

Spatial Patterns of Social Inequality in India: A Geographical Analysis

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Abstract

Social inequality in India is expressed not only through differences in income and wealth but also through uneven access to education, employment, nutrition, housing, infrastructure and other capabilities. These inequalities have a pronounced geographical dimension, with substantial variation across states, districts, rural and urban areas, and social groups. This paper examines the spatial patterns and multidimensional character of social inequality in India using a descriptive, analytical and comparative secondary-data research design. Evidence is drawn primarily from the National Multidimensional Poverty Index 2023, based on NFHS-5 (2019–21), the Household Consumption Expenditure Survey (HCES) 2023–24, the Periodic Labour Force Survey (PLFS) 2025, AISHE 2022–23 provisional results reported by the Ministry of Education, and the National Family Health Survey (NFHS-5), supplemented by peer-reviewed geographical and development research. The analysis demonstrates substantial progress in reducing multidimensional poverty and consumption inequality at the national level, but also reveals persistent territorial concentrations of disadvantage. Bihar, Jharkhand, parts of central and eastern India, and several rural regions continue to experience comparatively high multidimensional deprivation, while social identity, gender and class interact with location in differentiated ways. Consumption, educational participation and female labour-force participation show distinctive and sometimes contradictory spatial patterns, indicating that no single indicator adequately represents social inequality. The paper concludes that Indian social inequality is multi-scalar, intersectional and spatially embedded. Policy therefore requires geographically targeted universalism, stronger sub-state monitoring and interventions addressing both territorial disadvantage and unequal capabilities within regions.

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Introduction

India's economic transformation during recent decades has been accompanied by substantial improvements in living standards, educational participation, infrastructure and poverty reduction. Yet the benefits of development remain unevenly distributed across space and social groups. States and districts differ markedly in their economic opportunities, human-development outcomes, public-service provision and social structure. Within states, differences between metropolitan centres, secondary towns, prosperous agricultural zones, remote rural regions and historically marginalised areas create additional layers of inequality. Social inequality in India must therefore be understood not merely as a hierarchy between individuals or households but as a geographical phenomenon shaped by the places in which people live and by their position within social structures.

A geographical approach is particularly important because location influences access to schools, healthcare, infrastructure, labour markets, public institutions and networks. At the same time, caste, Scheduled Tribe status, gender, household wealth and rural or urban residence interact with territorial conditions. Sen's capability perspective shifts attention from monetary resources alone to the substantive freedoms people possess to achieve valued ways of living (Sen, 1999). The multidimensional poverty framework similarly recognises that simultaneous deprivation in health, education and living standards cannot be adequately captured by income measures alone (Alkire & Foster, 2011). Geography adds another dimension: identical individual characteristics may produce different outcomes depending upon the institutional, infrastructural and economic context of a region.

Recent official evidence illustrates both progress and persistence. According to NITI Aayog's National Multidimensional Poverty Index, the proportion of India's population classified as multidimensionally poor declined from 24.85% in 2015–16 to 14.96% in 2019–21. Rural multidimensional poverty declined from 32.59% to 19.28%, whereas urban poverty declined from 8.65% to 5.27%. These are substantial improvements, but the 2019–21 rural incidence remained more than three times the urban incidence. The report also demonstrates large state and district variations.

Similarly, HCES 2023–24 indicates declining inequality in household consumption expenditure. The all-India Gini coefficient fell to 0.237 in rural areas and 0.284 in urban areas, compared with 0.283 and 0.363 respectively in 2011–12. Yet average monthly per-capita consumption expenditure (MPCE) in 2023–24 remained ₹4,247 in rural India and ₹7,078 in urban India when imputed benefits received through selected welfare programmes are included. The persistence of a 67% urban–rural difference under this measure demonstrates that declining interpersonal consumption inequality does not automatically imply territorial equality.

The central research problem addressed in this paper is therefore the coexistence of aggregate social progress with persistent and differently configured geographical inequalities. Much Indian inequality research has examined poverty, caste, education, gender or regional development independently. Other studies have convincingly demonstrated spatial clustering of poverty, but frequently using earlier survey rounds. A contemporary geographical synthesis is needed that considers economic resources, multidimensional deprivation, education, labour participation and health together while respecting the differing definitions and reference periods of the datasets.

The study consequently pursues four objectives: first, to identify the principal state, sub-state and rural–urban patterns of social inequality in India; second, to examine how geographical location intersects with caste, tribal status, gender and economic position; third, to compare the spatial messages produced by multidimensional poverty, consumption, education, labour-market and health indicators; and fourth, to assess the implications of these patterns for geographically differentiated social policy.

Correspondingly, the study asks: **(1)** What broad geographical patterns characterise contemporary social inequality in India? **(2)** How do place and social identity interact in producing unequal capabilities and outcomes? **(3)** To what extent do recent improvements in poverty, consumption and educational indicators represent spatial convergence? **(4)** What form of policy response follows from understanding social inequality as a multi-scalar geographical process?

The central argument is that social inequality in India cannot be reduced to a simple prosperous-south/poor-north division, a rural–urban dichotomy or a single hierarchy of states. Such contrasts remain relevant, but contemporary evidence reveals multiple and overlapping geographies. Areas performing favourably in one dimension may remain unequal in another; comparatively poor regions can record high female labour participation, while economically advanced regions may show low female participation. A geographical analysis must therefore identify both persistent concentrations of disadvantage and these cross-dimensional contradictions.

Literature Review

The conceptual foundation for analysing social inequality has progressively moved beyond income-based explanations. Sen (1999) conceptualises development in terms of capabilities and substantive freedom, directing attention towards what people are effectively able to be and do. Alkire and Foster (2011) operationalise multidimensional deprivation through a counting approach that identifies simultaneous disadvantages across selected indicators. The importance of multidimensionality is especially evident in India, where improvements in household income can coexist with inadequate nutrition, schooling, sanitation or healthcare. Alkire and Seth (2015), examining earlier Indian data, found significant multidimensional poverty reduction but emphasised that progress was uneven across regions and social groups.

Geographical scholarship complements the capability perspective by treating space as socially produced rather than merely a neutral container. Massey (1994) emphasises that spatial relations reflect differentiated power and social relations, while Tilly's (1998) concept of durable inequality explains how categorical distinctions can become institutionally reproduced. In the Indian context, these perspectives imply that caste, gender, economic class and tribal status operate through specific regional labour markets, settlement structures, public institutions and patterns of infrastructure. Consequently, the disadvantages associated with social categories may be amplified or moderated by place.

Empirical work on Indian poverty demonstrates this contextual role of geography. Palmer-Jones and Sen (2006) used spatial econometric methods to show that the geography of rural poverty cannot be understood independently of spatially differentiated agricultural development, including irrigation and agro-ecological conditions. Their work is important because it challenged analyses treating state borders as sufficient explanations of poverty.

Kim, Mohanty and Subramanian (2016) subsequently developed a multilevel analysis encompassing states, regions, districts and villages. Using National Sample Survey data from 2009–10 and 2011–12, they reported that approximately 13% of variation in poverty was attributable to states and 12% to villages after accounting for household characteristics, while districts and regions accounted for smaller but non-negligible shares. Their principal contribution is methodological as well as substantive: poverty geography exists simultaneously at multiple scales, and analysis at only one administrative level can conceal important contextual variation.

Social identities complicate this geography further. Kijima (2006) found persistent welfare disparities between Scheduled Caste/Scheduled Tribe and non-SC/ST households and concluded that a substantial part of structural disparity affecting Scheduled Tribes was related to the different geographical areas in which they lived. Zacharias and Vakulabharanam (2011) similarly documented substantial caste stratification in household wealth. Their findings show why caste inequality and geographical inequality should not be viewed as competing explanations. Rather, historically disadvantaged social groups can be disproportionately concentrated in areas where economic opportunities, asset bases and public-service accessibility are themselves weaker.

Research on social development has also identified enduring regional divisions. Kumar and Rani (2019), using a composite social-development index based on Census 2011 indicators, found extensive state- and district-level disparities and a broad northern–southern divide. Such macro-regional categories are analytically useful but risk concealing internal heterogeneity. Kerala, Haryana and Bihar, for example, displayed significant district differentiation even within very different state-level development contexts.

More recent district-level research strengthens this argument. Vasishtha and Mohanty (2021) applied the Alkire–Foster method and spatial statistical techniques to NFHS-4 data and

demonstrated significant clustering of multidimensional and consumption poverty across Indian districts. Jain et al. (2023), using NFHS-5 (2019–21), found that states and small-area clusters were major sources of variation across several poverty measures and that significant inequality persisted within districts. These results caution against assuming that district averages themselves capture the lowest meaningful spatial scale of inequality.

The emerging literature has become even more explicitly spatial. Midya and Roy (2026), analysing NFHS-5 district data with spatial econometric methods, identify significant concentrations of multidimensional poverty in parts of Uttar Pradesh, Bihar, Jharkhand, Chhattisgarh, Odisha and Assam. Their analysis associates the observed geography with rurality, socio-ethnic composition, primary-sector employment, education and infrastructural factors. This contemporary evidence demonstrates that poverty has declined without losing its pronounced spatial organisation.

Educational research produces a parallel conclusion. Asadullah and Yalonetzky (2012) showed that inequality of educational opportunity differed considerably between states and changed unevenly over time. More recently, Menon and Madheswaran (2026), using several NFHS rounds, conclude that parental education, household wealth and regional location are major determinants of children's unequal opportunities. Their analysis indicates stronger access outcomes in many southern and western regions than in central and eastern India and identifies particularly severe cumulative disadvantage among poorer rural SC and ST children.

Three limitations in the existing literature motivate the present study. First, many spatial studies use earlier Census, NSS or NFHS data and therefore cannot alone characterise recent patterns. Second, individual studies frequently concentrate on one domain—poverty, educational opportunity, consumption or health—although social inequality is multidimensional. Third, state-level comparisons may reproduce a misleading assumption that states constitute internally homogeneous social spaces. The present analysis addresses these limitations through a cross-domain synthesis of the most recent comparable official datasets while explicitly recognising their differing survey periods and avoiding construction of an artificial composite index from non-synchronous data.

Research Methodology

This paper adopts a **descriptive, analytical and comparative secondary-data-based research design**. No primary survey, questionnaire, interview or field observation has been undertaken, and consequently no primary sample or respondent population is claimed. The study area is India as a whole, with the principal comparative units being states and Union Territories, rural and urban sectors, and, where reliable published evidence permits, districts and smaller geographical clusters.

The empirical analysis draws on five principal sources. First, NITI Aayog's *National Multidimensional Poverty Index: A Progress Review 2023* provides national, state and district measures derived from NFHS-5 (2019–21), together with comparable change from NFHS-4 (2015–16). The report contains information for all states and Union Territories and more than 700 districts. Second, MoSPI's HCES 2023–24 provides MPCE and consumption-distribution indicators, with statistics explicitly distinguished according to whether the imputed value of selected items received free through welfare programmes is included.

Third, PLFS 2025 is used to analyse labour-force participation according to usual status for persons aged 15 years and above. The PLFS sampling design was substantially revised from January 2025 to improve frequency and geographical representation; therefore, this study uses the 2025 results primarily as a contemporary cross-sectional spatial comparison and does not mechanically construct long-term trends across the redesign. Fourth, AISHE 2022–23 provisional indicators reported in the Ministry of Education's Annual Report 2024–25 are used for higher-education participation. Fifth, NFHS-5 (2019–21) indicators are used for health and nutritional inequality.

The selected indicators are multidimensional-poverty headcount ratio; rural and urban MPCE; Gini coefficients of consumption expenditure; male and female labour-force participation rates; higher-education GER by gender and social category; and child stunting. These variables capture distinct components of capabilities and social advantage rather than being treated as interchangeable measures.

Analysis is conducted through state contrasts, rural–urban comparison, comparison of social categories and triangulation with peer-reviewed spatial research. The theoretical interpretation combines the capability approach with the concepts of durable and spatial inequality. No new spatial-autocorrelation coefficient, regression estimate or GIS model is presented because unit-level geocoded datasets have not been independently processed for this paper.

An important methodological limitation is temporal non-equivalence. NFHS-5 refers to 2019–21, HCES to 2023–24, AISHE indicators discussed here to 2022–23 and PLFS to January–December 2025. They are therefore used to identify recent domain-specific geographies, not merged into a single numerical ranking. Additional limitations include the inability of state averages to reveal all intra-state variation, the risk of ecological inference when group patterns are interpreted geographically, and the fact that descriptive associations cannot establish causation.

Analysis and Discussion

Spatial Concentration of Multidimensional Poverty

The most direct contemporary evidence of the geographical concentration of deprivation comes from the National MPI. India's multidimensional-poverty headcount declined by 9.89 percentage points between 2015–16 and 2019–21, from 24.85% to 14.96%. The intensity of deprivation among those classified as poor also fell, from 47.14% to 44.39%. The direction of change is unambiguously positive, but the national average conceals a striking state geography.

Table 1. Selected state-level multidimensional-poverty headcount ratios

State	2015–16 (%)	2019–21 (%)
Bihar	51.89	33.76
Jharkhand	42.10	28.81
Meghalaya	32.54	27.79
Uttar Pradesh	37.68	22.93
Madhya Pradesh	36.57	20.63
Assam	32.65	19.35
Chhattisgarh	29.90	16.37
Odisha	29.34	15.68
Rajasthan	28.86	15.31
Tamil Nadu	4.76	2.20
Goa	3.76	0.84
Kerala	0.70	0.55

Source: NITI Aayog, National MPI 2023; NFHS-4 and NFHS-5 periods.

Bihar remained the state with the highest headcount ratio in 2019–21 at 33.76%, followed by Jharkhand at 28.81% and Meghalaya at 27.79%. Uttar Pradesh and Madhya Pradesh also remained above 20%. At the opposite end, Kerala recorded 0.55%, Goa 0.84% and Tamil Nadu 2.20%. These figures demonstrate a broad concentration of deprivation in parts of the eastern, central and north-central regions, although Meghalaya and other north-eastern cases make clear that the pattern does not correspond neatly to conventional zonal boundaries.

The dynamic picture is more complex than a static ranking. Bihar's headcount fell by over 18 percentage points, Madhya Pradesh by almost 16 points and Uttar Pradesh by nearly 15 points. Thus, several states that continued to record relatively high poverty also achieved some of the largest absolute reductions. Spatial inequality should consequently be understood as a

combination of **persistent positional disadvantage and uneven convergence**, rather than as geographical immobility.

District evidence strengthens this interpretation. NITI Aayog's report maps more than 700 districts, while only 575 districts were strictly comparable between NFHS-4 and NFHS-5 because of boundary and survey comparability issues. Of those, statistically significant changes were identified for 436 districts. Independent spatial research likewise finds clusters of high multidimensional deprivation across parts of Bihar, Uttar Pradesh, Jharkhand, Chhattisgarh, Odisha and Assam (Midya & Roy, 2026). These results imply that policies based only on state averages may allocate insufficient attention to deprived districts located in otherwise better-performing states and to relatively advantaged districts within poorer states.

Consumption Inequality and the Rural–Urban Gradient

Consumption data reveal a second geography. HCES 2023–24 estimated all-India average MPCE, including imputed selected welfare benefits, at ₹4,247 in rural areas and ₹7,078 in urban areas. The corresponding urban–rural difference was 67%. Without imputation, MPCE was ₹4,122 and ₹6,996 respectively, producing a 70% difference. It is essential to specify the definition because mixing the two versions would create misleading comparisons.

Table 2. MPCE with imputation in selected major states, HCES 2023–24

State	Rural MPCE (₹)	Urban MPCE (₹)	Urban–rural difference (%)
Chhattisgarh	2,927	5,114	75
Jharkhand	3,056	5,455	79
Madhya Pradesh	3,522	5,589	59
Uttar Pradesh	3,578	5,474	53
Bihar	3,788	5,165	36
West Bengal	3,815	5,903	55
Maharashtra	4,249	7,415	75
Punjab	5,874	7,383	26
Tamil Nadu	5,872	8,325	42
Kerala	6,673	7,834	17
India	4,247	7,078	67

Source: MoSPI, HCES 2023–24, NSS Report No. 592.

The inter-state range is large. Among the major states shown above, rural MPCE in Kerala was more than twice that of Chhattisgarh. Equally significant is variation in the rural–urban gap: the difference was only 17% in Kerala but 79% in Jharkhand and 75% in both Chhattisgarh and

Maharashtra. Maharashtra's case demonstrates that high urban consumption does not automatically translate into small territorial inequality inside a relatively prosperous state.

National consumption Gini coefficients nevertheless moved downward. Rural consumption Gini declined from 0.283 in 2011–12 to 0.266 in 2022–23 and 0.237 in 2023–24, whereas the urban coefficient declined from 0.363 to 0.314 and then 0.284. These trends should not be dismissed, but nor should they be interpreted as evidence that geographical inequality has disappeared. Gini coefficients describe distribution among households or persons within the measured population; spatial inequality concerns differences between places as well. A country may simultaneously experience declining national consumption dispersion and substantial differences in average living standards between rural and urban areas or between states.

This distinction is crucial for geographical analysis. Consumption convergence at the lower end of the distribution can coexist with unequal labour-market structures, infrastructure, public services and asset opportunities across territories. It is therefore necessary to distinguish **interpersonal inequality**, **inter-regional inequality** and **intra-regional inequality** rather than treating them as a single phenomenon.

Caste, Tribal Status and the Geography of Social Disadvantage

The spatial structure of inequality is inseparable from India's social stratification. Scheduled Castes and Scheduled Tribes have historically experienced unequal access to land, education, assets, occupations and social institutions, but the mechanisms differ geographically. Kijima (2006) found that differences in returns to productive characteristics accounted for a substantial share of SC/ST welfare disparities and that the geographical concentration of Scheduled Tribe populations was especially important in explaining structural differences between ST and non-SC/ST households.

This finding helps explain why "social-group inequality" cannot be spatially neutral. Tribal populations are disproportionately represented in many forested, hilly and relatively remote regions where transport connectivity, service accessibility and diversified employment historically developed more slowly. Such geographical concentration does not mean that remoteness alone causes tribal deprivation; rather, historical exclusion, resource relations, land institutions and uneven state capacity operate through particular places.

Wealth research reaches a related conclusion from another direction. Zacharias and Vakulabharanam (2011) found substantial differences in household wealth between caste categories, with SC and ST groups occupying markedly disadvantaged positions relative to forward-caste households in the survey periods examined. Because wealth includes accumulated assets, such differences can reproduce inequalities across generations even where current consumption gaps narrow.

The analytical implication is that spatial targeting should not replace social targeting. A programme aimed exclusively at “poor districts” can overlook marginalised groups in better-performing districts, whereas social-category programmes that ignore territorial context may underestimate the additional costs associated with remote settlements, weak infrastructure or narrow labour markets. The appropriate perspective is intersectional: social position changes the experience of place, while place changes the consequences of social position.

Educational Participation: Progress with Unequal Capabilities

Higher education provides an instructive example of substantial gender progress alongside continuing social and geographical differentiation. AISHE 2022–23 provisional results reported an overall higher-education GER of 29.5 for the 18–23 age group. Female GER reached 30.2 compared with 28.9 for males, and the Gender Parity Index was 1.04. Among Scheduled Castes, female GER was 28.0 and male GER 26.6; among Scheduled Tribes, the corresponding figures were 23.9 and 23.1.

These data complicate any simple narrative of gender exclusion. Nationally, women now participate in higher education at a slightly higher GER than men under the AISHE measure. Yet parity between men and women within a social group does not remove inequality between social groups. The 2022–23 ST female GER of 23.9 remained 6.3 points below the overall female GER of 30.2. Gender parity can therefore improve while structural inequalities associated with social background persist.

Spatial variation is also visible in enrolment composition. The Ministry of Education reports that women constituted 58.1% of higher-education enrolment in Kerala in 2022–23, with female shares also above half in Meghalaya, Nagaland and Chhattisgarh. At the same time, aggregate participation depends on the geographical distribution of institutions, household resources, mobility possibilities and earlier schooling outcomes.

The importance of circumstances is confirmed by inequality-of-opportunity research. Asadullah and Yalonzky (2012) found substantial state variation in educational opportunity, while Menon and Madheswaran (2026) identify parental education, wealth and region as major determinants of children’s access to education and basic services. Education therefore functions both as an outcome of spatial inequality and as a mechanism through which inequality can be transmitted or reduced across generations.

Gendered Geography of Labour-Force Participation

Labour participation reveals perhaps the clearest warning against constructing a single development ranking. According to PLFS 2025, the usual-status LFPR for persons aged 15 years and above was 79.1% for men and 40.0% for women nationally. Rural female LFPR was 45.9%, while urban female LFPR was only 27.7%. The corresponding male rates were 80.5% and 76.2%.

State differences among women were exceptionally wide.

Table 3. Female LFPR for persons aged 15+ in selected states, PLFS 2025

State	Female LFPR (%)
Sikkim	66.7
Himachal Pradesh	64.7
Nagaland	64.5
Meghalaya	64.3
Chhattisgarh	59.8
Rajasthan	52.3
Tamil Nadu	47.3
Madhya Pradesh	46.1
Andhra Pradesh	44.8
Jharkhand	43.7
Kerala	41.2
Maharashtra	39.9
West Bengal	37.5
Uttar Pradesh	32.4
Punjab	30.2
Bihar	24.7
Haryana	23.8
Delhi	13.1
India	40.0

Note: Usual status (principal + subsidiary status), rural and urban combined. Source: PLFS Annual Report 2025.

The geography is striking. Some relatively poorer or less urbanised states record considerably higher female participation than richer and more urbanised areas. Chhattisgarh's female LFPR of 59.8%, for instance, substantially exceeded those of Haryana (23.8%) and Delhi (13.1%). Kerala combined very low multidimensional poverty with a female LFPR of 41.2%, only slightly above the national average, whereas Sikkim combined comparatively low poverty with very high participation.

These contrasts demonstrate why LFPR should not automatically be interpreted as an empowerment index. High participation can reflect favourable opportunities, but it can also arise

from necessity-driven work, family agriculture, self-employment or limited household income. Conversely, low participation may reflect inadequate suitable employment, social norms, household-income effects, care responsibilities, education participation, safety constraints or labour-market structure. Establishing the relative contribution of these mechanisms would require causal analysis beyond the scope of this paper.

The rural–urban difference is itself significant. The substantially higher rural female LFPR suggests that urbanisation does not automatically convert into greater measured economic participation for women. This complicates theories that assume a linear transition from agricultural development to urban female employment. Labour-market inequality has a distinct geography shaped simultaneously by economic structure, gender norms, occupational availability and household strategies.

Methodological caution is necessary. MoSPI revised the PLFS sample design from January 2025, substantially expanding the sample and altering stratification and selection procedures to improve representativeness and frequency. The 2025 state pattern is consequently valuable as contemporary evidence, but direct trend comparisons with the pre-2025 design require caution.

Health and Nutrition as Spatially Unequal Capabilities

Health and nutrition demonstrate how material, infrastructural and social inequalities become embodied. NFHS-5 (2019–21) reported that 35.5% of Indian children under five were stunted, compared with 38.4% in NFHS-4. The national improvement coexisted with a substantial rural–urban divide: stunting affected 37.3% of rural children compared with 30.1% of urban children.

State variation was greater still. Ministry of Health and Family Welfare statistics based on NFHS-5 show stunting at 46.5% in Meghalaya, 42.9% in Bihar and 39.7% in Uttar Pradesh, compared with 23.4% in Kerala, 25.0% in Tamil Nadu and 20.0% in Puducherry. This distribution overlaps partly with the geography of multidimensional poverty but not perfectly. Meghalaya, for example, combines a high stunting rate and high multidimensional poverty with very high female labour participation. Such contrasts reinforce the argument that social inequality is multidimensional rather than reducible to a single continuum.

NFHS-based research also consistently finds a strong socioeconomic gradient in child nutrition, including substantially higher stunting among children in poorer households and disadvantaged social groups. These associations should not be interpreted as the consequences of household income alone. Nutrition reflects maternal health and education, sanitation, food quality, healthcare access, disease environment and public-service delivery, all of which have geographical dimensions.

The spatial significance of health inequality is therefore twofold. First, regions experiencing overlapping deficits in poverty, nutrition and public infrastructure may face cumulative

disadvantage. Second, even better-performing states may contain pockets of deprivation concealed by averages. Health policy requires local monitoring because the relevant geographical unit for service access may be a village, tribal settlement, urban informal settlement or neighbourhood rather than the state.

Beyond the North–South Divide: A Multi-scalar Geography of Inequality

Taken together, the indicators do not produce a single map of “advanced” and “backward” India. They instead reveal several overlapping spatial configurations. An eastern and central concentration of multidimensional deprivation remains visible in Bihar, Jharkhand, Uttar Pradesh, Madhya Pradesh and adjoining areas, while Kerala and Tamil Nadu perform particularly well on multidimensional poverty. Recent district research confirms significant clusters crossing administrative boundaries.

Yet consumption, education and employment modify this picture. Kerala’s relatively high consumption and exceptionally low MPI coexist with only moderately above-national female labour participation. Haryana combines relatively high household consumption with comparatively low female LFPR. Chhattisgarh has low rural MPCE and substantial multidimensional deprivation but high female labour participation. Meghalaya combines comparatively high multidimensional poverty and child stunting with high female economic participation. These are not contradictions in the data; they are evidence that different dimensions of inequality respond to different social and economic processes.

The traditional north–south formulation identified in earlier social-development research (Kumar & Rani, 2019) therefore retains explanatory value only as a broad tendency. Contemporary social geography is better interpreted through multiple scales: macro-regional historical development, state institutional capacity, district economic structure, rural–urban settlement, local infrastructure and household social position. Jain et al. (2023) reinforce this conclusion by demonstrating important variation even below districts.

This multi-scalar perspective has important policy implications. First, national universal programmes remain necessary because rights to health, education, nutrition and social protection should not depend upon location. Universal provision, however, should be combined with **geographically targeted universalism**: additional resources and implementation intensity should be directed towards districts, blocks and settlements displaying overlapping deprivation.

Second, territorial targeting must include social disaggregation. Improving the average of a district cannot be considered sufficient when particular caste, tribal, gender or wealth groups remain systematically behind. Dashboards and administrative monitoring systems should therefore cross-tabulate outcomes by location and relevant social characteristics wherever sample size and privacy safeguards permit.

Third, policy should distinguish between deficits in infrastructure and deficits in effective access. The existence of a school, health facility or transport connection does not guarantee equal capability to use it. Quality, affordability, mobility, discrimination, safety and time constraints mediate access. This distinction is particularly important for women, tribal communities, low-income households and geographically isolated settlements.

Finally, statistical systems need to facilitate consistent small-area analysis. State averages increasingly appear inadequate for understanding India's social geography. More interoperable sub-state data, careful geographical harmonisation across survey rounds and transparent documentation of boundary changes would permit stronger longitudinal GIS and spatial-econometric research. Such improvements would also reduce the risk of policies treating administrative boundaries as if they corresponded automatically to homogeneous social regions.

Conclusion

This study examined the spatial patterns of social inequality in India through multidimensional poverty, consumption, education, labour-market participation and health indicators. The evidence provides a clear answer to the first research question: India's social inequality continues to display strong geographical organisation, but the pattern is more complex than a binary division between developed and underdeveloped regions. Multidimensional deprivation remains concentrated particularly in parts of eastern, central and north-central India and in selected north-eastern areas, while comparatively favourable outcomes occur in several southern and other states. Significant intra-state and district-level differences mean that state boundaries alone cannot adequately represent this geography.

Regarding the second research question, geographical location interacts with social identity rather than operating independently from it. Historical caste and tribal disadvantages, wealth differences and gender relations are mediated by settlement patterns, regional labour markets, infrastructure and service accessibility. Scheduled Tribe disadvantage, for example, cannot be interpreted without recognising the geographical concentration of many tribal communities in particular ecological and infrastructural contexts. Similarly, inequalities in child opportunity reflect combinations of parental education, wealth, social category and regional location.

The third research question concerns whether recent progress represents spatial convergence. The answer is qualified. India has achieved substantial reductions in multidimensional poverty, and HCES data show lower rural and urban consumption Gini coefficients. Higher-education gender parity has also improved considerably. Nevertheless, large inter-state and rural–urban differences persist. Moreover, dimensions do not move uniformly: female labour participation displays a geography very different from the MPI or consumption map. National convergence on one indicator therefore cannot be taken as evidence of comprehensive territorial convergence.

The fourth research question concerns policy. The results support a combination of universal social provision and finer geographical targeting. States and districts experiencing overlapping poverty, nutritional, educational and consumption disadvantages require enhanced resources, but policies must simultaneously identify marginalised populations within better-performing regions. The appropriate objective is not simply to equalise state averages but to reduce unequal capabilities across places and social groups.

Academically, the principal contribution of the paper is to conceptualise Indian social inequality as **multi-dimensional, intersectional and multi-scalar**. National progress, regional disparities and local exclusion can coexist. Declining consumption inequality does not imply the disappearance of spatial disadvantage, high female labour participation cannot by itself establish empowerment, and gender parity in enrolment does not remove inequalities between social categories.

The analysis is limited by the differing reference periods and methodologies of the official datasets and by its reliance on published aggregate evidence rather than original geocoded microdata. It therefore identifies robust spatial patterns and associations rather than causal effects. Future research should integrate harmonised district- and sub-district-level datasets with GIS, spatial regression and longitudinal methods, while paying greater attention to urban intra-city inequalities and intersectional differences within districts. Such work would strengthen both geographical theory and the capacity of public policy to address the places and populations where disadvantage remains most durable.

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