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Who Lives in Deprived Housing: Descriptive Evidence from India's Housing Deprivation Index*

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Abstract

Despite a significant decline in extreme poverty rates, the rising inequalities and rapid urbanization in mega cities of India have exacerbated the problems of inadequate housing, overcrowding, and the proliferation of informal settlements. Given the multidimensional nature of housing deprivation, the study employed 18 key indicators of housing deprivation from the 76th National Sample Survey on Drinking Water, Housing, and Sanitation to develop the "Housing Deprivation Index" at the household level for the year 2018. Multiple Correspondence Analysis (MCA) was employed to endogenously weight the 18 housing quality indicators, with the first dimension explaining 73% as a latent construct of the housing deprivation level. State level estimates of housing deprivation reveal stark interstate disparities. Housing deprivation in India is shaped by social, spatial and economic inequality with disadvantaged caste, rural households and poorer households experiencing significantly high deprivation. These findings underscore the need for housing policy to occupy a central position in India amid rapid urbanization and persistent spatial and socio-economic inequalities in adequate housing.

Keywords: Housing deprivation ; Multiple Correspondence Analysis ; Housing Adequacy ; Urbanisation.

JEL Classification: R21,R31, I32, C38

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1 Introduction

India being the most populous country, plays a pivotal role in the global achievement of sustainable development goals by 2030. The alarming trends of urbanization and population growth in urban areas underscore the critical importance of SDG 11, which aims to make cities and human settlements inclusive, safe, resilient, and sustainable by focusing on key dimensions such as the provisioning of affordable, adequate, and safe housing for all, along with inclusive and sustainable urban planning (Kushwaha et al., 2023). Thus, housing policy is a very important policy area, especially for emerging economies, since the demand for houses outpaces the construction of new homes. International human rights law assigns a central place to the right to an adequate standard of living for every individual, which includes adequate housing as well (UN-Habitat, 2018). Healthy or adequate house is defined as a shelter that supports a state of complete physical, mental, and social well-being (World Health Organization, 2018). Housing is an important social determinant of health, as environmental and social inequality translates to health inequality through poor housing conditions. Thus, access to an adequate house is fundamental for economic well-being, human dignity, physical and mental health, and quality of life (Behr et al., 2021).

Inadequate houses are characterized as housing units that exhibit overcrowding, poor construction for protection against heat or cold, inadequate access to water and sanitation, and insecure property titles. With the demand for housing being higher in urban areas, access to good quality housing is not just a challenge for informal settlements (slums) but also for individuals in formal settlements, irrespective of their income level. In many countries, certain groups such as indigenous people, minority populations, disabled individuals, and single parent families, are increasingly seen to live in unsuitable housing. Thus, inequality in housing conditions goes beyond an individual's income level (World Health Organization, 2018).

Despite adequate housing being recognised as a fundamental human right, socio-economic inequalities still limit access to it (World Health Organization, 2018). Housing, being a major driver of social and economic well-being, the studies and data on housing deficit (the difference between the number of households and available dwellings), adequate housing, and the characteristics that shape these disparities are sparse (Behr et al., 2021). Thus, the paper attempts to aggregate 18 indicators across four dimensions of housing adequacy using Multiple Correspondence Analysis to understand the inequities in housing deprivation among the Indian States.

2 Literature Review

2.1 Prominence of Adequate Housing

Housing adequacy extends beyond structural competence of a dwelling to include the locational and neighborhood context. Sinha et al. (2017) reviewed that housing quality is neither "ABSOLUTE" nor "STATIC" as it evolves with changing income level, societal expectations, and lifestyle changes. Thus, the concept of housing "QUALITY" is inherently subjective and context dependent. To address this variability, UN-Habitat (2018) introduced the concept of housing "ADEQUACY" and further explained the right to adequate housing through seven interrelated dimensions. These dimensions link the notion of adequacy to fundamental issues such as accessibility, habitability, affordability, cultural adequacy, location, availability of basic services, and tenure security. Hence no single value or indicator can encompass all the aforementioned dimensions to effectively measure housing adequacy. A number of indicators representative of each dimension must be identified and aggregated into a single index value to measure regional disparities in housing conditions.

Along these lines, Behr et al. (2021) developed an "Adequate Housing Index (AHI)" to assess the housing conditions for 64 emerging economies through indicators from the above-mentioned dimensions. The results highlight that Sub-Saharan African countries have the lowest AHI, whereas European, central Asian, Latin American, and Caribbean countries have relatively high AHI. India has an AHI of 0.68, which is higher than the mean AHI of all the countries considered. Alternatively, Brown et al. (2023) developed the Housing Environment for Protection Index (HEP) using seven major indicators defined as HEP(k) to indicate the proportion of the population in a country that satisfies at least k of the indicators considered. Only close to 8% of households in these 41 developing countries have full compliance with all 7 standards of the HEP index ($k = 7$). Hence the literature has evidenced widespread gaps in housing adequacy across countries.

Disparities in housing conditions are attributed to factors like unexpected rise in population and rapid urbanization which exert excessive pressure on housing markets of Asia and Sub-Saharan Africa. Notably, in countries like India, China, and Nigeria, factors such as intra-household dynamics, socio-demographic transitions, and migration to urban areas due to climate change can drive the urban housing demand (Behr et al., 2021). UN-Habitat (2018) estimates that about a billion people across the world are living in slums, and this is expected to increase exponentially in the forthcoming years, thereby placing significant pressure on governments worldwide to provide decent housing for all (Vaid, 2021). As it is well established in the literature that inadequate housing is associated with an increased risk of adverse physical and mental health outcomes, access to adequate housing has major implications for individual welfare. Additionally, the urban poor, especially the slum residents located in unhealthy areas, incur considerable expenses to secure proper shelter, thus diverting their resources from basic amenities, making it harder for them to escape poverty. This stands to reason the prominence of adequate housing in enhancing people's health, economic stability, and quality of life.

2.2 Evidence on Housing Adequacy in India

In India, while extreme poverty has declined, the rise in inequality driven by growth in population and shifts in employment patterns and rural-urban migration has contributed to challenges pertaining to adequate housing, living space, and overcrowding in megacities. Several cities such as Delhi, Kolkata, Mumbai, and Chennai, are plagued by a number of issues like pollution, water shortage, poor housing quality, high population density, and inadequate infrastructure. In line with this, Ahmad et al. (2025) analyzed the state of housing adequacy in Delhi, Dhaka, and Karachi, which are the three rapidly urbanised cities with limited built environment. Housing adequacy, measured through dwelling space, structural quality, improved sanitation, and drinking water, has revealed that despite having a relatively higher housing adequacy of 56%, progress in Delhi has stagnated compared to Karachi and Dhaka between 2006–07 and 2016–17. This can be attributed to socio-economic inequalities and uncontrolled growth in urban settlements that has reduced the proportion of households with access to improved water sources and structurally adequate dwelling units.

The extent of the housing challenge faced by the urban poor is not adequately represented, as the type of housing deprivation they experience is often overlooked in developing countries by focusing only on slum residents. But the definition of slum is very subjective and varies across standards set by the Government. This is further evidenced in the Indian context by Patel et al. (2014), through the redefinition of slum households according to the UN-Habitat criterion of adequate housing. UN-Habitat classifies a household as a slum if any element representing the aforementioned dimensions is not possessed by a household. Accordingly, the Slum Severity Index (SSI) that was computed as the number of elements a household is deprived of using NFHS-3 for Mumbai and Kolkata reveals that by defining the slums at neighbourhood level, Census has underestimated slum population by 30% in both cities compared to the UN-Habitat adequate housing definition. Extending this approach across all the States, Patel et al. (2020) introduced additional indicators and the results reveal that approximately 171.2 million people in India are living under at least one element of deprivation, which is nearly 2.6 times higher than the slum count reported by the census. These findings highlight that the estimation of housing deprivation based on census slum counts is largely underestimated, thus under-reporting substantial housing deprivation experienced by non-slum poor.

Spatial patterns reveal that there exist regional heterogeneity across dimensions. Complementing these findings, Ashrit and Joshi (2025) analyzed the geospatial inequities in housing conditions using 2018 NSS data and identified stark interstate disparities in housing conditions. The states with better housing outcomes have better implementation of centrally sponsored schemes. Collectively, the literature underscores the importance of housing in the UN 2030 Agenda for Sustainable Development, particularly SDG 11 that focuses on providing adequate and affordable housing for all. Hence housing has to be integrated within the urban policy framework to achieve interrelated goals.

3 Data and Methodology

3.1 Data and Variables

To analyze the inequities in housing deprivation across the States in India, the 76th NSS (National Sample Survey) data on drinking water, sanitation, hygiene, and housing conditions conducted between July and December 2018 has been employed. This is the most recent and comprehensive nationally representative dataset available at the household level to identify the indicators that measure housing deprivation, which are then aggregated to provide state level estimates of housing deprivation. Around 19 indicators across 4 dimensions of housing by UN-Habitat (2018) have been identified for the analysis. All the variables used in the analysis are discrete in nature with categories constructed by regrouping original NSS classification; the source of classification is provided in **Appendix 1**. For the HDI (Housing Deprivation Index) at the household level, 18 indicators were chosen as part of the analysis, excluding the tenurial status of the dwelling, since it is not accurately represented in the dimension along which housing deprivation is measured in the analysis.

3.2 Methodology

3.2.1 Deprivation Patterns and Cronbach Alpha

Following Patel et al. (2014, 2020), the study quantifies the proportion of households deprived across caste, place of residence, and income level for 8 key indicators that capture core dimensions of housing adequacy and are directly relevant for policy. These indicators include access to an improved source of drinking water; sanitation; fuel; electricity; and a bathroom in the premises; security of tenure; durability of the house; and spatial adequacy in the dwelling. A binary indicator defined as improved (0) and unimproved (1) is used for computing the deprivation rates to identify (i) the proportion of households facing multiple deprivations and (ii) the most vulnerable socio-economic group with respect to housing deprivation.

Cronbach Alpha: The measurement of latent traits through a set of variables should be both valid and reliable. A set of variables is considered to be valid if it captures the concept that it intends to measure, and this is evidenced by the literature on housing adequacy measurement. The reliability is concerned with the inter-relatedness among the variables and the extent to which they collectively measure the concept or construct, i.e., housing deprivation level in this case. Cronbach alpha measures the internal consistency of the instrument—which is the set of 18 indicators—based on the covariance or inter-relatedness among the variables (Tavakol and Dennick, 2011). Cronbach alpha measures internal consistency as a value between 0 and 1, and a very high value of alpha may be misleading due to the inclusion of a large number of variables. Alpha assumes homogeneity rather than testing for it; hence, Correspondence Analysis is taken up to unfold patterns between the variables.

3.2.2 Simple Additive Index

A Simple Additive Index (SAI) was constructed by giving equal weights to all 19 indicators by coding the indicators as a binary variable, i.e.,

$$d_{ij} = \begin{cases} 1, & \text{if household } i \text{ is deprived in indicator } j \\ 0, & \text{otherwise.} \end{cases}$$

Thus, the SAI of the ith household is the number of deprivations faced by a household across all 19 indicators. The value of SAI ranges from 0 to 19, with high scores indicating greater housing deprivation. Households are classified into low, moderate, and high deprivation categories based on the 33rd and 66th percentile cut-off values of the SAI. State-wise proportions of households for each category were estimated, and the states were ranked based on the dominant deprivation category among the three. While the SAI framework adopts an equal weighting scheme for all the indicators, this approach may underestimate the deprivation because of the relative severity of certain housing indicators. The framework, by relying on the binary classification of the indicator, fails to capture the intensity differences.

3.2.3 Multiple Correspondence Analysis (MCA)

Multiple Correspondence Analysis (MCA), also known as homogeneity analysis, is an extension of Correspondence Analysis and is used to examine the associations among several categorical variables that are conceptually homogeneous and whose underlying latent trait is unknown (Kohn, 2012). MCA is particularly suitable for dimensionality reduction when the data is discrete in nature, unlike Principal Component Analysis (PCA) which is designed for continuous data that implicitly assumes the same distance between categories.

MCA is often computed by performing Correspondence Analysis on the Burt matrix, a symmetric matrix that is a two-way cross-tabulation of the categorical variables. The diagonal block represents the frequency distribution of the individual categories, whereas the off-diagonal blocks represent the cross-tabulations of the joint occurrence of categories across different variables. Suppose there are Q categorical variables with k_q categories for the qth categorical variable; then the total number of categories across all the variables is given by

$$K = \sum_{q=1}^{Q} k_q.$$

An indicator matrix Z of order $N \times K$ is defined for N households, which is binary coded (1 if the household chooses the category and 0 otherwise) across all the K categories; the corresponding Burt matrix B is defined as

$$B = Z^T Z.$$

Correspondence Analysis on the Burt matrix transforms it to the correspondence matrix, which is then scaled and decomposed in order to obtain the coordinates of the categories along the latent trait that explains the maximum association between the categories. However, the Correspondence Analysis on the Burt matrix inflates the inertia, which has to be normalised. The correspondence matrix P of order $K \times K$ represents the relative frequencies, where off-diagonal elements denote joint occurrence of categories, and the diagonal elements represent the proportion of households choosing a particular category. The row and column masses of the categories are computed to transform the correspondence matrix to the standardised residual matrix, which is then decomposed using singular value decomposition to extract the latent structures that represent the main patterns between the categories. The eigenvalue represents the strength of association along the dimension and the eigenvector provides the category scores that define the position of the category along the corresponding dimension.

In the study, the Housing Deprivation Index at the household level is computed using 18 indicators through MCA. The coordinates determined through MCA for all the categories serve as the endogenous weights to compute the index values. The Housing Deprivation Index (HDI) for the ith household is obtained as a weighted sum of the category coordinates as follows:

$$\mathrm{HDI}_i = \sum_{k=1}^{K} x_{ik} \cdot F_k$$

where HDI_i represents the Housing Deprivation Index of the ith household, x_{ik} represents the response of household i for the category k (i.e., $x_{ik} = 1$ if the household chooses the category and 0 otherwise), and F_k represents the coordinates or the endogenous weights of the category k along the first dimension. Based on the index value, households are classified as deprived (1) and non-deprived (0) based on the national average of the MCA index:

$$D_i = \begin{cases} 1 & \text{if } HDI_i \geq \mu, \\ 0 & \text{if } HDI_i < \mu. \end{cases}$$

where μ denotes the national average of HDI. The proportion of deprived households in each state is then computed to provide a picture of inter-state inequities in terms of housing deprivation.

4 Results and Discussion

4.1 Deprivation Patterns and Cronbach Alpha

Using the methodology described in **Section**-3.2.1, **Table** -1 reflects the inequalities in housing deprivation for the eight key indicators across caste , place of residence, and income level are computed, since these factors consistently and systematically shape the housing inequalities. The caste system still shapes living conditions to a great extent in India. Scheduled caste (SC) and Scheduled Tribe(ST) face high levels of deprivation across all indicators, notably for clean fuel and bathroom facilities (45%-60%).But tenure deprivation is lower for the marginalized due to government land allocation.

Spatial disparities are evident in housing deprivation in all key indicators due to persistent infrastructural gaps in access to basic amenities. Rural households face high deprivation in sanitation (24%), crowding (93%), access to clean fuel (51%) and bathroom facilities (52%), while Urban households face high tenure deprivation (34%). Thus, underscoring persistent rural disadvantage in housing deprivation. The deprivation for all the key indicators has declined from 1st to the 4th quartile as income increases, particularly for overcrowding, clean cooking fuel, and bathroom availability. In contrast, tenure deprivation is higher among rich households, reflecting greater reliance on rental accommodation. Thus, a systematic economic gradient is evident across all MPCE quartiles.

Table 1: **Distribution of Housing Deprivation Indicators Across Social, Spatial and Economic Groups (%)**

	Social Groups				**Residence**		**MPCE Quartiles**			
Indicators	**ST**	**SC**	**OBC**	**Others**	**Rural**	**Urban**	**Q1**	**Q2**	**Q3**	**Q4**
Source of drinking water	9.8	3.0	4.6	3.0	5.3	2.5	5.3	4.2	4.8	3.0
Improved sanitation	24.2	20.2	18.2	13.8	24.4	7.9	24.8	21.5	17.8	9.3
Durable house	7.2	6.3	3.1	1.9	5.4	0.6	8.7	3.6	1.2	1.5
Crowding	92.2	93.0	90.7	90.5	93.1	87.6	99.9	99.9	99.5	65.1
Access to clean fuel	61.8	44.9	35.2	24.7	51.0	8.0	62.8	43.0	23.0	15.9
Availability of electricity	9.0	6.6	4.1	1.5	6.1	0.9	9.6	4.3	1.3	2.1
Security of tenure	7.7	9.1	13.9	17.2	2.8	34.0	2.6	5.7	14.8	31.3
Bathroom in premise	60.3	51.9	38.1	24.0	52.0	13.9	70.3	46.9	22.0	16.2

Notes: Authors' estimates based on NSSO data.

Cronbach Alpha: The internal consistency for the 18 indicators comprising the housing deprivation index has yielded an alpha value of 0.81, indicating the reliability of these indicators in measuring the underlying latent trait, i.e., housing deprivation level. The average inter-item covariance among the variables is 0.0602, which is indicative of moderate correlation—strong enough for consistency but not for redundancy. The MCA analysis, by extracting latent dimensions to explain the variation in data, empirically provides a single deprivation measure along one of the dimensions.

4.2 Simple Additive Index

The Simple Additive Index (SAI), estimated using the approach outlined in Section-3.2.2, facilitates identification of the states where a significant proportion of households experience a high level of housing deprivation. Appendix 4 has provided the estimates of low, moderate, and high deprivation categories across all the states, revealing that high deprivation is in Uttar Pradesh, Bihar, Tripura, Assam, West Bengal, Jharkhand, Odisha, Chhattisgarh, and Madhya Pradesh, while Maharashtra, Andhra Pradesh, Karnataka, Goa, Tamil Nadu, Pondicherry, Telangana, Andaman and Nicobar Islands, Himachal Pradesh, Punjab, Chandigarh, Uttarakhand, and Haryana exhibit low deprivation levels (Figure 1). Though stark disparities are prevalent, the equal weighting and additive nature of the indicators may not be sufficiently representative of the complex nature of housing deprivation.

4.3 Multiple Correspondence Analysis

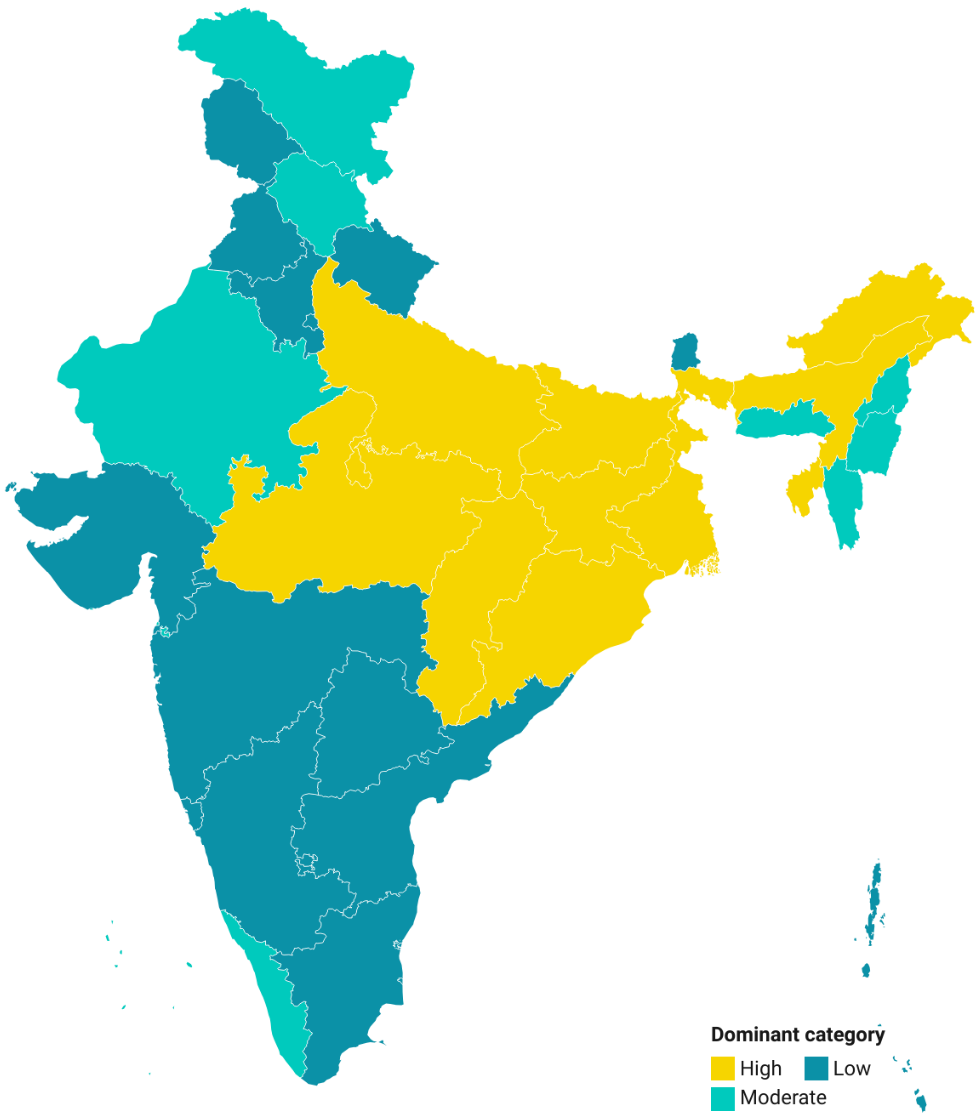
The MCA analysis operationalises the 18 indicators selected to construct the Housing Deprivation Index, based on the UN-Habitat (2018) definition of housing adequacy across four dimensions out of seven mentioned earlier. The framework adopted for the MCA analysis and subsequent construction of the Housing Deprivation Index at the household level is explained in **Section**-3.2.3.

Further, the proportion of deprived households in each state and union territory is computed, and the corresponding Z-score is used to map the inter-state disparities in housing deprivation through a choropleth map. The Z-score for the jth state is defined as follows:

$$Z_j = \frac{X_j - \mu}{\sigma}$$

where X_j is the proportion of households that are deprived in the jth state; μ is the national average; and σ is the standard deviation.

The categories across all the variables were ordered from worst to best, and the



Source: Based on Author's calculations.

Figure 1: **Inter State Disparities in Housing Deprivation using SAI**

MCA was applied to extract various dimensions that are suggestive of the patterns or associations among them. The first dimension, which usually corresponds to the highest proportion of inertia (data variation), accounts for 73% in the study, capturing a clear gradient from deprivation to adequacy. This is evidenced by deprived categories loading on the positive side of the axis, and the most adequate (best) categories clustering on the negative side. The coordinates are then used as endogenous weights in determining the HDI at the household level. Consequently, MCA is more preferred than SAI because it uncovers latent dimensions representing the associations, relies on data-driven weights, and captures joint occurrence of multiple deprivation across indicators. This underscores the validity of MCA in capturing the multidimensional nature of housing deprivation.

The housing deprivation is highest for Ladakh (86.8%), Tripura (84.9%), Manipur (82.2%), Assam (74.9%), and Arunachal Pradesh (69%), whereas it is lowest for Chandigarh (1.1%), Delhi (5%), Puducherry (5.3%), Goa (5.4%), Telangana (8.8%), and Tamil Nadu (10.4%). The spatial patterns reveal pronounced deprivation in north-eastern and eastern states as against southern and western states (Appendix 3). The MCA approach has reaffirmed that housing deprivation is multidimensional in the Indian context as it is contingent upon location, inaccessibility to services, and structural inadequacies that interact differently across various regions/states, thus necessitating state-level policies to improve housing quality.

Parametric Tests and Kernel Density Plots: Although the MCA-derived HDI scores reflect an underlying latent trait with unknown distribution, the large sample size allows us to assume that the sample means are normally distributed. Hence, parametric tests are used to statistically examine if there are differences in survey-adjusted mean HDI scores across social groups, economic strata, and rural-urban residence. The social hierarchy in shaping housing deprivation is clearly evident, with ST (mean HDI score of 0.75) facing high deprivation compared to SC (mean HDI score of 0.24), OBC (mean HDI score of -0.043), and Others (mean HDI score of -0.25) households.

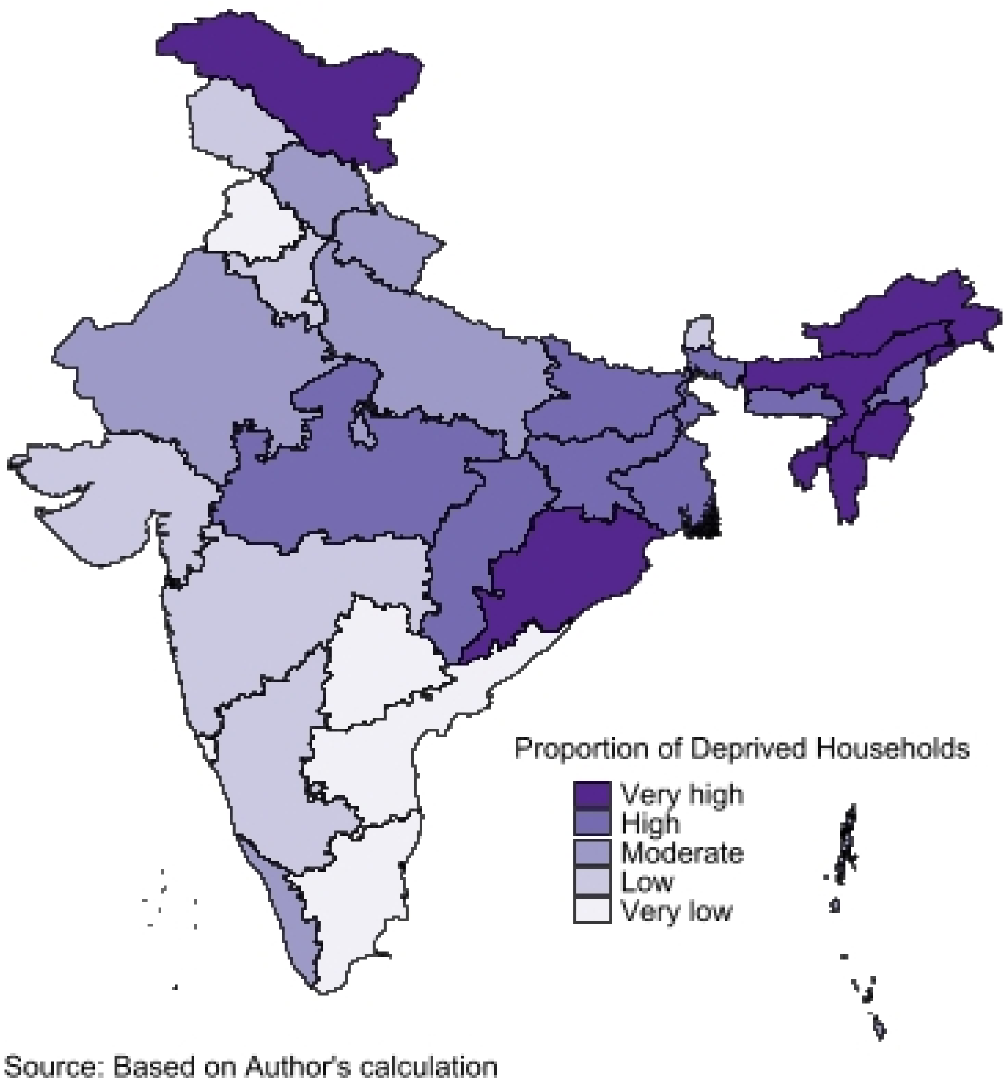
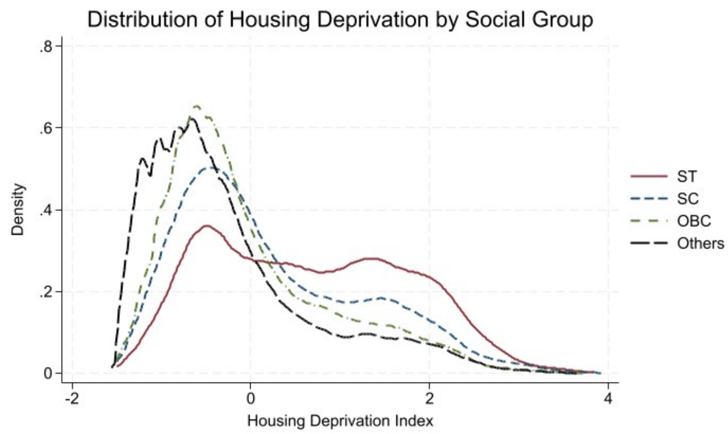
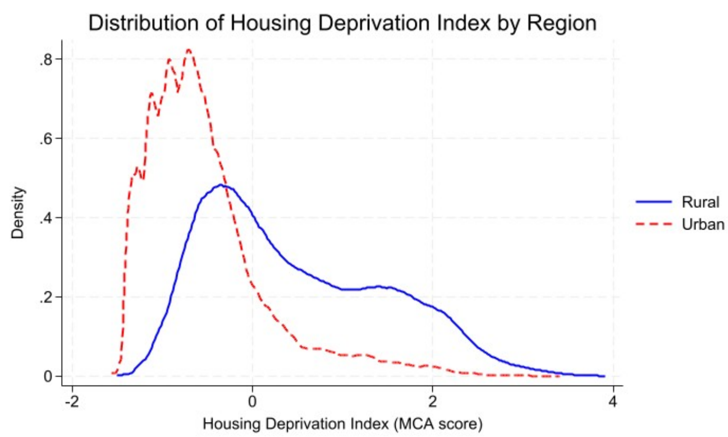


Figure 2: **Inter State Disparities in Housing Deprivation using MCA**

There is significant rural-urban disparity in terms of housing conditions, with rural households (mean HDI score of 0.428) experiencing substantially higher housing deprivation compared to their urban counterparts (mean HDI score of −0.631), reflecting persistent regional inequality in housing conditions.



(a) Distribution of HDI by Social Group



(b) Distribution of HDI by Region

Housing deprivation decreases systematically with rising economic status: households belonging to the lowest MPCE quartile (mean HDI score of 0.82) face the highest level of deprivation compared to those belonging to Lower-Middle (mean HDI score of 0.21), Upper-Middle (mean HDI score of −0.30), and Richest (mean HDI score of −0.617) economic strata.

Overall, the findings on housing deprivation in India reveal that there exist substan-

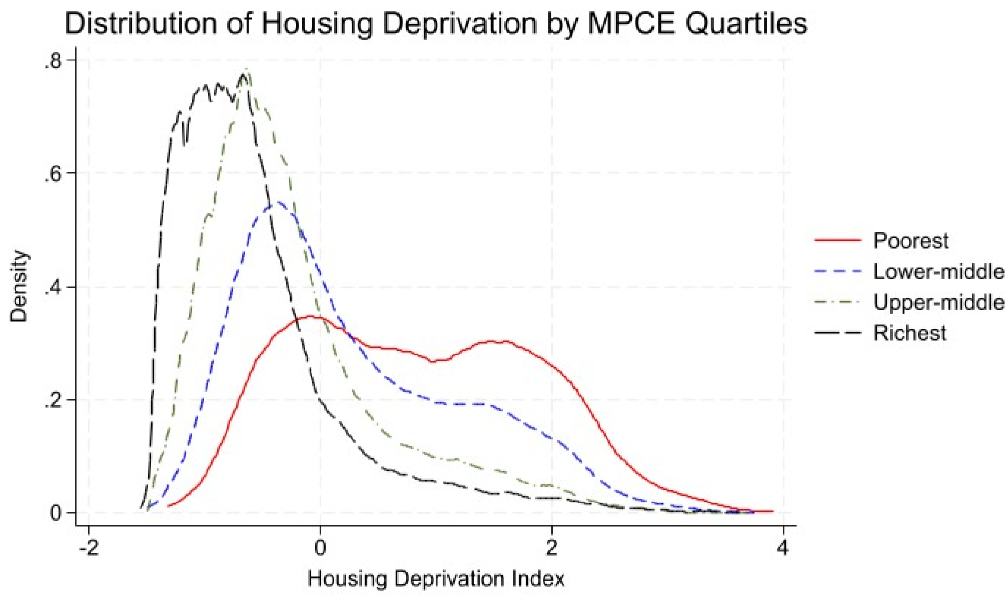


Figure 4: **Distribution of HDI by Income**

tial inter-state disparities with high concentration of disadvantaged caste groups, rural households, and economically weaker households experiencing higher levels of multidimensional housing deprivation—reflecting the prominence of social, spatial, and economic factors in shaping housing deprivation.

5 Conclusion

Given the prominence of adequate housing in sustainable urban development, measuring and addressing "Housing Deprivation" is essential for realising SDG 11. The study contributes to the literature by quantifying the concept of "Housing Deprivation" in the Indian context, recognising its multidimensional nature, encompassing several dimensions based on UN-Habitat (2018) definition to highlight substantial intra- and inter-state inequalities. By employing MCA, data-driven weights are determined to remove the subjectivity and to extract multiple latent structures.

The stark inequities in housing deprivation across the states indicate that the cooccurrence patterns among the indicators of housing conditions are region-specific due to factors like population density, urban congestion, physical terrain, migration-driven urban growth, land use patterns and restrictions, and tenure insecurity. Furthermore, rapid urbanisation in India has intensified resource inequities since it has created significant imbalances in demand and supply of essential utilities in Indian cities, which has degraded the quality of life. In lieu of this, SDG 11: Sustainable Cities and Communities is an effective tool that provides measurable targets and indicators which can help identify the gaps that exist in urban development. Identifying such gaps in housing adequacy, infrastructure, and service delivery can enable more targeted interventions towards creating sustainable urban growth.

References

Ahmad, S., Munir, F., Avtar, R., Sowgat, T., Kundu, D., and Wang, Y. P. (2025). Housing adequacy in Delhi, Dhaka and Karachi: Strategies for promoting sustainable and inclusive housing. *Cities*, 160:105779.

Ashrit, R. R. and Joshi, S. (2025). Analysis of NSSO data sets for a spatial evaluation of water and housing inequality in India. *Environmental Development*, 55:101104.

Behr, D. M., Chen, L., Goel, A., Haider, K. T., Singh, S., and Zaman, A. (2021). Introducing the Adequate Housing Index (AHI): A new approach to estimate the adequate housing deficit within and across emerging economies. Technical report, World Bank Group, Washington, DC, USA.

Brown, C., Ravallion, M., and van de Walle, D. (2023). Child health and the housing environment. *World Development*, 168:106265.

Kohn, J. L. (2012). What is health? A multiple correspondence health index. *Eastern Economic Journal*, 38(2):223–250.

Kushwaha, N., Nangia, C., and Adhvaryu, B. (2023). Achieving localization of SDG11: A critical review of South Asian region and learnings for India. *International Review for Spatial Planning and Sustainable Development*, 11(3):102–115.

Patel, A., Koizumi, N., and Crooks, A. (2014). Measuring slum severity in Mumbai and Kolkata: A household-based approach. *Habitat International*, 41:300–306.

Patel, A., Shah, P., and Beauregard, B. E. (2020). Measuring multiple housing deprivations in urban India using Slum Severity Index. *Habitat International*, 101:102190.

Sinha, R. C., Sarkar, S., and Mandal, N. R. (2017). An overview of key indicators and evaluation tools for assessing housing quality: A literature review. *Journal of The Institution of Engineers (India): Series A*, 98(3):337–347.

Tavakol, M. and Dennick, R. (2011). Making sense of Cronbach's alpha. *International Journal of Medical Education*, 2:53.

UN-Habitat (2018). *The Right to Adequate Housing*. Fact Sheet No. 21 (Rev. 1). United Nations Human Settlements Programme, Geneva.

Vaid, U. (2021). Delivering the promise of 'better homes'? Assessing housing quality impacts of slum redevelopment in India. *Cities*, 116:103253.

World Health Organization (2018). *WHO Housing and Health Guidelines*. World Health Organization.

World Health Organization and UNICEF (2021). Progress on household drinking water, sanitation and hygiene 2000–2020: Five years into the SDGs. Technical report, World Health Organization, Geneva. Accessed: April 2026.

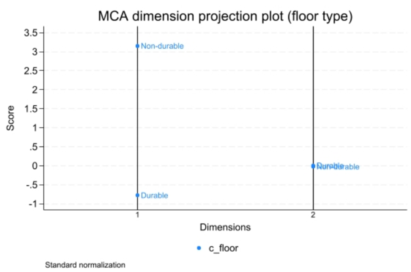
Appendix 1: Variables and corresponding categories

Dimension	Indicators	Categories	Source of criterion for Categorisation
Availability of services	Source of drinking water	1. Piped (Improved) 2. Non-piped (Improved) 3. Non-piped (Unimproved) 4. Surface water	(World Health Organization and UNICEF, 2021) (Joint monitoring programme)
	Source of non-drinking water	1. Piped (Improved) 2. Non-piped (Improved) 3. Non-piped (Unimproved) 4. Surface water	(World Health Organization and UNICEF, 2021) (Joint monitoring programme)
	Latrine type	1. Networked (Improved) 2. On-site (Improved) 3. Non-networked (Unimproved) 4. Open defecation	(World Health Organization and UNICEF, 2021) (Joint monitoring programme)
	Fuel type	1. Clean fuel 2. Moderately polluting 3. Highly polluting	(Behr et al., 2021) (Adequate Housing Index)
	Drainage system	1. Most efficient 2. Less efficient 3. No drainage	(Behr et al., 2021) (Adequate Housing Index)
	Electricity	1. Yes (available) 2. No (not available)	NSS data, 2018 (National Sample Survey)
	Waste water disposal	1. Safe disposal 2. No treatment	NSS data, 2018 (National Sample Survey)

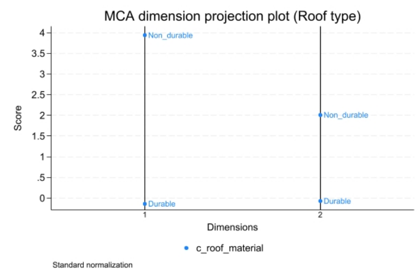
Dimension	Indicators	Categories	Source of criterion for categorisation
	Kitchen type	1. Separate with tap 2. Separate without tap 3. No separate kitchen	NSS data, 2018 (National Sample Survey)
	Bathroom and latrine in premise	1. Yes (available in premise) 2. No	NSS data, 2018 (National Sample Survey)
Habitability	Ventilation	1. Good 2. Bad/No ventilation	NSS data, 2018 (National Sample Survey)
	Crowding	1. Not crowded 2. Crowded **Crowded if:** space per person $<$ 97 sq.ft Persons per room $>$ 3	(Behr et al., 2021) (Adequate Housing Index)
	Flood experience	1. No 2. Yes	NSS data, 2018 (National Sample Survey)
	Roof type	1. Durable 2. Non-durable	NSS data, 2018 (National Sample Survey)
	Wall type	1. Durable 2. Non-durable	NSS data, 2018 (National Sample Survey)
	Floor type	1. Durable 2. Non-durable	NSS data, 2018 (National Sample Survey)
	Durability of house	1. Durable 2. Semi-durable 3. Non-durable	NSS data, 2018 (National Sample Survey)

Dimension	**Indicators**	**Categories**	**Source of criterion for categorisation**
	Water in and around premise	1. No 2. Yes	NSS data, 2018 (National Sample Survey)
Security of Tenure	Tenure of status	1. Hired 2. Owned 3. No	NSS data, 2018 (National Sample Survey)
Location	Approach Road	1. Motorable access to road 2. Non-motorable 3. No access to road	NSS data, 2018 (National Sample Survey)

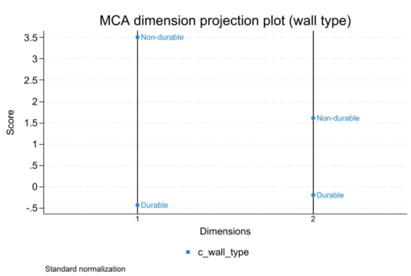
Appendix 2: MCA projection



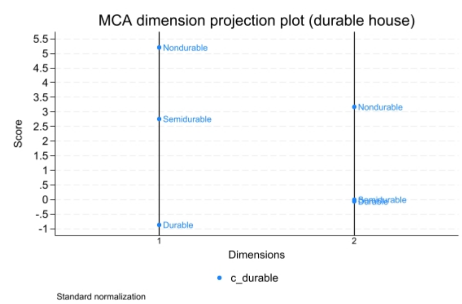
MCA dimension projection plot (Floor type)



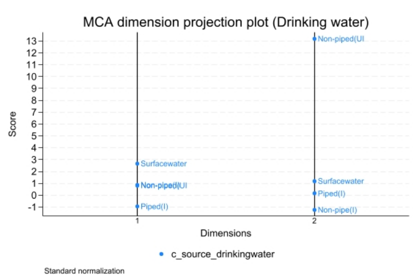
MCA dimension projection plot (Roof type)



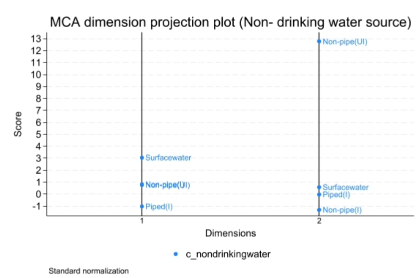
MCA dimension projection plot (wall type)



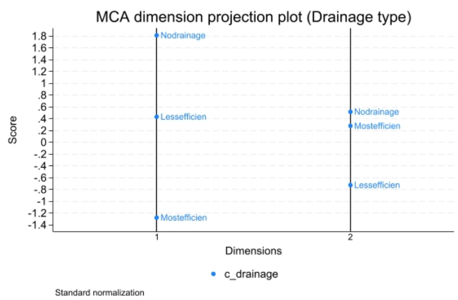
MCA dimension projection plot (Durable house)



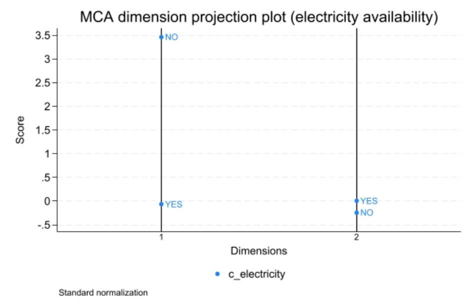
MCA dimension projection plot (Drinking water)



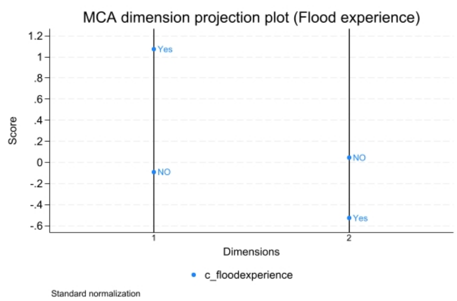
MCA dimension projection plot (Non drinking water)



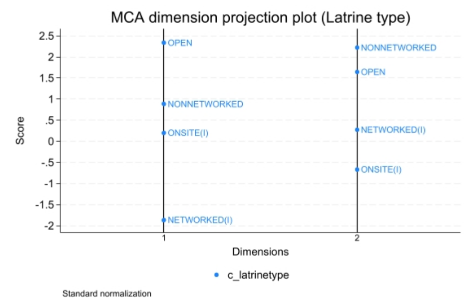
MCA dimension projection plot (Drainage type)



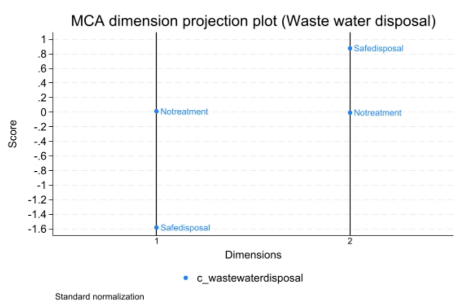
MCA dimension projection plot (electricity availability)



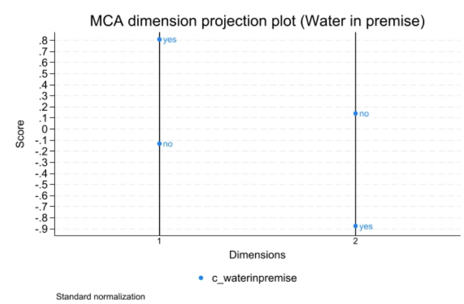
MCA dimension projection plot (flood experience)



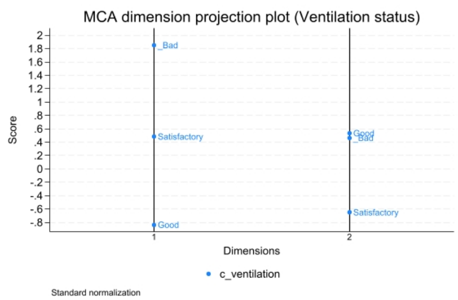
MCA dimension projection plot (Latrine type)



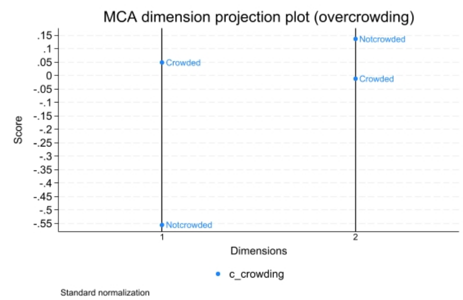
MCA dimension projection plot (Waste disposal)



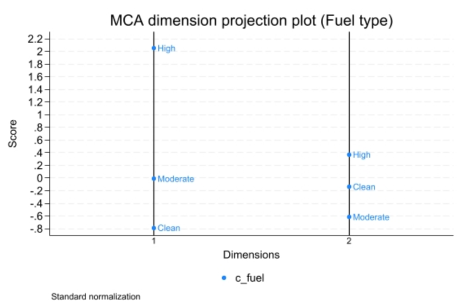
MCA dimension projection plot (water in premise)



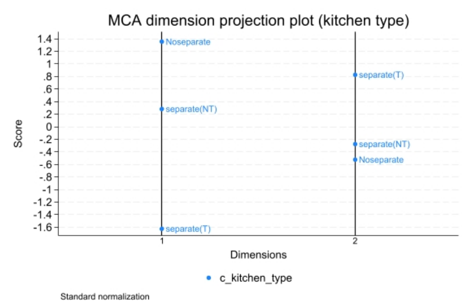
MCA dimension projection plot (Ventilation)



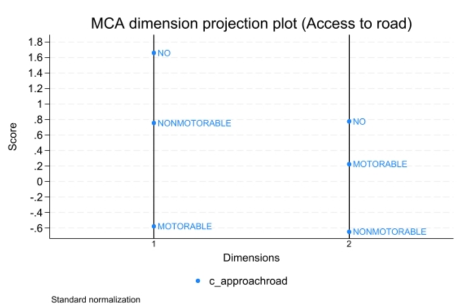
MCA dimension projection plot (overcrowding)



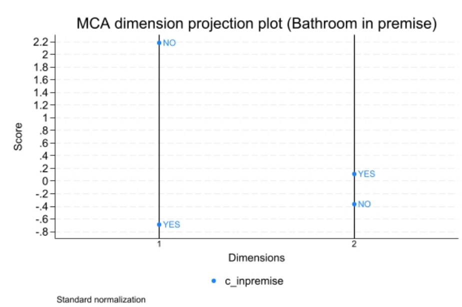
MCA dimension projection plot (fuel type)



MCA dimension projection plot (Kitchen type)



MCA dimension projection plot (Access to road)



MCA dimension projection plot (bathroom in premise)

Appendix 3

Estimates of proportion of households deprived across the states and union territories and corresponding Z-score using MCA approach

State name	Deprived prop	Z-score	Mean HDI
Ladakh	0.868	1.760	0.874
Tripura	0.849	1.700	1.251
Manipur	0.822	1.600	1.018
Assam	0.749	1.340	0.927
Arunachal Pradesh	0.690	1.120	0.855
Jharkhand	0.683	1.100	0.780
Odisha	0.658	1.000	0.664
Chhattisgarh	0.654	0.980	0.707
Meghalaya	0.653	0.980	0.552
Bihar	0.649	0.980	0.537
West Bengal	0.639	0.940	0.630
Nagaland	0.609	0.820	0.509
Mizoram	0.595	0.780	0.289
Madhya Pradesh	0.564	0.660	0.430
Uttar Pradesh	0.537	0.560	0.321
Daman & Diu and D&N Haveli	0.390	0.020	-0.016
Rajasthan	0.349	-0.120	-0.155
Uttarakhand	0.304	-0.280	-0.276
Himachal Pradesh	0.270	-0.400	-0.230
Kerala	0.235	-0.540	-0.256
Maharashtra	0.225	-0.580	-0.375
Gujarat	0.193	-0.680	-0.500

Lakshadweep	0.188	-0.720	-0.294
Haryana	0.177	-0.740	-0.484
Jammu & Kashmir	0.162	-0.800	-0.419
Sikkim	0.155	-0.840	-0.506
Karnataka	0.150	-0.840	-0.544
Andhra Pradesh	0.136	-0.900	-0.401
A&N Islands	0.136	-0.900	-0.475
Punjab	0.122	-0.940	-0.600
Tamil Nadu	0.104	-1.020	-0.507
Telangana	0.088	-1.080	-0.573
Goa	0.054	-1.200	-0.837
Pondicherry	0.053	-1.200	-0.735
Delhi	0.050	-1.220	-0.826
Chandigarh	0.011	-1.360	-1.107

Appendix 4

State-wise Distribution of Low, Moderate, and High Housing Deprivation (SAI-based)

State name	Lowest	Moderate	High	Dominant category
Jammu & Kashmir	0.480	0.380	0.140	Lowest deprivation
Himachal Pradesh	0.440	0.480	0.080	Moderate deprivation
Punjab	0.700	0.260	0.040	Lowest deprivation
Chandigarh	0.800	0.200	0.020	Lowest deprivation
Uttranchal	0.500	0.380	0.100	Lowest deprivation
Haryana	0.580	0.380	0.020	Lowest deprivation
Delhi	0.640	0.320	0.040	Lowest deprivation
Rajasthan	0.320	0.440	0.240	Moderate deprivation
Uttar Pradesh	0.220	0.380	0.400	High deprivation
Bihar	0.180	0.360	0.460	High deprivation
Sikkim	0.700	0.300	0.020	Lowest deprivation
Arunachal Pradesh	0.240	0.320	0.440	High deprivation
Nagaland	0.300	0.420	0.280	Moderate deprivation
Manipur	0.200	0.440	0.360	Moderate deprivation
Mizoram	0.280	0.520	0.200	Moderate deprivation
Tripura	0.120	0.280	0.600	High deprivation
Meghalaya	0.280	0.440	0.280	Moderate deprivation
Assam	0.200	0.360	0.440	High deprivation
West Bengal	0.200	0.320	0.480	High deprivation
Jharkhand	0.180	0.260	0.580	High deprivation
Odisha	0.140	0.260	0.600	High deprivation
Chhattisgarh	0.260	0.340	0.400	High deprivation
Madhya Pradesh	0.260	0.340	0.400	High deprivation
Gujarat	0.480	0.340	0.180	Lowest deprivation

State name	**Lowest**	**Moderate**	**High**	**Dominant category**
Daman & Diu and D&N Haveli	0.160	0.640	0.200	Moderate deprivation
Ladakh	0.100	0.520	0.380	Moderate deprivation
Maharashtra	0.460	0.380	0.160	Lowest deprivation
Andhra Pradesh	0.500	0.400	0.100	Lowest deprivation
Karnataka	0.520	0.380	0.100	Lowest deprivation
Goa	0.780	0.180	0.040	Lowest deprivation
Lakshadweep	0.460	0.480	0.060	Moderate deprivation
Kerala	0.260	0.580	0.160	Moderate deprivation
Tamil Nadu	0.540	0.400	0.060	Lowest deprivation
Pondicherry	0.800	0.160	0.020	Lowest deprivation
A&N Islands	0.660	0.280	0.060	Lowest deprivation
Telangana	0.640	0.300	0.080	Lowest deprivation

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