

Original Research Article

Mapping child vulnerability in India: where does the compass point

Nayan Chakravarty, Emma Emily De Wit*, Barbara Regeer, Joske G. F. Bunders-Aelen

Faculty of Science, Athena Institute, Vrije Universiteit, Amsterdam, The Netherlands

Received: 14 April 2026

Revised: 13 May 2026

Accepted: 14 July 2026

*Correspondence:

Dr. Emma Emily De Wit,

E-mail: e.e.wit@vu.nl

Copyright: © the author(s), publisher and licensee Medip Academy. This is an open-access article distributed under the terms of the Creative Commons Attribution Non-Commercial License, which permits unrestricted non-commercial use, distribution, and reproduction in any medium, provided the original work is properly cited.

ABSTRACT

Background: Exposure to multiple and overlapping social and economic risks shapes children's developmental outcomes, yet India lacks an integrated framework to systematically identify and map these vulnerabilities. This study addresses this gap by developing a multidimensional and spatially disaggregated framework for child vulnerability using a transdisciplinary research (TDR) approach.

Methods: Drawing on iterative consultations with academic experts, practitioners and policy stakeholders, an initial set of over 70 indicators across four domains, health, education, child protection and resilience, was identified and refined to 24 indicators based on relevance and data availability. These indicators were derived from eight large-scale, open-source government datasets covering all states in India and applied to generate district-level vulnerability rankings across 665 districts. Statistical analysis was undertaken using STATA Version 17.

Results: The resulting national and state-level maps reveal significant spatial heterogeneity in child vulnerability, both across- and within states, highlighting substantial intra-state disparities that are often masked by aggregate statistics. The findings demonstrate that vulnerability is unevenly distributed and closely linked to local socio-economic, infrastructural and demographic conditions.

Conclusions: The study contributes both empirically and conceptually by illustrating how multidimensional vulnerability frameworks can be operationalized under data constraints. At the same time, it highlights critical gaps in existing data systems, particularly in relation to psychosocial wellbeing, protection and empowerment. Overall, the study provides a scalable framework for mapping child vulnerability and underscores the need for more integrated, spatially disaggregated and child-centred data systems to support evidence-based policymaking in India.

Keywords: Child vulnerability, Child-centred, Evidence-based policymaking, Transdisciplinary

INTRODUCTION

The literature on childhood development consistently demonstrates that exposure to multiple and overlapping risk factors, such as poverty, malnutrition, inadequate healthcare, limited stimulation and social exclusion, can have long-term consequences for children's cognitive, socio-emotional and physical development.^{1,2} Increasingly, scholars have argued that these risks are not isolated but interdependent and cumulative, requiring multidimensional frameworks to understand children's

wellbeing and vulnerability.^{3,4} In response, a growing body of research has moved beyond income-based approaches toward multidimensional perspectives on child wellbeing, drawing on traditions such as multidimensional poverty measurement and the capability approach (CA).⁵⁻⁷ These approaches emphasize that children's wellbeing depends not only on material resources but also on their access to health, education, protection and enabling environments. However, translating such multidimensional frameworks into empirically usable tools remains a persistent challenge.^{8,9}

In India, these challenges are particularly acute. With more than 472 million children (nearly 36% of the population), the country is characterised by profound heterogeneity across regions, social groups and institutional contexts.^{10,11} While national datasets such as the National family health survey (NFHS) and the Census provide valuable insights into specific domains (e.g. nutrition, mortality, education), they remain fragmented across sectors and uneven in spatial resolution, limiting their ability to support integrated and context-sensitive policy design.^{44,45}

Existing research highlights that children in India continue to experience high levels of multidimensional deprivation, with disparities across caste, gender, geography and rural–urban divides.¹² At the same time, many critical dimensions of vulnerability, such as psychosocial stress, exposure to violence and lack of early childhood stimulation, remain under-measured or absent from large-scale datasets.^{13,14} This reflects a broader limitation identified in the literature: data systems tend to prioritise measurable outcomes over relational, subjective and contextual dimensions of wellbeing.¹⁵

A key implication is that current approaches to measuring child vulnerability in India are both conceptually incomplete and spatially insufficient. National-level indicators often mask substantial intra-state and intra-district variation, while district-level averages may obscure micro-level disparities.¹⁶ As a result, children in marginalized or remote contexts may remain invisible in policy processes, limiting the effectiveness of targeted interventions.

Despite increasing recognition of these challenges, there remains a lack of integrated, multisectoral frameworks capable of systematically identifying and mapping child vulnerability across domains and spatial scales. Existing efforts, such as multidimensional poverty indices, provide important insights but often rely on a limited set of indicators and may not fully capture the breadth of risks relevant to children's development.¹⁷ Moreover, the operationalization of such frameworks is constrained by the availability, comparability and granularity of data.

This paper addresses this gap by exploring how a more domain-comprehensive and spatially sensitive framework for mapping child vulnerability in India can be developed using existing datasets in India. Rather than assuming that all relevant dimensions can be fully captured, the study takes a pragmatic approach, examining how far available data can support multidimensional mapping and where important gaps remain prominent.

To this end, the study adopts a transdisciplinary research (TDR) approach, bringing together academic experts, practitioners and policy stakeholders to co-develop an indicator framework. This approach responds to calls in the literature for more contextually grounded and

participatory approaches to measurement, particularly in complex and heterogeneous settings.¹⁸ The study addresses four main research questions. Which indicators of child vulnerability are available within existing national datasets in India? At what spatial scales (state, district, block, village) are these indicators accessible? What patterns of child vulnerability emerge when these indicators are combined into a composite mapping framework? How can a comparison of integrated, spatially disaggregated and child-centred data help to better understand the impact of policy interventions and can be used to support evidence-based policy making in India?

The intention of this paper is twofold. Primarily, it aims to conduct one of the first attempts to generate a national, multidimensional mapping of child vulnerability across districts in India. Conceptually, it contributes to debates on the operationalization of multidimensional wellbeing by demonstrating how the process of indicator selection is shaped by both normative considerations and data constraints. In doing so, it highlights the need for more integrated, spatially disaggregated and child-centred data systems to support evidence-based policy-making.

METHODS

Transdisciplinary research

To address the limitations of previous studies, this research employs a TDR methodology to investigate child vulnerability in India. Unlike multi- or interdisciplinary approaches that remain within disciplinary boundaries, TDR transcends these, directly engaging with social actors and non-academic knowledge.¹⁹ This approach is particularly suited to bridging India's inter-state and regional disparities, which hinder effective, focused interventions on the ground.

Multidisciplinary studies typically integrate various disciplinary perspectives to expand theoretical understanding or address practical problems, but often stop short of co-creating solutions with non-academic stakeholders. TDR, by contrast, actively incorporates lay knowledge and practice-based expertise to co-produce knowledge that is contextually relevant and action-oriented. In this study, this meant working jointly with practitioners and policymakers to define indicators and interpret findings.

The project reported in this article was jointly initiated by Institute of Financial Management and Research and J-PAL with extensive experience in child development, consistent with recommendations for TDR projects. Actors participated at two levels.

Expert group

Nine experts, two each from four key domains (child health, education, child protection and resilience) plus

one policy expert, met in four rounds of workshops. Initial meetings established shared expectations. Subsequent sessions deliberated on vulnerability dimensions and proposed indicators, resulting in a consultative, iterative process. This group generated an initial list of more than 70 potential indicators.

Review group

Four senior specialists (Heads of Departments, Directors and Country Directors) reviewed and refined the proposed indicators to ensure validity and practical relevance.

Selection of indicators and data sources

Four domains, including health, education, child protection and resilience, guided the expert discussions. To ensure feasibility and policy relevance, the mapping relied on existing and reliable government datasets, reducing cost and time constraints and enhancing policy adoption. Through iterative consultation with expert and review groups, 70 indicators were selected, which were narrowed down, through prioritization based on relevance and availability at village/block or district level, to 24 representative indicators.

Following a set of inclusion and exclusion criteria (Table 1), eight open-source datasets were selected.

Census of India (2011), national sample survey office (NSSO, 2011), sample registration system (SRS, 2013), annual status of education Report (ASER, 2016–2017), National family health survey (NFHS-4, 2015–2016), state planning commission (2011–2012), farmers portal of India, department of agriculture (2018), socio-economic caste census (SECC, 2011).

It would have been impossible to gather new data across India's vast territory. Moreover, existing government datasets are broadly reliable and readily used by policymakers and practitioners, again raising the likelihood of adoption. While there remain persistent data limitations, working with available data allows for more aligned development to address pressing child vulnerabilities. These population-level datasets provide broad coverage across India's 29 states. Preference was given to sets that had block-level data available to enhance spatial detail.

Mapping specifications and analysis

The method used to calculate the mapping is analogous to the way in which the United Nations human development index (HDI), commonly used as an index of development, is calculated.²⁰ This method is also relevant for calculating an HDI using national data. Accordingly, we came to the composite child-development score using a normalised geometric aggregation of several (n) indicators.

Each indicator value for region bds was normalized to a (0,1) scale using.

$$Z_{bds}^i = \frac{x_{bds}^i - x_{min}^i}{x_{max}^i - x_{min}^i}$$

where x_{bds}^i is the observed value for indicator i in a given region and x_{min}^i and x_{max}^i represent the minimum and maximum values of that indicator across all regions.

For negatively oriented indicators (e.g., stunting), values were reversed prior to normalization so that higher values consistently indicate better outcomes.

The composite score was then calculated as:

$$S_{bds} = \sqrt[n]{n \cdot (Z_{bds}^1 \times Z_{bds}^2 \times \dots \times Z_{bds}^n)}$$

This method is useful to rank blocks or regions according to the degree of child vulnerability.

Statistical analysis

In this study, statistical analysis was undertaken using STATA version 17. The software was used for data cleaning, data validation, harmonization and integration of multiple datasets obtained from the open-source large governmental data sets, as mentioned above. Understanding the datasets in terms of reporting timeframe, reporting formats, preprocessing procedures were undertaken to standardize variables. In some cases, the data were normalized to ensure data consistency across all 665 districts included in the analysis.

Composite vulnerability scores were generated using aggregated indicator value at each district level. The scores generated were used to rank all districts based on relative childhood vulnerability score. Cross-domain comparisons as well as district level analysis were conducted using STATA to ensure analytical transparency and consistency through the study.

Ethics

This study was based on secondary, aggregated data obtained from publicly available government datasets. As no other data were collected at the individual level and no identifiable information was used, formal ethical approval was not required. For the consultation component, informed consent was obtained from all participating experts, practitioners and policy stakeholders. Participants were informed about the purpose of the study, the voluntary nature of their involvement and how their inputs would be used in the development of the framework. No personally identifiable information was recorded and responses were considered in an anonymized manner.

RESULTS

In this section the results of our study are presented. First, we present the vulnerability indicators that are prioritized as part of the transdisciplinary exercise and to what extent these data points were available across India. Secondly, we present the average outcomes on child development mapped across the country and the variety of vulnerability observable within states. Finally, we map the same vulnerability for two example states, including Maharashtra and Assam to explore the heterogeneity of results across regions and try to link these to known policy and organisational efforts in these regions.

Prioritising vulnerability indicators

As described above, for the selection of indicators to define childhood vulnerability, a TDR team included members with diverse and mixed experiences from academics and practice. A nine-member TDR team with years of experience working in the domain of child health, education, protection and resilience formed the expert group who discussed the relevance of all indicators and ranked the most vital. The selection of indicators was primarily exploratory and finalised after rounds of discussions within the TDR group. External specialists also gave their feedback before deciding on the indicators. The core group considered the 70+ indicators proposed by the expert group. They reviewed the data against two criteria: are these data points relevant for measuring children's vulnerability and proportionally distributed over the domains? are these data points available beyond state level?

This led to a final selection of 24 indicators. The original indicators that were thus excluded are untouchability, bullying, separated parents or single parent, time used by household members in childcare or education, participation of women in decision-making, religious discrimination, human rights violation, availability of accessible green land or children's park, children with depression, academic pressure on children, number of incidents of different forms of disaster. Major reasons for exclusion were the lack of state-level data or, preferably, beyond state level.

The final 24 indicators were indicative for child vulnerability from Health, Education, Child protection and Resilience subcategories (Table 2). Most indicators (12) were in the health category, including maternal health and antenatal care. Other indicators (5) were from the education category. Child protection had four indicators representing the status on early marriage, child labour, sex ratio and disability. The final sub-category, resilience, contains four indicators and was defined in terms of economic, natural disasters and household food security. The availability of reliable data on all identified indicators at block (sub-district) level influenced the selection of the indicators from district and state levels.

Of the 24 indicators three were found at the block level, 17 at the district level and four at the state level.

National mapping

The study used the indicators to calculate the state and district ranking (including 665 districts). The district averages were based on 24 indicators (Table 2). All the districts were ranked based on their specific values and further segregated and represented in quintiles. The national childhood vulnerability map shows considerable diversity across states, spanning a wide spectrum across each state (Figure 1). Similar pronounced spatial disparities and significant variation in childhood vulnerability across multiple countries and states has been reported in previous studies as well.²¹ States marked in dark blue reflect all four quintiles, while the lighter-coloured states reflect just one quintile.

The spatial distribution of the vulnerability mapping suggests that there is clustering of states with diverse quintiles, which are mostly at the western, eastern and north-eastern parts of the country, including Arunachal Pradesh, Assam, Chhattisgarh, Gujarat, Karnataka, Maharashtra and Odisha, with all four quintiles within each state. The diversity could be due to variations in terms of land use, cropping patterns, livelihoods, urban or rural population, cultural, economic as well as demographic factors. Very few states, including Himachal Pradesh, Jammu & Kashmir, Kerala, Sikkim and Tripura are states where child vulnerability is reflected in a single quintile, showing the least diversity across the state.

The national-level map on childhood vulnerability provides a high-level view that needs deeper understanding with respect to the diversity across states. The presence of all four quintiles within large states suggests that state-level averages mask substantial inequalities, limiting their usefulness for targeted policy design. The map shows the need to look at more detailed data to understand the intra-state variations in order to guide state-level policymakers to allocate resources rationally and focus interventions to those districts that are most in need. The study conducted by Pezzulo et al, suggested a similar observation of spatial distributions as crucial for targeting and increasing the efficiencies of resources, noting that national and state averages conceal local disparities.²²

State mapping

Understanding that some states show more diversity than others, we were curious to see the actual distribution of quintiles across two sample states- Maharashtra and Assam (Figure 2 and 3). The first quintile includes the most vulnerable districts (lowest scores) and is shown in the lightest shades, while the fourth quintile includes the least vulnerable districts and is shown in the darkest shades.

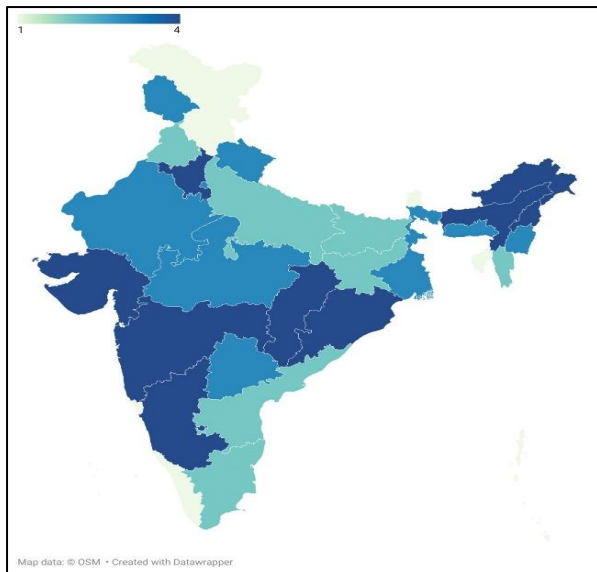


Figure 1: India map of child vulnerability in percentile groups.

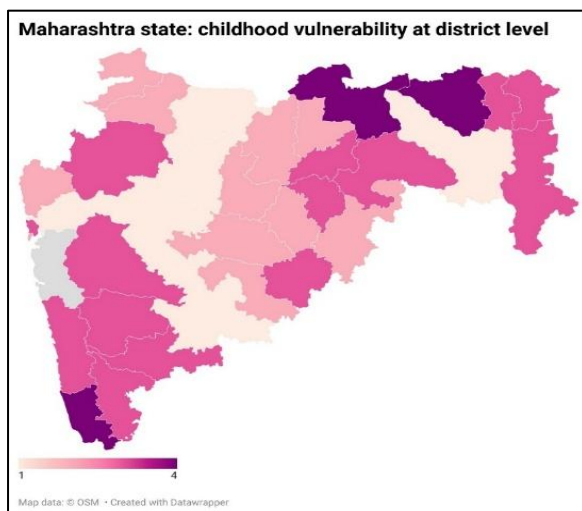


Figure 2: Maharashtra state map.

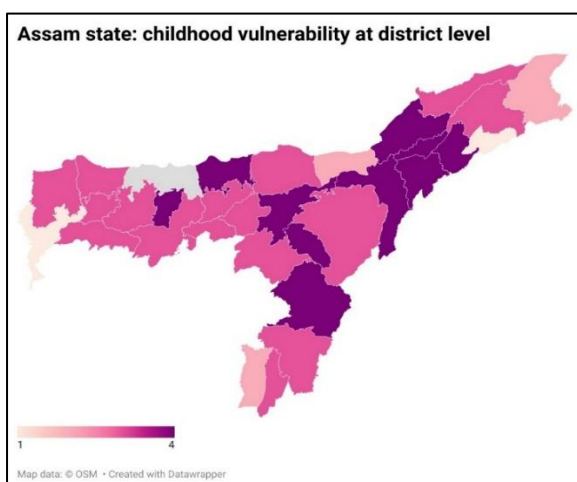


Figure 3: Assam state map.

Maharashtra

The district-level findings for Maharashtra demonstrate substantial heterogeneity and diversity across districts, spanning a wide spectrum of vulnerability quintiles, but showing clusters with multiple adjoining districts representing the same quintiles with respect to childhood vulnerability. There are many districts with the highest vulnerability along the state's north-south corridors, namely Ahmednagar, Aurangabad, Chandrapur, Jalgaon, Solapur and Wardha. This clustering suggests that child vulnerability is spatially embedded and shaped by region-specific, socioeconomic structural conditions, rather than randomly distributed.

Similar spatial clustering of districts with same vulnerability quintiles across districts has been reported in previous studies, with respect to childhood mortality in India and attributed these patterns to regional socioeconomic and health system performances. As the socioeconomic conditions and health system performances are expected to be similar across neighboring districts.²³ As we know that stunting, wasting and underweight are key vulnerabilities for children's wellbeing, the districts mentioned above are those where such factors show relatively worse outcomes.

Looking at state-level nutrition profiles for Maharashtra, for children under the age of two, districts such as Ahmednagar (weight-for-age under 2SD 46.8 %) and Chandrapur (51.1 %) register among the most vulnerable. Comparisons between NFHS-4 and NFHS-5 indicate that some districts showed limited progress across several nutrition indicators.^{44,45} Many of these districts lie in relatively less-developed regions of Maharashtra (Marathwada, northern Maharashtra, Vidarbha). These areas tend to have poorer infrastructure, less investment and higher poverty/agrarian distress. This shows the importance of other sectors that contribute significantly to children's wellbeing. Amravati has also received much more attention from policies and schemes in the past years, because of some of the starvation-related deaths that happened here. So, this might also explain the stark differences that now appear between Amravati and neighboring Wardha. The worst 25% of the blocks in terms of child vulnerability occupied the top-most quintile (1st quintile) and the best 25% occupied the lowest (4th quintile).

The potential impact of policies and organisational efforts

The districts showing the highest quintiles (least vulnerability) are in the southern, north-western and north-eastern corridors. Districts in these categories include Amravati, Nagpur, Sindhudurg, Wardha, etc (Figure 1). The map highlights an important difference between districts such as the earlier mentioned Wardha (lowest quintile) and nearby states such as Amravati and Nagpur. What could explain these stark differences of

three quantiles? A few factors might justify the better performance of these districts as opposed to that of proximate areas. Besides the fact that districts such as Nagpur have received more administrative attention as urban hubs, whereas districts such as Wadra have been predominantly focused on agricultural activities, differences in child-focused policies and the way these have been rolled out similarly explain variation in child development outcomes.²⁴

According to the 'State Nutrition Profile; Maharashtra' compiled by NITI Aayog, better early intervention and better nutrition and health service coverage might have affected the diverse outcomes. In some districts the coverage of key maternal and child interventions (e.g., first-trimester antenatal care, giving birth in an institutional setting, child immunisation) is relatively high across the aforementioned districts. There is substantial evidence that demonstrates that higher coverage of maternal and child health interventions is associated with improved district level maternal and child health outcomes, while districts with lower intervention coverage exhibit poorer outcomes.²⁵

For instance, Amravati achieved about 89.1% coverage in antenatal first trimester in one table and Wardha about 87.9%. It is also interesting to note that these districts demonstrate not only higher per-capita income but also higher female literacy, which performed better on the composite health index than other districts.²⁶ The social infrastructure analysis (Rural Development Infrastructure Index by NABARD) also lists Nagpur, Sindhudurg and Wardha among the 'relatively better performing compared to other districts, subsequently classified as high-performance districts. But then what makes Wardha perform less well overall? Singling out factors such as underweight, stunting and wasting for Maharashtra shows that these factors, at least partly, bring down the average for Wardha, with significantly worse outcomes on these domains.²⁷

In highly remote and underserved regions such as Gadchiroli, the work of the Society for Education, Action and Research in Community Health has demonstrated that community-based health interventions can significantly reduce child mortality despite severe geographic constraints (Figure 1; dark pink).

Similarly, in the tribal belt of Melghat, organisations such as KHOJ Melghat help bridge last-mile delivery gaps by improving access to nutrition and health services. In contrast, urban areas like Mumbai reveal that geographic advantage does not guarantee improved outcomes, as NGOs such as SNEHA address persistent vulnerabilities within informal settlements. In drought-prone regions like Marathwada, organizations such as Watershed Organisation Trust demonstrate how interventions in water management and livelihoods can indirectly improve child nutrition by enhancing household resilience. Together, these examples show that NGOs

play a critical role in shaping child wellbeing by compensating for weak state capacity, improving policy implementation and addressing structural determinants, thereby altering expected outcomes based on geography alone.

Assam

The district-level findings for the state of Assam demonstrate substantial heterogeneity and diversity across districts, spanning a wide spectrum of vulnerability quintiles. As in the state of Maharashtra, there are clusters of districts with the same quintile with respect to childhood vulnerability mapping. The districts of Dhubri, Karim Ganj and Tinsukia come under the lowest quintile (worst performing); whereas Dima Hasao, Golaghat, Jorhat, Nagaon and Sivasagar are among the highest (best performing) quintiles. It is worth noting that the districts of Dhubri, Karim Ganj and Tinsukia are on the border of Assam, whereas the districts which are relatively better, are more or less centrally located.

It is important to note that these districts have among the highest burden of childhood malnutrition in the state of Assam, with Dhubri and Karimganj districts among those showing high prevalence of malnutrition within a double or triple burden.²⁸ Dhubri reports a high percentage of child marriage and there is evidence to suggest that more than half of the girls are married before they attain the legal age of marriage, which leads to early pregnancy.

International Institute of Population Sciences also reported that the district level data for Assam, including Dhubri, indicates elevated rates of early marriage and adolescent motherhood relative to the national and state average.^{44,45} These are also the districts with poor infrastructure and are demographically disadvantaged compared to better-performing districts of Assam.

The better-performing districts show positive performance and improvement across multiple underlying factors, such as maternal literacy, delayed marriage and household sanitation; districts like Dima Hasao, Golaghat and Sivasagar also show improvement. This can also be explained in terms of better coverage of maternal and child health services in these districts, where uptake is strong.⁴³ The districts of Golaghat, Jorhat and Sivasagar in upper Assam also have better connectivity, education and infrastructure than that enjoyed in many remote districts and thus may benefit from fewer access barriers.

Similar results have been reported by Bora et al that districts with weaker infrastructure, poorer connectivity and lower socioeconomic development experiences worse child health outcomes and higher mortality risk.²⁹ Further, the Nutrition Profile shows that in many categories, these districts show positive improvement (percentage point gains) on earlier rounds.

The potential impact of policies and organisational efforts

In Assam, the outcomes as per district illustrate how policy effectiveness can either reinforce or counteract geographic disadvantage in shaping child development outcomes. Border and flood-prone districts such as Dhubri and Karim Ganj, located along the frontier with Bangladesh, perform poorly not only due to environmental vulnerability but also because welfare schemes like the integrated child development services struggle to reach highly mobile populations in char areas, where flooding frequently disrupts service delivery. Studies have shown that welfare schemes such as the ICDS face significant implementation challenges in Assam's char (riverine) areas, where geographical isolation, poor infrastructure and population mobility limit access. These regions experience persistent barriers to service delivery, including supply disruptions and weak Anganwadi coverage.^{30,31} Recurring floods frequently damage infrastructure and displace communities, further interrupting access to nutrition and health services.³¹ Similarly, the region of Tinsukia presents a case where relatively strong economic activity

does not translate into improved child wellbeing, as tea garden communities remain inadequately covered by public health and nutrition policies under programmes such as the National Health Mission (NHM).

In contrast, Dima Hasao demonstrates better-than-expected outcomes despite its remoteness, partly due to decentralized governance through autonomous district councils and targeted outreach strategies that improve service access. This can be substantiated by studies showing that autonomous governance structures in Northeastern India influence local development administration and improved service in tribal regions.³³ Districts such as Jorhat and Sivasagar further benefit from stronger administrative capacity and infrastructure, enabling more effective implementation of maternal and child health interventions. Notably, Nagaon shows that even flood-prone areas can achieve relatively positive outcomes when policies are adapted to local risks through improved monitoring and service delivery. These examples highlight that while geography sets important constraints, the design, adaptability and inclusiveness of policy implementation play a decisive role in shaping child vulnerability across Assam.

Table 1: Inclusion and exclusion criteria for dataset selection.

Inclusion criteria	Exclusion criteria
Large sample sizes	Small sample sizes or insufficient information
Available in English	Not available in English
Credible sources (government or government-supported)	Poorly documented or low-credibility sources
Complete datasets representing all 29 Indian states	Incomplete datasets covering only a few states
Block-level data preferred over purely national or regional	Datasets restricted to national or regional aggregates

Table 2: Final indicators, sources and years of data considered for analysis.

Indicators	Expressed as	Used as	Source	Level	Year
Health					
Immunisation–BCG, Polio (3 doses), DPT each – children aged 12–23 months fully immunised	Percentage of all children of the same age	Inverse	NFHS-4	District	2015-16
Underweight–under-fives who are underweight (%)	Percentage	Direct	NFHS-4	District	2015-16
Stunting–children under 5 years who are stunted (%)	Percentage	Direct	NFHS-4	District	2015-16
Infant mortality rate (IMR)	Deaths /1,000 live births	Direct	SRS – NITI Aayog	<u>State</u>	2013
Households without drinking water and sanitary latrines within premises	Percentage		NFHS-4	District	2012-2013
Anaemia level for children	Percentage	Direct	NFHS-4	District	2015-16
Pregnancy registration	Percentage	Inverse	NFHS-4	District	2015-16
Antenatal care (at least 3 visits)	Percentage	Inverse	NFHS-4	District	2015-16
Place of childbirth – institution, public facility/others	Percentage	Inverse	NFHS-4	District	2015-16
Birth weight (<2.5 kgs)	Percentage	Direct	NFHS-4	District	2015-16
Breastfeeding within one hour of childbirth	Percentage	Inverse	NFHS-4	District	2015-16
Exclusively breastfed (up to six months, beyond six months)	Percentage	Inverse	NFHS-4	District	2015-16

Continued.

Indicators	Expressed as	Used as	Source	Level	Year
Education					
Population aged 5-19 years not attending educational institutions	Percentage	Direct	Census	District	2011
Proportion of children between 6 and 12 years able to read and comprehend	Percentage	Inverse	ASER	State	2016
Proportion of children between 6 and 12 years with arithmetic/numerical skills	Percentage	Inverse	ASER	State	2016
Literacy rate – females	Percentage	Direct	Census	Block	2011
Enrolment Level	Percentage	Inverse	Census	Block	2011
Child Protection					
Working children in in the 5–18 years age group	Percentage	Direct	Census	District	2011
Adolescents who are married (12 to 19 years)	Percentage	Direct	Census	District	2011
Disability in children from birth to the age of majority (18 years)	Percentage	Direct	Census	District	2011
Sex ratio (<6 years)	Females/1000 males	Inverse	Census	Block-wise	2011
Resilience					
Landless households/those who do not own land	Percentage	Direct	Census, NSSO	District	2011
No. of droughts	Number of droughts in the last 15 years	Direct	Farmers Portal, Ministry of Agriculture	State	2018
Percentage of households with food security–calorie consumption by household data	Percentage	Direct	Census, NSSO	District	2011-12

DISCUSSION

Spatial heterogeneity and multidimensional vulnerability

This study set out to address a persistent gap in India's child development landscape: the absence of an integrated, multisectoral mapping of childhood vulnerability at a sufficiently granular spatial scale. Previous studies by Pezzulo et al and others have similarly emphasized the importance of integrated spatial analysis because national and state averages frequently obscure local inequalities and vulnerabilities.²² By combining a TDR approach with secondary data analysis, the present study not only provides empirical insights into the spatial distribution of vulnerability, but also reflects on the practical and conceptual challenges of constructing such a framework using existing datasets. The findings reveal substantial spatial heterogeneity in childhood vulnerability across India, but more importantly, within states. Similar intra-state inequalities and district-level clustering have been documented in previous studies on under-five mortality, multidimensional poverty and child development indicators.^{16,22,23,29} The present findings reinforce the argument that aggregate state-level

indicators often conceal local disparities, thereby limiting the effectiveness of uniformly designed policy interventions.³⁸ The presence of multiple vulnerability quintiles within large states such as Maharashtra and Assam suggests that intra-state disparities are often as significant as or even greater than, differences between states. This has important implications for policy design because reliance on state-level averages risks masking pockets of acute deprivation, particularly in geographically large and socio-economically diverse regions.

Health, nutrition and cumulative disadvantage

The concentration of vulnerability in districts characterized by high levels of stunting, underweight prevalence, poor maternal health coverage and inadequate infrastructure aligns with previous evidence linking nutritional deprivation to broader socioeconomic and health system inequalities.^{25,27,32} The findings from Maharashtra and Assam particularly demonstrate how health vulnerabilities tend to cluster geographically in districts affected by poverty, weak infrastructure, environmental stress and limited service access. Similar associations between maternal education, sanitation, healthcare access and child nutritional outcomes have

been widely documented in India and other low- and middle-income countries.^{15,32} The present study further demonstrates how these vulnerabilities overlap spatially, reinforcing cumulative disadvantage across districts.

Education, child protection and the capability approach

The findings relating to educational exclusion, child marriage and child labour similarly support previous research demonstrating that childhood vulnerability is multidimensional and deeply interconnected.^{3,11,17} Districts with weaker educational attainment and higher rates of early marriage frequently also experience poorer health and nutrition outcomes, suggesting that deprivation accumulates across multiple domains rather than occurring in isolation. These findings reinforce multidimensional approaches to child wellbeing that move beyond single-sector indicators and instead recognize the interrelated nature of social disadvantage.^{6,15}

From a capability approach perspective, these patterns highlight the importance of understanding not only developmental outcomes, but also the contextual conditions under which children are able to achieve them.^{5,8} The clustering of vulnerability in certain districts reflects the influence of local “conversion factors”, such as infrastructure, access to services, environmental risks, institutional capacity and social norms, which shape how resources translate into actual wellbeing. Districts facing agrarian distress, poor infrastructure, social marginalization or environmental vulnerability may therefore experience persistent disadvantages across multiple indicators, even when broader state-level progress is observed. This suggests that future research on child vulnerability in India would benefit from incorporating more explicit measures of these contextual and relational factors, as well as children’s own experiences and agency.

Data limitations and implications for policymaking

A key contribution of this study lies in demonstrating how multidimensional frameworks of child wellbeing can be operationalized under real-world data constraints. While multidimensional approaches to poverty and wellbeing have been widely discussed in the literature, their empirical application frequently requires compromises between conceptual completeness and data availability.^{6,34} In the present study, the process of narrowing more than 70 proposed indicators to a final set of 24 illustrates how indicator selection is shaped not only by normative considerations, but also by the structure and availability of existing datasets.³⁵ The final indicator set therefore reflects both expert judgement about what constitutes child vulnerability and the practical limitations of existing data systems. Consistent with previous scholarship on multidimensional wellbeing measurement, the present findings also demonstrate that certain dimensions of child wellbeing remain

systematically underrepresented within large-scale data systems.^{9,15,36} While health and education indicators are comparatively well represented, dimensions such as psychosocial wellbeing, agency, social inclusion and everyday lived experiences remain difficult to capture through conventional survey instruments.^{15,37} As such, the resulting vulnerability mapping should be understood as a meaningful but partial representation of children’s realities. The transdisciplinary research process proved particularly valuable in making these limitations more explicit, as the limited availability of block-level data and the uneven representation of certain domains emerged directly through expert deliberation and stakeholder engagement.

Within these limitations, an important contribution of this study lies in demonstrating how spatially disaggregated vulnerability mapping can support more targeted and context-sensitive policymaking. By identifying clusters of both high and unexpectedly low vulnerability across districts, the analysis enables policymakers and practitioners to move beyond aggregate state-level assessments and instead focus interventions on specific geographic areas where outcomes diverge from broader structural expectations. The findings further suggest that policy effectiveness depends not only on economic development, but also on the adaptability, inclusiveness and local implementation of health, nutrition, education and social protection systems.

More broadly, the study highlights the need for integrated, child-centred and spatially disaggregated data systems capable of supporting multidimensional approaches to child wellbeing. Future research could build more explicitly on the Capability Approach by incorporating indicators that better capture children’s agency, relational wellbeing and lived experiences within their specific social and geographic environments.

CONCLUSION

Finally, the study highlights both the potential and the limitations of using existing datasets for vulnerability mapping. On the one hand, the framework provides a practical and scalable approach for identifying high-risk districts, supporting resource allocation and enabling longitudinal monitoring of multidimensional outcomes. On the other hand, it exposes significant structural gaps in India’s child-related data systems. In particular, the limited availability of disaggregated data below the district level and the absence of indicators capturing psychosocial wellbeing, protection and empowerment, constrain the depth and inclusiveness of the analysis. These gaps reflect broader challenges in development data systems, where certain dimensions of wellbeing are easier to measure than others, leading to systematic biases in what is captured and prioritized.⁴¹ Overall, this study demonstrates that while it is both possible and valuable to construct a multidimensional vulnerability mapping framework using existing data, such efforts are

inevitably shaped by data availability, methodological choices and normative priorities. Addressing child vulnerability in India therefore requires not only improved analytical tools, but also sustained investments in more integrated, frequent and spatially disaggregated data systems. From a theoretical perspective, future research could build more explicitly on the capability approach by developing indicators that better capture children's agency, relational wellbeing and the contextual conditions shaping their opportunities. Such an approach would move beyond measuring outcomes alone, towards a more comprehensive understanding of what children are effectively able to be and do within their specific environments.

Funding: No funding sources

Conflict of interest: None declared

Ethical approval: Not required

REFERENCES

1. UNICEF. The State of the World's Children 2019: Children, Food and Nutrition. United Nations Children's Fund. 2019. Available at: <https://www.unicef.org/media/106506/file/The%20State%20of%20the%20World%E2%80%99s%20Children%202019.pdf>. Accessed on 3 June 2026.
2. Black MM, Walker SP, Fernald LC, Andersen CT, DiGirolamo AM, Lu C, et al. Early childhood development coming of age: science through the life course. *Lancet*. 2017;389(10064):77-90.
3. Minujin A, Delamonica E, Davidziuk A, Gonzalez ED. The definition of child poverty: a discussion of concepts and measurements. *Envir Urbaniz*. 2006;18(2):481-500.
4. Roelen K, Gassmann F. Measuring child poverty and well-being: A literature review. Maastricht Graduate School of Governance Working Paper Series No. 2008. Available at: https://mpira.ub.uni-muenchen.de/8981/1/MPRA_paper_8981.pdf. Accessed on 3 June 2026.
5. Sen A. *Freedom. Development*, Oxford University Press, Oxford. 1999.
6. Alkire S, Foster J. Counting and multidimensional poverty measurement. *J Publ Econom*. 2011;95(7-8):476-87.
7. Biggeri M, Libanora R, Mariani S, Menchini L. Children conceptualizing their capabilities: results of a survey conducted during the first children's world congress on child labour. *J Human Dev*. 2006;7(1):59-83.
8. Robeyns I. The capability approach: A theoretical survey. *J Human Dev*. 2005;6(1):93-117.
9. Hotez E, Perrigo JL, Morales J, Stanley L, Halfon N. Middle Years Development Instrument (MDI) Child Well-Being and Assets in a Predominantly Hispanic/Latinx Student Population. *Child Indicators Res*. 2026;4:1-24.
10. Jain R. Mapping childhood vulnerability in India: A systematic overview. *Child Indicators Res*. 2023;16(4):1123-42.
11. Gupta S, Sharma R, Patel V. Multidimensional child poverty in India: Progress and challenges. *Economic & Political Week*. 2021;56(15):34-42.
12. Aayog NI. India—National Multidimensional Poverty Index: A Progress Review (Government of India), India. 2024. Available at: <https://www.niti.gov.in/sites/default/files/2023-08/India-National-Multidimensional-Poverty-Index-2023.pdf>. Accessed on 3 June 2026.
13. Pérez-Urbe MA, Palacios P. Effects of weather shocks on multidimensional rural poverty: evidence for Colombia. *Clim Dev*. 2025;17(1):9-23.
14. Ganguly BB, Kadam NN. Understanding social determinants for children in difficult circumstances: an Indian perspective. *Int J Pediatr Child Heal*. 2016;4(2):77-88.
15. Domínguez-Serrano M, Moral-Espín L, Gough I. A capability approach to child well-being measurement. *Social Ind Res*. 2019;142(2):615-38.
16. Kim R, Kumar A, Singh P. Village-level variation in child development indicators in rural India. *Pop Dev Rev*. 2021;47(3):579-604.
17. Radhakrishna R, Ravi C. Multidimensional child poverty in India: Insights from National Sample Surveys. *J Pov Social Just*. 2016;24(2):137-55.
18. Bunders JF, Broerse J, Bunders-Aelen JFG. *Transdisciplinary Research in Health: Collaborative Approaches for Solving Complex Problems*. Springer. 2010.
19. Karvonen A, Cvetkovic V, Herman P, Johansson K, Kjellström H, Molinari M. The 'New Urban Science': Towards the interdisciplinary and transdisciplinary pursuit of sustainable transformations. *Urban Transf*. 2021;3(1):9.
20. Roser M. Human development index (HDI). Our world in Data. 2014. Available at: <https://ourworldindata.org/human-development-index>. Accessed on 3 June 2026.
21. Liu S, Yang A, Horm D, Zhu M, Cai C. Developing an early childhood environmental health vulnerability index to assess cumulative health impacts across contiguous US. *medRxiv*. 2026;7:21-3.
22. Pezzulo C, Tejedor-Garavito N, Chan HM, Dreoni I. A subnational reproductive, maternal, newborn, child, and adolescent health and development atlas of India. *Scientific Data*. 2023;10(1):86.
23. Singh A, Masquelier B. Continuities and changes in spatial patterns of under-five mortality at the district level in India (1991-2011). *Int J Heal Geog*. 2018;17(1):39.
24. Azam M. Accounting for growing urban-rural welfare gaps in India. *World Dev*. 2019;122:410-32.
25. Panda BK, Kumar G, Awasthi A. District level inequality in reproductive, maternal, neonatal and child health coverage in India. *BMC Publ Health*. 2020;20(1):58.

26. Das A, Ghosal J, Khuntia HK, Dixit S, Pati S, Kaur H, Ota AB, Bal M, Ranjit MR. Malnutrition and anemia among particularly vulnerable tribal groups of Odisha, India: needs for context-specific intervention. *Indian J Comm Med*. 2024;49(3):519-28.
27. Khadse RP, Chaurasia H. Nutrition status and inequality among children in different geographical regions of Maharashtra, India. *Clinical Epidemiol Global Health*. 2020;8(1):128–37.
28. Boro P. Childhood malnutrition and child marriage in Assam: Patterns and interventions. *J Indian Social Res*. 2025;12(1):45–62.
29. Singh A, Pathak PK, Chauhan RK, Pan W. Infant and child mortality in India in the last two decades: a geospatial analysis. *Plos nOe*. 2011;6(11):26856.
30. Saikia M, Mahanta R. An assessment of the nature and structure of institutions in the char areas of Assam, India. *Asian Ethnicity*. 2026;27(1):54-75.
31. Gogoi C, Das S, Senapati T, Narah U. Unravelling Assam's Water Woes: Exploring Floods, Erosion and Disaster Governance in the Brahmaputra Valley. *Indian J Publ Administr*. 2025;71(2):287-302.
32. Smith LC, Haddad L. How potent is economic growth in reducing undernutrition? What are the pathways of impact? New cross-country evidence. *Economic Dev Cultural Chan*. 2002;51(1):55-76.
33. Baruah S. Citizens and denizens: Ethnicity, homelands, and the crisis of displacement in Northeast India. *J Refugee Stud*. 2003;16(1):44-66.
34. Alkire S, Foster J. Understandings and misunderstandings of multidimensional poverty measurement. *J Econom Inequal*. 2011;9(2):289-314.
35. Booysen F. An overview and evaluation of composite indices of development. *Social Ind Res*. 2002;59(2):115-51.
36. Ben-Arieh A. The child indicators movement: Past, present, and future. *Child Indic Res*. 2008;1(1):3-16.
37. Mah JC, Penwarden JL, Pott H, Theou O, Andrew MK. Social vulnerability indices: a scoping review. *BMC Publ Heal*. 2023;23(1):1253.
38. World Health Organization. Handbook on health inequality monitoring: with a special focus on low- and middle-income countries. World Health Organization. 2013. Available at: <https://www.who.int/publications/i/item/9789241548632>. Accessed on 3 June 2026.
39. Mariani F, Ciommi M. Measuring human development: A systematic review of composite indicators. *Social Indic Res*. 2022;161(3):443–73.
40. Ravallion M. On multidimensional indices of poverty. *J Econ Inequal*. 2011;9(2):235-48.
41. Domínguez-Serrano M, Blancas Peral FJ. A gender wellbeing composite indicator: The best-worst scaling approach. *Social Indic Res*. 2019;142(2):849–73.
42. Christopher A, Gune S, Avula R, Nguyen PH. Coverage of nutrition and health interventions in India: Insights from the National Family Health Surveys. *Intl Food Policy Res Inst*. 2023;4:856.
43. Mahadevia G, Vikas M. International institute for population sciences (IIPS) and ICF. 2017. National family health survey (NFHS-4), 2015-16: India. Mumbai: IIPS. *Int Sci J Environ Sci*. 2012;21:7-15.
44. Gogoi P, Nath MJ. Spatial patterns and determinants of anaemia among women of reproductive age in Assam in Northeast India based on the National Family Health Survey 2019–2021. *Disc Publ Heal*. 2026;23(1):1142.
45. Das A, Ghosal J, Khuntia HK, Dixit S, Pati S, Kaur H. Malnutrition and anemia among particularly vulnerable tribal groups of Odisha, India: needs for context-specific intervention. *Indian J Comm Med*. 2024;49(3):519-28.

Cite this article as: Chakravarty N, Wit EE, Regeer B, Aelen JGFB. Mapping child vulnerability in India: where does the compass point. *Int J Contemp Pediatr* 2026;13:1299-309.