ghats varied sharply with ecological and demographic factors Raj & Sofi (2023). These parallels reinforce the present study’s observation that intra-village heterogeneity in Garbada is as critical as inter-village differences Fig.5.

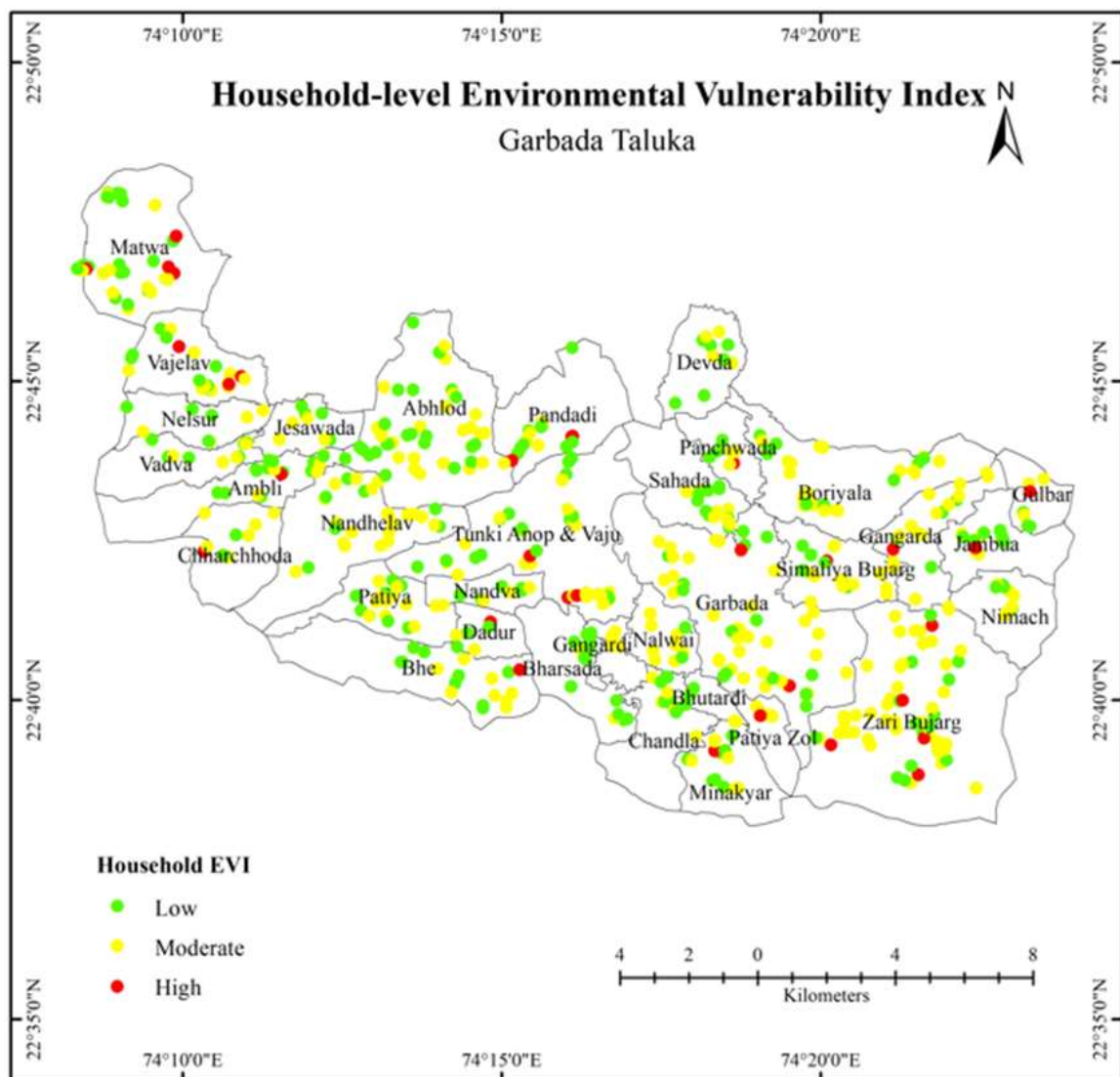


Fig. 5: Household-level Environmental Vulnerability Index (EVI) in Garbada Taluka

This map illustrates the distribution of environmental vulnerability at the household scale. Households shaded green represent low vulnerability, yellow indicates moderate vulnerability, and red denotes high vulnerability. High-vulnerability households are scattered across villages such as Matwa, Garbada, and Zari Bujarg, while most households in Jesawada, Ambli, and Devda show low vulnerability. The household-level analysis reveals intra-village disparities, where even villages with medium overall vulnerability include both resilient and highly vulnerable households.

The integration of spatial mapping further strengthened the explanatory power of household survey data. Remote sensing-based eco-environmental assessments have demonstrated the value of combining climatic and anthropogenic indicators for dynamic vulnerability mapping (Lan et al. 2023). Although this study primarily relied on household survey data integrated with GIS, the consistency of its results with both composite indices and remote sensing approaches underscores its methodological robustness. The findings were subsequently interpreted in relation to broader concerns of food and nutrition security, given the close link between environmental vulnerability, crop diversity, and household well-being. Similar GIS-based spatial studies have revealed how flood and drought risks influence food security across vulnerable regions (Rosalia et al. 2021). Given the cross-sectional design of the study, the observed relationships should be interpreted as associations rather than causal effects. The spatial analysis presented in this study is primarily descriptive, and formal spatial autocorrelation statistics (e.g., Moran's I or Getis-Ord G_i^*) were not applied; therefore, spatial clustering patterns should be interpreted cautiously.

3.4 Implication for food and nutrition security

Although direct nutrition indicators were not collected, the environmental variables used in the EVI are well-established determinants of food and nutrition security. Crop diversity has been linked to dietary adequacy (Sibhatu, Krishna & Qaim 2015), and water and sanitation access have been associated with reduced child stunting and underweight (Pickering et al. 2019; Nair, Augustine & Konapur 2017). The clustering of vulnerable villages in Garbada therefore suggests a potential overlap with nutritional insecurity, consistent with national studies linking climate vulnerability and child malnutrition (Gao et al. 2022; NITI Aayog 2024). However, a key limitation of this study is the absence of direct nutritional indicators, such as dietary diversity or anthropometric measures; therefore, links to food and nutrition security are interpreted contextually based on existing literature rather than measured outcomes.

4. CONCLUSIONS

This study assessed environmental vulnerability among 645 tribal households in Garbada Taluka of Dahod district, Gujarat, using a composite Environmental Vulnerability Index (EVI) that incorporated landholding, crop diversity, water sufficiency, and sanitation access. The results demonstrated that a majority of households fell into the medium vulnerability category, with villages such as Matwa, Zari Bujarg, and Garbada consistently emerging as hotspots of high vulnerability. Household-level mapping further revealed significant intra-village disparities, underscoring the importance of considering both aggregate and micro-level scales in vulnerability assessment.

Although nutritional outcomes were not directly measured, the environmental and infrastructural indicators used in the EVI are well-established determinants in the literature of food and nutrition security. The clustering of low crop diversity, poor sanitation, and inadequate water sufficiency suggests potential heightened risks to livelihoods and nutrition security in the study area. Evidence from both India and other smallholder contexts shows that higher crop diversity is strongly associated with improved household dietary adequacy (Sibhatu, Krishna & Qaim 2015).

From a policy perspective, these findings have implications for targeted, location-specific interventions. Villages with high EVI may warrant priority attention in climate adaptation planning, agricultural diversification programmes, and WASH (water, sanitation, and hygiene) infrastructure development. At the same time, household-level disparities suggest the relevance of micro-level interventions, ensuring that vulnerable families within relatively resilient villages are not overlooked. Access to safe water and toilet facilities has been consistently linked with reduced risks of stunting and underweight among children by lowering exposure to diarrhoeal and parasitic infections, while food-based interventions that improve diet diversity have also proven effective in addressing multiple micronutrient deficiencies (Nair, Augustine & Konapur 2017).

The dual-scale approach demonstrated here can support tribal development schemes, the State Action Plan on Climate Change, and national programmes such as ICDS and POSHAN 2.0 by identifying critical hotspots and informing more targeted interventions. Future research should integrate direct nutrition indicators, such as dietary diversity and child growth outcomes, with environmental vulnerability frameworks to provide a more holistic understanding of food and nutrition security.

Author Contributions: “Conceptualization, S.P. and S.C.; methodology, S.P.; software, S.P.; validation, S.P., S.C.; formal analysis, S.P.; investigation, S.P.; data curation, S.P.; writing—original draft preparation, S.P.; writing—review and editing, S.P. and S.C.; visualization, S.P.; supervision, S.C.; All authors have read and agreed to the published version of the manuscript.”

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Informed Consent Statement: Informed consent was obtained from all participants prior to data collection. The objectives of the study, the procedures involved, and the voluntary nature of participation were clearly explained to each respondent in their local language. Participants were assured that their responses would remain confidential and anonymous. They were informed that participation was voluntary and they could withdraw at any stage if they wished to do so. For participants with limited literacy, the consent form was read aloud, and verbal or thumbprint consent was obtained in the presence of a witness.

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