Pen & Prosperity

Website: https://penandprosperity.vgcet.com

Volume 2 :: Issue 3 :: September 2025 :: e-ISSN- 3048-9555 :: DOI Link : https://doi.org/10.70798/PP/020300040

Integrating Livelihood Capitals and Geospatial Determinants: A Multi-Method Analysis of Household Occupational Choices and Spatial Clustering in Ajodhya Hill, West Bengal, India

Asad Ali Sarkar

Corresponding Author, Research Scholar, Centre for Adivasi Studies and Museum, Vidyasagar University, West Bengal, India, Email ID: hiasadsarkar@gmail.com

Sebak Kumar Jana

Professor, Department of Economics, Vidyasagar University, West Bengal, India

Email ID: sebakjana@mail.vidyasagar.ac.in

Abstract:

This research investigates the socio-spatial determinants and distribution patterns of rural livelihood strategies in the tribal mountainous region of Ajodhya hill, West Bengal, India. The primary objective is to evaluate how capital endowments and geospatial constraints influence household choices among five distinct livelihood pathways: Labour-Dependent (45.19%), Cultivated (28.61%), Ecotourism (18.99%), Service (4.81%), and Business (2.40%). The methodology integrates the Entropy Weighting Method for objective capital evaluation with Multinomial Logistic Regression and multi-scale spatial techniques, including Global Moran's I, Nearest Neighbour Index, and the Geographical Detector method.

Major findings reveal a profound economic divide, where Service-based households earn an average annual income of Rs. 360,735, more than ten times the income of Labour-dependent households. Regression results indicate that Natural capital serves as a significant anchor for agricultural stability, while Human and Financial capitals are the critical drivers for transitioning into high-return sectors. Geospatial analysis confirms significant clustering (Global Moran's I = 0.0688), particularly for tourism and service strategies near infrastructure. Crucially, Topographic Roughness emerged as the dominant deterrent to diversification, reducing the odds of non-agricultural adoption by 51% to 81% per unit increase. Geographical Detector results further demonstrate that individual factors like slope and elevation have limited independent explanatory power (q-statistics < 0.02), suggesting spatial heterogeneity is driven by complex interactions rather than solitary environmental constraints. These results highlight how geographic barriers and capital deficiencies hinder tribal participation in the tourism economy, underscoring the need for targeted infrastructure and educational support to promote resilient rural revitalization.

A R T I C L E I N F O

Article history:

Received: 10 August 2025

Received in revised form 20 August 2025

Accepted 29 August 2025

Citation: **Ali Sarkar. A. & Jana. S. K.,** (2025) "Integrating Livelihood Capitals and Geospatial Determinants: A Multi-Method Analysis of Household Occupational Choices and Spatial Clustering in Ajodhya Hill, West Bengal, India", *Pen and Prosperity*, Vol. 2, Issue. 3, September 2025.

Keywords: *Livelihood Strategies; Multinomial Logistic Regression; Spatial Clustering; Geographical Detector.*

1. Introduction:

Ecotourism has emerged since the 1980s as a response to the dual imperatives of environmental conservation and the socio-economic development of local communities(Huang et al., 2021). Initially conceptualized by conservationists and formalized by Hector Ceballos-Lascurain,(Scheyvens, 1999) it has evolved into a form of nature-based tourism that minimizes ecological impact, promotes cultural integrity, and generates inclusive economic benefits—distinguishing it from mass tourism through an ethical framework emphasizing conservation, education, and community participation(Patil & Pattanshetti, 2024). This approach integrates conservation with the empowerment of indigenous and rural communities, aligning with global sustainable development objectives(Carr et al., 2016).

Livelihood means of securing the necessities of life, encompassing not just income but also social, human, natural, and physical capital, which are all vital for sustainable existence and well-being within a community (Samal & Dash, 2022). Households typically mobilize and diversify these capitals to sustain their livelihood strategies and ensure survival(Huang et al., 2021). Residents of impoverished regions rely on diverse alternative activities as primary income sources alongside ecotourism(Sun et al., 2023); for instance, animal husbandry predominates in Georgia's Upper Svaneti(Huang et al., 2021), while agriculture constitutes the primary activity in India's Upper Brahmaputra River Basin, Assam(Roy et al., 2024). Livelihood pursuits depend on capital endowments and access to assets, the enhancement of which creates opportunities for impoverished populations(Rahman & Siddik, 2019)—thereby underscoring the need to examine how these factors influence choices such as the adoption of ecotourism(Huang et al., 2021).

Tourism as a livelihood strategy has received considerable scholarly attention. Empirical studies on tourism-based livelihoods across diverse countries and regions highlight its critical role in poverty alleviation and community well-being enhancement(Hahury et al., 2023). However, rural households' livelihood strategy choices—and the factors influencing them—vary substantially due to differences in national development priorities, economic capacities, and tourism endowments(Huang et al., 2021).The UK Department for International Development's Sustainable Livelihoods Framework advocates context-specific analyses tailored to unique national contexts(Huang et al., 2021).

The Ajodhya hillis situated in the southwestern part of West Bengal, specifically within Purulia district—a prominent ecotourism destination in the state. Extant literature on ecotourism and livelihoods in West Bengal's Ajodhya hill region furnishes foundational insights into the area's intricate socio-economic dynamics and the effects of tourism development(Paul & Ganguly, 2021). Prior studies have mainly utilized GIS-based spatial analysis, the Analytic Hierarchy Process, ethnographic surveys, and socio-economic assessments to evaluate ecotourism potential and outcomes(Paul & Ganguly, 2021). For example, GIS analyses identified sites such as Banduan and Ghatihuli as promising yet hindered by infrastructural deficits(Dolui & Chakraborty, 2022; Ghosh et al., 2023); AHP and accessibility-attraction models further exposed barriers including poor road networks, inadequate accommodation, and rugged terrain(Dolui & Chakraborty, 2022; Ghosh et al., 2023).

These studies document rapid infrastructure growth—such as sixteen resorts established in Baranti within five years—while underscoring challenges like tribal community marginalization, erosion of traditional knowledge due to forest degradation, and shifts to non-farm livelihoods(Chakrabarty et al., 2019; Hazari et al., 2025). Although state-led ecotourism initiatives create employment, benefits accrue unevenly, with outsiders dominating high-value roles amid tensions between cultural preservation and conservation priorities(Ghosh et al., 2024; Mondal, 2020; Paul & Ganguly, 2021).

Existing research on Ayodhya Hills and Purulia district has employed a range of methodologies—including GIS-based spatial analysis, the Analytic Hierarchy Process, ethnographic surveys, and socio-economic assessments—to evaluate ecotourism potential(Paul & Ganguly, 2021). GIS-based analyses have identified sites such as Banduan and Ghatihuli, which are constrained by inadequate infrastructure(Dolui & Chakraborty, 2022; Ghosh et al., 2023). Applications of the Analytic Hierarchy Process and accessibility-attraction models have revealed barriers, including insufficient roads, lack of accommodation facilities, and rugged terrain—particularly for visitors with disabilities(Dolui & Chakraborty, 2022; Ghosh et al., 2023). Field surveys have documented rapid development—such as the establishment of sixteen resorts in Baranti within five years—but have also observed the marginalization of tribal communities, the erosion of traditional knowledge amid forest degradation, and a shift toward non-farm livelihood activities(Chakrabarty et al., 2019; Paul & Ganguly, 2021). Socio-economic analyses have identified a paradox in state-led initiatives: although they generate employment, benefits are distributed unevenly, with outsiders capturing most high-value positions amid conflicts between cultural preservation and conservation imperatives(Ghosh et al., 2024; Mondal, 2020). Nevertheless, the livelihood capitals of the indigenous peoples of Ayodhya Hills have not been examined in these studies, thereby leaving a significant gap in understanding their socio-economic resilience and adaptive strategies amid ecotourism development. Moreover, previous research has neither employed multinomial logistic regression nor incorporated spatial factors.

However, previous research has neither employed multinomial logistic regression to analyse indigenous livelihood capitals nor incorporated spatial factors to clarify their effects on livelihood strategies within ecotourism settings—a critical gap this study addresses by investigating the interplay among capital endowments, socio-demographic attributes, and geospatial variables shaping rural households' choices among diverse activities, including ecotourism adoption.The main objective of this study are

- To categorize rural households in the Ajodhya hill region into distinct livelihood strategy groups
- To quantitatively evaluate the different types of livelihood capital
- To analyse the spatial distribution patterns and clustering of livelihood strategies
- To identify the key determinants of livelihood strategy choices

2. Study Area:

The Ayodhya Hills region, located in Purulia district of West Bengal, exemplifies such a landscape where environmental features, ethnicity, and underdevelopment converge(Paul & Ganguly, 2021). As the easternmost extension of the Chota Nagpur Plateau(Ghosh et al., 2023; Sahoo et al., 2020), the region boasts undulating scenic landscapes, numerous waterfalls, diverse flora and fauna in deciduous forests, and tribal communities' profound dependence on natural resources—particularly medicinal plants(Sahoo et al., 2020). Despite infrastructural deficits and socio-economic challenges, Purulia has been the focus of state-led initiatives to promote ecotourism as a viable development pathway(Dey et al., 2020; Ghosh et al., 2023). Nevertheless, the region's indigenous communities, such as the Santal and Birhor, continue to experience marginalization and are often portrayed as disconnected from mainstream society(Kundu & Nag, 2018; Paul & Ganguly, 2021).The livelihood structure of tribal residence of Ajodhya hill demonstrates a complex interplay of traditional practices and emerging opportunities, where ecotourism initiatives are poised to either exacerbate existing inequalities or foster sustainable development (Paul & Ganguly, 2021). The livelihood captial of household of tribal people can be significantly impacted by the integration of ecotourism, necessitating a closer examination of how various capital forms are leveraged and developed within these communities to ensure equitable benefits and sustained well-being (Das & Hussain, 2016; Samal & Dash, 2024). This study examines the livelihood assets and geospatial determinants of tribal households in the Ajodhya hill ecotourism destination.

3. Data Based and Methodology:

The selection of suitable variables is crucial for the rigorous multinomial logistic regression and spatial analyses employed to identify socio-environmental constraints shaping household decision-making processes in livelihood category choices within the distinctive landscape of the Chotanagpur Plateau's eastern extension, Ajodhya hill(Santarém et al., 2018). This study employed 10 socio-economic and 6 geospatial variables. This variables were selected by extensive literature review(Acharya et al., 2022; Das & Hussain, 2016; Dash et al., 2016; Guerrero et al., 2020; Huang et al., 2021; Mandal et al., 2022). Primary data were collected via household surveys, questionnaires, and focus group discussions. Primary and secondary indicators for livelihood categories are presented in Table 1.

Socio-economic data were gathered from eight villages in the Ajodhya hill region. These are Ajodhya, Chhatni, Sonahara, Bhunighara, Hatinada, Barria, Kudna, and Kudlung. These villages were purposively selected within a 5 km radius of the Ajodhya Hill top, a prominent tourist attraction in the area. A stratified random sample of 416 households was subsequently drawn from these villages employing a mixed-methods approach, including structured surveys to quantify socio-economic and livelihood indicators.

Table 1: Selection of evaluation indicators and descriptions for rural household livelihood capital

Primary Indicator	Secondary Indicator	Description	Source
Natural Capital	Cultivated Land	Bigha	Field Survey
Physical Capital	Number of Livestock	Cow=1-unit, Pig=0.75-unit, Goat=0.50-unit, Hen=0.10 units	
	Durable goods	Car=2.50-unit, Motor-bike=1-unit, Mobile=0.75 unit, By-cycle=0.25 unit	
	Housing Structure	Pacca=1-unit, Semi-pacca=0.75-unit, Kancha=0.25-unit	
Financial Capital	Number of Occupation		
	Number of civil servants	Yes=1, No=0	
	Total Income (Rs)	Total annual household income (INR-Rs)	
Human Capital	Number of family member	Number of family members per household (person)	
	Education Score	The educational scores were assigned as follows: Illiterate = 0.00, Learner = 0.15, Primary = 0.35, Madhyamik (secondary level) = 0.50, Higher Secondary (H.S.) = 0.75, Graduate = 1.00, and Postgraduate (PG) = 1.25	
	Dependency ratio	Percentage	

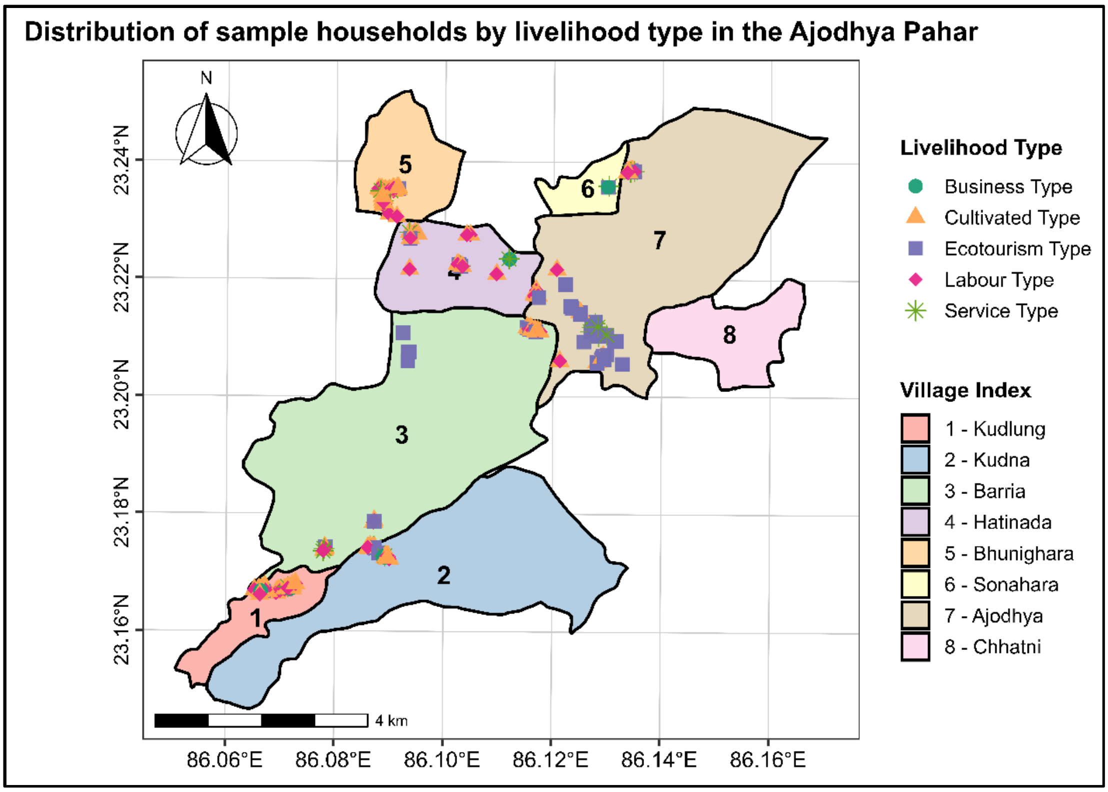
The geospatial data and sources are given into table2. Distance from geo-sites were digitize into Google Earth Pro. The geospatial data were further processed into ArcGIS version 10.8 to calculate Euclidean distances from each household to key infrastructure, including the nearest major geo-sites, roads.

Table 2: Inventory and data sources of geospatial environmental covariates used in the spatial analysis

Covariates	Abbr.	Units	Source
Distance from geo-sites	GOS	Metres	Digitization Google Earth Pro
Elevation	ELV	Metres	https://earthexplorer.usgs.gov/)
Distance from the road	ROD	Metres	(https://www.openstreetmap.org/#map=9/23.201/86.363)
Distance from the river	RVR	Meter	(https://www.hydrosheds.org/).
Slope	SLP	Degree Minutes Seconds	(https://earthexplorer.usgs.gov/)
Topographical roughness	TGR	----------	(https://earthexplorer.usgs.gov/)

The research design utilizes a mixed-methods approach to quantify the four core assets—natural, human, physical, financial—which determine the capacity of households to navigate different livelihood pathways (Pasanchay & Schott, 2020).

Fig:1 Geographical distribution of sampled households by livelihood type in the Ajodhya Hill



This section first introduces the framework for evaluating rural households' livelihood capitals, followed by the computation of their capital stocks to assess the prevailing livelihood conditions in the Ajodhya hill. Spatial analytical methods—including Moran's I index, Nearest Neighbour Hierarchical Spatial Clustering, and Ripley's K function—were then applied to examine the spatial distribution patterns of households across different livelihood types. Then, multinomial logistic regression was employed to investigate the influence of livelihood capitals on households' livelihood choices in the Ajodhya hill. Finally, the geographical detector was employed to evaluate the impacts of geospatial and socioeconomic factors on households' livelihood choices in the Ajodhya hill.

3.1 Construction of a livelihood capital evaluation system for rural households

Drawing on the Sustainable Livelihoods Approach framework adapted to the Ajodhya hill, a comprehensive livelihood capital evaluation index system was developed [Eq. 1- Eq. 6]. This system encompasses 10 indicators across the four capital domains: natural, physical, financial, and human. Indicator weights were determined by the entropy weighting method, predicated on the 'difference-driven' principle. Following data standardization, optimal weights were derived directly from the sample data by capturing each indicator's information entropy utility to ensure objectivity, accuracy, and feasibility. For m participating objects and n evaluation indicators $X_1, X_2, \dots, X_n$, the dimensional discrepancies among indicators necessitated initial data standardization as follows:

$$X_{ij}^{'} = \frac{X_{ij} - \min(X_j)}{\max(X_j) - \min(X_j)} \quad \text{(Eq. 1)}$$

Where Xprime_{ij} represents the standardized value for the i-th object and j-th indicator, and $min(X_j)$ and $max(X_j)$ denote the minimum and maximum values for the j-th indicator, respectively.

$$X_{ij}^{'} = \frac{X_{ij} - \min(X_j)}{\max(X_j) - \min(X_j)} \quad \text{(Eq.2)}$$

For a negative indicator (like the dependency ratio), the formula is:

$$X_{ij}^{'} = fracmax(X_j) - X_{ij}max(X_j) - min(X_j) \quad \text{(Eq. 3)}$$

3.1.1 Entropy Weighting Method

This method was used to derive objective weights for the 10 socio-economic indicators (Li et al., 2022). While the entropy weighting method was used to derive objective weights and mitigate initial subjective biases (Nasrnia & Ashktorab, 2021), it remains a strictly data-driven technique that does not account for the theoretical hierarchy of capital indicators (Zhou et al., 2018).". Subsequently, the information entropy for each indicator j was computed using the following formulas [Eq. 4-Eq. 6]:

$$p_{ij} = \frac{X_{ij}^{'}}{\sum_{i=1}^{m} X_{ij}^{'}} \quad \text{(Eq. 4)}$$

$$e_j = -\frac{1}{\ln m} \sum_{i=1}^{m} p_{ij} \ln p_{ij} \quad \text{(Eq. 5)}$$

$$w_j = \frac{1 - e_j}{\sum_{k=1}^{n} (1 - e_k)} \quad \text{(Eq. 6)}$$

These calculated weights (w_j) were then applied to the standardized indicator values to derive a composite livelihood capital score for each household, thereby quantifying their overall livelihood status within the study area. This comprehensive score facilitates comparative analysis of household resilience and adaptive capacities (Sun et al., 2025), highlighting critical areas for intervention to enhance sustainable livelihood development (Zhang et al., 2022).

These derived weights were then applied to the standardized indicator scores to compute the aggregate livelihood capital scores for each household, providing a quantitative basis for subsequent analyses (Fang et al., 2020).

Table 3 Livelihood capital indicators and their weights derived from the entropy weighting method

Indicators	Livelihood Capital	Weights
TotalIncomesample	Financial	0.2263
Number of Occupation		0.0761
service		0.1641
Number of Family Member	Human	0.0796
Educational Qualification		0.0902
Dependencyratio		0.0770
Land (Bigha)	Natural	0.0746
Housing Structure	Physical	0.0299
Livestock		0.0831
Durable Good		0.0992

3.2 Multinomial logistic regression

This study employs a multinomial logistic regression model [Eq. 7-Eq.9] to examine the probabilitiesof households selecting particular livelihood strategies, predicated on the assumption that individualschoose activities to maximize utility given their distinctive capital endowments (Huang et al., 2021).Individual scores for each livelihood capital and other influencing factors were designated asindependent variables(X), with the four livelihood strategy types set as the dependent variable (Y).Assuming the non-ordinal dependent variable comprises K categories (four types of livelihoodcategory)—with the Kth category as the reference—the multinomial logistic regression model is expressed as K−1 binomial logistic regression models. For a household i^{th}, the probability of choosing category j (j=1,2, … K−1) relative to the reference category K[Eq.7] is

$$P(Y_i = j \mid X_i) = \frac{\exp\left(X_i^T \beta_j\right)}{1 + \sum_{m=1}^{K-1} \exp\left(X_i^T \beta_m\right)} \quad \text{(Eq. 7)}$$

the probability [Eq.8] for the reference category K is:

$$P(Y_i = K \mid X_i) = \frac{1}{1 + \sum_{m=1}^{K-1} \exp\left(X_i^T \beta_m\right)}, \quad j = 1,2, \ldots, K-1 \quad \text{(Eq. 8)}$$

The model is usually expressed in terms of the log-odds (logit) [Eq. 9] For each non-reference category j:

$$\ln\left(\frac{P(Y_i = j \mid X_i)}{P(Y_i = K \mid X_i)}\right) = X_i^T \beta_j = \beta_{0j} + \sum_{p=1}^{P} \beta_{pj} X_{pi} \quad \text{(Eq. 9)}$$

3.3 Spatial distribution patterns of rural households

A series of spatial analysis methods—including spatial autocorrelation analysis (to detect spatial autocorrelation), nearest neighbour hierarchical spatial clustering (to identify clustering patterns), and Ripley's K function (to assess multi-scale characteristics)—were employed to investigate the spatial distribution patterns of households across different livelihood types.

3.3.1 Spatial autocorrelation

Spatial autocorrelation has been extensively used in tourism research, for example, in studies on regional tourism disparity in Turkey, tourist recreation flow, Ukraine, and tourism potential in Nízký Jeseník Highlands(Khan, 2018; Prudencio-Vázquez et al., 2023; Rafique et al., 2020; Stankov et al., 2017). Spatial autocorrelation analysis was employed to quantify the spatial dependence each livelihood categories. This approach not only distinguishes among distribution patterns of point features but also elucidates the spatial configurations of rural households in the Ajodhya hill from a correlation standpoint. The global Moran's I index is formulated as follows [Eq. 10]:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\left(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\right)\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad \text{(Eq. 10)}$$

where n represents the number of observations; y_i and y_j denote the attribute values at locations i and j, respectively; $\bar{y}$ is the mean attribute value; and w_{ij} constitutes the spatial weight, determined by contiguity or distance criteria. A positive global Moran's $I > 0$ signifies positive spatial autocorrelation, manifesting as high-high or low-low clustering. Conversely, $I < 0$ indicates negative spatial autocorrelation, characterized by high-low dispersion.

3.3.2 Nearest neighbour hierarchical spatial clustering

Nearest neighbourhierarchical clustering were used in tourism geography to delineate the spatial density of tourism-related enterprises and to detect specific points of interest that form localized nuclei of economic activity within a landscape. This technique facilitates the identification of multi-level clusters by iteratively grouping points that meet a predefined probability threshold and minimum cluster size, effectively mapping the hierarchical structure of rural settlements (Puebla et al., 2017). Nearest neighbour hierarchical spatial clustering employs the nearest neighbour index to evaluate spatial clustering patterns, thereby revealing the extent of aggregation among rural households pursuing distinct livelihood strategies. The NNI is computed as follows [Eq. 11]:

$$R = \frac{\bar{d}_{obs}}{\bar{d}_{exp}} = \frac{\sum_{i=1}^{n} d_i / n}{1/\left(2\sqrt{n/A}\right)} \quad \text{(Eq. 11)}$$

where R (or NNI) is the ratio of the observed mean distance between nearest neighbors ($bard_{obs}$) to the expected mean distance under a random distribution ($bard_{exp}$), n is the total number of household points in the study area; is the distance from any point to its nearest neighbour; and is the total area of the study region (Liao et al., 2022). When, it indicates a clustered distribution; when, it indicates dispersion; and signifies a random spatial distribution (Liao et al., 2022)."

3.3.3 Ripley's K function

The Ripley's K function was used in the spatial distribution characteristics and influencing factors of key villages in rural tourism in China (Liao et al., 2022). Ripley's K function enables the analysis of spatial patterns in point data across multiple scales and is among the most widely used methods for identifying clustering extents. Its formula is[12]:

$$K(d) = \frac{A}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(d) \quad \text{(Eq. 12)}$$

where n is the number of point features; $w_{ij}(d)$ denotes the distance weight between the ith and jth points within distance d; and A is the study area size. $K(d)$ represents the expected number of neighbouring points within distance d relative to point density. For comparison against theoretical complete spatial randomness, the L(d) index is defined as[13]:

$$L(d) = \sqrt{\frac{K(d)}{\pi}} - d \quad \text{(Eq. 13)}$$

Values of $L(d) > 0$ suggest clustering at distance d, while $L(d) < 0$ indicates dispersion, and $L(d) = 0$ corresponds to a random spatial distribution. This function, therefore, provides a robust method for discerning whether the observed spatial arrangements of households align with patterns of aggregation, dispersion, or randomness at varying geographical scales, which is crucial for understanding the underlying socio-economic and ecological drivers.

Under CSR, $L(d) = 0$ indicates randomness; $L(d) > 0$ signifies clustering; and $L(d) < 0$ denotes dispersion. Confidence envelopes are derived from goodness-of-fit tests or simulations. Significant clustering is confirmed when observed$L(d)$exceeds the upper envelope; significant dispersion occurs below the lower envelope. Deviations from the expected $L(d) = 0$ quantify pattern intensity: positive values indicate clustering (peaking at maximum deviation), while negative values reflect dispersion.

3.4 The geographical detector method

The Geographical Detector is a statistical method designed to detect spatial stratified heterogeneity, identify explanatory factors, and examine interactions among variables(Song et al., 2020). Its core principle posits that if the spatial distributions of two variables exhibit consistency within discretised subregions of the study area, a statistical correlation exists between them(Guo et al., 2020). Compared to traditional regression techniques—which capture spatial patterns along one-dimensional curves—the Geographical Detector operates in two-dimensional space, offering superior reliability in discerning spatial causality(Zhang et al., 2022).

The method comprises four detectors: risk, factor, interaction, and ecological. In this study, the factor detector was applied to quantify the explanatory power of geographical and socioeconomic factors on rural households' livelihood strategies in the Ajodhya hill. Relevant variables were input into the R Studio's "GD" library to compute the q-statistic, which measures the proportion of spatial variation in livelihood strategies attributable to each factor [14]:

$$q = 1 - fracsum_{h=1}^{L} N_h sigma_h^2 N sigma^2 \quad \text{(Eq. 14)}$$

Here, $h = 1, dots, L$ refers to the strata of the dependent variable, N_h and N are the number of units in stratum h and the total population, respectively, and $sigma_h^2$ and $sigma^2$ denote the variance of the dependent variable in stratum h and the total population, respectively

4 Results

4.1 Basic characteristics of different livelihood strategies

In the study area, rural households pursue a diverse yet asymmetrical array of livelihood strategies, predominantly comprising labour-intensive activities table 4 (45.19% of the sample) followed by cultivated livelihoods (28.61%), ecotourism (18.99%), service household (4.81%), and business household (2.40%). Service households yield the highest incomes, underpinned by superior education, housing, durable goods, and civil servant presence. Ecotourism households follow with balanced assets, moderate land, and income diversity. Business households, though fewest, feature concentrated incomes and strong physical capitals. Cultivated households command extensive land and livestock yet suffer low education and assets. Labour households, most prevalent, endure minimal incomes despite high diversification, large families, and livestock for resilience.This pattern of distribution illustrates the enduring dominance of traditional and wage-labour strategies within an established tourism destination, while underscoring the emerging significance of tourism-oriented livelihood pathways. It also illustrates marked socio-economic disparities among these livelihood strategies, mirroring distinct asset endowments and vulnerability patterns that align with the Sustainable Livelihoods Framework.

Table 4: Socio-economic characteristics of rural households by livelihood strategy

Indicator	Labour	Cultivated	Business	Ecotourism	Service
Proportion of sample (%)	45.19	28.61	2.40	18.99	4.81
Cultivated Land	0.21	6.91	5.50	5.22	9.10
HousingStructure	0.32	0.37	0.70	0.71	0.81
Durable Goods	1.94	1.95	3.72	4.13	4.15
Numberof Family Members	6.45	6.24	6.00	6.01	5.20
Number of Occupation	6.10	4.87	1.60	4.33	3.55
Educational Score	0.22	0.20	0.52	0.46	0.76
DependencyRatio	93.79	107.51	110.17	113.57	87.50
Number of Livestock	10.07	9.90	5.16	6.22	5.01
Numberof Civil Servants	0.03	0.05	0.10	0.14	1.10
TotalIncome (INR)	33,779.26	69,285.29	181,030.00	189,602.53	360,735.00

Labour-dependent households, the largest group, are characterised by minimal cultivated land (0.21 bigha), low durable consumer goods (1.94), and modest housing quality (0.32), yet they maintain the highest income diversity (6.10) and relatively large family sizes (6.45 members) and minimum total income (33,779.26 INR). Their elevated livestock holdings (10.07) and low dependency ratio (93.79) suggest a reliance on flexible, multi-activity portfolios—often combining casual wage work with subsistence elements—to buffer shocks. In contrast, cultivated households display the highest land endowments (6.91) and livestock (9.90) but similarly low physical assets (durable goods 1.95; housing 0.37), low educational attainment (0.20), a higher dependency ratio (107.51) and minimum total income (69,285.29 INR), indicating entrenched agricultural dependence with limited diversification (income diversity 4.87). These patterns match findings from similar ecotourism areas, where natural capital-rich households stay in farming due to barriers to higher-return activities.

Ecotourism-linked strategies reveal stronger asset bases. Ecotourism households exhibit moderate land (5.22 bigha), higher durable goods (4.13), improved housing (0.71), and moderately total income (181,030.00 INR), solid income diversity (4.33), with educational levels (0.46) notably above agricultural baselines. Business households, though marginal in share, stand out for concentrated income streams (lowest diversity at 1.60), superior durable goods (3.72), and housing quality (0.70), and moderately total income (189,602.53 INR) (suggesting specialised, capital-intensive operations. Service-oriented households—often anchored in civil service or formal employment (1.10 civil servants per household)—emerge as the most advantaged: highest educational attainment (0.76), best housing (0.81), largest cultivated land holdings (9.10 bigha), lowest family size (5.20), and lowest dependency ratio (87.50). This group's profile signals upward mobility through stable, skill-intensive livelihoods.

These characteristics have profound implications for sustainable rural development in tourism destinations. Labour- and cultivation-dependent strategies, which comprise nearly three-quarters of households, confer resilience through diversification and natural capital endowments whilst remaining vulnerable to external shocks owing to deficiencies in physical and human capital. Conversely, ecotourism and service strategies exhibit superior capital accumulation and lower dependency, presenting scalable models for poverty alleviation—yet their limited adoption indicates structural barriers such as education, networks, and location.

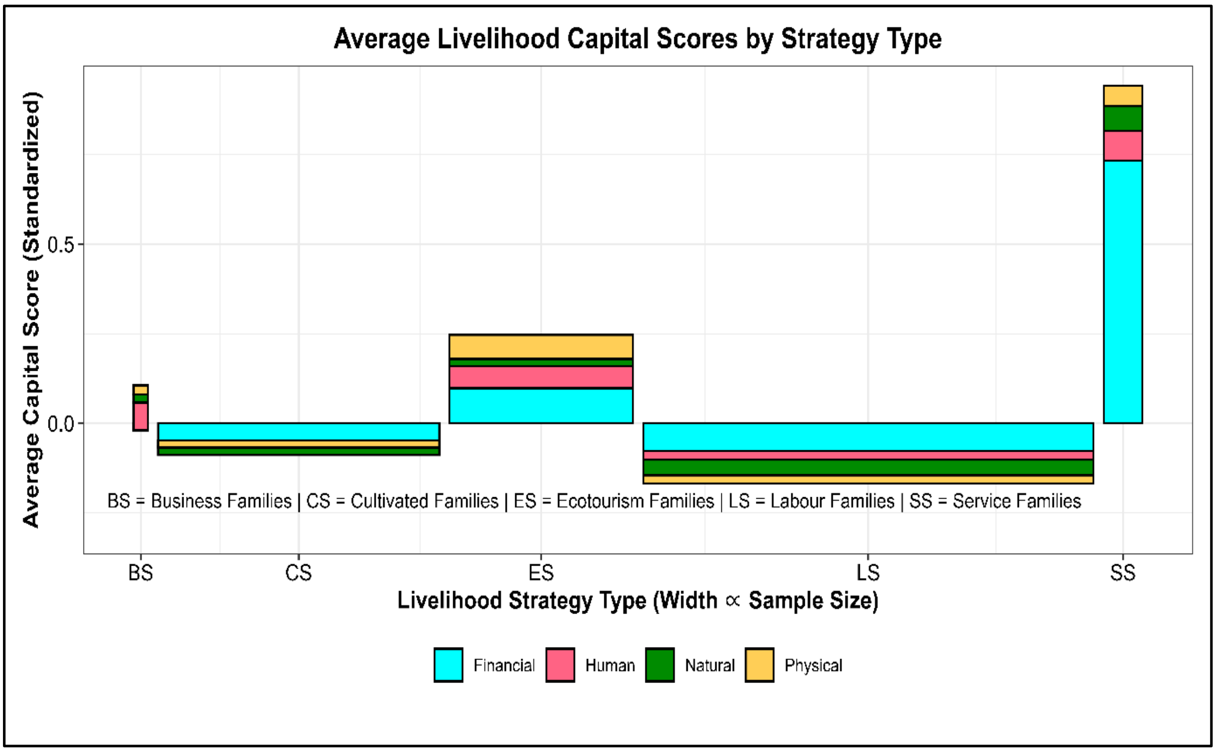


Figure 2: Standardized average scores of the four livelihood capitals across rural household strategy types in Ajodhya Hill

4.2 Evaluation of Different Types of Livelihood Capital

The stacked bar chart (Figure 2) illustrates the average standardized livelihood capital scores across five rural household strategy types in a tourism destination: Business (BS), Cultivated (CS, agricultural-dominant), Ecotourism (ES, tourism-dominant), Labour (LS, working-dominant), and Service (SS, service-dominant). Scores are disaggregated by capital type—financial (cyan), human (pink), natural (green), and physical (yellow)—with bar widths proportional to sample sizes, highlighting the dominance of labour (45.19%) and cultivated (28.61%) strategies (Table 4).

Overall, tourism enhances livelihood capital overall, though it varies substantially across strategies. Service households exhibit the highest total score (~0.9), driven by strong financial (~0.6) and balanced human/physical contributions, reflecting superior education (0.76), housing (0.81), and durable goods (4.15). Ecotourism and labour households follow with moderate scores (~0.2–0.3), bolstered by financial capital in labour (diverse income 6.10) and mixed assets in ecotourism (goods 4.13). Cultivated and business households score near or below zero, constrained by low financial/human capital despite natural strengths (land 6.91/5.50; livestock 9.90/5.16).

4.2 Factors Influencing Livelihood Strategy Choices: Multinomial Logistic Regression Analysis

Multinomial logistic regression was employed to examine how standardised livelihood capital scores—financial capital, human capital, natural capital and physical capital determine the primary livelihood strategy choices of rural households in this tourism-influenced destination, Ajodhya Hill, Purulia. Two models were estimated for robustness, one with cultivated households as the reference category and the other with labour-dependent households as the reference. Both models were statistically significant overall ($p < 0.001$) and demonstrated strong explanatory power, with coefficients indicating the change in log-odds of selecting a given strategy (relative to the base) for a one-unit increase in each capital score.

4.2.1 Model with Cultivated (Agricultural) Households as Reference Category

When agricultural households serve as the reference (table 5), natural capital exhibits the strongest anchoring effect, likely because abundant natural resources (such as larger cultivated land holdings and livestock) tie households closely to farming activities, making exit costly or unnecessary due to high opportunity costs of abandoning productive land. A one-unit increase in natural capital score decreases the log-odds of choosing labour by 76.21 ($z = -7.19$, $p < 0.001$), ecotourism by 9.08 ($z = -3.79$, $p < 0.001$), and service by 11.08 ($z = -2.79$, $p < 0.01$). The negative effect on business (−6.81) is directionally consistent but insignificant ($p = 0.135$).

Financial capital acts as the main driver of escape from agriculture, probably due to its role in providing liquidity for investments in non-farm activities, such as starting tourism services, acquiring equipment, or covering training costs. A one-unit increase raises the log-odds of ecotourism by 3.60 ($z = 4.03$, $p < 0.001$) and service by 5.79 ($z = 5.52$, $p < 0.001$).

Human capital strongly favours skill-intensive and higher-return pathways, as better educational qualification, and household labour quality lower entry barriers to knowledge-based or tourism-related work requiring qualifications or expertise. Higher human capital increases the log-odds of business by 6.68 ($z = 2.58$, $p < 0.01$), ecotourism by 5.67 ($z = 4.13$, $p < 0.001$), and service by 6.78 ($z = 3.07$, $p < 0.01$).

Table 5: Multinomial Logistic Regression results for the determinants of livelihood strategy choice (Reference Category: Cultivated Households)

Cultivated Type as a Base Family								
Level	term	estimate	std.error	z	p.value	lower_CI	upper_CI	significant
Labour Type	(Intercept)	-1.53	0.45	-3.38	0.00	-2.42	-0.64	TRUE
	F	1.39	1.10	1.26	0.21	-0.78	3.55	FALSE
	H	2.17	1.32	1.64	0.10	-0.42	4.76	FALSE
	N	-76.21	10.60	-7.19	0.00	-96.99	-55.44	TRUE
	P	-1.66	1.31	-1.27	0.21	-4.24	0.91	FALSE

Business Type	(Intercept)	-2.33	0.40	-5.88	0.00	-3.10	-1.55	TRUE
	F	1.76	1.81	0.97	0.33	-1.79	5.31	FALSE
	H	6.68	2.59	2.58	0.01	1.60	11.76	TRUE
	N	-6.81	4.56	-1.49	0.14	-15.75	2.13	FALSE
	P	1.96	2.77	0.71	0.48	-3.46	7.38	FALSE
Ecotourism Type	(Intercept)	-0.29	0.19	-1.54	0.12	-0.65	0.08	FALSE
	F	3.60	0.89	4.03	0.00	1.85	5.35	TRUE
	H	5.67	1.37	4.13	0.00	2.98	8.35	TRUE
	N	-9.08	2.40	-3.79	0.00	-13.78	-4.39	TRUE
	P	4.17	1.31	3.18	0.00	1.60	6.74	TRUE
Service Type	(Intercept)	-2.25	0.38	-5.94	0.00	-2.99	-1.51	TRUE
	F	5.79	1.05	5.52	0.00	3.73	7.84	TRUE
	H	6.78	2.21	3.07	0.00	2.46	11.11	TRUE
	N	-11.08	3.97	-2.79	0.01	-18.85	-3.30	TRUE
	P	2.05	2.13	0.96	0.34	-2.13	6.23	FALSE

Physical capital shows a targeted positive effect only on ecotourism (coefficient 4.17, z = 3.18, $p < 0.01$), most likely because tangible assets like improved housing quality and durable consumer goods are essential for practical tourism operations, such as homestays, guiding equipment like motor bike, or visitor facilities (Fig. 3).

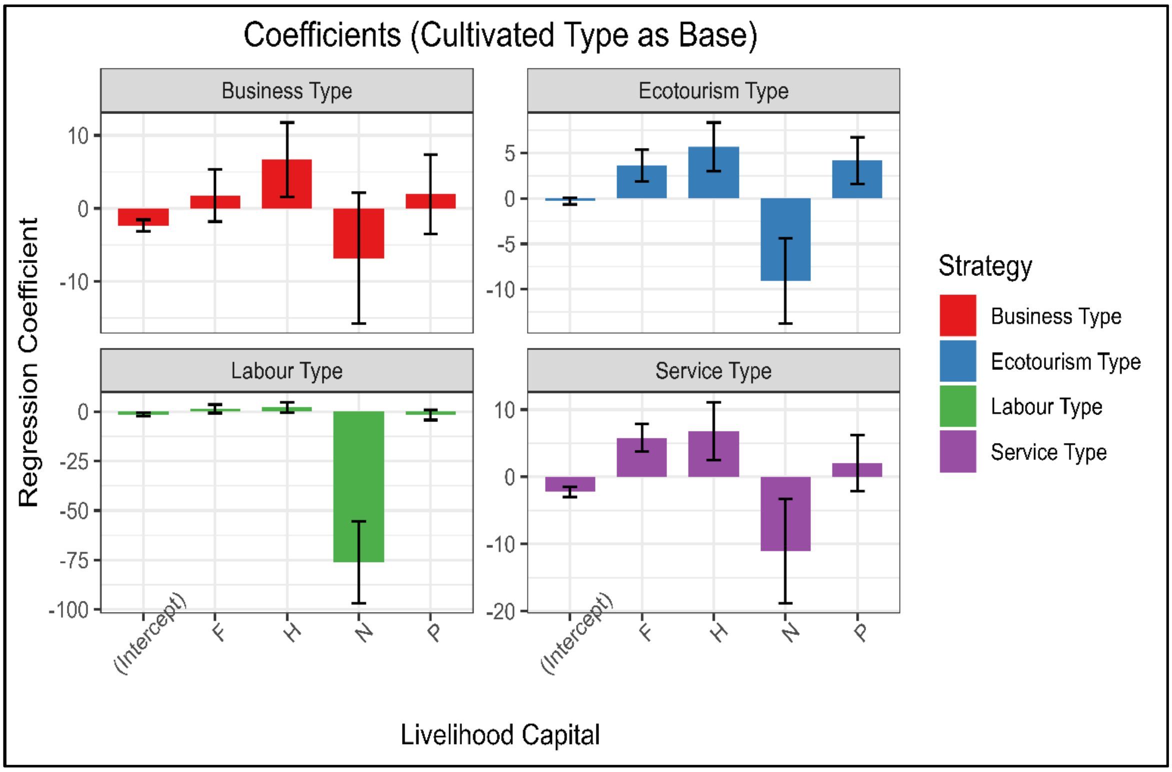


Figure 3: Coefficients of the Multinomial Logistic Regression for livelihood determinants (Reference Category: Cultivated Households)

4.2.2 Model with Labour-Dependent Households as Reference Category

With labour households as the reference (table 6), natural capital dominates by pulling households away from the precarious wage-labour default, as even small land access enables self-provisioning, farming, or livestock rearing, reducing reliance on unstable casual work and providing a buffer against shocks. A one-unit increase dramatically raises the log-odds of cultivated agriculture by 76.21 ($z = 7.19$, $p < 0.001$), business by 69.40 ($z = 6.13$, $p < 0.001$), ecotourism by 67.13 ($z = 6.32$, $p < 0.001$), and service by 65.13 ($z = 5.91$, $p < 0.001$).

Financial capital continues to facilitate shifts to tourism and service strategies, likely by overcoming initial capital requirements for tourism entry (e.g., startup costs, marketing, or seasonal income gaps) and enabling greater income stability beyond wages. It increases the log-odds of ecotourism by 2.21 ($z = 2.61$, $p < 0.01$) and service by 4.40 ($z = 4.60$, $p < 0.001$) relative to labour.

Human capital supports upward mobility into skilled or formal activities, as higher education, skills, and labour quality open doors to better-paid or less physically demanding options with lower vulnerability. It positively affects ecotourism (coefficient 3.50, $z = 2.97$, $p < 0.01$) and service (coefficient 4.61, $z = 2.23$, $p < 0.05$), with a marginally positive effect on business (coefficient 4.51, $z = 1.79$, $p = 0.074$).

Table 6: Multinomial Logistic Regression results for the determinants of livelihood strategy choice (Reference Category: Labour-Dependent Households)

Multinominal Logistic Regression Based Labour Type								
Level	term	estimate	std.error	z	p.value	lower_CI	upper_CI	significant
Business Type	(Intercept)	-0.8	0.57	-1.39	0.16	-1.92	0.33	FALSE
	F	0.38	1.82	0.21	0.84	-3.19	3.94	FALSE
	H	4.51	2.52	1.79	0.07	-0.43	9.44	FALSE
	N	69.4	11.32	6.13	0	47.2	91.59	TRUE
	P	3.63	2.77	1.31	0.19	-1.81	9.06	FALSE
Cultivated Type	(Intercept)	1.53	0.45	3.38	0	0.64	2.42	TRUE
	F	-1.39	1.1	-1.26	0.21	-3.55	0.78	FALSE
	H	-2.17	1.32	-1.64	0.1	-4.76	0.42	FALSE
	N	76.21	10.6	7.19	0	55.43	96.98	TRUE
	P	1.66	1.31	1.27	0.21	-0.91	4.23	FALSE
Ecotourism Type	(Intercept)	1.24	0.46	2.72	0.01	0.35	2.13	TRUE
	F	2.21	0.85	2.61	0.01	0.55	3.88	TRUE
	H	3.5	1.18	2.97	0	1.19	5.81	TRUE
	N	67.13	10.62	6.32	0	46.31	87.95	TRUE
	P	5.83	1.28	4.57	0	3.33	8.33	TRUE

Service Type	(Intercept)	-0.72	0.56	-1.28	0.2	-1.82	0.38	FALSE
	F	4.4	0.96	4.6	0	2.52	6.27	TRUE
	H	4.61	2.07	2.23	0.03	0.56	8.66	TRUE
	N	65.13	11.03	5.91	0	43.51	86.75	TRUE
	P	3.71	2.09	1.77	0.08	-0.39	7.81	FALSE

Physical capital has a particularly strong link to ecotourism (coefficient 5.83, $z = 4.57$, $p < 0.001$), probably because labour households often lack suitable infrastructure or assets for tourism hosting or services, making physical improvements a key enabler for participation (Fig.4).

The dual-reference models yield highly consistent directional effects, magnitudes, and significance levels (all major coefficients $p < 0.05$ or lower, except marginal cases), confirming robustness. The results reveal a clear capital hierarchy: high natural capital with low financial and human capital leads to agricultural lock-in (due to land dependence and high exit costs); low natural capital with limited financial and human resources results in labour dependence (asset-poor trap with few alternatives); while high financial and human capital—often with physical capital support for ecotourism—enables transitions to ecotourism, service, or business (facilitated by investment capacity, educational qualification, and infrastructure).

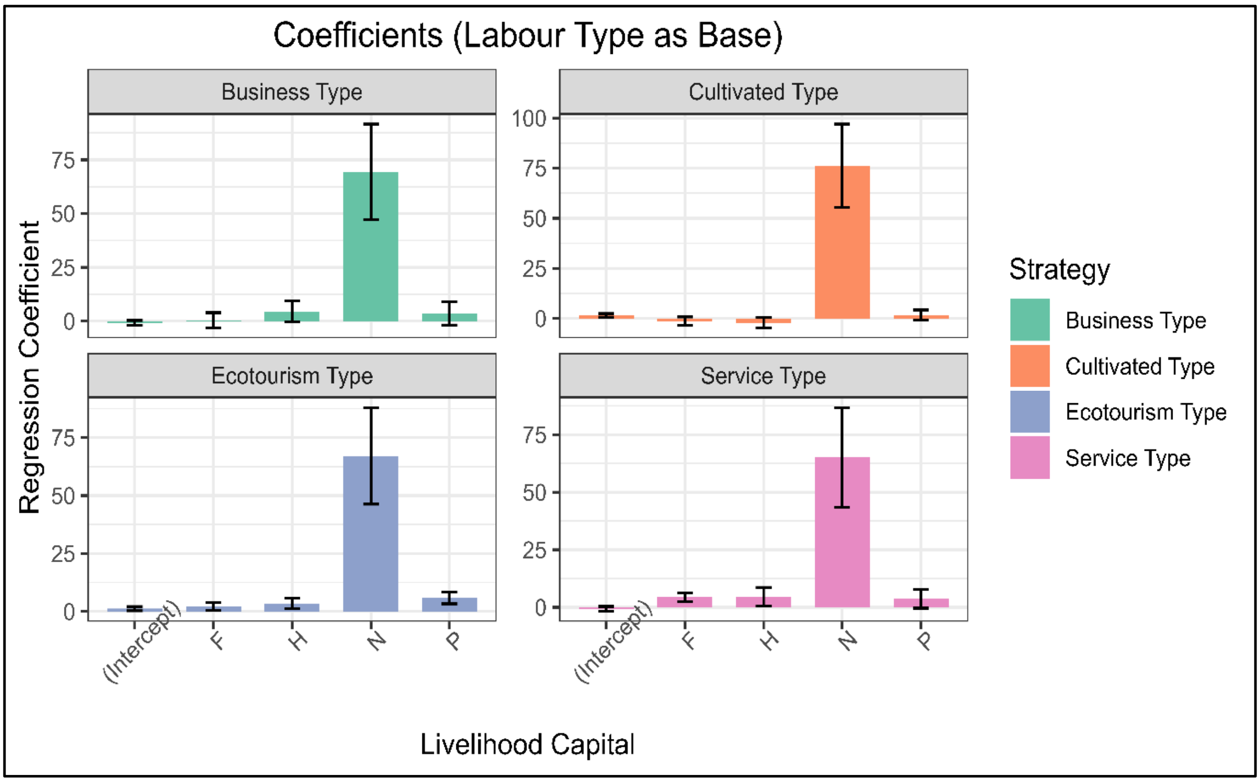


Figure 4: Coefficients of the Multinomial Logistic Regression for livelihood determinants (Reference Category: Labour-Dependent Households)

4.3 Spatial distribution patterns of rural households

The Global Moran's I test confirms statistically significant positive spatial autocorrelation in livelihood types. (Moran's $I = 0.0688$, $z = 3.0749$, $p = 0.0021$; expected value = –0.0057, variance = 0.00059). The results indicate that households engaged in similar livelihood strategies display statistically significant spatial clustering, surpassing expectations under complete spatial randomness. These patterns highlight the effects of proximity to GOS, to rivers, and to roads, along with shared social networks, resource access, and collective learning, on livelihood choices. Such clusters constitute the spatial manifestation of underlying social and economic dynamics. To delineate these localised concentrations more precisely, the nearest neighbour hierarchical clustering method was applied to identify high-density hotspots dominated by specific livelihood strategies.

Strategy-specific clustering intensity was quantified using the Nearest Neighbour Index (NNI) (Table 7). NNI values below 1 with $p < 0.05$ denote statistically significant clustering, while values near 1 with $p > 0.05$ indicate random distribution.(Walelign & Jiao, 2017).

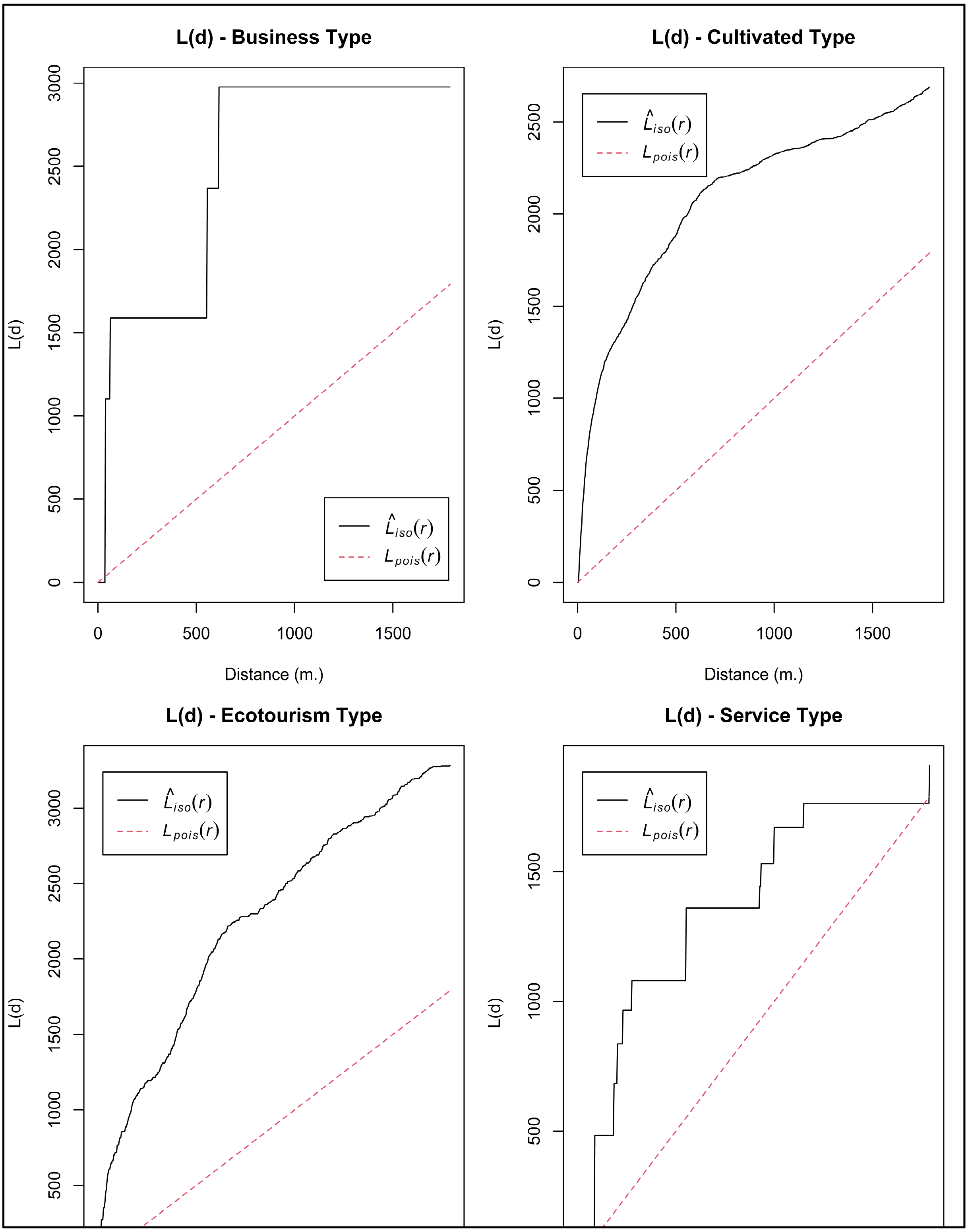
Table 7. Nearest Neighbour Index statistics for each livelihood strategy"

Livelihood Type	NNI	Z-score	p-value
Business Type	0.963	0.963	0.8615
Cultivated Type	0.213	0.213	0.0000
Ecotourism Type	0.550	0.550	0.0000
Labour Type	0.858	0.858	0.3096
Service Type	0.590	0.590	0.0047
All	0.218	0.218	0.0000

Cultivated households showed the strongest clustering (NNI = 0.213, $p < 0.001$), followed by Ecotourism (NNI = 0.550, $p < 0.001$) and Service (NNI = 0.590, $p = 0.0047$). Labour (NNI = 0.858, $p = 0.3096$) and Business (NNI = 0.963, $p = 0.8615$) households exhibited patterns consistent with complete spatial randomness. The overall pattern (All) confirmed strong clustering (NNI = 0.218, $p < 0.001$).

To examine these patterns at multiple scales, Ripley's L-function (transformed K-function) was applied to five livelihood-type subsamples (Business, Labour, Ecotourism, Cultivated, and Service). In all cases the observed L̂_iso(r) curve lies above the expected L_pois(r) reference line (complete spatial randomness), confirming clustering rather than dispersion or regularity across distances from near-zero to ~1,750 m. However, the shape, timing, and intensity of departure from randomness differ markedly between livelihood types, revealing distinct ecological and social signatures (Fig. 5).

- Cultivated households exhibit the strongest, most consistent clustering above L_{pois}, with continuous upward curvature. This reflects attachment to fertile land, water sources, and traditional knowledge, offering mutual support but heightening vulnerability to climate shocks, degradation, or market fluctuations.
- Business households show an abrupt, stepped $\widehat{L_{iso}}$ profile: rapid rises at short-to-medium distances followed by a plateau. This indicates discrete agglomerations near markets, roads, or tourist points, forming entrepreneurial micro-economies with mutual support yet potential competition.



Fi

gy

ess

plateau. This suggests initial clustering near tourist zones, expanding along accessibility corridors.

- Labour households feature staircase progression with plateaus and steps at larger distances, mirroring hierarchical migration networks linking local to regional and distant opportunities.

- Ecotourism households show smooth, continuous upward deviation above L_{pois}, indicating self-organization around dispersed natural assets responsive to environmental cues.

Taken together, the ranking of clustering intensity—from strongest in cultivated households to near-random in business and labour—mirrors findings from comparable tourism destinations(Huang et al., 2021) and underscores a critical livelihood-diversification gradient. This spatial differentiation carries direct humanistic consequences: tightly clustered agricultural communities enjoy strong bonding social capital and cultural continuity but face higher systemic vulnerability to shocks; more flexible tourism-oriented, service, business, and labour-migratory clusters access broader opportunities yet experience weaker local cohesion and greater dependence on external markets.

Table 7: Factor detector results (q-statistic and p-value) of the geographical detector for geospatial determinants of livelihood strategies

Result of Geodetector						
Variable	SLP	GOS	ELV	ROD	RVR	TGR
q-statistic	0.011	0.008	0.003	0.003	0.002	0.001
p-value	0.21	0.599	0.713	0.889	0.922	0.966

The factor detector results of the Geographical Detector analysis (table 7) reveal that individual geospatial environmental variables possess limited independent explanatory power regarding the spatial distribution of livelihood strategies in Ajodhya hill. None of the tested variables, including SLP ($q = 0.011$, $p = 0.21$) and Elevation ($q = 0.003p = 0.713$), achieved statistical significance ($p < 0.05$). Consequently, the spatial patterns of livelihoods in this region appear to be primarily influenced by intricate socio-economic capital endowments or interactions among multiple geospatial factors, rather than any solitary environmental constraint

From a sustainable-livelihoods perspective, these patterns highlight opportunities and policy imperatives. Positive spatial autocorrelation and livelihood-specific clustering show households already leveraging proximity and social capital—assets policies should reinforce—yet pronounced clustering in tourism-dependent households signals over-reliance on volatile sectors. Interventions fostering "balanced" livelihood clusters—mixing cultivation, services, and ecotourism—could enhance resilience while preserving the social fabric revealed by Moran's I and Ripley's L-function, alongside strengthening cooperatives in agricultural and tourism clusters, improving connectivity for dispersed households, and addressing multi-scale dynamics for more equitable, resilient rural livelihoods.

These statistically robust patterns illustrate livelihood strategies as spatially patterned outcomes shaped by differential access to capitals, calling for nuanced, people-centred policies.

4.3.1 Impact of geospatial factors on livelihood strategy

Multinomial logistic regression models were fitted to examine the effects of six geospatial predictors— SLP (Degree, Minutes, second), ELV (metres), ROD (metres), RVR (metres), distance to nearest GOS (metres), and the TGR — on the categorical livelihood strategy outcome (Business, Cultivated, Ecotourism, Labour, Service). Two separate models were estimated for robustness, using Cultivated (Table 8) and Labour (table 9) as alternative reference categories. All models were estimated via maximum likelihood; coefficients (β) represent changes in log-odds, with standard errors (SE), z-statistics, p-values, and 95% confidence intervals reported. Odds ratios (OR = e^β) are provided for significant terms.

Table 8: Multinomial logistic regression results for the influence of geospatial factors on the choice of livelihood strategy (Reference Category: Cultivated Households)

Multinominal Logistic Regression of Geospatial Variable (Cultivated Based)								
Level	term	estimate	std.error	z	p.value	lower_CI	upper_CI	significant
Business Type	(Intercept)	3.476	0	1184584.293	0	3.476	3.476	TRUE
	SLP	-0.02	0.004	-4.923	0	-0.028	-0.012	TRUE
	ELV	-0.007	0.005	-1.544	0.123	-0.017	0.002	FALSE
	ROD	0	0	0.78	0.435	0	0.001	FALSE
	River	0	0	-1.459	0.144	0	0	FALSE
	RVR	0	0	-1.347	0.178	-0.001	0	FALSE
	TGR	-0.714	0	-93053.101	0	-0.714	-0.714	TRUE
Ecotourism Type	(Intercept)	-4.7	0	-72842.558	0	-4.7	-4.7	TRUE
	SLP	0.12	0.047	2.571	0.01	0.029	0.212	TRUE
	ELV	-0.007	0.002	-3.035	0.002	-0.012	-0.003	TRUE
	ROD	0.001	0	4.738	0	0	0.001	TRUE
	River	0.001	0	8.024	0	0	0.001	TRUE
	RVR	-0.001	0	-5.29	0	-0.001	-0.001	TRUE
	TGR	-1.642	0	-87551.293	0	-1.642	-1.642	TRUE
Labour Type	(Intercept)	-1.082	0	-14170.312	0	-1.082	-1.082	TRUE
	SLP	-0.074	0.038	-1.979	0.048	-0.148	-0.001	TRUE
	ELV	-0.001	0.002	-0.69	0.49	-0.004	0.002	FALSE
	ROD	0	0	0.804	0.421	0	0	FALSE
	River	0	0	3.167	0.002	0	0	TRUE
	RVR	0	0	0.992	0.321	0	0	FALSE
	TGR	-0.029	0	-232.854	0	-0.029	-0.028	TRUE
Service Type	(Intercept)	-5.952	0	-1468494.321	0	-5.952	-5.952	TRUE
	SLP	-0.072	0.016	-4.438	0	-0.104	-0.04	TRUE
	ELV	-0.004	0.003	-1.376	0.169	-0.01	0.002	FALSE
	ROD	0.001	0	3.412	0.001	0	0.001	TRUE
	River	0	0	3.835	0	0	0	TRUE
	RVR	0	0	-0.773	0.44	-0.001	0	FALSE
	TGR	-0.158	0	-49152.964	0	-0.158	-0.158	TRUE

Geospatial factors exerted statistically significant and substantively important influences on livelihood strategy selection, with effects highly consistent across both reference models. In the Cultivated-reference model, a one-unit increase in SLP significantly reduced the log-odds of choosing Business ($\beta = -0.020$, SE =

0.004, z = –4.923, p < 0.001; OR = 0.980), Ecotourism (β = 0.120, p = 0.010; OR = 1.128), Labour (β = –0.074, p = 0.048; OR = 0.929), and Service (β = –0.072, p < 0.001; OR = 0.931). ELV negatively affected Ecotourism (β = –0.007, p = 0.002; OR = 0.993) and, to a lesser extent, other non-agricultural strategies. Proximity to ROD and RVR consistently increased the log-odds of Ecotourism (Road: β = 0.001, p < 0.001; River: β = 0.001, p < 0.001), Service (Road: β = 0.001, p = 0.001; River: p < 0.001), and several Labour comparisons. GOS distance showed small but significant negative effects, particularly for Ecotourism (β = –0.001, p < 0.001). Most strikingly, TGR emerged as the dominant deterrent across all non-agricultural strategies (Business: β = –0.714, p < 0.001; Ecotourism: β = –1.642, p < 0.001; Labour: β = –0.029, p < 0.001; Service: β = –0.158, p < 0.001), with odds reductions ranging from 51% to 81% per unit increase in TGR.

The Labour-reference model confirmed identical directional effects and significance levels. SLP positively influenced Business (β = 0.054, p < 0.001; OR = 1.056) and Ecotourism (β = 0.195, p < 0.001; OR = 1.215), while TGR again exerted strong negative effects (Business: β = –0.686, p < 0.001; Ecotourism: β = –1.614, p < 0.001; Service: β = –0.130, p < 0.001). ROD and RVR proximity remained positive and significant enablers for tourism- and service-oriented strategies.

Table 9: Multinomial logistic regression results for the influence of geospatial factors on the choice of livelihood strategy (Reference Category: Labour-Dependent Households)

Multinominal Logistic regression of Geospatial variables (Labour Family as Based								
Level	term	estimate	std.error	z	p.value	lower_CI	upper_CI	significant
Business Type	(Intercept)	4.56	0.00	2753257.46	0.00	4.56	4.56	TRUE
	SLP	0.05	0.00	14.30	0.00	0.05	0.06	TRUE
	ELV	-0.01	0.01	-1.32	0.19	-0.02	0.00	FALSE
	ROD	0.00	0.00	0.44	0.66	0.00	0.00	FALSE
	RVR	0.00	0.00	-2.61	0.01	0.00	0.00	TRUE
	GOS	0.00	0.00	-1.74	0.08	0.00	0.00	FALSE
	TGR	-0.69	0.00	-128762.67	0.00	-0.69	-0.69	TRUE
Cultivated Type	(Intercept)	1.09	0.00	20275.02	0.00	1.08	1.09	TRUE
	SLP	0.07	0.04	1.94	0.05	0.00	0.15	FALSE
	ELV	0.00	0.00	0.69	0.49	0.00	0.00	FALSE
	ROD	0.00	0.00	-0.80	0.42	0.00	0.00	FALSE
	RVR	0.00	0.00	-3.17	0.00	0.00	0.00	TRUE
	GOS	0.00	0.00	-0.99	0.32	0.00	0.00	FALSE
	TGR	0.03	0.00	210.23	0.00	0.03	0.03	TRUE
Ecotourism Type	(Intercept)	-3.62	0.00	-57058.85	0.00	-3.62	-3.62	TRUE
	SLP	0.20	0.05	4.14	0.00	0.10	0.29	TRUE
	ELV	-0.01	0.00	-2.66	0.01	-0.01	0.00	TRUE
	ROD	0.00	0.00	4.19	0.00	0.00	0.00	TRUE
	RVR	0.00	0.00	6.16	0.00	0.00	0.00	TRUE
	GOS	0.00	0.00	-6.04	0.00	0.00	0.00	TRUE
	TGR	-1.61	0.00	-162578.42	0.00	-1.61	-1.61	TRUE

Service Type	(Intercept)	-4.87	0.00	-888973.20	0.00	-4.87	-4.87	TRUE
	SLP	0.00	0.02	0.15	0.88	-0.03	0.03	FALSE
	ELV	0.00	0.00	-1.04	0.30	-0.01	0.00	FALSE
	ROD	0.00	0.00	2.96	0.00	0.00	0.00	TRUE
	RVR	0.00	0.00	2.29	0.02	0.00	0.00	TRUE
	GOS	0.00	0.00	-1.35	0.18	0.00	0.00	FALSE
	TGR	-0.13	0.00	-64492.84	0.00	-0.13	-0.13	TRUE

These regression results integrate directly with the point pattern analyses. The strongest spatial clustering of cultivated households—evident as continuous upward deviation above L_{pois} in Ripley's L-function across all scales—is consistent with the negative Slope and TGR effects on non-agricultural strategies, coupled with minimal proximity requirements, favouring flatter, low-TGR zones that enable tight aggregation around contiguous farmland. Conversely, the moderate clustering of ecotourism (smooth continuous deviation) and service households (gradual stepped $\widehat{L_{iso}}$ profiles) aligns with positive ROD/RVR proximity effects and negative elevation/TGR coefficients, concentrating these strategies along accessible tourism corridors. The near-random patterns of business (abrupt plateau after short-range rise) and labour households (staircase progression at larger scales) reflect weaker geospatial constraints, permitting greater dispersion and mobility.

Collectively, the multinomial logit coefficients—interpreted alongside Ripley's L-functions—demonstrate that livelihood choices are spatially structured by topographic accessibility (SLP, ELV, TGR), hydrological proximity (RVR), and transport infrastructure (ROD). Households in steeper, higher-elevation, high-TGR areas are directed toward agriculture or mobile wage labour, whereas those near roads/rivers with favourable TGR adopt clustered ecotourism/service strategies. These findings offer evidence for targeted interventions, including road upgrades, slope-terracing in agricultural clusters, and TGR optimisation at tourism nodes, to foster resilient diversification.

5. Discussion:

This study provides a robust analysis of rural livelihood strategies in the Ajodhya hill region, demonstrating that households adopt an asymmetrical array of five distinct strategies: Labour type, Cultivated type, Ecotourism type, Service type, and Business type. Our findings clarify how specific capital endowments and geospatial factors interact to shape these choices.

5.1 Livelihood Strategy Characteristics

The results indicate that Labour households constitute the largest group (45.19%), characterized by high income diversity and livestock holdings, which serve as a buffer against shocks despite minimal land and physical assets. Cultivated households (28.61%) remain anchored in traditional agriculture due to high natural capital endowments (mean land = 6.91), yet they face constraints in educational attainment and physical assets. In contrast, Ecotourism households (18.99%) demonstrate stronger asset bases, with higher durable goods and educational levels compared to agricultural baselines. Service households emerge as the most socio-economically advantaged, boasting the highest educational attainment and housing quality, while Business households exhibit concentrated income streams and specialized, capital-intensive operations.

5.2 Determinants of Livelihood Choices

The multinomial logistic regression confirms that capital endowments are the primary drivers of these strategies. Natural capital functions as the central anchor for "agricultural lock-in," as households with higher natural assets are significantly less likely to diversify into non-farm or tourism activities, a finding that corroborates existing theories on land-based dependence (Huang et al., 2021). Conversely, Financial capital is the key enabler for transitioning to higher-return strategies like Service and Ecotourism, providing the necessary liquidity to overcome entry barriers (Huang et al., 2021). Human capital (education and skills) significantly facilitates participation in skill-intensive pathways such as Business, Service, and Ecotourism (Daud et al., 2018), while Physical capital—including improved housing and durable goods—is a targeted driver specifically for Ecotourism participation.

5.3 Spatial Patterns and Geospatial Influences

Spatial analysis reveals that these strategies are not randomly distributed but exhibit significant clustering (Moran's I = 0.0688, p = 0.0021). Cultivated households show the strongest clustering (NNI = 0.213), reflecting their tight bond to contiguous fertile land. Ecotourism and Service households demonstrate moderate clustering around accessible tourism corridors, driven by proximity to roads and rivers and influenced by slope and elevation. The near-random distribution of Business and Labour households suggests greater spatial mobility and a lack of restrictive geospatial constraints. Notably, the Tourism-Geospatial Resilience index emerged as a dominant deterrent for non-agricultural strategies, significantly favouring agricultural retention in specific zones.

6. Conclusion:

This study provides a robust empirical analysis of rural livelihood strategies in the Ajodhya hill region, identifying a diverse yet asymmetrical distribution of five distinct household types: Labour (45.19%), Cultivated (28.61%), Ecotourism (18.99%), Service (4.81%), and Business (2.40%) [doc:4.1]. The findings demonstrate a profound socio-economic divide; while Service households achieve the highest annual total income (Rs. 360,735.00), the numerically dominant Labour households remain the most economically vulnerable with a total income of only Rs. 33,779.26.

The research concludes that livelihood choices are systematically dictated by an interplay of capital endowments and geospatial constraints. Natural capital acts as a powerful anchor, creating an "agricultural lock-in" effect where households with high land and livestock holdings are significantly less likely to transition into non-farm sectors. Conversely, Financial and Human capital (education) are the critical enablers for upward mobility into high-return Service and Ecotourism strategies.

Spatial analysis further reveals that these strategies are not random but significantly clustered (Moran's I = 0.0688, p = 0.0021), with Cultivated households showing the highest spatial aggregation (NNI = 0.213). The strong influence of geospatial factors—specifically the deterrent effect of Topographic Roughness and the enabling effect of road/river proximity—suggests that geography itself pre-determines much of the livelihood potential in the Ajodhya hill. Ultimately, while tourism offers a pathway for diversification, structural barriers related to capital deficits and rugged terrain must be addressed through spatially targeted policies to ensure equitable and sustainable rural development.

7. Policy Recommendations:

Policy interventions should prioritize facilitating the conversion of livelihood capitals by augmenting financial access and delivering targeted skills training to Labour and Cultivated households. This would enable transitions toward higher-return Ecotourism or Service-oriented activities while preserving natural capital for those remaining in agriculture. Strategic investments in infrastructure—such as improving accessibility to roads and rivers—can channel tourism benefits more equitably (Huang et al., 2021). Furthermore, promoting community-based ecotourism models that ensure local ownership, especially for indigenous populations, is vital to prevent marginalization and ensure the sustainability of the region's cultural and natural heritage (Ghosh et al., 2024; Patil & Pattanshetti, 2024; Scheyvens, 1999).

"Limitations of the Weighting Approach"

"While the entropy weighting method was selected to eliminate subjective biases inherent in expert-driven schemes, it is important to acknowledge its inherent limitations. Because EWM derives weights solely from the mathematical dispersion of the data, it is highly sensitive to sample-specific variation and data quality; an indicator with high variance receives a larger weight even if its theoretical importance to livelihood sustainability is secondary (Gao et al., 2023; Zhou et al., 2018). Consequently, the derived weights reflect the specific socio-economic profile of the Ajodhya hill sample and may not be universally generalizable to other mountainous or tribal contexts (Li et al., 2024). To mitigate this, future research should consider triangulating objective entropy weights with subjective methods such as the Analytic Hierarchy Process or the Delphi method(Jia et al., 2024; Liu et al., 2024). Such a hybrid approach would allow for a 'subjective-objective' synthesis, ensuring that the final indices reflect both the empirical reality of the data and the established theoretical priorities of the Sustainable Livelihoods Framework (Liu et al., 2024; Zhou et al., 2018)."

Acknowledgements:

I extend my sincere gratitude to all individuals and organizations who contributed to this research. My deepest appreciation goes to Prof. Sebak Kumar Jana, Department of Economics, Vidyasagar University, for his invaluable guidance and insightful feedback throughout this study. Special thanks are due to the local communities of the Ajodhya hill region, particularly the tribal households, for their gracious participation and for sharing the invaluable insights that form the empirical foundation of this research. Finally, I acknowledge the support of all colleagues and research assistants who assisted in data collection and analysis.

References:

- Aboye, A. B., Kinsella, J., & Leza, T. (2022). Effects of climate change on livelihood strategies of farm households: the case of the Lowlands of Wolaita Ethiopia. *Research Square (Research Square)*. https://doi.org/10.21203/rs.3.rs-2302237/v1

- Acharya, A., Mondal, B. K., Bhadra, T., Abdelrahman, K., Mishra, P. K., Tiwari, A., & Das, R. (2022). Geospatial Analysis of Geo-Ecotourism Site Suitability Using AHP and GIS for Sustainable and Resilient Tourism Planning in West Bengal, India. *Sustainability*, *14*(4), 2422. https://doi.org/10.3390/su14042422

- Carr, A., Ruhanen, L., & Whitford, M. (2016). Indigenous peoples and tourism: the challenges and opportunities for sustainable tourism. *Journal of Sustainable Tourism*, *24*, 1067. https://doi.org/10.1080/09669582.2016.1206112

- Chakrabarty, S. P., Ghosh, J. K., Bhattacharya, B., & Panda, S. (2019). Unraveling the Socio-Economic Condition of Tribal Peoples in West Bengal. *International Journal of Recent Technology and Engineering (IJRTE)*, *8*(4), 12317. https://doi.org/10.35940/ijrte.d8346.118419

- Das, D., & Hussain, I. (2016). Does ecotourism affect economic welfare? Evidence from Kaziranga National Park, India. *Journal of Ecotourism*, *15*(3), 241. https://doi.org/10.1080/14724049.2016.1192180

- Dash, M., Behera, B., & Rahut, D. B. (2016). Determinants of household collection of non-timber forest products (NTFPs) and alternative livelihood activities in Similipal Tiger Reserve, India. *Forest Policy and Economics*, *73*, 215. https://doi.org/10.1016/j.forpol.2016.09.012
- Daud, A. S., Awoyemi, T. T., Omotoso, A. B., & Omotayo, A. O. (2018). HUMAN CAPITAL AND INCOME DIVERSIFICATION AMONG CROP FARMERS IN RURAL OYO STATE, NIGERIA. *Journal of Agribusiness and Rural Development*, *49*(3), 251. https://doi.org/10.17306/j.jard.2018.00422
- Dey, A., Nandy, S., Mukherjee, A., & Modak, B. K. (2020). Sustainable utilization of medicinal plants and conservation strategies practiced by the aboriginals of Purulia district, India: a case study on therapeutics used against some tropical otorhinolaryngologic and ophthalmic disorders. *Environment Development and Sustainability*, *23*(4), 5576. https://doi.org/10.1007/s10668-020-00833-8
- Dinku, A. M. (2018). Determinants of livelihood diversification strategies in Borena pastoralist communities of Oromia regional state, Ethiopia. *Agriculture & Food Security*, *7*(1). https://doi.org/10.1186/s40066-018-0192-2
- Dolui, S., & Chakraborty, S. (2022). *Selection of Preferable Eco-Tourism Destinations using Analytical Hierarchy Process in Purulia District, West Bengal (India)*. https://doi.org/10.21203/rs.3.rs-2080258/v1
- Fang, J., Liu, M., Liu, W., Pathak, S., Li, S., Tang, X., Zhou, L., & Sun, F. (2020). Piloting a capital-based approach for characterizing and evaluating drivers of island sustainability- An application in Chongming Island. *Journal of Cleaner Production*, *261*, 121123. https://doi.org/10.1016/j.jclepro.2020.121123
- Ghosh, A., Kisku, A., & Chakrabarty, P. (2024). Proposing Tribal Heritage Protection through Ethnotourism: A Study on Disom Sendra Festival of Ajodhya hill in India. *Journal of Sustainability Research*, *6*(2). https://doi.org/10.20900/jsr20240008
- Ghosh, A., Mandal, R., & Chakrabarty, P. (2023). Inclusive Tourism Adopted to Geosites: A Study in the Ajodhya hill of West Bengal in India. *Tourism and Hospitality*, *4*(2), 321. https://doi.org/10.3390/tourhosp4020020
- Guerrero, J. V. R., Gomes, A. A., Lollo, J. A. de, & Moschini, L. E. (2020). Mapping Potential Zones for Ecotourism Ecosystem Services as a Tool to Promote Landscape Resilience and Development in a Brazilian Municipality. *Sustainability*, *12*(24), 10345. https://doi.org/10.3390/su122410345
- Guo, S., Fräser, M. W., & Chen, Q. (2020). Propensity Score Analysis: Recent Debate and Discussion. *Journal of the Society for Social Work and Research*, *11*(3), 463. https://doi.org/10.1086/711393
- Hahury, H. D., Saptenno, F., Batkunda, L., Louhenapessy, F. H., & Oppier, H. (2023). Tourism Development and Impacts of Local Livelihood Transition on The Highlands Of Mount Nona, Ambon Island. *International Journal of Professional Business Review*, *8*(1). https://doi.org/10.26668/businessreview/2023.v8i1.1255
- Hazari, T. M., Mandal, P., & Bhui, S. (2025). *Indigenous Knowledge of Santal Community on Agricultural Practices* (p. 1). https://doi.org/10.1007/978-981-97-4547-0_240-1

- Huang, L., Yang, L., Tuyến, N. T., Colmekcioglu, N., & Jun, L. (2021). Factors influencing the livelihood strategy choices of rural households in tourist destinations. *Journal of Sustainable Tourism*, *30*(4), 875. https://doi.org/10.1080/09669582.2021.1903015

- Jacqueline, G. K., Göran, B., Yonika, M. N., & Jumanne, M. (2024). Assessing livelihood strategy choices among spice farmers in the Eastern Arc Mountains of Tanzania. *Journal of Development and Agricultural Economics*, *16*(2), 54. https://doi.org/10.5897/jdae2024.1406

- Khan, A. A. (2018). The spatial distribution and relationship of tourist flow in Turkey. *European Journal of Tourism Research*, *19*, 40. https://doi.org/10.54055/ejtr.v19i.324

- Kundu, A., & Nag, S. K. (2018). Assessment of groundwater quality in Kashipur Block, Purulia district, West Bengal. *Applied Water Science*, *8*(1). https://doi.org/10.1007/s13201-018-0675-0

- Li, T., Cai, S., Singh, R. K., Cui, L., Fava, F., Li, T., Xu, Z., Li, C., Cui, X., Du, J., Hao, Y., Liu, Y., & Wang, Y. (2022). Livelihood resilience in pastoral communities: Methodological and field insights from Qinghai-Tibetan Plateau. *The Science of The Total Environment*, *838*, 155960. https://doi.org/10.1016/j.scitotenv.2022.155960

- Liao, Z., Zhang, L., & Wang, X. (2022). Spatial distribution characteristics and accessibility analysis of beautiful leisure villages in China. *PLoS ONE*, *17*(10). https://doi.org/10.1371/journal.pone.0276175

- Mandal, S., Sarangi, S. K., Mainuddin, M., Mahanta, K. K., Mandal, U. K., Burman, D., Digar, S., Sharma, P. C., & Maji, B. (2022). Cropping system intensification for smallholder farmers in coastal zone of West Bengal, India: A socio-economic evaluation. *Frontiers in Sustainable Food Systems*, *6*. https://doi.org/10.3389/fsufs.2022.1001367

- Mondal, M. R. (2020). Tourism as a livelihood development strategy: a study of Tarapith Temple Town, West Bengal. *Asia-Pacific Journal of Regional Science*, *4*(3), 795. https://doi.org/10.1007/s41685-020-00164-6

- Nasrnia, F., & Ashktorab, N. (2021). Sustainable livelihood framework-based assessment of drought resilience patterns of rural households of Bakhtegan basin, Iran. *Ecological Indicators*, *128*, 107817. https://doi.org/10.1016/j.ecolind.2021.107817

- Pasanchay, K., & Schott, C. (2020). Community-based tourism homestays' capacity to advance the Sustainable Development Goals: A holistic sustainable livelihood perspective. *Tourism Management Perspectives*, *37*, 100784. https://doi.org/10.1016/j.tmp.2020.100784

- Patil, S., & Pattanshetti, M. (2024). The Role of Ecotourism in Sustainable Development: A Comprehensive Systematic Review. *Research Square (Research Square)*. https://doi.org/10.21203/rs.3.rs-4843585/v1

- Paul, B., & Ganguly, R. (2021). *Interface Between Tribes and Ecotourism: A Study on Sustainability and Development in Purulia, West Bengal* (p. 179). https://doi.org/10.1007/978-981-33-6248-2_11

- Prudencio-Vázquez, J. A., Martínez-Rodríguez, A., Pérez-Victorino, L., & Álvarez-García, J. (2023). Spatial patterns on tourism establishments in five CIP´s in Mexico, 2010–2022. *Quality & Quantity*. https://doi.org/10.1007/s11135-023-01750-4

- Puebla, J. G., Palomares, J. C. G., Romanillos, G., & Salas-Olmedo, M. H. (2017). The eruption of Airbnb in tourist cities: Comparing spatial patterns of hotels and peer-to-peer accommodation in Barcelona. *Tourism Management*, *62*, 278. https://doi.org/10.1016/j.tourman.2017.05.003

- Rafique, A., Karaş, İ. R., Abujayyab, S. K. M., Khan, A. A., & Demiral, E. (2020). APPLICATION OF EXPLORATORY SPATIAL TECHNIQUES IN THE IDENTIFICATION OF TOURISM HOTSPOTS IN THE AEGEAN REGION OF TURKEY. *˜The œinternational Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences/International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 351. https://doi.org/10.5194/isprs-archives-xliv-4-w3-2020-351-2020

- Rahman, M., & Siddik, Md. A. (2019). Livelihood Analysis of the Char Dwellers Using Capital Asset Framework. *Journal of Environmental Science and Natural Resources*, *11*, 27. https://doi.org/10.3329/jesnr.v11i1-2.43362

- Roy, K., Sarma, R., Barua, S., & Chanu, E. (2024). Livelihood strategies of farm households of lower Brahmaputra valley zone of Assam: An empirical study. *International Journal of Agriculture Extension and Social Development*, *7*(9), 889. https://doi.org/10.33545/26180723.2024.v7.i9l.1163

- Sahoo, A. K., Behera, H. C., & Behura, A. K. (2020). Ethnomedicine and Traditional Health Care System of a Particular Vulnerable Tribal Group in India: Application of Plant Extracts. *Research Square (Research Square)*. https://doi.org/10.21203/rs.3.rs-25202/v1

- Samal, R., & Dash, M. (2022). Ecotourism, biodiversity conservation and livelihoods: Understanding the convergence and divergence. *International Journal of Geoheritage and Parks*, *11*(1), 1. https://doi.org/10.1016/j.ijgeop.2022.11.001

- Samal, R., & Dash, M. (2024). Stakeholder engagement in advancing sustainable ecotourism: an exploratory case study of Chilika Wetland. *Discover Sustainability*, *5*(1). https://doi.org/10.1007/s43621-024-00233-2

- Santarém, F., Campos, J. C., Pereira, P., Dieng, H., Saarinen, J., & Brito, J. C. (2018). Using multivariate statistics to assess ecotourism potential of water-bodies: A case-study in Mauritania. *Tourism Management*, *67*, 34. https://doi.org/10.1016/j.tourman.2018.01.001

- Scheyvens, R. (1999). Ecotourism and the empowerment of local communities. *Tourism Management*, *20*(2), 245. https://doi.org/10.1016/s0261-5177(98)00069-7

- Senganimalunje, T. C., Chirwa, P. W., & Babalola, F. D. (2020). Exploring the Role of Forests as Natural Assets in Rural Livelihoods and Coping Strategies Against Risks and Shocks in Dedza East, Malawi. *Journal of Sustainable Forestry*, *41*(6), 503. https://doi.org/10.1080/10549811.2020.1745654

- Song, Y., Wang, J., Ge, Y., & Xu, C. (2020). An optimal parameters-based geographical detector model enhances geographic characteristics of explanatory variables for spatial heterogeneity analysis: cases with different types of spatial data. *GIScience & Remote Sensing*, *57*(5), 593. https://doi.org/10.1080/15481603.2020.1760434

- Stankov, U., Armenski, T., Klaučo, M., Pavluković, V., Cimbaljević, M., & Drakulic-Kovacevic, N. (2017). Spatial autocorrelation analysis of tourist arrivals using municipal data: A Serbian example. *Geographica Pannonica*, *21*(2), 106. https://doi.org/10.5937/geopan1702106s

- Sun, Q., Fu, C., Bai, Y., Oduor, A. M. O., & Cheng, B. (2023). Livelihood Diversification and Residents' Welfare: Evidence from Maasai Mara National Reserve. *International Journal of Environmental Research and Public Health*, *20*(5), 3859. https://doi.org/10.3390/ijerph20053859

- Sun, Y., Gan, Y., Luo, J., Han, T., Wang, H., Yang, R., & Tian, L. (2025). Farm households' livelihood adaptive capacity under multiple pressures of small watershed management. *Ecological Indicators*, *178*, 114035. https://doi.org/10.1016/j.ecolind.2025.114035

- Walelign, S. Z., & Jiao, X. (2017). Dynamics of rural livelihoods and environmental reliance: Empirical evidence from Nepal. *Forest Policy and Economics*, *83*, 199. https://doi.org/10.1016/j.forpol.2017.04.008

- Zhang, Q., Haili, X., Lan, X., Dai, L., Wang, B., Cui, F., & Haiping, T. (2022). Livelihood vulnerability of pastoral households in the semiarid grasslands of northern China: Measurement and determinants. *Ecological Indicators*, *140*, 109020. https://doi.org/10.1016/j.ecolind.2022.109020

- Zhang, Z., Song, Y., & Wu, P. (2022). Robust geographical detector. *International Journal of Applied Earth Observation and Geoinformation*, *109*, 102782. https://doi.org/10.1016/j.jag.2022.102782