Measuring Access to Surgical Care in Rural India: Synthesis of Data and Novel Index

by

Siddhesh Zadey

Duke Global Health Institute
Duke University

Date:_______________________
Approved:

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Joao Ricardo Nickenig Vissoci, Advisor

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Catherine Staton

____
Tamara Fitzgerald

A thesis submitted in partial fulfillment of
the requirements for the degree of
Master of Science in the Duke Global Health Institute
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ABSTRACT

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Abstract

Background: Globally, 5 billion people lack timely access to safe and affordable surgical care, with over a fifth of them living in India. Solving India's surgical access issues can have high returns on investment. While healthcare access and unaffordability problems are well-known in India particularly among its rural people, research on surgical care is scant. This study attempts to fill the research gap through high-resolution nationwide estimates that have direct implications for India's national surgical plan.

Methods: Secondary data analysis with a diverse geospatial and statistical toolbox was used to create the national, state, and district-level estimates in four surgical care access dimensions. The four access dimensions were: timeliness (proportion of population within 2 hours of a surgical are facility), capacity (met surgical need for operative volumes), safety (proportion of post-operative surgical site infections), and affordability (proportion of surgery-seeking households facing catastrophic expenses). A novel composite index was introduced for assessing surgical access integrating the above dimensions. Distributional and spatial inequalities in access across Indian districts and states were measured to depict regions needing policy intervention. Correlations with Sustainable Development Goals (SDG) scores were computed. Validation and sensitivity analyses were conducted to check the robustness of the findings.

Results: Timely access to surgical care was achieved by > 99% of the rural population, but only 6.81% of surgical need was met. SSI proportion was 0.19% and 60.99% of surgery-seeking households faced catastrophic health expenditure. Heterogeneities in these dimensions were observed at state and district-levels. Significant rural-urban differences were observed in surgical care access dimensions and other considered surgical care variables. The Zadey-Vissoci Access to Surgical Care Index (ZV-ASCI) depicted limited access across several states and districts. Within-state distributional inequality in ZV-ASCI was about three times that of between-states. We found limited support for spatial autocorrelations and identified the low access district clusters. For aspirational districts, whose development is high on the national agenda, ZV-ASCI was not correlated with SDG composite score.

Conclusions: Our methodological workflow has high translational value for global surgery research in low-and-middle-income countries. For India, these are the first such nationwide findings that can direct the development of a National Surgical, Obstetric, and Anesthesia Plan (NSOAP). The proposed index can encourage buy-in from policymakers and raise surgical care on the global and national agenda.

Dedication

I dedicate the thesis in memory of my grandfather, Vinayak Paralikar, who taught me to love and live.

Contents

Abstract iv

List of Tables ix

List of Figures x

Acknowledgements xiii

1. Introduction 1

2. Methods 22

3. Results 48

4. Discussion 77

5. Conclusion 92

Appendix A 93

Appendix B 96

Appendix C 100

Appendix D 103

Appendix E 104

Appendix F 105

Appendix G 106

Appendix H 107

Appendix I 108

Appendix J 116

Appendix K...124

Appendix L..125

Appendix M...126

Appendix N...128

References...129

List of Tables

Table 1: Surgical access and other estimates relevant to India from LCoGS (2015)……...11

Table 2: Data sources used in the current analysis for India..24

List of Figures

Figure 1: Chance tree representation of the global surgical access (GSA) model adapted from LCoGS (1). ………………………………………………………………………...3

Figure 2: Selection of surgical care facilities for geodatabase. 32

Figure 3: Generic raster-based estimation pipeline used for creating criteria-specific regional population counts. 35

Figure 4A: Heatmap of travel times to nearest surgical care facility for India. 49

Figure 4B: Densigram of travel time values..50

Figure 5: Geographic variations in timeliness, i.e. % rural population within 2 hours of surgical care facilities at – A) district and B) state-levels. 51

Figure 6: Rural-urban differences in timely access to surgical care facilities at A) district and B) state-levels. 52

Figure 7: Geographic variations in rural surgical capacity, i.e. met need for major surgeries at – A) district and B) state-levels..54

Figure 8: Rural-urban differences in surgical capacity, i.e. met need for major surgeries at A) district and B) state-levels. 54

Figure 9: Geographic variations in met c-section need (at 10% threshold) for rural regions at – A) district and B) state-levels...56

Figure 10: Rural-urban differences in met c-section need (at 10% threshold) at A) district and B) state-levels. 57

Figure 11: Geographic variations in rural surgical safety, i.e. proportion of post-op surgical site infections (SSI) to all surgeries at – A) district and B) state-levels. 58

Figure 12: Linear correlations between log-transformed surgical site infections (SSI) and total surgical volumes for rural regions at – A) district and B) state-levels.......................59

Figure 13: Rural-urban differences in out-of-pocket expenditures (OOPE) per surgical case at A) district and B) state-levels. 60

Figure 14: Geographic variations in surgical care affordability, i.e. % rural households with surgical cases facing catastrophic health expenditures (CHE) (at 10% threshold) at – A) district and B) state-levels. 61

Figure 15: Rural-urban differences in surgical care affordability, i.e. % households with surgical cases facing catastrophic health expenditures (CHE) (at 10% threshold) at A) district and B) state-levels...62

Figure 16: Geographic variations in % rural households with surgical cases facing impoverishing health expenditures (IHE) at – A) district and B) state-levels. 63-64

Figure 17: Rural-urban differences in % households with surgical cases facing impoverishing health expenditures (IHE) at A) district and B) state-levels. 65

Figure 18: Geographic variations in rural Zadey-Vissoci Access to Surgical Care Index (ZV-ASCI) at – A) district and B) state-levels. 66

Figure 19: Scissor diagram showing the relationship between the mean and penalty terms of ZV-ASCI for states. 67

Figure 20: Variability in ZV-ASCI sensitivity estimates for the state of Maharashtra. 68

Figure 21: Lorenz curves for assessing ZV-ASCI distributional inequalities with A) districts and B) states, as units of analysis. 69

Figure 22A: Histogram of distribution of the number of neighbors. 70

Figure 22B: Connectivity graph for Indian districts. 70

Figure 23: Global Moran's I scatterplot for ZV-ASCI. 71

Figure 24: Spatial Correlogram for ZV-ASCI showing changes in spatial autocorrelation with over-distance. 72

Figure 25A: Significance map of Local Moran's I for district ZV-ASCI values based on multiple pseudo-p-thresholds. 73

Figure 25B: Corresponding cluster map depicting outliers and clusters of districts for ZV-ASCI.
....74

Figure 26: Correlation of state-level ZV-ASCI with A) Composite SDG Score (2018), and B) SDG Health Score (2018). 75

Figure 27: Correlation between ZV-ASCI and SDG Composite Score (2018) for aspirational districts. 76

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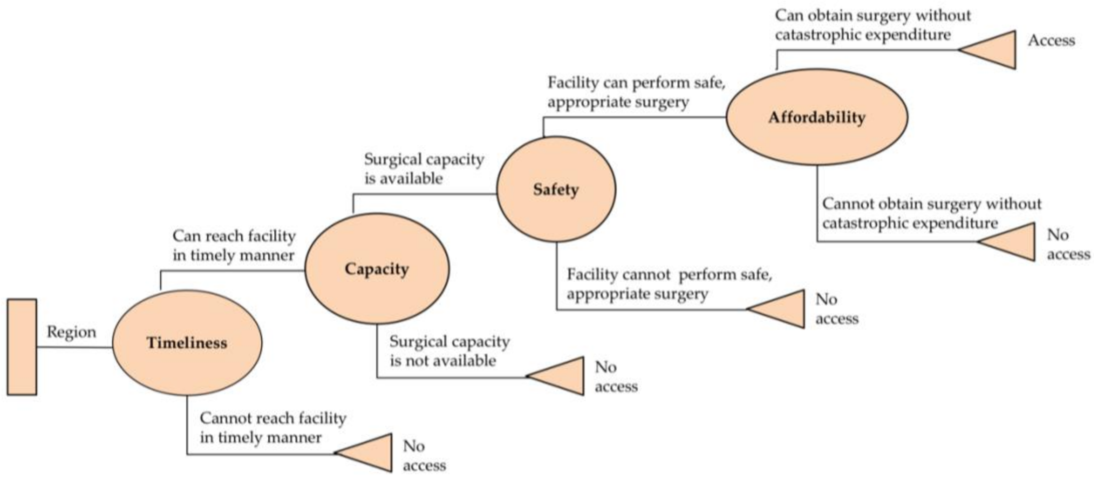
1. Introduction

In 2015, the Lancet Commission on Global Surgery (LCoGS) reported that 5.3 billion people globally lack timely access to safe and affordable surgical care (1,2). Of these, 3.3 billion people with no access to surgical care reside in low-and-middle-income countries (LMICs). In relative terms, 99.3% and 96.7% of people in low- and lower-middle-income countries lack access compared to 68.3% and 26.4% in upper-middle- and high-income countries. The disparity in access to essential and emergency surgery (3) is thought to be responsible for 4.7 million avertable deaths in LMICs (4).

1.1 Access to surgical care: concepts & estimates

Access to care as defined by the LCoGS is based on four ordered dimensions – timeliness to care, the capacity of the system, the safety of surgeries, and their affordability **(Figure 1)**. The premier model referred to as global surgical access (GSA), used the proportion of serious injuries transported by ambulance (timeliness - T), the proportion of met surgical procedures need (capacity - C), the proportion of operating theatres with pulse oximetry (safety - S), and proportion of surgery seekers protected from out-of-pocket (OOP) catastrophic health expenditures (CHE) (affordability - A) as proxies to estimate absolute counts and proportion of population lacking access to surgery (1). Data was collected for timeliness while estimated or modeled for others. This chance tree model calculated the joint probability of an individual in a country having access to surgery (1= has access, 0= no access) based on conditional dependence of access dimensions. At population-level inference, the probabilities translate to proportions, and multiplying these with country-level populations gave the absolute counts. Two tree models were run – baseline i.e. full tree (including four dimensions) and selective (four dimensions for rural populations but no timeliness dimension for urban population). As the authors acknowledge, the selective model underestimates access in rural settings. The investigators also conducted imputation, uncertainty, and extensive sensitivity analyses to assess robustness. Based on the full tree model, the authors found 5.3 billion [95% posterior credible interval: 5.0 - 5.5] people lack surgical access while the selective tree model found the number to be 4.8 billion [95% p-CI: 4.6 - 5.0]. Excluding affordability from the model and changing its proxy to include only direct costs were the only instance where the number of people with no access dropped below 4 billion. The GSA model depicted that the multidimensional approach leads to much higher estimates for people with no surgical care access than previously thought. It also demonstrated geographical differences in surgical access across the globe with 1 million (0.2%) people with no surgical access in high-income North America compared to 1636 million (99.1%) in South Asia. The limited data resolution prevented the model from creating subnational estimates for investigating differences across socioeconomic determinants such as rural vs. urban residence, wealth quintiles, education levels, and others.



$$P(Ac) = P(T \cap C \cap S \cap A)$$

$$P(Ac) = P(T) \times P(C|T) \times P(S|T, C) \times P(A|T, C, S)$$

where P(Ac) = probability of having access to surgery, P(A) = probability of affordable surgical care, P(C) = probability that surgical capacity is available, P(S) = probability that the surgery can be delivered in a safe manner, and P(T) = probability of timely access to surgical care

Figure 1: Chance tree representation of the global surgical access (GSA) model adapted from LCoGS (1).

Since its proposal, the GSA model has been adopted across different settings and populations (5,6). For instance, its adaptation was used to estimate the number of children and adolescents without access to surgical care globally (6). The investigators used the same proxies as the original model and assumed that they apply equally to children and adolescent populations. They found that 1.7 billion [95% CI: 1.6-1.8] children and adolescents lack access to surgical care with over 65% of them residing in LMICs. More starkly, 453 million children below 5 years do not have access to life-saving surgical care. Another study investigating orthopedic surgical care in five northern regions (NR) of Tanzania adapted the GSA model to the local context (5). Here, the proxies for capacity and affordability were chosen as in the original model, but timeliness and safety were estimated differently to better contextualize the dimensions. Timeliness was determined by creating <2 hours travel-time catchment areas around each hospital and estimating the proportion of the population within that catchment area compared to the total population. Safety was proxied by a sliding score created using multiple hospital indicators from the World Health Organization's (WHO) 'Tool for Situational Analysis to Assess Emergency and Essential Surgical Care' (7). The investigators conducted sensitivity analyses for timeliness and affordability, but not uncertainty analysis. The ability of the model to estimate surgical access at global and local levels along with the flexibility of the measurements used to proxy the access dimensions speak to its wide-ranging applications.

While elegant, the GSA model has certain limitations. First, the model does not truly capture the joint probability distribution of the dimensions. It creates binomial variables (0 or 1) for each dimension and reduces the joint probabilities to the marginal probabilities based on the simplified variables. The only 'true' conditional probability was calculated for $P(C|T)$ through the incorporation of adjustment factors derived through regression between $P(C)$ and $P(T)$. Hence, effectively, the model assumes conditional independence among most dimensions. While the description of the GSA model is unclear on how the covariance across the simplified dimension variables was mapped, the investigators clearly stated conditional independence across dimensions by calling the probability of access a "product of all four dimensions" (5). Second, it is unclear how the model decides the sequence of conditional probabilities (i.e. why $P(A)$ should be conditioned upon $P(T)$ than the other way around since it is plausible from the patients' perspective) or if other conditionalities could be better learned from the data. Third, estimation of joint probability distributions over multiple dimensions is often statistically difficult to conceptualize and computationally expensive due to the unknown data dependency (i.e. covariance) structures. Hence, modeling the current conception of GSA as a multivariate joint probability distribution is challenging, and adding any more dimensions in the future would only make the model more intractable. Fourth, the complex nature of the modeling exercise prevents easy application or interpretation, particularly for health policymakers and planners that may lack the necessary statistical background. Hence, there is a need for a transparent and simple way to summarize the surgical care access dimensions.

1.2 Access to Surgical Care Index (ASCI)

1.2.1 Need for index

A simpler way to summarize surgical access dimensions could enhance their use among researchers and policymakers. In recent years, synthesis and use of composite indices have generated large interest as depicted by the Human Development Index (8), Sustainable Development Goal (SDG) Index (9), Global Health Security Index (GHSI) (10), among 400 or so other indices used by global and local decision-makers. Such indices weight and aggregate multiple normalized indicators into a single metric for easy interpretation and reporting (details ahead in **Section 1.2.2**). Further, a well-constructed index can be used for intra- and inter-regional comparisons and dynamic monitoring over time. Hence, we propose that the construction of an access to surgical care index (ASCI) that incorporates the access dimensions can potentially be valuable for better integration of surgical care in the global and public health agenda.

An important policy output of the LCoGS was the set of six surgical care indicators that can be sued for evaluating the surgical system of a region and monitor the progress (11). In addition to the proxies for access dimensions for timeliness and affordability, the indicators include surgical workforce, surgical volumes (the numerator in the proxy for capacity), the peri-operative mortality rate (POMR), and impoverishing health expenditure (IHE) due to uptake of surgery. Conceptually, surgical workforce availability could be considered to proxy capacity, POMR for safety, and IHE for affordability. Hence, these indicators are an extension of the access dimensions. Country-level surgical care indicators have also been added for several countries to the World Development Indicators dataset, while the data for LMICs remains scant (12). Recently, subnational mapping of these indicators was conducted for Brazil (13), Colombia (14), and Uganda (15). Recommendations for the inclusion of surgical indicators in the health-related SDGs are on the rise (16). Our proposed ASCI can be extended to incorporate the surgical care indicators that are not access dimensions and included effortlessly in the SDGs akin to the universal health care service coverage index (UHC-SCI) (17).

Arguably, the most significant implementation offshoot of the LCoGS was the notion of National Surgical, Obstetric and Anesthesia Plans (NSOAPs) that could bring political attention to surgical care issues and advocate for the incorporation of surgery in the national health policy agenda (18). Recently, NSOAPs have been proposed for Zambia, Rwanda, and others to direct evidence-based participatory national surgical system strengthening (19). A quintessential step in developing an NSOAP is a comprehensive country-wide assessment of the surgical care system to benchmark the baseline and determine target achievement (19,20). The proposed index can help in easy benchmarking of progress from baseline and communication of evidence to involved stakeholders. While innovative and beneficial, the synthesis of any form of ASCI is contingent upon the estimation of surgical access dimensions at national and sub-national levels.

1.2.2 Framework for constructing a composite index

A composite index systematically combines multiple attributes or dimensions of a system or concept into a single metric that in turn is meant to act as a model for the system (21). Index construction is a multi-step process that can involve several stakeholders. To reduce subjectivity and manipulation, the Organization for Economic Co-operation and Development (OECD) has created a checklist for the process of conceptualizing and constructing an index (22). Even so, the objective methods rely on chosen assumptions. Furthermore, no particular methodological option is above criticism with all methods having merits and limitations. Therefore, it is crucial to provide transparent reporting of all involved steps and explicit choice rationale. The index construction involves the following steps (23):

1) The need for a composite index should be justified and the indicators used in it should be agreed upon by the stakeholders or rationalized by the index-makers using evidence at hand.

2) All indicators should be normalized and scaled so that they are comparable and can be combined.

3) The indicators should be weighted according to their relative importance or considerations about the pairwise trade-offs. There are main methods of weighting are – a) equal or no weighting, which is considered acceptable (or less controversial) in several instances (24), b) plural weighting systems that often rely on beliefs of the index-makers or the preferences of the stakeholders, and c) data-driven weights that affirm to be “more objective” as they are derived from the parameters of statistical models for correlation, regression, dimensionality reduction, or linear programming. Weighting has generated considerable controversy due to its ability to significantly change the inference (e.g. ranks in case of comparison analysis) even for the same set of indicators. Hence, weighted indices are susceptible to bias and manipulation. Recently,

optimization approaches have been suggested to explore the importance of weights and bridge them to the desired importance in the composite index (25).

4) Weighted (or unweighted) indicators should be aggregated to form the composite. Aggregation can follow a compensatory or non-compensatory approach. The compensatory approaches use averages where progress on one indicator can fully (linear) or partially (geometric) offset the deterioration on another – geometric having lesser compensability than linear average. The use of weights in the case of compensatory aggregation is difficult as the weights not only depict importance coefficients but also the trade-offs between the pairwise comparison of indicators. Non-compensatory multi-criteria (NCMC) approaches aggregate indicators where their weights act only as importance coefficients. They are less popular due to the complexity involved in the creation, higher computation costs, and their ability to provide only rank-based metrics that can be followed over time but no 'absolute' information.

5) The mixed approaches are not specific to the weighting or aggregating step but attempt to resolve the compensability problems by penalizing the imbalance between two indicators. A popular mixed approach is Mazziotta-Pareto Index (MPI) which is simple to construct and interpret and that penalizes the imbalance created by compensability in an unweighted linear average (26). Additionally, it can also help in comparison based on absolute information and its tracking over time (27). 6) Post-construction, the index should undergo robustness checks (equivalent to quality

assurance) to make sure that it is not overly sensitive to certain construction steps and assumptions. The uncertainty analysis (UA) looks at the changes in the outputs due to changes in the inputs while the sensitivity analysis (SA) investigates the variance in the output due to uncertainties. The stochastic multi-criteria acceptability analysis (SMAA) is another technique to deal with the uncertainties along the construction process. Most importantly, it helps to account for the plurality of weight vectors that can represent the beliefs or preferences of stakeholders from different communities. Recently, specification curve analysis has been proposed to test scientific hypotheses under a set of reasonable specifications instead of relying on a particular model (28). Such an analysis could also be useful for robustness checks of a composite index.

1.3 Evidence on Surgical Care in India

1.3.1 Insights from the LCoGS

Research accompanying LCoGS generated country-level data for access dimensions among several other variables as summarized in **Table 1**. In some instances, the data were aggregated at a higher level corresponding to World Bank Income Groups or Global Burden of Diseases (GBD) Regions. Erring on the higher side, <20% of the Indian population had access to surgery with around one-fifth of surgical needs met and >80% people facing the risk of catastrophic expenditure. India also depicted deficits in surgical volumes/rates and workforce. Further, it was estimated that at the current levels, it would be well beyond 2030 to reach the targeted surgical rates, denoting the need to integrate surgical care in the SDGs-2030. When compared to forgone macroeconomic losses, it is evident that investments in scaling up surgical care are beneficial.

Table 1: Surgical access and other estimates relevant to India from LCoGS (2015)

Reference and notes	**Measure**	**Estimate for India (or relevant region in absence of Indian estimate)**
Estimates modeled for South Asia(1) **Access to surgical care estimate**	Millions without access [95% CrI] Proportion without access [95% CrI] Millions without access (selective tree model) [95% CrI] Proportion without access (selective tree model) [95% CrI]	1636 [1594 – 1649] 99.1% [96.6 – 100] 1608 [1540 – 1642] 81% [74.5 – 86.9]
Estimates modeled for Southern Asia(29) **Relevant for Capacity Dimension and Surgical Care Indicator 3**	Minimum need - cases Met need - cases Minimum unmet need - cases Minimum unmet need rate - cases per 100,000 people Met-to-total need ratio	72,919,681 15,128,131 57,791,550 3582 0.21

Modeled estimate for India with per capita health expenditure as a predictor(30) **Relevant for Capacity Dimension and Surgical Care Indicator 3**	Average imputed number of operations per 100,000 people per year for 2012 The expected range of operations in 2012	904 9,801,319 – 12,556,488
Insurance claims data of 23 districts in Andhra Pradesh and Telangana from mid-2008 to mid-2012(31) **Relevant for Capacity Dimension and Surgical Care Indicator 3**	No. of surgical admissions Mean annual rate of major surgeries excluding cataracts and c-sections - per 100,000 beneficiaries [95% CoI] Annual per capita cost of surgical claims in USD [95% CoI]	677,332 259 [235 – 283] 1.49 [1.32 – 1.65]
Estimates modeled for India(32) **Relevant for Affordability Dimension and Surgical Care Indicator 5**	Risk of catastrophic expenditure if surgery is required - probability	~ 0.85 – 0.95
Data for 2009 from specialist	No. of surgeons (per 100,000 people)	31560 (2.5)

associations membership(33) **Relevant for Surgical Care Indicator 2**	No. of anesthesiologists (per 100,000 people) No. of obstetricians (per 100,000 people) Total SAO workforce (per 100,000 people)	20280 (1.6) 29310 (2.4) 81150 (6.5)
Country-level modeled estimates for the time taken to scale up, where actual rate of scale-up and costs are based on GNI per capita; Cost estimates provided at the income group level(34)	For India, year to reach 5000 operations per 100,000 people at - the average actual rate of scale-up (5.1% per year) aspirational Mongolian rate of scale-up (8.9% per year) aspirational Mexican rate of scale-up (22.5% per year) Costs of scaling up at actual rate in billion USD (2012) for LMICs - Total costs [95% UI] Surgical procedures [95% UI] Operating rooms [95% UI]	 2035 2025 2017 152 [95 – 224] 115 [79 – 169] 37 [7 – 90]
Modeled estimates for India for neoplasms, injuries, maternal, neonatal, and	Cumulative forgone GDP in millions (2010 USD, PPP) for all conditions % potential GDP secondary to surgical	1,795,914 1.51%

digestive disorders(35)	disease during 2015-30, VLO approach Economic welfare losses in thousands (2010 USD, PPP) for all conditions Losses by % of GDP 2010, VLW approach	808, 493, 541 14.74%

Footnotes: CrI = Credible Interval, CoI = Confidence Interval, UI = Uncertainty Interval, GNI = Gross National Income, GDP = Gross Domestic Product, USD = United States Dollars, PPP = Purchasing Power Parity, VLO = Value of Lost Output, VLW = Value of Lost Welfare

The LCoGS estimates were novel and fill in important gaps in the global surgery research, particularly for LMICs. Even so, in the Indian context, these estimates have limitations. Most of the data used for the estimates dated back to the late 2000s (2009 - for the workforce (33)) or early 2010s (2012 - for surgical volumes (30) used for surgical capacity analysis). At several instances data was not collected but imputed (e.g., proxies for safety and capacity dimensions) through modeled approximations for India. No subnational estimates were presented. In CHE-risk calculations underlying affordability, deliveries through cesarean sections (c-sections) were used to index essential surgery. While easy-to-use, c-sections have a complicated history in India's population health. Their rates and expenses are known to be much higher in urban areas and the private health sector compared to the rural and public sector counterparts (see **Appendix A** for a brief review). Several reasons ranging from differences in care-seeking behaviors to medical malpractice underly the inequities in India's c-section rates. Hence, looking solely at c-sections for benchmarking CHE can be problematic for India. Post-LCoGS, the Global Surgical Care Indicators Initiative reports (36,37) regularly update the six indicators. However, the two reports (2015 and 2017) published yet contain no new data on India.

Regardless of the limitations at the research end, the Commission generated enough momentum to bring together several national actors in India that could push forward the surgical care agenda. The Karad Consensus Statement (KCS) (2015) (38) framed initially by the Association of Rural Surgeons of India (ARSI) (http://www.arsi-india.org/) was endorsed by several stakeholders at the National Indian Surgical Forum (2016) (39). KCS identified that strengthening rural surgical systems, expanding and optimizing the surgical workforce, and tackling the blood deficit, particularly for rural locations should be a high priority for India. Subsequently, the 'Implementing The Lancet Commission on Global Surgery in India' (i-LCoGS-India) provided the action items towards sustainable resolution of the above-mentioned problems (40). Backed by the Commission and WHO and driven by local stakeholders from diverse backgrounds, i-LCoGS-India has two Secretariats in New Delhi and Mumbai and a field office in Bihar to facilitate the administrative and research goals arising from the ARSI-LCoGS-others collaboration. Access to surgical care in rural India is unequivocally the highest policy priority and in turn, requires urgent research focus.

1.3.2 Other evidence

Apart from the LCoGS, the Disease Control Priorities Network (DCPN) in its 3rd volume (DCP3) (2015) focused on essential surgery (3). DCP3 defined essential surgical conditions as that – a) are primarily or extensively treated by surgical procedures and other surgical care, b) have large health burden, and c) can be successfully treated by a surgical procedure and other surgical care that is cost-effective and feasible to promote globally. Surgical programs and packages catering to essential surgical conditions formed essential surgery. DCP3 provided comprehensive evidence on the cost-effectiveness and benefits of surgical scale-up in LMICs. Particularly for India, it reviewed the literature for various surgical platforms including cataracts, mosquito-net mesh hernia repair, etc., demonstrated that high benefit-to-cost ratio (BCR) of cleft-lip surgical repairs, and pointed to access problems in rural places due to surgical setup unavailability at health facilities lower than the district hospitals in the referral hierarchy.

Apart from the LCoGS and DCP3, surgical care access research for India has been scarce and scattered. Only one study till now has investigated the geographical accessibility at the national level to find that surgically-treatable acute abdominal mortality was significantly higher in people living >50 km from a well-functioning district hospital (41). However, this study did not consider the travel-time component, looked at mortality due to a specific cause, and included only government district hospitals from the outdated 2007-08 District-Level Household and Facility Survey (DLHS) data. Therefore, it did not truly measure timely access to surgical care. Small-to-medium scale regional studies have looked at surgical need in rural and urban areas (42–44). The national-level surgical need benchmark using data from a universal healthcare coverage (UHC) cohort (n = 88,273, Contributory Health Service Scheme (CHSS) members) was estimated to be 3646 procedures per 100,000 people (42). However, this cohort did not demographically and socioeconomically match the Indian population, excluded certain kinds of surgeries, and assumed no accessibility or acceptability issues. Two studies using the Surgeons OverSeas Assessment of Surgical Need (SOSAS) self-reports in low-income households in Ahmedabad city (n= 10,330 from 2066 households) (43) and rural Haryana (n= 93 from 50 households) (44) estimated the surgical need at 3.46% and 30.1% with unmet proportions at 42.33% and 6.5%, respectively. While useful, these estimates have low reliability for national-level planning and limited use for rural India. Two indicators, POMR and surgical site infections (SSI) have been studied extensively in the context of surgical safety. A recent systematic review compiling POMR evidence till 2015 from LMICs found 87 studies conducted in India with high heterogeneity for surgical conditions, procedures, study types, etc. thereby limiting a national-level meta-analytic estimate (45). The pooled SSI incidence in LMICs has been found to be around 11.8% (46). In India, small-scale studies have demonstrated variable SSI incidence (see **Appendix B** for review) with limited translation value for national decision-making. While comprehensive national-level studies investigating OOPE and CHE are popular for generic healthcare (47,48), studies specific to surgical care are limited. Only one study investigating the introduction of user charges in a district hospital in Haryana found a 5.6% prevalence of CHE in 180 surgery-seekers with an average OOPE of 4564 rupees (74.6 USD) (49). Hence, nationwide surgical access dimension estimates for India and specifically rural India are urgently needed to create a strong foundation for surgical planning.

1.4 The two 'India-s': Health in Rural Bharat

Regardless of growing urbanization, the most recent 2011 census revealed that about 833 million (68.84%) of the 1.21 billion Indians lived in rural areas (50). The colloquial saying is that India hosts two countries – the minority and materially-rich urban India and the majority and naturally-gifted rural *Bharat* (Hindi name for India). While India is steadily moving towards UHC, *Bharat* is thought to grapple for basic healthcare. The National Burden Estimates (NBE) demonstrated that, in 2017, rural India accounted for over 75% of all deaths and DALYs. The DALY rate (per 100,000) for all ages was 40,400 in rural areas compared to 27,400 in the urban counterparts (51). Among the top 15 causes of DALYs, rural areas have a greater burden of all causes except ischemic heart disease and musculoskeletal disorders, relative to urban areas. The stark rural-urban health differences can be attributed to a plethora of healthcare and socioeconomic differences and disparities.

Rural India faces deficits in access to healthcare (52), health infrastructure, and manpower (53) Further, the quality of health service delivery remains questionable in large parts of the rural public health system due to a lack of underlying resources and quality control processes. Hence, people in these areas often have to travel large distances to seek good-quality care in urban private hospitals forcing them to spend a larger proportion of their limited incomes on healthcare compared to the urban counterpart (54). As a result, rural households are at a significantly higher risk for CHE (47). Complementing the supply-side factors, the demand for health-seeking for rural households is also limited by lower education rates, higher unemployment, and greater poverty (55) compared to their urban counterparts, forcing the 'rural poor' to take the brunt (56). The problems of the rural health systems can only be expected to exacerbate for the rural surgical systems.

The National Rural Health Mission (NRHM) launched in 2005 (now subsumed under National Health Mission - NHM) has been instrumental in improving the rural public health infrastructure (57) and manpower (58), which, in turn, has enhanced accessibility and had some positive impact on affordability (59). To extend NRHM's promise of UHC for rural India, the Ayushman Bharat (AB) program was launched in 2018. AB has two objectives targeted by one component each – to expand the primary healthcare system through the creation and scale-up of Health and Wellness Centers (AB-HWCs) and to initiate comprehensive social health insurance (SHI) under the

Pradhan Mantri Jan Arogya Yojana (AB-PMJAY) for reducing OOP expenditure (OOPE) among the members of the deprived classes seeking good quality care at secondary and tertiary public and private hospitals (60). While it is too early to understand AB's impact, NHM has contributed to significant improvements in the population-level health outcomes particularly for maternal and child health and communicable diseases (61). However, its contribution specifically to rural surgical care remains elusive, or largely unassessed.

It could be speculated that a large proportion of the rural DALYs could be surgically averted and that surgery is the largest contributor to rural OOPE and CHE, making surgical care an important focus of research and policy. Paradoxically, rural India is a neglected population in global surgery research although being of high interest in the Indian health policy and planning domains pointing to a chasm that needs urgent addressing.

1.5 Rural surgical care in India: Behind the hour

To ensure UHC for India, it is essential to bring UHC to its rural people. UHC cannot be achieved without adequately attending to surgical care, a critical and integral component of any healthcare system. A comprehensive NSOAP could lay out the roadmap and targets for rural surgery in India, however, such a plan would require robust nationwide evidence. As pointed before, there is negligible data on rural surgical care with no high-resolution nationwide assessment. India is running behind the hour when it comes to generating evidence to strengthen its rural surgical care. The aims of this study are directed towards filling the critical evidence gap. The first two aims fill in the research gap on the topic while the other two aims are policy-oriented. For clarity, the study aims can be described as follows:

Aim 1: To synthesize national and subnational (district and state-level) estimates for surgical care access dimensions for rural populations of India for 2017-2018.

Aim 2: To create and apply a novel composite index (referred to as – Zadey-Vissoci Access-to-Surgical Care Index or ZV-ASCI ahead) for measuring surgical access in rural India.

Aim 3: To conduct a formal inequality analysis of ZV-ASCI to highlight the regions requiring greater public investment and policy attention.

Aim 4: To assess the performance of the Indian states and the special districts included in the 'SDG Aspirational Districts Programme' (62) for surgical care access to inform the integration of surgery in SDG targets. The high-level government policy think-tank National Institution for Transforming India (NITI) Aayog in 2018 listed 101 districts needing a developmental boost. The program aims to expedite development in these districts through mass movement and competition to bring them to the level of best-performing districts in their states.

2. Methods

2.1 Data Sources

A significant study product of the current study is assimilating data from eclectic international, national, and subnational sources. Identification and compilation of relevant data sources and the methodological workflow for harmonization have high value for surgical care and health systems research in LMICs. **Table 2** presents a detailed list of data sources and data use considerations. Our secondary data assimilation workflow can be described as:

1. We identified the contextually relevant proxy variables for the surgical care access dimensions based on a literature review that match closely with those used in the original GSA model.
2. Other (non-surgical) variables required for calculating the access dimensions were enlisted. For instance, population aggregates at the requisite geographic resolution, poverty line thresholds, etc.
3. We reviewed data contingencies of high-level national health reports, census data, household surveys, nationally representative sample surveys, health registries, and the country's health management information system (HMIS) to identify the required variables. While tedious, this step was critical to ensure that 'most appropriate' data are used to create the estimates. For

instance, we decided to use HMIS over sample survey data for surgical volumes as HMIS is supposed to have wider coverage, regular (monthly) upkeep, and greater utility towards local health planners. Cross-dataset variable enlisting also points to variable overlaps and data collection heterogeneities. Similar variables recorded across different datasets can aid validation. For instance, we compared the c-section volumes across HMIS and the corresponding National Family Health Survey-4 (NFHS-4) estimates from another study (63), helping us validate HMIS data.

4. We assessed the data quality by reviewing literature previously citing the data sources. Understanding the source limitations early on helps in designing analyses that could accommodate limitations. Here, knowing that National Sample Survey (NSS) underestimates the state-level expenditure projections for smaller states/ union territories (UTs) (64) leading to large error estimates helped us demonstrate caution for affordability estimates.
5. We assessed the highest possible geographic resolution and a common period across data sources for reliable large-scale situational analysis. Here, we identified districts to be geographic-administrative units of the highest possible resolution and the years 2017-2018 suitable for situational analysis. The HMIS data used for surgical capacity and safety dimensions was obtained for April 2017 to March 2018 while the NSS data used for the

affordability dimension was obtained from the survey conducted from July 2017 to June 2018. 2017 population estimates were used for all calculations.

Table 2: Data sources used in the current analysis for India.

Data source	Source information	Extracted data and considerations
WorldPop (65) (India files)	It is a global high-resolution geospatial population datasets library with well-characterized and validated estimates (66).	Raster (.tif) for UN-adjusted unconstrained population counts (people per pixel) at 1 km^2 resolution for India for 2017 (67). These were used for population estimation.
GADM version 3.6 (68) (Indian boundaries)	It is a data repository for administrative boundaries standardized across countries that is commonly used in GIS studies.	Shape boundary files (with associated polygon data frames) for India (admin level = 0), Indian states (admin level = 1), and districts (admin level = 2). State boundaries do not depict the administrative split of the state of Jammu and Kashmir into two UTs – Jammu & Kashmir and Ladakh. District boundaries do not include all districts present in other Indian data sources. 39 and 29 districts present in HMIS and NSS had no matches in GADM,

		respectively. A detailed list is presented in the corresponding dataset file (see **Appendix D**). Such districts were excluded from the current analysis. Data were used in all visualizations and for creating unique IDs for cross-referencing districts and states between datasets.
URCA (Urban-Rural Catchment Areas) raster (69)	The recent study presented global raster with ordinal catchment area categories based on population densities and nearness to high-density urban centers. Hence, this dataset can help in generating globally standardized rural-urban regions and populations.	Global raster (.tif) of 1 km^2 resolution and each pixel representing catchment area category label. We defined binary categories: rural for CA category label > 7, while urban for CA category label from 1 to 7. Details on category are presented in the ReadMe accompanying the original dataset (69). Data was used in population estimation.
The Malaria Atlas Project (MAP) (70)	MAP provides global friction surface rasters for different transportation modes that have been previously used and	We used the explorer (73) to retrieve the 2019 accessibility friction surface motorized transport raster for India. The R script for calculating values

	validated for accessibility to urban centers (71) and healthcare facilities (72). MAP also provides an R script to get travel-time values from the accessibility raster.	travel times from the raster was retrieved from (74). Generated data was used in the analysis of timely access to surgical facilities.
National Health Profile (NHP) 2019 (75)	It is an apex-level comprehensive annual health report published by the Central Bureau of Health Intelligence (CBHI) that includes an updated list of public, private, trust (non-profit) medical schools, referred to as teaching hospitals.	All teaching hospitals are tertiary care facilities that provide surgical care. The data was extracted from PDFs and addresses were geocoded using both manual and machine/API-based approaches. This dataset was also used for the validation of machine-based geocoding. Generated data were used in the analysis of timely access to surgical care.
National Identification Number (NIN) health facilities directory 2017	Publicly available geocoded dataset of healthcare facilities provided by Ministry of Health and Family Welfare (MoHFW) on national data portal (77).	The datasheet (.csv file) was downloaded from the portal. We determined surgical care facilities based on facility types – bedded hospitals, facilities from community

(76)		healthcare centers and above in the public health system referral hierarchy, maternity homes, etc. See **Figure 2** for the complete list. Almost all facilities had geocodes. However, codes for 5 surgical care facilities were completed manually. Generated data were used in the analysis of timely access to surgical care.
Pradhan Mantri Jan Arogya Yojana (PMJAY) empaneled hospitals (78)	PMJAY is the largest social health insurance scheme in India launched in 2018. The National Health Authority (NHA) maintains an online publicly available list of empaneled hospitals that is regularly updated.	We web-scrapped the list of active empaneled hospitals in January 2021. Geocoding was conducted through API. Hospitals with at least one surgical care package in empaneled or upgraded specialties were considered under surgical care facilities. Generated data were used in the analysis of timely access to surgical care.
Central Government	CGHS dataset includes are hospitals and dispensaries in	Data was extracted from city-wise PDF files to create datasheets.

Health Scheme (CGHS) empaneled hospitals (79)	over 70 cities providing subsidized care to government employees and retirees. A list of empaneled facilities is maintained online public resource.	Geocoding was conducted through API. Facilities were classified to provide surgical care based on their listed domains (see **Figure 2**). Generated data were used in the analysis of timely access to surgical care.
Health Management and Information System (HMIS), India (80)	HMIS captures facility-wise health statistics for the entire country. The HMIS Standard Reports publish monthly subdistrict data for several variables for each financial year.	We extracted the surgical care variables relevant for capacity and safety domains for the period April 2017 – March 2018 and aggregated over subdistricts and months to get district-level annual estimates that were in turn used for state and national aggregations. Variables were partitioned by rural, urban, public and private along. We were interested in rural, urban, and total values. Data were managed and wrangled on the Google BigQuery cloud platform (81). Some districts that did not match with GADM were

		excluded from the analysis for consistent calculations and visualization. A detailed list of such districts is presented in the corresponding dataset file (see **Appendix D**).
National Sample Survey (NSS) 75th Round on Social Consumption in Health (July 2017 – June 2018) (82)	Nationally representative sample survey with >95% geographical coverage conducted by Ministry of Statistics and Programme Implementation. The 75th round surveyed health expenditures.	We extracted data from the household files for surgery-related health and overall household expenditures (see **Section 2.2.3.4** for details). Data were managed and wrangled using the Google BigQuery cloud platform (81). Upsampling for the district, state, and national estimates was conducted using the NSS statistical manual (82) in BigQuery. Generated data was used for analyzing the affordability dimension.
Guilmoto and Dumont (2019) (63)	The article presents state-level c-section proportions relative to institutional deliveries and	Data in the article's Table 2 was extracted from the PDF file for comparison with corresponding

	sampled births using data from National Family Health Survey-4 (2015-16).	values from HMIS in the overlapping period (see **Sections 2.2.3.2 and 2.3.4** for details).
Reserve Bank of India (RBI) – poverty lines (83)	2011-12 state and all India poverty lines based on mixed reference period in Indian National Rupee (INR).	Data was extracted from a PDF table and used in impoverishing health expenditure analysis.
Census-based 2017 population projections (84)	The National Commission on Population reports mid-year state-level population projections for 2011-36. These are arguably the most reliable population projections for India.	We extracted state-level projections from PDF files for 2017 to compare with corresponding raster-based population estimates (see **Section 2.3.4** for details). Populations for Jammu and Kashmir and Ladakh from the report were combined under Jammu and Kashmir.
National Institution for Transforming India (NITI) Aayog SDG 2018 baseline dataset (85)	The government policy think-tank NITI Aayog in 2018 created a baseline report for SDG scores for Indian states to help monitor subnational SDG achievement. The health SDG score for India comprises maternal mortality	We obtained datasheets (.csv files) for state-level SDG overall composite and health (SDG-3) scores to check association with access to surgical care index (see **Section 2.3.3** and **Introduction Section 1.5**).

	ratio (MMR), under-5 mortality rate (U5MR), child immunization coverage, tuberculosis notification rate, and health workforce density.	
NITI Aayog Aspirational Districts Programme baseline 2018 dataset (62)	NITI Aayog in 2018 created baseline scores and ranks for 101 districts needing a developmental boost. The program aims to expedite development in these districts through mass movement and competition to bring them to the level of best-performing districts in their states.	SDG composite scores and ranks were extracted from the PDF file. Two districts that did not match with GADM were excluded. The scores were used for correlation with access to the surgical care index (see **Section 2.3.3** and **Introduction Section 1.5**).

2.2 Data Variables

2.2.1 Geocoding surgical care facilities

Multiple databases were assessed for extracting geolocation data on surgical care facilities **(Figure 2)**. We included four datasets where information on surgical provision could be easily ascertained. Surgical care provision for private facilities was determined by the domain information. We assumed secondary care level facilities (community health centers - CHCs) and those above in the referral hierarchy in the public health system to be capable of providing surgical care (3,86).

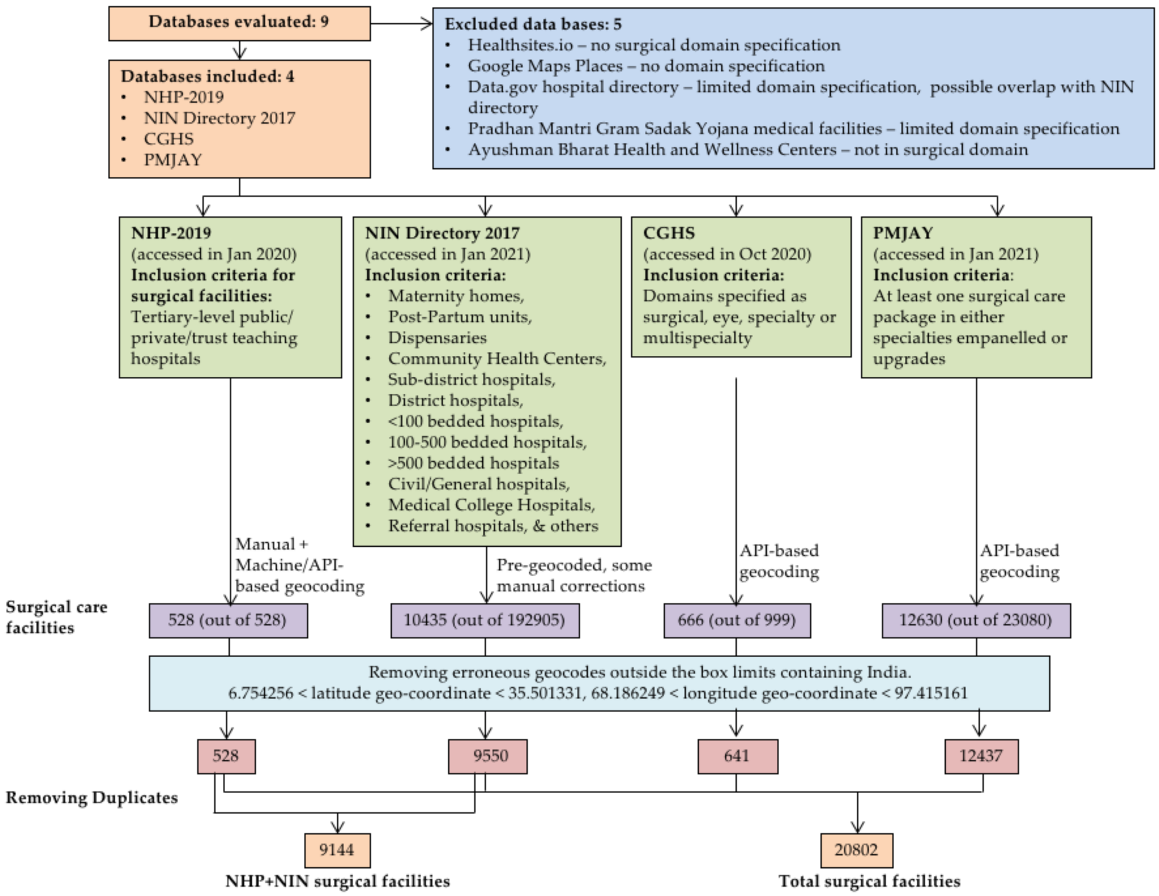


Figure 2: Selection of surgical care facilities for geodatabase.

For geocoding, addresses were cleaned manually for easier machine readability. City, state, and country names were added where needed. We used the Google Maps Platform application programming interface (API) (87) and the 'Awesome Table' add-on (88) for Google Sheets for machine or API-based geocoding. For places where multiple sets of coordinates were returned, those with the most relevant returned address string were chosen. Places without geocodes were tried again manually in Google Maps. Erroneous points identified as those beyond the latitude-longitude box limits around India were removed (see **Figure 2**). The above steps were conducted for each database followed by merging. Duplicates within and across databases identified on the basis of geo-coordinates were removed. One small dataset (NHP-2019) was also manually geocoded using Google Maps. We compared the manual and machine (Awesome Table) generated geocodes for this dataset as part of validation (see **Section 2.3.4**).

2.2.2 Rural-Urban population estimation

We used raster-based (rectangular grid of pixels) analysis for creating high-resolution population estimates **(Figure 3)**. The analytical choice was made due to missing district-level 2017 Indian population estimates for rural areas. Hence, district and state-level population aggregations were created for rural areas by partitioning the WorldPop population counts as per the rural-urban dichotomization of catchment areas derived from the multiple catchment area (CA) categories in the URCA dataset (69). We defined CA categories >7 in URCA's category label classification as rural. Rural populations were estimated as follows – first, the global multi-category URCA raster (1 km^2 resolution at the equator, pixel = agglomeration category label value) was clipped to the Indian national boundary (admin level-0). Next, the raster was reclassified into two categories: urban (URCA agglomeration and CA labels ≤ 7) and rural (URCA agglomeration and CA labels > 7). Further, the binarized rural-urban CA raster for India was overlayed on the WorldPop 2017 Indian population counts raster (1 km^2 resolution at equator, pixel = population count) (65). The CA raster was resampled to align the origin and match the extent and resolution of the population raster. The rural population at each pixel was calculated by multiplying the categorical value (1 for rural areas in the rural raster) with the persons per pixel values. Put otherwise, all urban population was weighted by ‘0’ in the rural raster. Similarly, rural CAs were weighted by ‘0’ in the urban raster. Hence, separate rural and urban population rasters were created for India. State (admin level-1) and district (admin level-2) boundaries were imposed on the total, rural, and urban population rasters. Population aggregates (summations) within the boundaries were extracted as district and states population counts. Finally, state-level populations were validated against the Census-based rural, urban, total mid-year population projections for 2017 (84) (see **Section 2.3.4**).

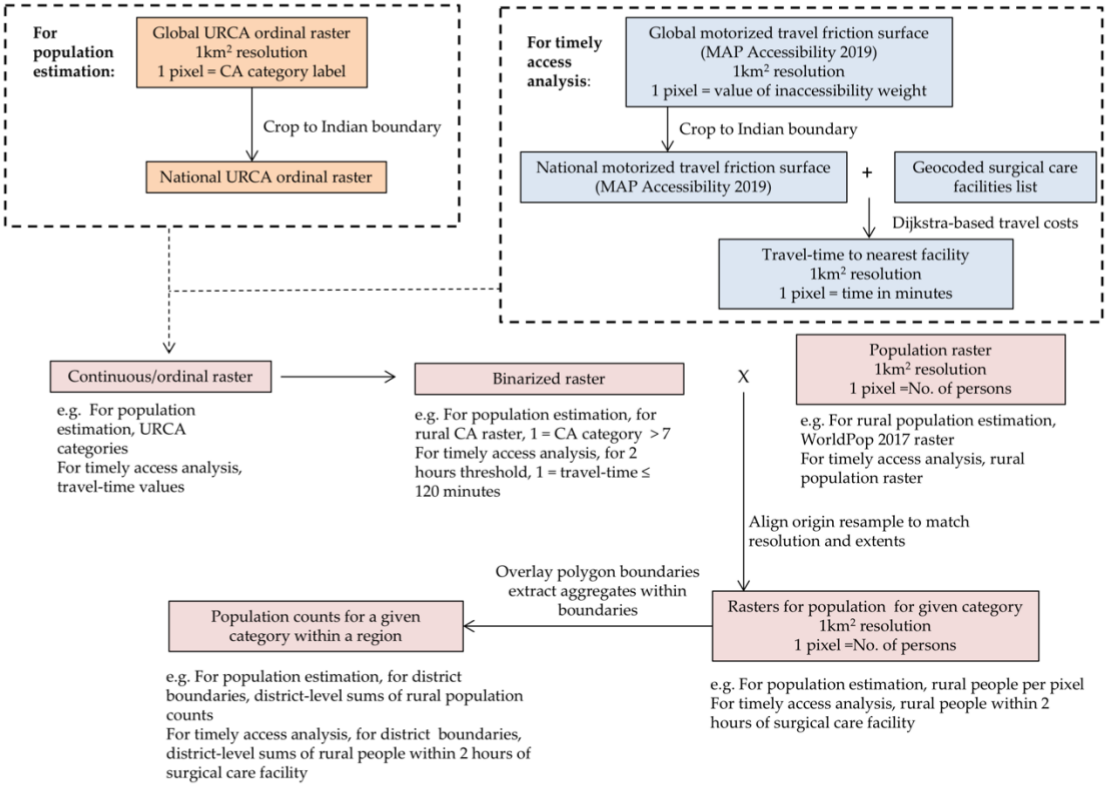


Figure 3: Generic raster-based estimation pipeline used for creating criteria-specific regional population counts.

2.2.3 Surgical Care Access Dimensions

2.2.3.1 Timeliness

Proportion (%) of the rural population within 120 minutes (2 hours) of their nearest surgical care facility was chosen as the primary proxy variable for the timeliness dimension (37). We obtained the 2019 accessibility motorized friction surface raster cropped for India from MAP) Explorer. Travel times (in minutes) were calculated for surgical care facilities from each raster grid cell within India using previously described methods (72). Briefly, we created a geo-corrected transition matrix for the supplied friction surface. Next, we rearranged the list of the surgical care facilities' geocoordinates into a matrix form. Finally, we calculated the minimum least-cost (in terms of time taken) required to traverse the friction surface from every pixel (grid cell) on the map to every set of facilities geocoordinates based on the implementation of the Dijkstra algorithm (89). To get population proportions, a similar process was followed as described above for rural-urban populations **(Figure 3)**. Briefly, binary accessibility raster was created with '1's for pixels within 120 minutes of their nearest surgical care facility and '0's for cases otherwise. This raster was overlayed on the rural population raster (extent matched) and population values at each pixel were multiplied with the weights (i.e. 1s and 0s) to get the rural population within 120 minutes of travel time. Imposing the administrative boundaries allowed us to extract the district and state-wise populations. These populations were divided by the respective overall rural populations to get the proportions, also expressed in percentages. Additional proxy variables were used for sensitivity analyses (see **Section 2.3.5**) that were calculated similarly to the steps above.

2.2.3.2 Capacity

The met surgical need was used as the proxy for surgical capacity. For a given region (district, state, or country-level), the surgical rate was defined as the number of surgical operations (OPs) conducted per 100,000 people in the region. Met need was defined as the ratio of observed surgical rates to the threshold of 5000 surgeries per

100,000 people (29,90). For the primary analysis, we used the volumes of major surgical OPs (those requiring general or spinal anesthesia) (36) from the HMIS (April 2017-March 2018) for rate and need calculations. For sensitivity analyses (see **Section 2.3.5**), we also calculated the need based on rates for total surgeries (major and minor- not requiring anesthesia) and select major surgeries excluding gynecology (OBGYN) and ophthalmic procedures. For all rate calculations, we used the 2017 raster-estimated populations. C-section proportions w.r.t. institutional deliveries were also calculated. The met need for c-sections was calculated as the ratio of c-sections as the proportion (%) of institutional deliveries relative to the WHO prescribed 10% and 15% thresholds (91). Additionally, we calculated absolute need gaps (i.e. threshold - value) for surgical rates and c-section proportions.

Since this is one of the first instances using HMIS in research, we compared the state-level estimates for two c-section proportions (relative to births and institutional deliveries) from HMIS (January 2015 - November 2016) with corresponding NFHS-4 estimates obtained from (63). This period was chosen to match closely to the data collection period of NFHS-4 (20^{th} January 2015 – 4^{th} December 2016).

2.2.3.3 Safety

The proportion (%) of post-operative surgical site infections (SSI) relative to the total surgical operation volumes as obtained from HMIS was used as the primary proxy for surgical safety (S). Additionally, the ratio of SSI to major surgeries was used for sensitivity analysis (see **Section 2.3.5**).

2.2.3.4 Affordability

Proportion (%) of households with at least one surgical hospitalization in the last 365 days facing catastrophic health expenditure (CHE) out of all such surgery-seeking households was used as the primary proxy for affordability. The above proportion was calculated as follows: (a) Households with at least one surgical hospitalization in the last 365 days were identified in the NSS-75 conducted from July 2017- June 2018. (b) For such households, total costs (in INR- Indian National Rupee) corresponding to the hospitalization were calculated as the sum of the cost of the treatment package components, doctor's or surgeon's fees, medicines, diagnostic tests, bed charges, other medical expenses (attendant charges, physiotherapy, personal medical appliances, blood, oxygen, etc.), transport for the patient, other non-medical expenses (registration fee, food, transport for others, expenditure on the escort, lodging charges if any, etc.) (c) The OOPE was calculated as the total costs after removing the total amount reimbursed by medical insurance company or employer. (d) In the primary analysis, the CHE threshold was defined as 10% of the annual household consumption expenditure (32,47,92). A household was considered to face CHE if the surgical OOPE exceeded the threshold. In the sensitivity analyses, 25%, 40%, and 60% of the annual household consumption expenditure were tested as thresholds (see **Section 2.3.5**). (e) Proportions (presented as percentages) were calculated as the number of households in (d) relative to those mentioned in (a). Further, the proportion of CHE-facing surgery-seeking households out of all households in a region (district or state) was also calculated. We also calculated similar proportions (as described in (d)) for households facing impoverishing health expenditures (IHE) (37). The calculations followed a similar approach as above with different threshold definitions. For IHE, thresholds were the rural-urban area-specific state-level poverty lines (in INR) (83) for a mixed reference period that have been previously used elsewhere (93). Here, we calculate the proportion of households that fell below the poverty line after surgery in addition to the below-poverty-line households pushed further into impoverishment.

2.2.4 Zadey-Vissoci Access to Surgical Care Index (ZV-ASCI)

Index creation involves defining the concept to be assessed, choosing, normalizing, and aggregating individual indicators, and validating the composite index. We define the Zadey-Vissoci access to surgical care index (ZV-ASCI, pronounced 'Zvasky') as the composite of four individual dimensions – timeliness to surgical care, surgical capacity, surgical safety, and affordability of care that captures the concept of access to surgery introduced by the LCoGS (1). We wanted ZV-ASCI to be:

1. Non-compensatory or partially compensatory i.e. improvement in one dimension should be substituted by the depreciation in another dimension. The aggregation should penalize the unbalance. From a health systems

perspective, this assumption is critical as it forces the policymakers and planners to realize that increase in surgical rates cannot happen at the cost of safety. Hence, it makes the index less prone to 'hacking' by an undue focus on a single access dimension.

2. Easily computable and interpretable. While several approaches can create non-compensatory composites, they often require inaccessible statistical methods that are difficult to conduct and interpret for the wider health audience. This is particularly critical for the acceptable integration of surgical care in the wider SDG framework with greater involvement from inter-disciplinary global stakeholders.
3. Comparable across space and time. Absolute comparability requires that the index value be dependent on exogenous parameters such as pre-assigned minimum and maximum bounds for individual dimensions. Rescaling is a common approach used for such normalization. The assumption is crucial as the primary purpose of introducing an index is to allow national and subnational comparisons by high-level policymakers and funders and monitoring of regional progress over time by local planners.

Hence, we considered an adaptation of the adjusted Mazziotta-Pareto Index (AMPI) methodology (26,27) that satisfies the above assumptions for constructing ZV-ASCI. Before describing normalization and aggregation procedures, it is noteworthy to mention the idea of the polarity of individual access dimensions. The polarity of a variable is positive (negative) if its greater value is desirable (undesirable). The proxies for timeliness and capacity have positive polarity while those for safety and affordability have negative polarity. The polarity of the composite ZV-ASCI is supposed to be positive.

The normalization can be described as –

For matrix $X = \{x_{ij}\}$ with i observations and j individual positive polar dimensions, normalized matrix $R = \{r_{ij}\}$ is calculated as:

$$r_{ij} = L_j + \left(\frac{x_{ij} - x_{2.5^{th}}}{x_{97.5^{th}} - x_{2.5^{th}}}\right) \times \left(U_j - L_j\right) \qquad (Eq. 1)$$

Where,

L_j = Lower limit for the possible values of dimension j

U_j = Upper limit for the possible values of dimension j

We set the upper and lower limits as 0 and 100 in the current analysis reducing Eq. 1 to:

$$r_{ij} = \left(\frac{x_{ij} - x_{2.5^{th}}}{x_{97.5^{th}} - x_{2.5^{th}}}\right) \times 100 \qquad (Eq. 2)$$

For dimensions with negative polarity, the complement of Eq. 2 was considered. Values below 0 and above 100 in the normalized dimensions were censored to these limits. Using the 2.5^{th} and 97.5^{th} quantiles and censoring makes the normalization robust to outliers. Hence, our normalization scheme is different from the original goal-posts approach used in AMPI.

Aggregation for the positive polar ZV-ASCI can be described as –

For a normalized observation r_i:

$$ZV - ASCI_i = \mu_{r_i} - \left(SD_{r_i} \times CV_{r_i}\right) \qquad (Eq. 3)$$

Where,

μ_{ri} = mean of the normalized values for i

SD_{ri} = standard deviation of the normalized values for i

CV_{ri} = coefficient of variation i.e. ratio of standard deviation to the mean of the normalized values for i

Censoring was also applied to ZV-ASCI so that the final index values fell in the 0-100 range with greater value depicting better surgical care access. Inclusion of the penalty term (SD_{ri} x CV_{ri}) term in the aggregation rewards the units (districts or states in our case) with greater balance among dimensions or smaller variability (26). This approach is advantageous over geometric mean that tends to underestimate the aggregate index. To present a non-controversial version of the index, we did not consider any weights (24).

2.3 Statistical Analysis

All statistical analysis except that for spatial inequality was conducted in RStudio (Version 1.3.1056) using user-created and validated R packages (94). A detailed list of used packages is provided in **Appendix C**. GeoDa platform (version 1.18) (95) was used for calculating spatial statistics. For scrapping values from reports, we used Abbyy

FineReader (96), ExtractTable (97), and Tabula (98). Tools used for geocoding are reported above. Links to the input datasets, analytical scripts, and generated data are presented in **Appendix D**.

2.3.1 Rural-urban comparisons

Given the known skewed data distribution, we used non-parametric pair-wise Wilcoxon tests adjusted for multiple comparisons (Holm-Bonferroni correction) to investigate rural-urban differences for various surgical care variables at state and district-levels. We used the conventional 5% threshold for determining statistical significance. No analysis was conducted for post-operative SSI proportions, any variables involving select major surgeries due to missing data for urban areas in HMIS.

2.3.2 Inequality analysis

We assessed the distributional and spatial inequalities in ZV-ASCI across regions. Inequality assessment was conducted through two methods. First, traditional econometric Theil (T_T) (99) and extended (i.e. decomposable) Gini indices (100) were used to evaluate distributional inequalities with states and districts as analysis units. For district analysis, the overall inequality was decomposed into within and between state components. Theil index ranges from 0 to ∞ with greater values depicting greater inequality in distribution. Gini index ranges from 0 to 1 with 0 depicting perfect equality among units and 1 depicting perfect inequality (i.e. one unit receiving all share of the measured resource). Decomposed Gini also has an overlap component along with between and within state inequality contributions. Lorenz Curves were also constructed for both state and district analyses.

Next, we used the global and local Moran's I statistics to compute the spatial autocorrelations for districts. Similar to the Pearson correlation coefficient, global Moran's I range from -1 to 1 with greater positive (negative) values depicting greater positive (negative) spatial autocorrelation (101). We used the symmetric weights matrix created using Queen's contiguity criteria. Global Moran's I scatterplot was constructed to visualize the association between the index value of a district and the corresponding spatial lag. We tested the significance of spatial autocorrelation based on pseudo-p-values using 99,999 permutations (i.e. permutation inference) (see (102) for tutorial). Additionally, we used a spatial correlogram (103) to assess the changes in spatial autocorrelation of ZV-ASCI over distance (in km). Maximum distance binned by 10 with 99,999 permutations were used for correlogram.

Local Moran's I (also known as a local indicator for spatial association or LISA) is similar to the global Moran's I except that evaluation is conducted over the values of the neighboring districts and not all districts (104). Hence, Local Moran's I can depict the actual positions of the clusters. In case of the scatterplot, the points in quadrant I (high-high clusters) depict districts with high ZV-ASCI surrounded by others with high ZV-ASCI. Similarly, quadrants II, III, and IV in the scatterplots represent low-high (low ZV-

ASCI district surrounded by high ZV-ASCI neighbors) outliers, low-low clusters, and high-low outliers, respectively. To identify clusters and outliers, the significance of Local Moran's I was tested at pseudo-p-thresholds of 0.05, 0.01, 0.001 with 99,999 permutations. For sensitivity, we also conducted analyses using significance thresholds based on Bonferroni bound and false discovery rate (FDR) corrections (see (105) for tutorial).

2.3.3 Correlation analysis

We used Pearson's product-moment correlations (*R*) to check the extent of association between given variables. Conventional thresholds of 0.10, 0.30, and 0.50 were followed for denoting small, medium, and large correlations. We used the conventional 5% threshold for determining statistical significance.

We assessed if reduced safety (i.e. greater SSI incidence) was associated with a greater burden in terms of absolute surgical volumes. Correlation analyses at the state and district-levels were conducted for log-transformed values of surgical volumes and SSI due to the non-normality of distributions.

We computed correlations for ZV-ASCI with the composite and health-specific (i.e. goal 3) SDG scores (2018) for states. A similar analysis was conducted for ZV-ASCI and SDG composite scores (2018) for the aspirational districts (see **Introduction Section 1.5, Aim 4**).

2.3.4 Validation of estimates

Validation in the form agreement analysis was conducted using Lin's concordance correlation coefficient (CCC) (106). Agreement was categorized as almost perfect for CCC > 0.99, substantial for CCC $\in$ [0.95-0.99], moderate for CCC $\in$ [0.90-0.95), and poor for CCC < 0.90 (107). The analysis was conducted for (a) the raster-estimated total, rural, and urban state populations vs. the corresponding Census-based mid-year projections for 2017 (84), (b) API or machine-generated vs. manual geocodes (latitudes and longitudes coordinates) for teaching hospitals from NHP-2019, (c) state-level c-section percentages relative to births and institutional deliveries from HMIS (January 2015-November 2016) vs. corresponding NSFH-4 based values (63).

2.3.5 Robustness checks

We conducted extensive sensitivity analyses to assess the impact of using different proxies for dimensions on ZV-ASCI. For timeliness, proportions of populations within a) 30 minutes, b) 60 minutes (1 hour), and c) 240 minutes (4 hours) were assessed. Additionally, the analysis was reconducted for the 2 hours threshold with only surgical facilities in the NIN-2017 directory and teaching hospitals in NHP-2019. This subset was chosen to include the public facilities at all levels of care, and public/private/trust teaching hospitals known to provide free or subsidized care. For capacity, proxies used for sensitivity included met surgical need defined with the rate of a) total (minor and major) surgeries, b) select major surgeries excluding gynecology and ophthalmology. Further, we also replaced the met surgical need by met need for c-sections where c-sections = 10% of all institutional deliveries was used as the threshold. For safety, major surgeries were used instead of total surgeries to calculate the ratio of post-operative SSI to surgical procedures. For affordability, we adjusted the OOPE thresholds considered for CHE to a) 25%, b) 40%, c) 60% of household consumption expenditure for sensitivity analyses. Additionally, the proportion of households out of all households seeking surgical care that suffer impoverishing health expenditure was used as a proxy for affordability. In addition to the primary index value, 199 unique combinations were run **(Appendix E)**. These analyses allowed us to present a library of ZV-ASCI values for a given region under varying proxy assumptions.

3. Results

3.1 Raster-based population estimates

The district and state-level 2017 population aggregates for rural, urban, and total populations are presented in the dataset (see **Appendix D** for link). The state-level total and rural estimates showed almost perfect agreement with corresponding RGI Census projections, while urban estimates had a substantial agreement as revealed by Lin's concordance correlation coefficient **(Appendix F)**.

3.2 Timeliness to surgical care

3.2.1 Locating surgical care facilities

20802 uniquely geocoded surgical care facilities from four different data sources were used in the primary travel-time analysis (see **Figure 2** above). Sensitivity analysis with the subset of NHP teaching hospitals and NIN directory surgical facilities included 9144 facilities. Machine-based geocoding for latitude and longitude geocoordinates of NHP-2019 teaching hospitals had a perfect agreement with manual geocodes, validating our overall approach **(Appendix G)**. However, a handful of obvious discrepant points were still present as marked in **Appendix H.**

3.2.2 Travel-time to surgical care facilities

Figure 4A depicts time-to-travel (in minutes) from each pixel to its nearest surgical care facility. The motorized travel-times distribution is highly right-skewed depicting that a large number of areas in India lie within 2 hours from the nearest surgical facility **(Figure 4B)**. The majority of points in the distribution tail belong to the hilly regions of North and North-eastern Indian states.

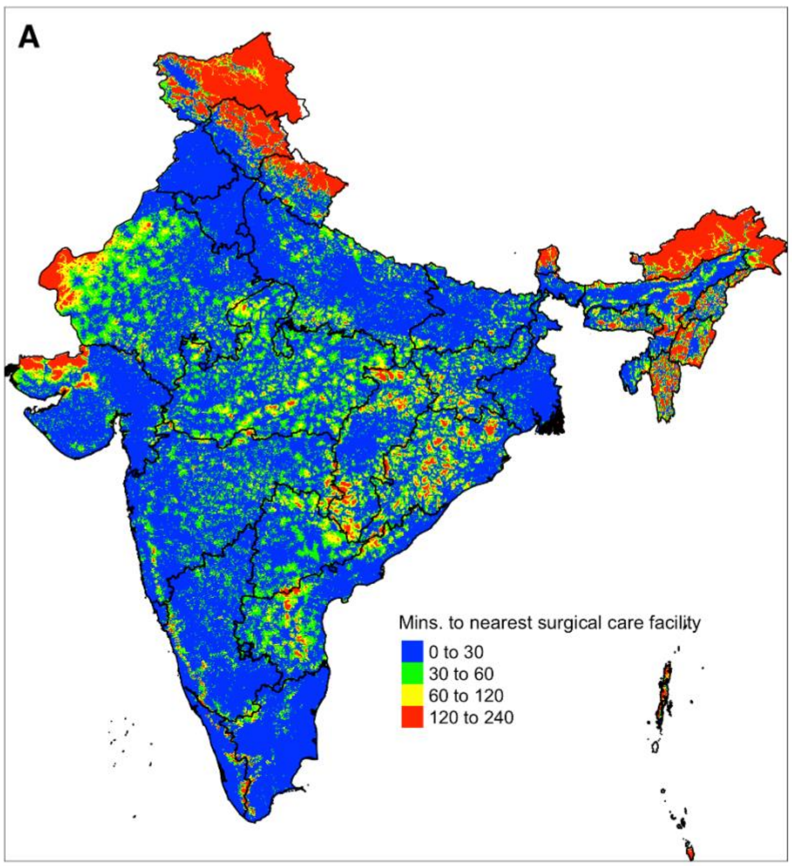


Figure 4A: Heatmap of travel times to nearest surgical care facility for India.

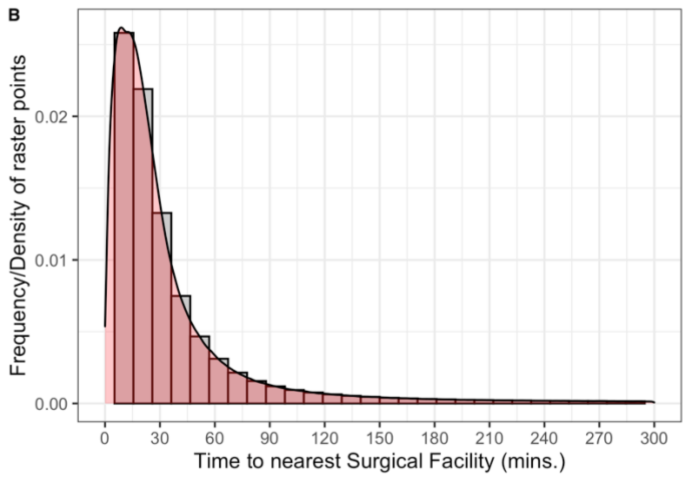


Figure 4B: Densigram of traveltime values.
Right-skewed distribution shows most places within 120 minutes of the nearest surgical care facility.

3.2.2 Populations with timely access

For the primary analysis, we defined timeliness dimension (T_0) (or timely access) as the proportion (%) of the population within 2 hours (120 minutes) of their nearest surgical care facility. At the national India level, 99.17% of the rural people had timely access compared to the 99.83% of the urban people. District and state-level differences in the timeliness among rural populations were minimal with >95% of rural residents having timely access to surgical care in most places **(Figures 5A-B)**. However, <80% of rural people in the northern-most and Northeast regions had timely access to care.

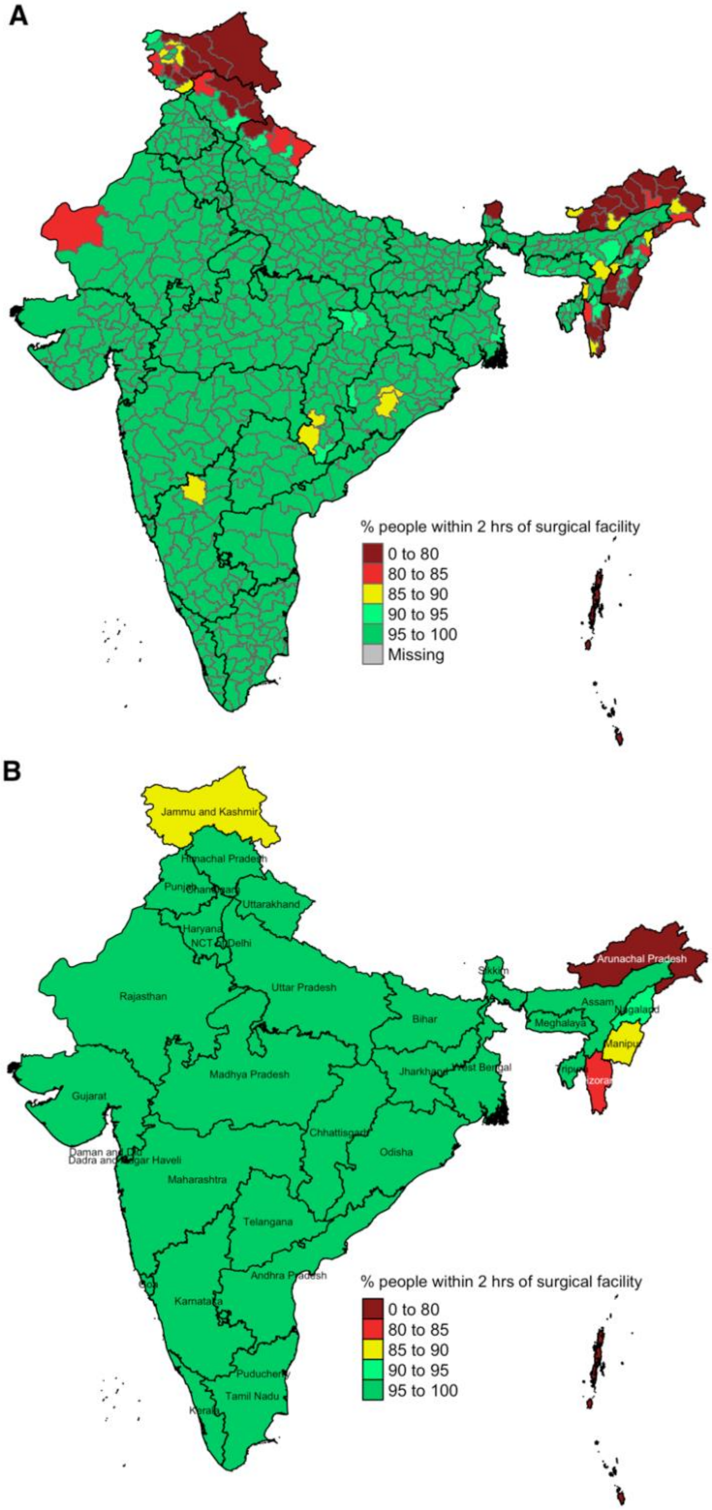


Figure 5: Geographic variations in timeliness, i.e. % rural population within 2 hours of surgical care facilities at – A) district and B) state-levels.

At district **(Figure 6A)** and state-levels **(Figure 6B)**, the rural and urban regions had a statistically significant difference of large effect size for timeliness **(Appendices I & J)**. Qualitatively similar differences (p<0.01, moderate-to-large effect size) were observed for other timeliness proxies – % population within 30, 60, and 240 minutes from nearest surgical care facilities and those within 2 hours from the facilities in the subset involving NHP and NIN databases **(Appendices I & J)**.

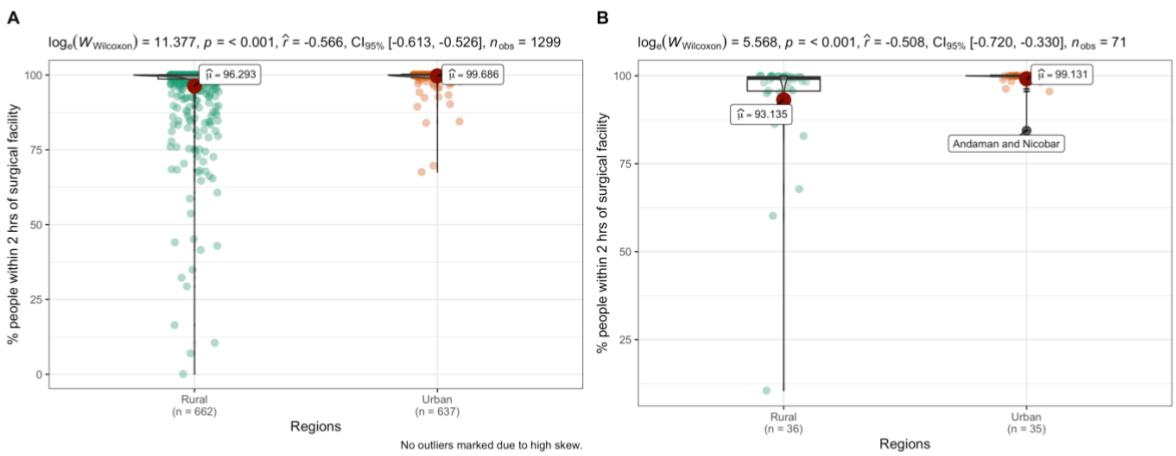


Figure 6: Rural-urban differences in timely access to surgical care facilities at A) district and B) state-levels.

3.3 Surgical capacity

3.3.1 Surgical rates and need

At the national level, rates (per 100,000 people) of the total, major (requiring general or spinal anesthesia), and select major (excluding gynecology, ophthalmic, and other procedures) surgical operations (OPs) in rural regions were 1274, 341, and 100, respectively. Significant differences between rural and urban of varying sizes were found at state and district-level comparisons for total and major rates, while no comparisons were conducted for select major OP rates due to limited data for urban regions **(Appendices I & J)**. We found higher surgical rates in rural regions compared to urban regions at the state level. However, this might be an artifact due to the limited upscale of HMIS in urban regions or misclassification of certain regions (see **Discussion Section 4.3**).

For the primary analysis, surgical capacity (C_0) was proxied by the met surgical need as the ratio of the rate of major surgical OPs to the threshold of 5000 surgical procedures. Nationally, rural regions' surgical capacity was at 0.0681 or 6.81% met need. For rural regions, most districts and states fell under the 0.20 mark for the met need w.r.t major surgeries **(Figures 7A-B)**. In certain states such as Arunachal Pradesh, Rajasthan, and Maharashtra, a small number of districts with a higher met need ratio skewed the surgical capacity at the state level in an upward direction although a greater number of districts had low capacity. Further, some differences between inference guided by state and district resolution maps arise due to skipping the HMIS districts that were not matched with GADM in the district-level map. However, these districts contribute to the state-level estimates altering the level of met need in the state-level map, e.g. Telangana and Sikkim.

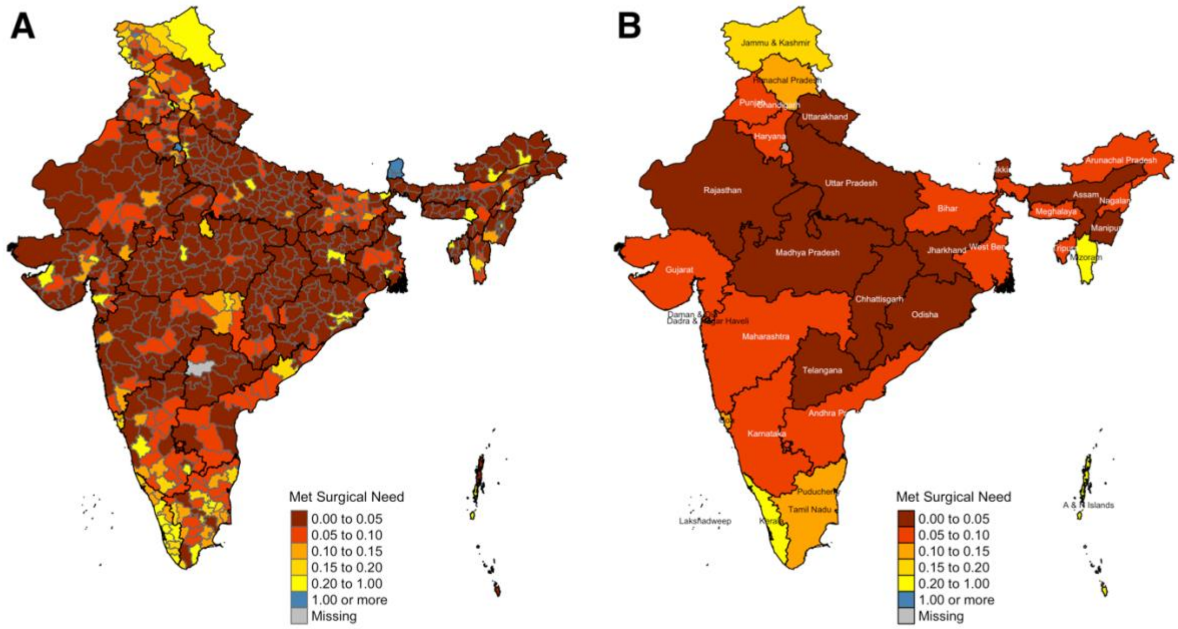


Figure 7: Geographic variations in rural surgical capacity, i.e. met need for major surgeries at – A) district and B) state-levels.

In district **(Figure 8A)** and state-level **(Figure 8B)** comparisons, surgical capacity based on the met need for major OPs differed significantly between rural and urban regions with small-to-moderate effect sizes **(Appendices I & J)**.

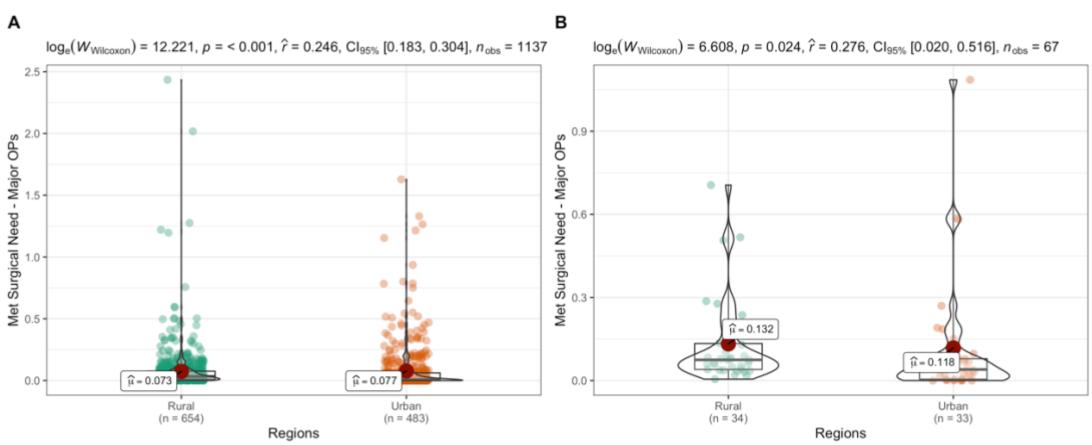


Figure 8: Rural-urban differences in surgical capacity, i.e. met need for major surgeries at A) district and B) state-levels.

The rural-urban differences held up for other variables such as met need w.r.t total surgical OPs, absolute surgical need gaps w.r.t total, and major OPs **(Appendices I & J)**. As mentioned before, the rural-urban comparisons should be considered with caution.

3.3.2 C-section proportions and need

Nationally, 13.57% of all rural institutional deliveries were c-sections falling within the WHO prescribed 10-15% range. Met c-section need w.r.t 10% threshold that was used as a proxy for surgical capacity in the sensitivity analysis was at 1.36. For rural regions, almost all districts and states in southern India depict satisfactory performance (met c-section need >1) pointing to a north-south divide with Bihar, Uttar Pradesh, and Rajasthan requiring attention **(Figures 9A-B)**.

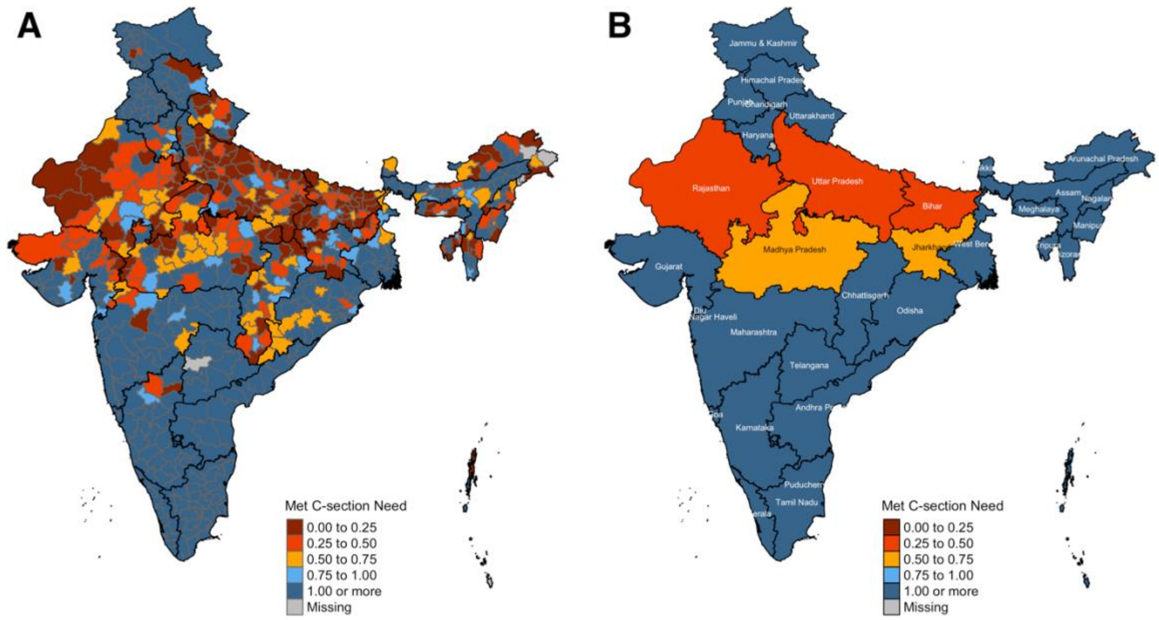


Figure 9: Geographic variations in met c-section need (at 10% threshold) for rural regions at – A) district and B) state-levels.

At the national level, 33.92% of institutional deliveries were c-sections in urban areas depicting an excess. State and district-level comparisons between rural and urban regions had significant small-to-moderate sized differences for the met need of c-sections at 10% threshold **(Figures 10A-B)**, proportion out of institutional deliveries, met need as per 15% threshold, and absolute gaps (excess or deficit) as per both thresholds **(Appendices I & J)** with high values for urban regions.

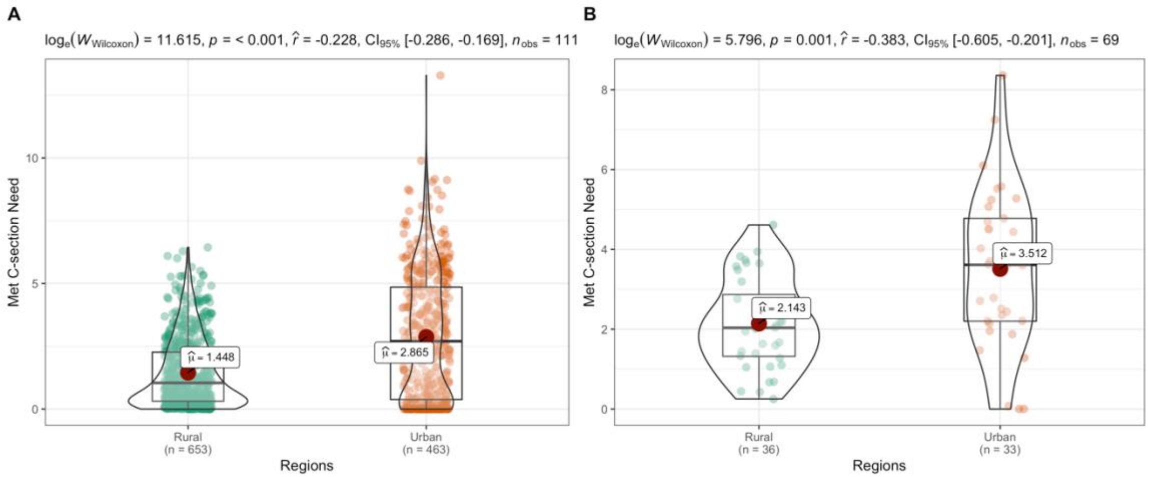


Figure 10: Rural-urban differences in met c-section need (at 10% threshold) at A) district and B) state-levels.

3.3.3 Validation of c-sections from HMIS vs. NFHS

For the overlapping period of January 2015 to November 2016, the state-level population and institutional c-section proportions showed poor agreement between HMIS and NFHS-4 **(Appendix K)**. Andhra Pradesh and Telangana that were formed in 2014 following an administrative split in the parent state of Andhra Pradesh were identified as outliers. The agreement improved after the removal of outliers with population c-section percentage reaching a moderate level.

3.4 Surgical safety

3.4.1 Post-operative surgical site infection proportions

In the primary analysis, we proxied surgical safety (S_0) by the proportions of post-operative SSI relative to total surgical OPs. Nationally, for rural regions, SSI proportions relative to the total and major surgical OPs were 0.19% and 0.73%, respectively. The rural SSI proportions relative to total surgical OPs were below 1% for several districts across India **(Figure 11A)** and all states except Assam and Mizoram **(Figure 11B)**. No rural-urban comparisons were possible due to missing data for urban regions. These findings should be taken with caution due to zero inflation in SSI data (see **Discussion Section 4.4**).

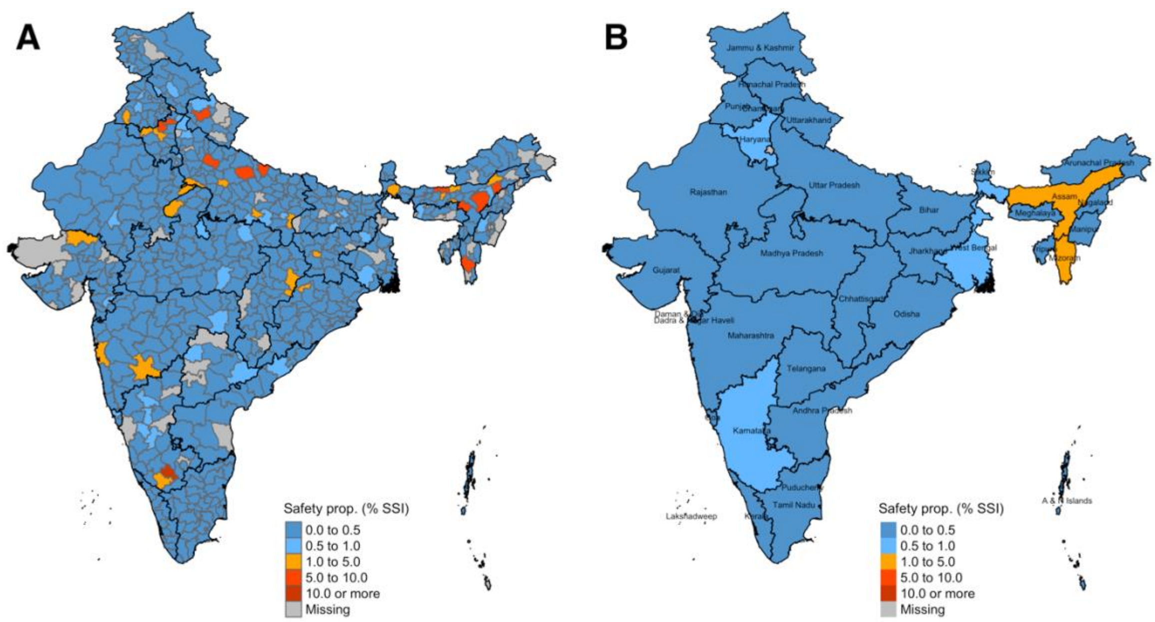


Figure 11: Geographic variations in rural surgical safety, i.e. proportion of post-op surgical site infections (SSI) to all surgeries at – A) district and B) state-levels.

3.4.2 Association of SSI with surgical volumes

We found significant positive linear correlations of moderate and large sizes between the log-transformed values of total surgical volumes and SSI at district **(Figure**

12A) and state-levels **(Figure 12B)**, respectively. The association points to the possible rise in compromising safety accompanying increased burden.

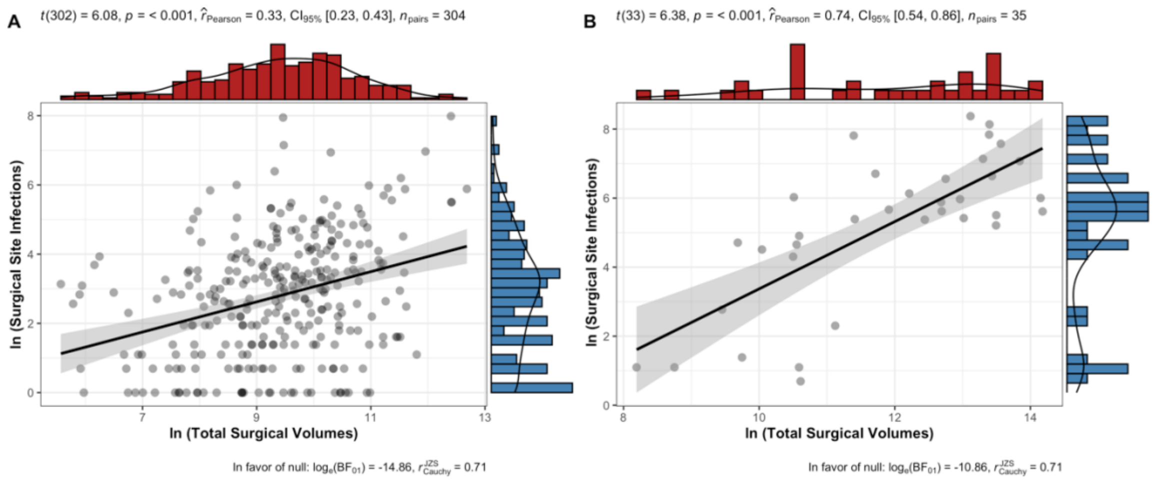


Figure 12: Linear correlations between log-transformed surgical site infections (SSI) and total surgical volumes for rural regions at – A) district and B) state-levels.

3.5 Affordability of surgical care

3.5.1 Surgical out-of-pocket expenditures

Nationally, the average OOPE per surgical case was 29540.58 INR (or 407.36 USD at 72.52 exchange rate) for rural regions compared to 40048.61 INR (552.26 USD). The district and state-level comparisons showed small-to-moderate sized significant differences between rural and urban regions for OOPE per surgical case **(Figures 13A-B)** and per capita **(Appendices I & J)**.

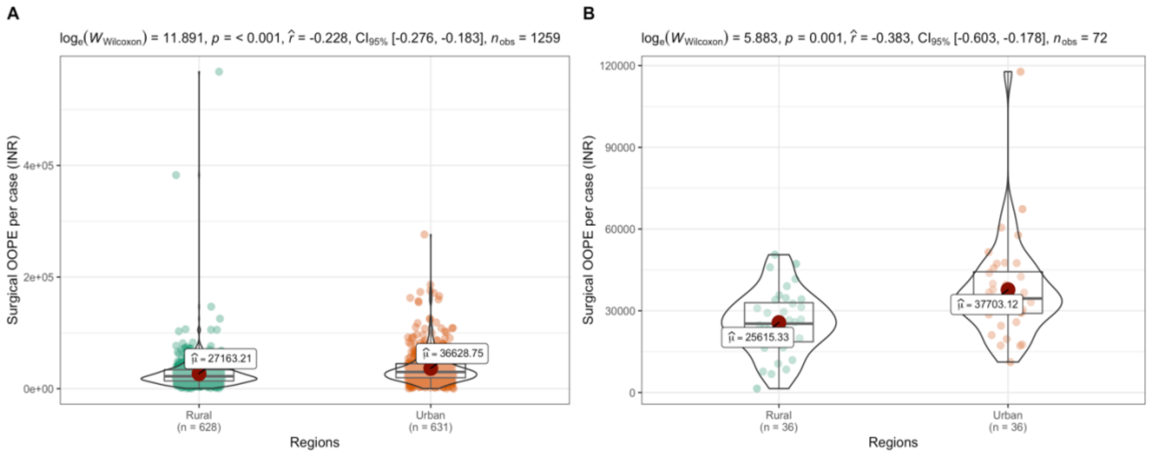


Figure 13: Rural-urban differences in out-of-pocket expenditures (OOPE) per surgical case at A) district and B) state-levels.

3.5.2 Catastrophic expenditures in surgery-seeking households

In the primary analysis, the affordability dimension (A_0) was proxied by the proportion (%) of surgery-seeking households facing catastrophic health expenditures (OOPE > 10% of the annual household consumption expenditure) out all households with surgical cases. Nationally, 60.99% and 56.32% of surgery-seeking rural and urban households faced CHE, respectively. Most districts and states had >10% surgery-seeking rural households with CHE **(Figures 14A-B)**. Several districts interspersed throughout India had over 50% CHE households, depicting unaffordability of care.

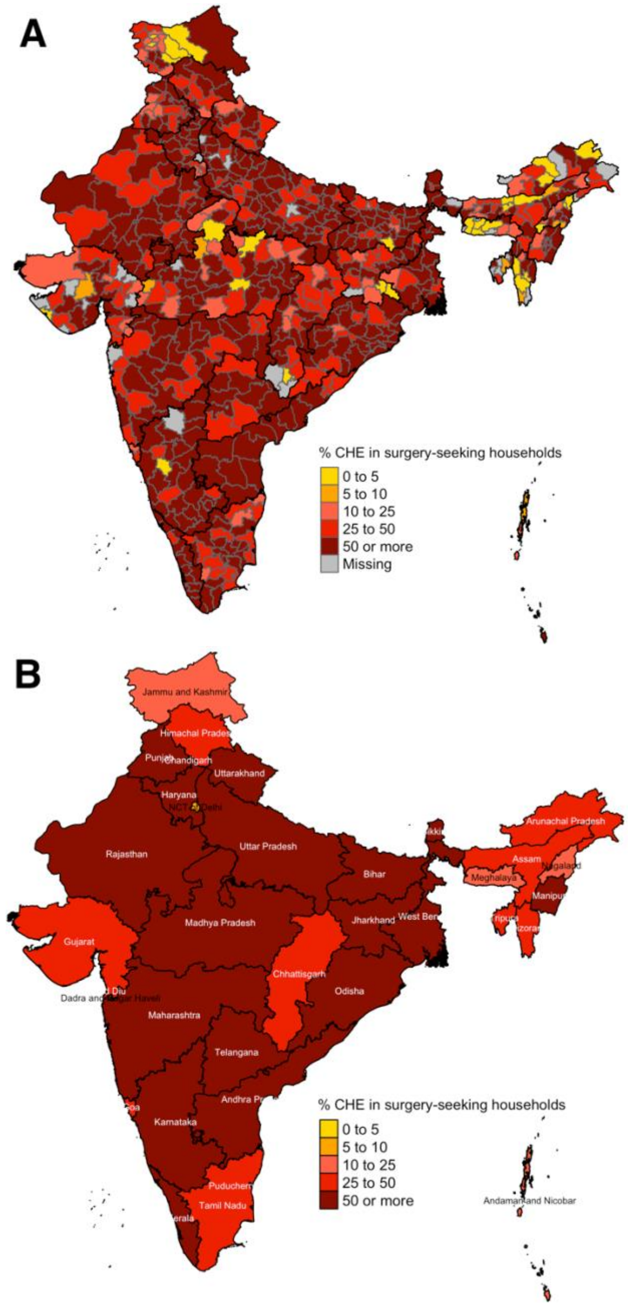


Figure 14: Geographic variations in surgical care affordability, i.e. % rural households with surgical cases facing catastrophic health expenditures (CHE) (at 10% threshold) at – A) district and B) state-levels.

District-level comparisons revealed non-significant differences between rural and urban regions, with rural residents at greater risk for catastrophe **(Figure 15A)**. The district-level rural-urban differences were significant for CHE defined at >40% and >60% of the annual household consumption expenditure but not for 25% threshold **(Appendix J)**. State-level rural-urban comparisons were nonsignificant for proportions of CHE-facing surgical case households for CHE at all thresholds. See **Figure 15B** for CHE at 10% threshold and **Appendix I** for others.

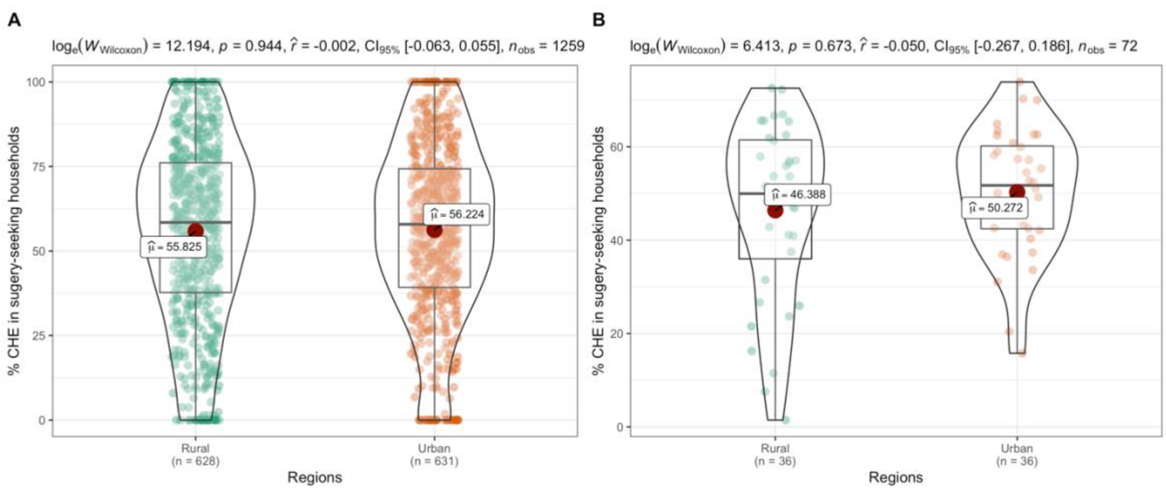
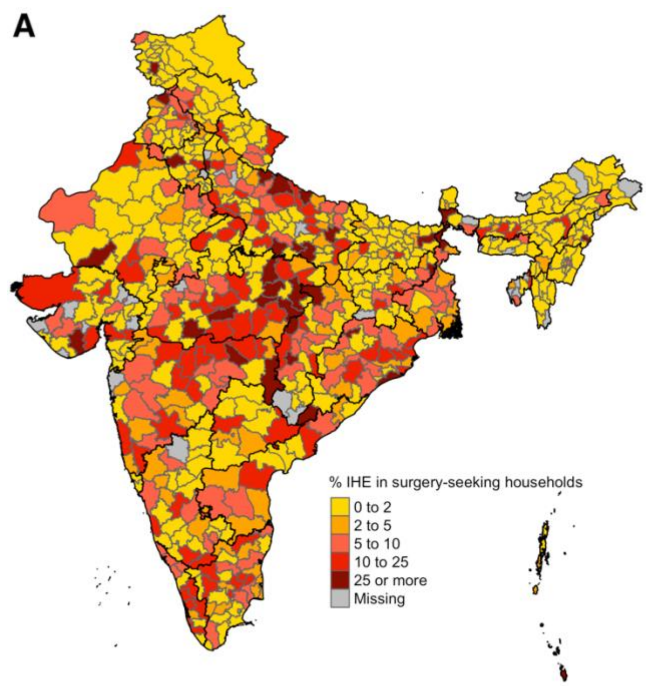


Figure 15: Rural-urban differences in surgical care affordability, i.e. % households with surgical cases facing catastrophic health expenditures (CHE) (at 10% threshold) at A) district and B) state-levels.

Further, the proportions of CHE-facing (at 10% threshold) surgery-seeking households w.r.t all households were 2.64% in rural regions compared to 2.90% in urban regions at the national level. Only district-level rural-urban comparison for these proportions at 10% threshold were significant **(Appendices I & J)**.

3.5.3 Impoverishment in surgery-seeking households

As part of sensitivity, the proportion (%) of households with impoverishing health expenditures (IHE) out of all surgery-seeking households was used as a proxy for affordability. Nationally, 7.67% and 4.89% of surgery-seeking rural and urban households faced IHE, respectively. Most districts had <2% surgery-seeking rural households with IHE with a few having >25% such households **(Figure 16A)**. Among states, Haryana, Uttar Pradesh, Madhya Pradesh, and Chhattisgarh had >10% surgery-seeking rural households with IHE **(Figures 16B)**.



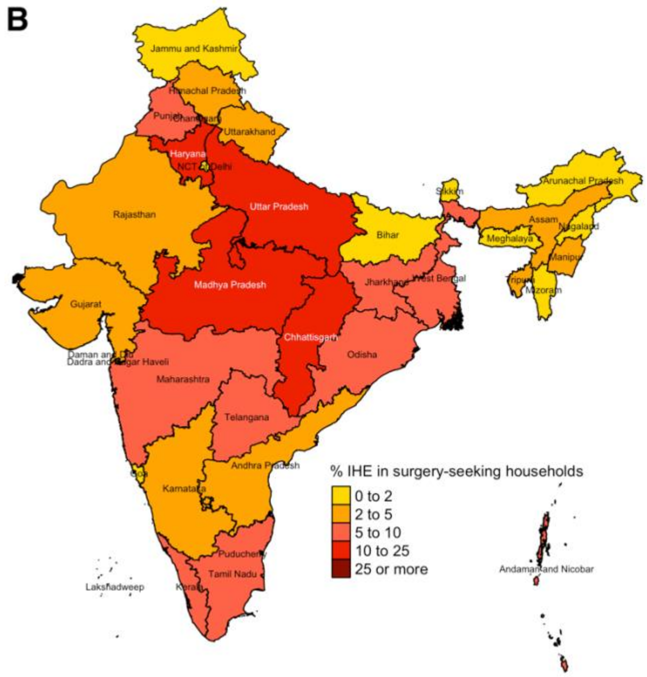


Figure 16: Geographic variations in % rural households with surgical cases facing impoverishing health expenditures (IHE) at – A) district and B) state-levels.

District-level comparisons revealed small-sized significant differences between rural and urban regions, with rural residents at greater risk for impoverishment **(Figure 17A)**. State-level rural-urban comparisons were nonsignificant **(Figure 17B)**. Further, the proportions of IHE-facing surgery-seeking households w.r.t all households were 0.33% in rural regions compared to 0.25% in urban regions at the national level. State-level rural-urban comparison for these proportions were nonsignificant, while district-level comparison was significant **(Appendices I & J)**.

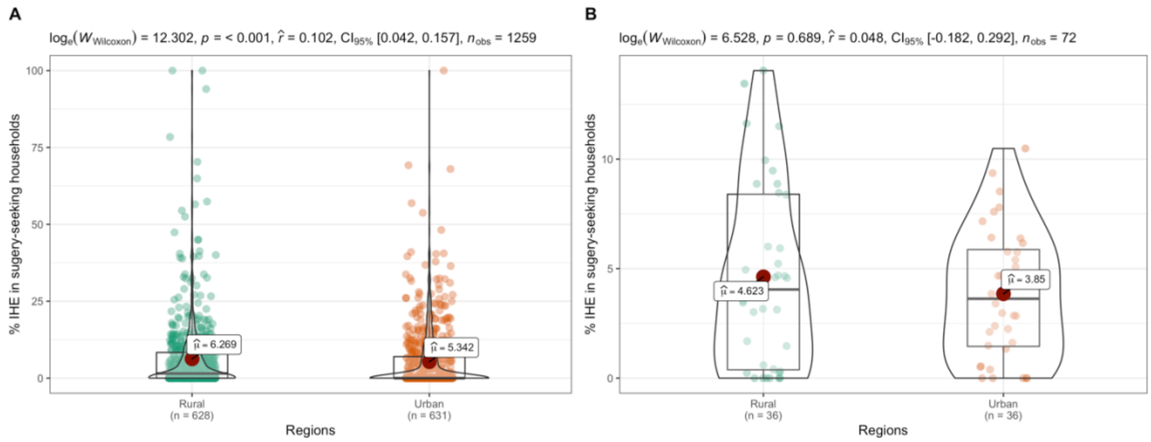


Figure 17: Rural-urban differences in % households with surgical cases facing impoverishing health expenditures (IHE) at A) district and B) state-levels.

3.6 Indexing access to surgical care using ZV-ASCI

Considering data availability, Zadey-Vissoci access to surgical care index or ZV-ASCI (0-100, 0 = worst, 100 = best) was synthesized based on primary proxies for timeliness (T_0), capacity (C_0), safety (S_0), and affordability (A_0) dimensions for 587 districts and 36 states (i.e. states and union territories). Among districts, Bhopal in Madhya Pradesh had the highest index value of 92.68 while North and Middle Andaman in the UT of Andaman and Nicobar Islands had the lowest value of 0. Most districts had ZV-ASCI below 60 **(Figure 18A)**. Among states and UTs, the UT of Chandigarh had the highest value of 77.29 while Andhra Pradesh had the lowest value of 0. Most states had values in the 0-20 range **(Figure 18B)**. The nature scaling prohibits comparisons between two geographic resolutions i.e. states vs. districts.

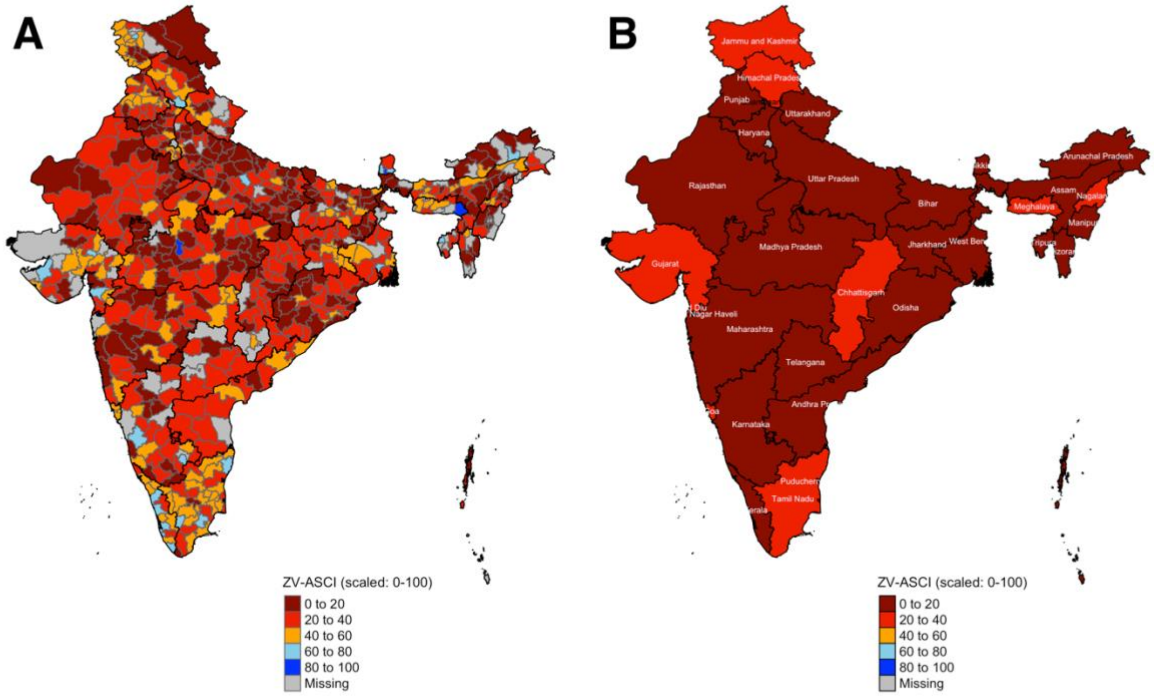


Figure 18: Geographic variations in rural Zadey-Vissoci Access to Surgical Care Index (ZV-ASCI) at – A) district and B) state-levels.

The penalty and mean terms were negatively correlated in ZV-ASCI constructed for districts (R = -0.82, p < 0.001) and states (R = -0.75, p < 0.001). **Figure 19** depicts lesser penalization of states with greater balance across dimensions. A similar effect is observed for districts **(Appendix L)**.

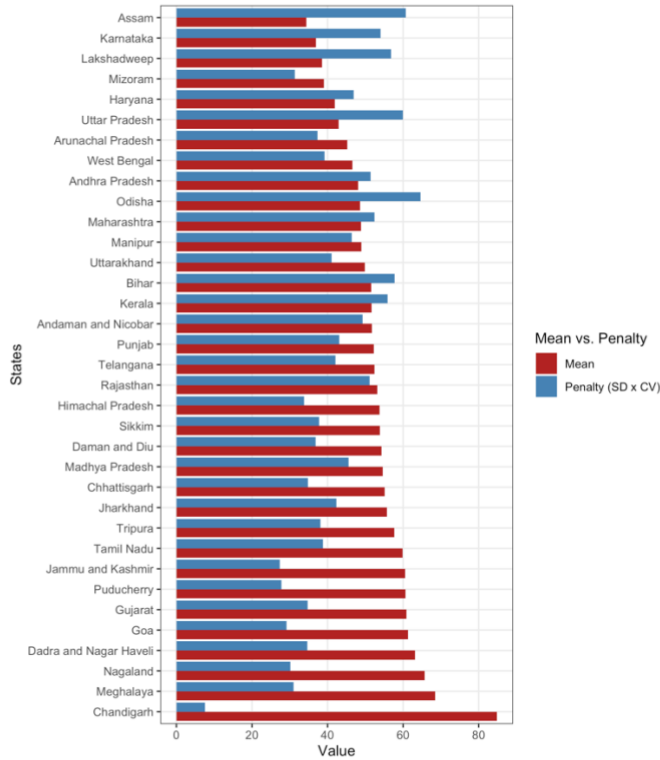


Figure 19: Scissor diagram showing the relationship between the mean and penalty terms of ZV-ASCI for states.

A library of 200 ZV-ASCI estimates, one primary value, and 199 sensitivity values is presented (see **Appendix D** for link). These estimates depict wide variation in the index value based on underlying proxies. For instance, **Figure 20** shows that Maharashtra has a primary ZV-ASCI ($T_0C_0S_0A_0$) of 0 and a maximum value of 47.43 for $T_2C_3S_1A_4$ combination. A clear 'jump' in values is observed for combinations with met c-section need as a proxy for surgical capacity (C_3).

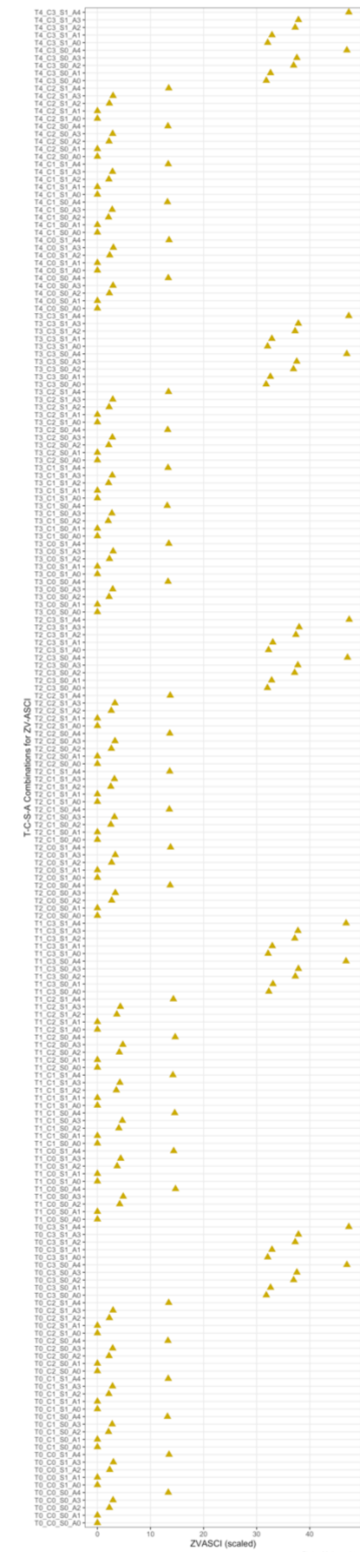


Figure 20: Variability in ZV-ASCI sensitivity estimates for the state of Maharashtra.

3.7 Inequality in surgical access

3.7.1 Inequalities in access through econometric methods

The Lorenz curves are presented in **Figures 21A-B**. With states as units of analysis, Theil index (T_T) was 0.281 while the extended Gini index was 0.405 **(Figure 21B)**, depicting non-zero inequality in ZV-ASCI distribution. With districts as units and states as groups, the overall Theil index was 0.151 with decomposition depicting between-state inequality (inter-group) of 0.040 and within-state inequality (intra-group) of 0.111. Hence, Theil index decomposition depicts that the within-state inequality was a little less than three times that of between-state inequality. For districts, the overall extended Gini index was 0.297 **(Figure 21A)** with decomposition depicting between-state inequality (inter-group) of 0.151, within-state inequality (intra-group) of 0.012, and overlap of 0.133. **Appendix M** summarizes the state-wise values and contributions to overall inequality for Theil and Gini indices.

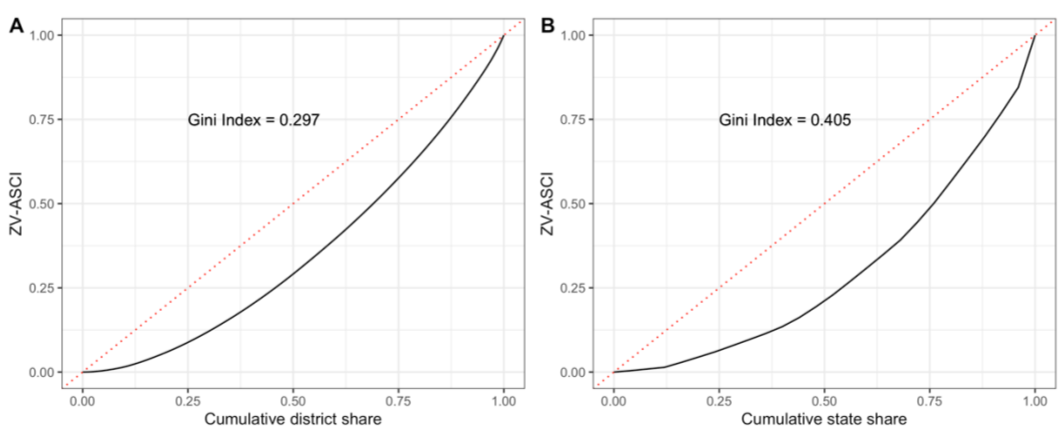
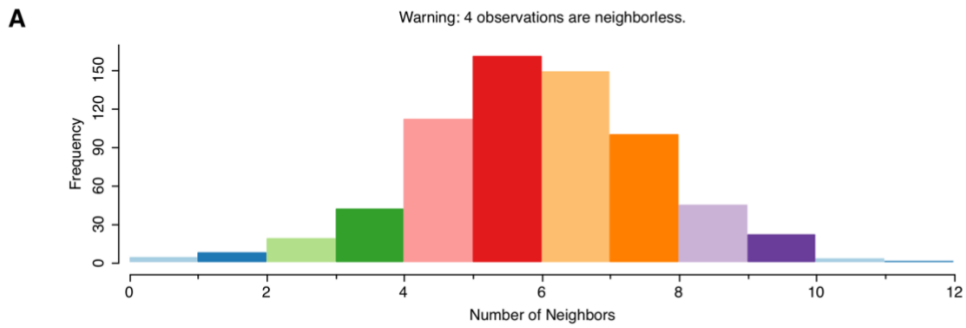


Figure 21: Lorenz curves for assessing ZV-ASCI distributional inequalities with A) districts and B) states, as units of analysis.

3.7.2 Inequalities in access through spatial metrics

The distribution of neighbors **(Figure 22A)** and the between-districts connectivity graph **(Figure 22B)** were assessed before Moran's I estimation.



from	0	1	2	3	4	5	6	7	8	9	10	11
to	1	2	3	4	5	6	7	8	9	10	11	12
#obs	4	8	19	42	112	161	149	100	45	22	3	1
% of total	0.601	1.201	2.853	6.306	16.817	24.174	22.372	15.015	6.757	3.303	0.450	0.150
sd from mean	-2.574	-1.994	-1.413	-0.832	-0.251	0	0.330	0.910	1.491	2.072	2.653	3.234

min: 0, max: 11, median: 5, mean: 5.43243, s.d.: 1.7218, #obs: 666

Figure 22A: Histogram of distribution of the number of neighbors.

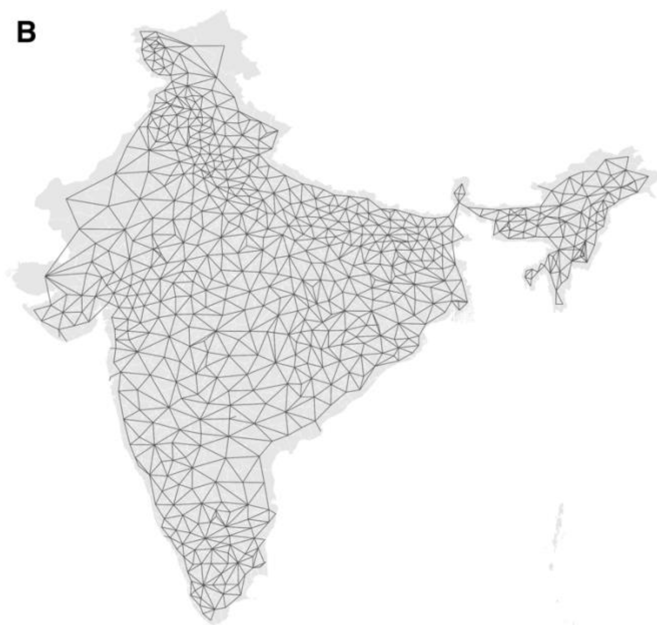


Figure 22B: Connectivity graph for Indian districts.

We found a small positive value for Global Moran's I **(Figure 23)** that was significantly based on permutation analysis (Z = 8.050, pseudo p = 0.00001, permutations = 99,999). However, low-high and high-low outliers are evident.

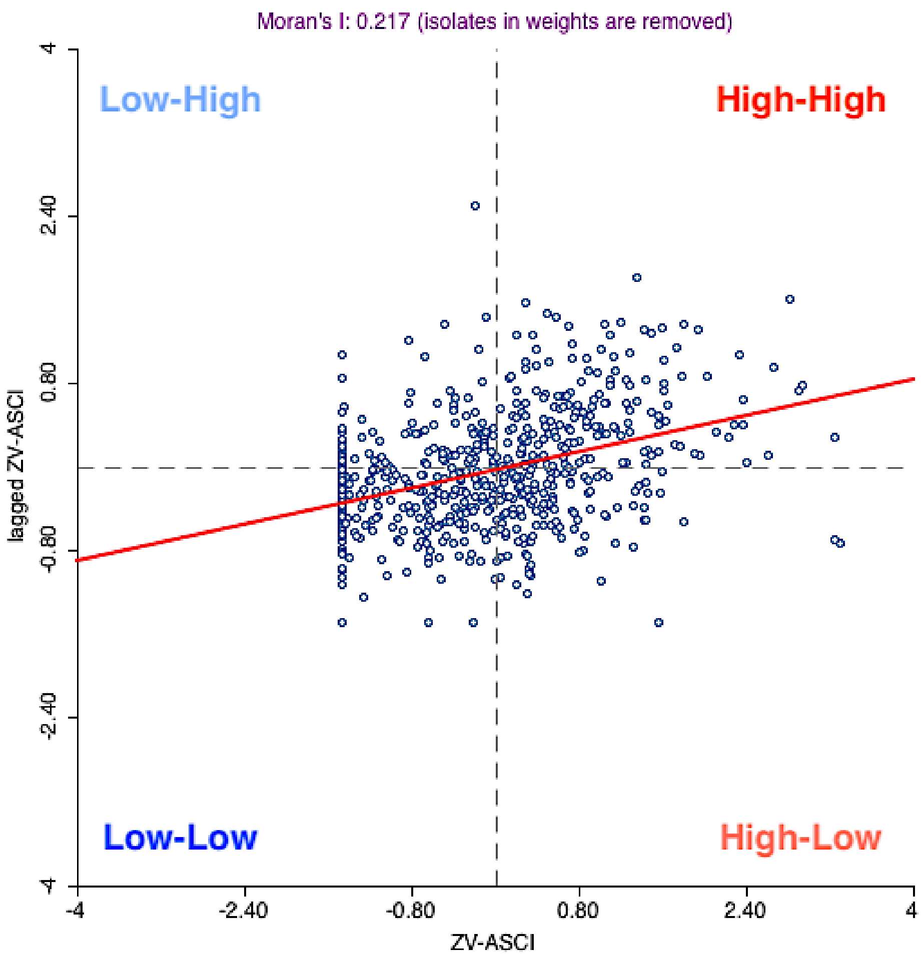
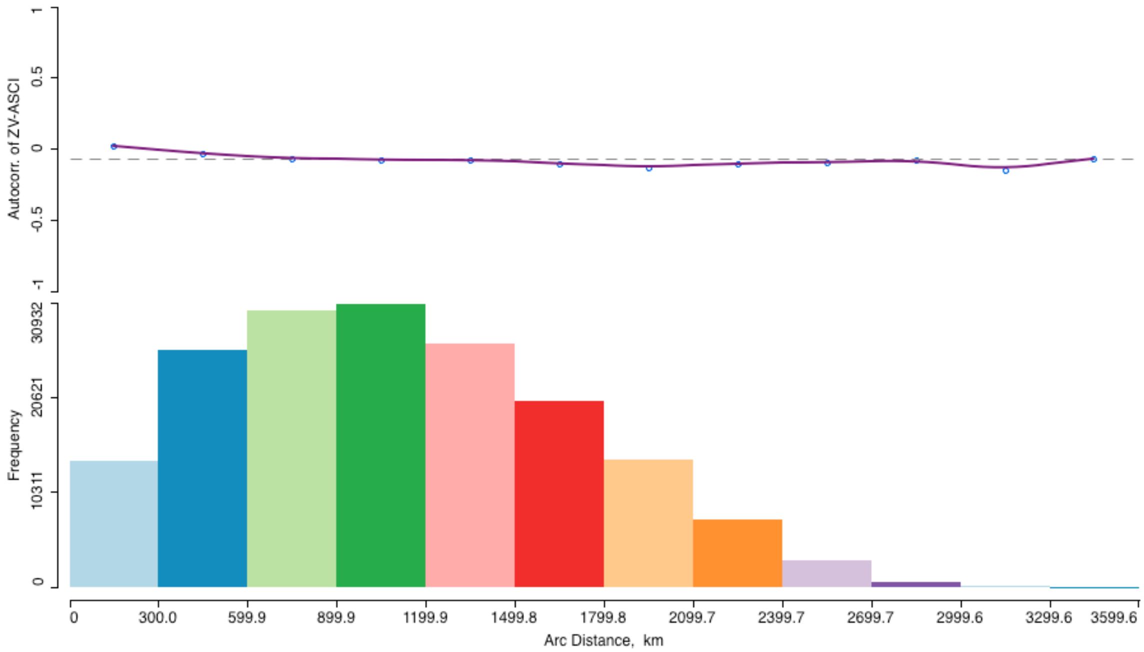


Figure 23: Global Moran's I scatterplot for ZV-ASCI.

The spatial correlogram depicted small changes from positive to negative autocorrelation over increasing distances, however, for the most part, values hovered around the zero-line **(Figure 24)**. Hence, there was some support for the spatial dependency of ZV-ASCI based on global statistics.



Autocorr.	0.101	0.043	0.004	-0.014	-0.012	-0.038	-0.071	-0.040	-0.033	-0.008	-0.091	0
Min	0	299.964	599.928	899.893	1199.857	1499.821	1799.785	2099.749	2399.713	2699.678	2999.642	3299.606
Max	299.964	599.928	899.893	1199.857	1499.821	1799.785	2099.749	2399.713	2699.678	2999.642	3299.606	3599.570
# Pairs	13655	25909	30190	30932	26540	20330	13844	7303	2791	474	23	0

min: 0, max: 3599.570, total # pairs: 171991, Autocorr. = 0 at 814.849 in range: [599.928, 899.893]

Figure 24: Spatial Correlogram for ZV-ASCI showing changes in spatial autocorrelation with over-distance.

Several districts with statistically significant Local Moran's I at different significance thresholds were identified **(Figure 25A)**. 65 districts had local spatial autocorrelation at the conventional 5% significance threshold, while only one district retained it at the most stringent 0.0001% threshold. The corresponding cluster map depicts the clusters and outliers based on district positions in the spatial correlation quadrants **(Figure 25B)**. Most high-high clusters (a district with high ZV-ASCI surrounded by neighboring districts with high ZV-ASCI) were found in the southern states of Kerala and Tamil Nadu while low-low clusters were interspersed in the northern state of Uttar Pradesh and parts of central and north-east India.

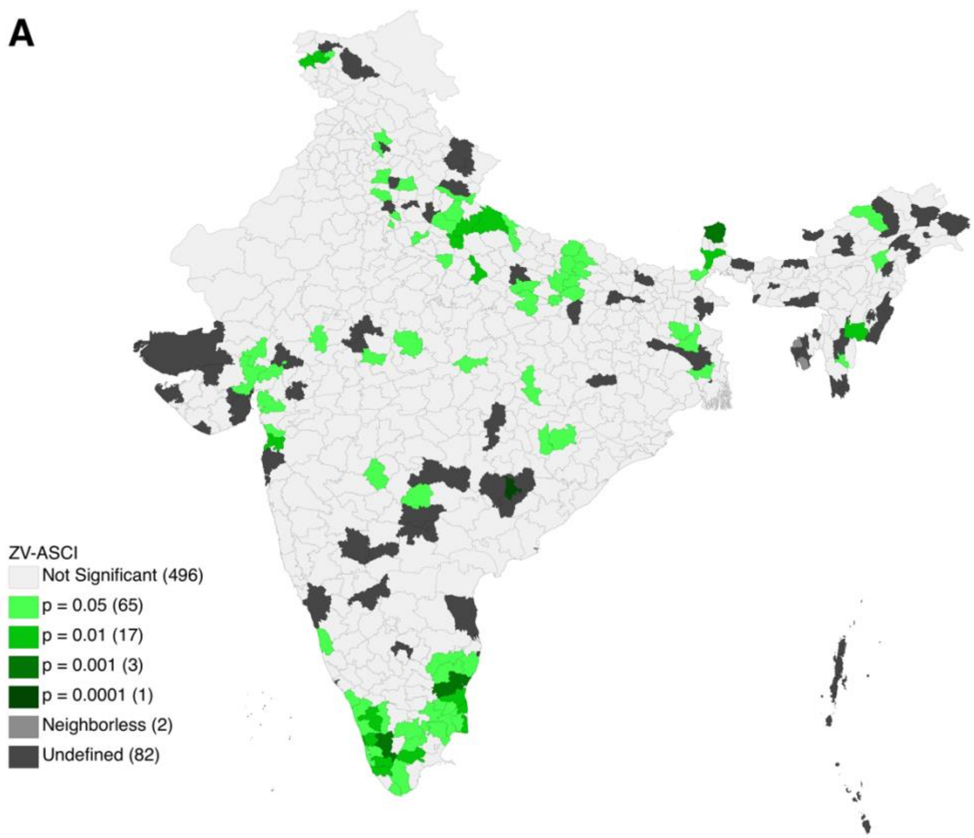


Figure 25A: Significance map of Local Moran's I for district ZV-ASCI values based on multiple pseudo-p-thresholds.

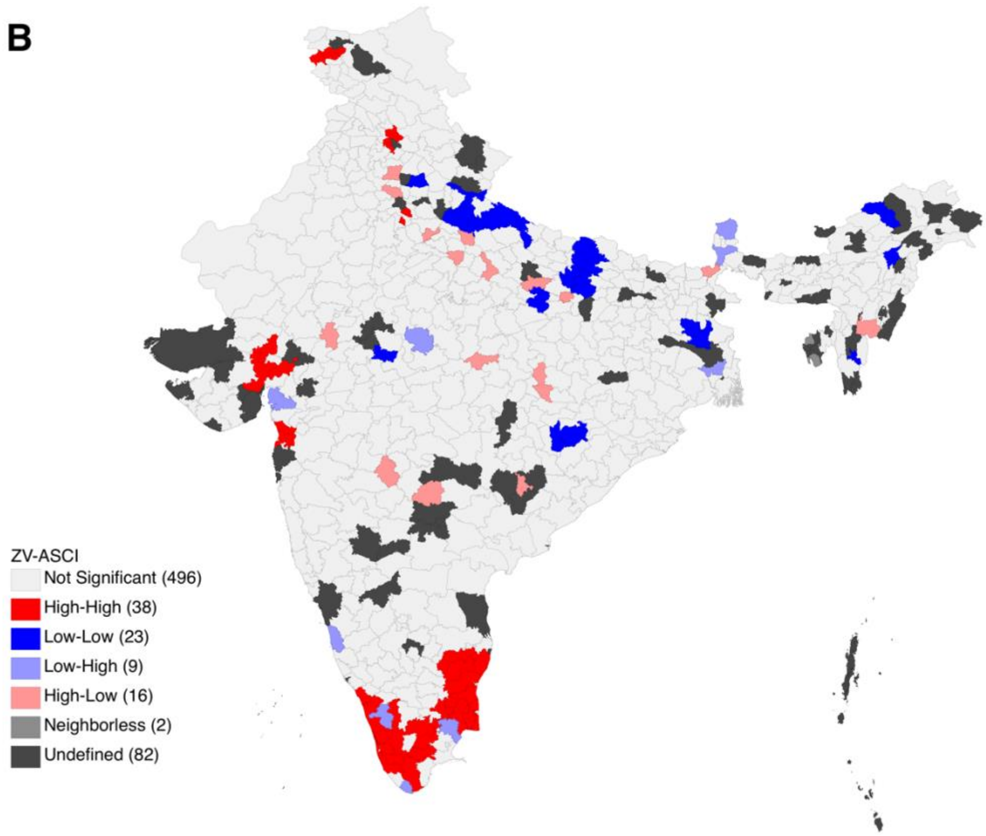


Figure 25B: Corresponding cluster map depicting outliers and clusters of districts for ZV-ASCI.

At the Bonferroni bound of pseudo p = 7.50751e-05, no districts met the criteria of significance or interest. However, the Dantewada district in Chhattisgarh was identified as a 'high-low' outlier. FDR-based analysis revealed two high-high clusters in Kerala and Tamil Nadu, one high-low outlier in Chhattisgarh, and one low-high outlier in Sikkim **(Appendix N)**.

3.8 Association between ZV-ASCI and SDG index scores

For state-level analyses, ZV-ASCI did not have statistically significant correlations with the 2018 baseline SDG overall composite **(Figure 26A)** and health

(SDG-3) scores **(Figure 26B)**. Surprisingly, the direction of correlation was negative for the health score i.e. states with better SDG health goals achievement had smaller value for surgical care accessibility.

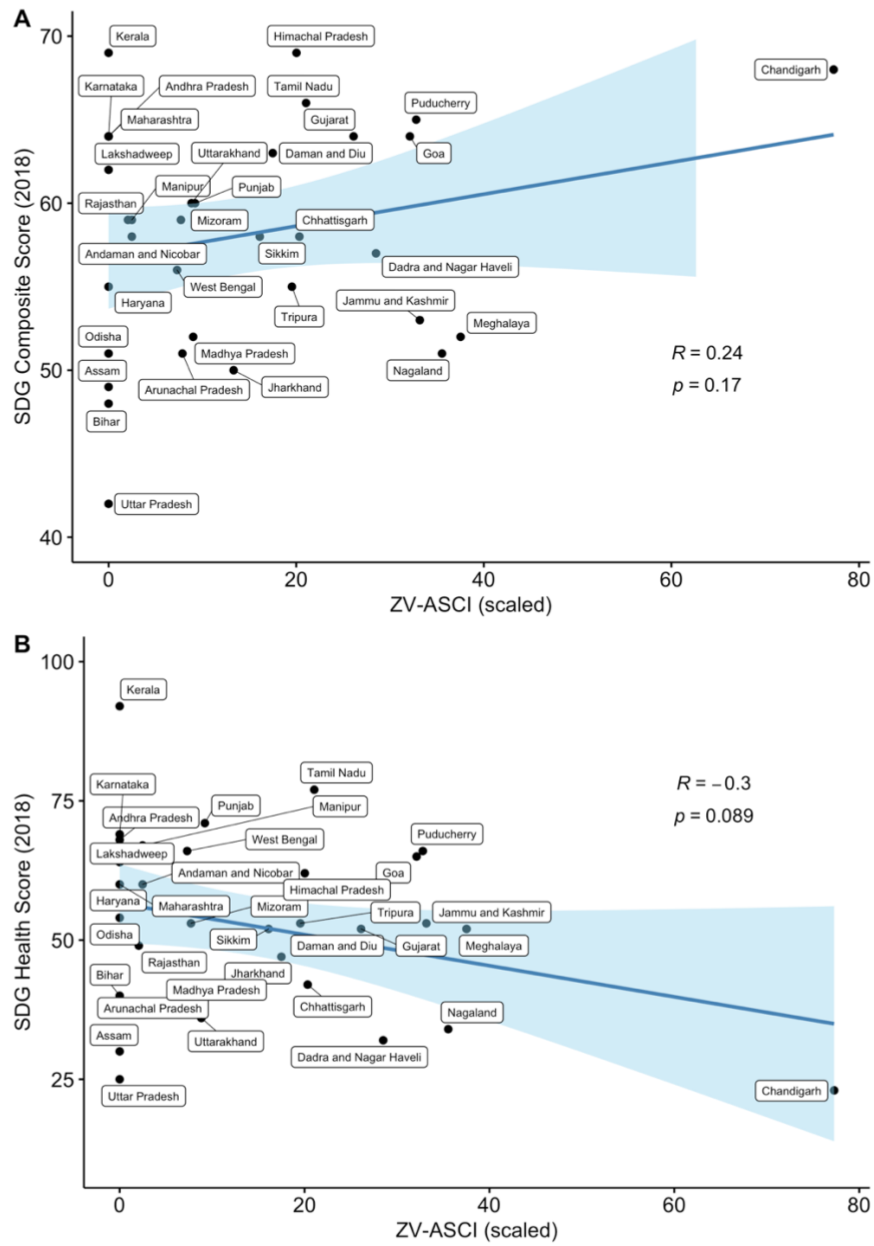


Figure 26: Correlation of state-level ZV-ASCI with A) Composite SDG Score (2018), and B) SDG Health Score (2018).

Note: While similar in magnitude, the directions for both correlations are opposite.

We synthesized ZV-ASCI for 90 out of 101 aspirational districts across 25 states. ZV-ASCI was missing (NA) for 9 districts while two districts that did not match with GADM were excluded from the analysis. ZV-ASCI did not have a significant correlation with the 2018 SDG composite score **(Figure 27)**.

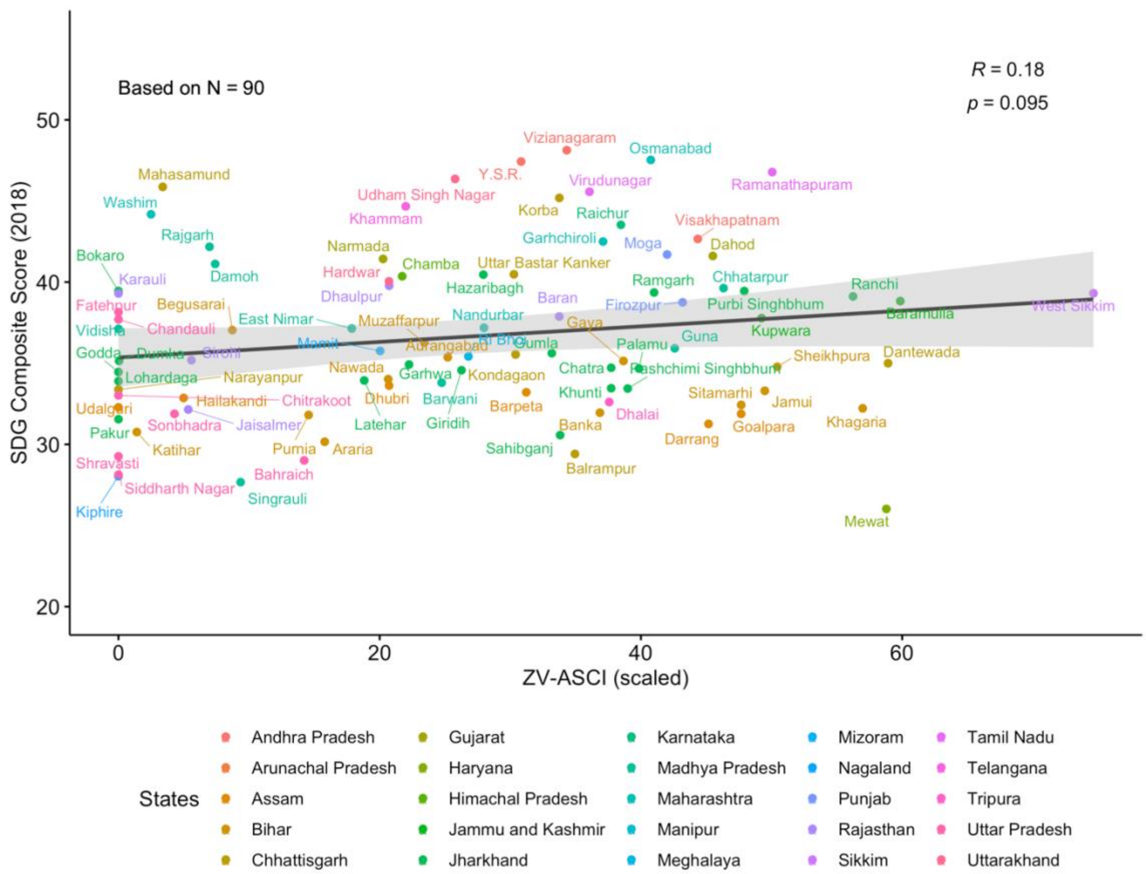


Figure 27: Correlation between ZV-ASCI and SDG Composite Score (2018) for aspirational districts.

4. Discussion

The current study primarily focused on rural India for the year 2017-18. We synthesized surgical care access dimension estimates for over 660 districts in 36 states and union territories for the rural populations. Briefly, we found that the majority of rural residents in India have timely geographical access to nearby surgical care facilities although the proportion is smaller compared to urban residents. Surgical rates fell short of the met need benchmark for major surgeries. Surgical site infections had low proportions and were associated with surgical volume burden. However, this data must be considered with caution. Rural populations suffer catastrophic and impoverishing expenditures due to surgical care at a higher level than their urban counterparts. To succinctly depict the state of surgical access for a region we proposed a novel easily interpretable access to surgical care index (ZV-ASCI). For rural regions of 587 districts, ZV-ASCI depicted limited balanced achievement across surgical care access dimensions. We found small inequalities in ZV-ASCI across states and districts, limited support for spatial associations, and identified clusters of low and high accessibility. For aspirational districts, the lack of association between ZV-ASCI and SDG scores depicts the uniqueness of ZV-ASCI and underscores the need to bring surgical care to overall developmental agenda. The validation steps throughout the primary analysis and the adjunct sensitivity analysis confirm the utility of our methodological approach and the robustness of our findings.

4.1 Contextualizing the study findings

4.1.1 Timeliness to surgical care

Nationally, >99% of rural Indian residents were within 2 hours of the nearest surgical care facility compared to 92.5% and 96.6% of the total (rural and urban) populations in Sub-Saharan Africa (108) and Bangladesh (109). These studies had different approaches to create hospital catchment areas (or zones) and time-to-travel maps. We relied on the MAP 2019 accessibility friction surface (72,73) making our analysis comparable to other future studies that might use MAP. While considerably high, these proportions often decline considering the subset facilities capable of providing quality surgical care as per globally set standards (109–111). For instance, the Bangladesh estimate drops to 50.6% when hospitals with Basic Surgical Standards are considered (109). Such a drop is possible for our India estimate on incorporating surgical capability standards. Studies specific to India investigating timely access to surgical care are scant. In the broader healthcare access domain, previous Indian studies have relied mostly on distance-based measures. For instance, 43% of the Indian population was estimated to be beyond 50 km (kilometers) of the nearest well-resourced district hospital (41). The taluka (sub-district) level median distance to the nearest medical school is estimated to be 50.13 km (112). It is also known that an increase of 1 km from the nearest health facility can cause a 4.4% reduction in the probability of institutional delivery, with access to roads and motorized vehicle ownership influencing this relationship (113). Comparison of our estimates with these studies is difficult considering that the time taken to travel 50 km can vary substantially across India. We recommend that more Indian studies should present travel-time findings. The current estimate should be considered an upper bound estimate as it assumes readily available motorized transport, which may not be true to all rural residents. Future models should also account for public transport and ambulance networks in measurement of timely access to surgical care.

4.1.2 Surgical capacity – rates and need

Our national-level rural surgical rate estimates fall within the range of LMIC values presented under Indicator 3 of the Global Indicators Initiative (36). The total and major surgical rates were higher than the LCoGS associated modeled estimates for India (30). However, this model is also known to underestimate surgical rates in other South Asian countries such as Myanmar and Sri Lanka (36). The rural rates of select major surgeries (excluding OBGYN, ophthalmic, and other procedures) for Andhra Pradesh (170 per 100,000 people) and Telangana (106 per 100,000) were quite under the previously known 259 per 100,000 beneficiaries from an insurance claims study in the region (31). This difference could be attributed to populations covered (beneficiaries at pre-dominantly private hospitals for (31)), surgical OPs considered, and study periods (data from mid 2008-12 for (31)). Our national estimates for total and major surgical rates in rural regions are less than the recently projected national population estimate of 3,646/100,000 (42). The projection in (42) was created based on the electronic medical records of surgical uptake in a well-characterized urban UHC cohort in Mumbai, Maharashtra. Our HMIS-based estimates (total: 1,851/100,000 major: 1,003/100,000) for the district of Bruhan Mumbai (urban) fall short of the UHC cohort estimate (4,642/100,000). Investigating the reasons underlying these differences would require assessment of data coverage and completeness for HMIS and further breakdown by surgical conditions to better match the inclusion of the surgical condition across studies. Our population-based met need calculations cannot be compared with small-scale household surveys investigating lifetime surgical uptake (114) or studies using self-report instruments such as SOSAS (43,44).

The c-section proportion estimates match with other similar nationwide studies using representative household surveys (see **Appendix A**). The north-south divide in the met c-section needs observed in our analysis matches with that presented by Guilmoto and Dumont (63). The met need for c-sections is much higher than that for overall major surgeries. This could be due to the following reasons: a) c-section scale-up in LMICs has been encouraged under the OBGYN, maternal and childcare programs (115) due to known deficits in the early 2000s (116) and b) India has observed an increasing incidence of unnecessary c-sections with large proportions of such procedures conducted in private facilities (see **Appendix A**). Regardless of the underlying reasons, it is important to note that the use of c-sections as a proxy for met need can be problematic.

4.1.3 Surgical safety

Previously, SSI incidence of 11.8% has been estimated in LMICs (46). In India, the estimates range from 39% in small samples to 1.6% in large samples (see **Appendix B**). Here, we calculated the 'indirect' proportion of post-operative SSI relative to surgical volumes, which is different from typical studies directly linking SSI to surgeries after the given follow-up. Hence, comparisons with other Indian SSI studies become difficult. Further, our low SSI proportion values can be attributed to a large number of unexplained zero values in HMIS data, making our estimates less reliable (see **Section 4.3**).

4.1.4 Affordability of surgical care

Previously, a global model estimated the average risks for catastrophe (OOPE > 10% of expenditure or income) and impoverishment (w.r.t national poverty line) in case of need of surgery at 59.6% and 36.5%, respectively (92). The CHE estimate is comparable with our national rural estimate for the proportion of CHE (at 10% threshold) of surgery-seeking households (61%). However, our national-level IHE estimate for rural households (7.7%) is quite lower in comparison. This difference in part could be attributed to limitations in IHE estimations mentioned in **Section 4.3**. Previous secondary analyses of nationally representative surveys have noted a rise in OOPE and CHE for healthcare generally (47,48), and for medicines specifically (93). However, these studies have not isolated surgical care expenditures. The state-level patterns in the surgical CHE proportions qualitatively match those presented for general CHE. For instance, relatively high proportions of CHE-facing households are found in Kerala, Punjab, Odisha, etc. in both cases, with lower proportions in north-eastern states (48). One multi-district field study in Haryana looking at ex-beneficiaries of a surgical package program found CHE (at 10% threshold) prevalence to be 5.6% (49). Our state-level urban estimate for Haryana is much higher at 62.6%. However, the difference can be attributed to the peculiar group of participants (ex-beneficiaries of a package program) with considerably different health-seeking than the population at large. More importantly, the study included secondary care level public hospitals that often operate patients at subsidized costs.

4.1.5 Indexing surgical care access with ZV-ASCI

ZV-ASCI is the first composite index in the global surgery academic literature. We constructed the index, primarily to have a simple metric that could facilitate comparative assessments and communication with policymakers. As a demonstration of its utility, we investigated geographical and distributional inequalities in accessibility indexed by ZV-ASCI. We did not find a correlation between ZV-ASCI and SDG composite scores for states and aspirational districts. This could be due to several reasons. There is a ‘flooring effect’ in ZV-ASCI values due to the censoring involved in normalization. Aspirational districts have a limited variation in their SDG composite scores since the districts included in the program are the ones needing a ’developmental push’ with generally low scores. The correlation of ZV-ASCI with SDG score may improve with the inclusion of more districts. It is possible that surgical care accessibility is not related to the broader developmental agenda, particularly in LMICs with struggling health systems. A lack of clear association has been previously observed between emergency care access and the regional socioeconomic development in Brazil (117). Hence, if future studies reveal that the lack of correlation between ZV-ASCI and SDG composite scores is a nonspurious finding, then it points to unique health system components captured by ZV-ASCI and argues towards the need of incorporating such an index within the SDG framework.

4.2 Implications for policy and practice

Two major policy and practice offshoots from the LCoGS research include the proposals for the global surgical care indicators (37) and national surgical plans (20). The current study contributes to both these proposals. First, we introduce a composite index for a succinct depiction of the state of surgical care access. While global surgery indicators or individual access dimensions have been popular with researchers, the composite index has a greater chance of garnering attention from health policymakers and practitioners. Increased advocacy, discourse, and policy focus on issues through the use of composite indices have been previously observed for HDI among others (118). The use of ZV-ASCI can help bring surgical care to the global and national health agenda by its incorporation in the SDG framework. Second, our methodological workflow from data assimilation to index application including the use of adaptable inexpensive tools can act as a blueprint for situational analysis essential for NSOAP development. Considering that several LMICs currently lack NSOAPs, the blueprint has high translational value for researcher-policymaker partnerships globally.

In India, the first-ever nationwide findings for rural populations can garner interest from the national and state government stakeholders. The government buy-in can encourage policymakers to put the current research findings to use. Engagement with policymakers using current analysis from eclectic sources could create avenues for data sharing from HMIS and PMJAY insurance claims databases for researchers. Most importantly, the development of ZV-ASCI, its application to the aspirational districts could be of high interest to NITI-Aayog that, in turn, has had a growing influence on the cross-sectoral policymaking in India. The considerable prevalence of CHE and IHE among surgery-seekers rationalizes the need for more surgical packages in PMJAY (119). Our state-level findings point to the specific access dimensions that each state should focus on. Particularly, using Theil index, we depict that within-state contribution was about three times that of between-state component towards total inequalities in ZV-ASCI. Hence, state authorities have a clear role to play in reducing the inequalities. Identification of low-access clusters can help local stakeholders, specifically the district health officers (DHOs) to address relevant health system issues.

4.3 Study strengths and limitations

To our best knowledge, this is the first study investigating nationwide surgical care access in India. More importantly, we generated the estimates for the rural populations that need them the most. The homogenized dataset of district-level surgical care variables has high value for researchers and policymakers alike. Our analytical pipelines are open-source and minimally expensive. Hence, they can be easily employed by other students and researchers working under financial resources constraints. Specifically, our data assimilation pipeline can be easily translated to other countries to generate surgical care variables datasets at subnational resolution. The raster-based population estimation pipeline can be extended to any global region to get general and sex-age specific population counts disaggregated by rural-urban partitions for a given administrative or geographic unit without requiring GIS expertise or high computing power. Further, we developed a novel simplistic analytical pipeline for estimating population proportions within certain travel-time thresholds from the nearest surgical facilities that is translatable to any region with known health facility geocoordinates. For India, we also created the first geocoded surgical care facilities dataset with over 20,000 data points. Our geocoding procedures can be deployed by health planners with limited resources and expertise to systematically synthesize desired health facility geo-datasets. The current study also marks one of the first instances using HMIS data for research and we provide a comparison of c-section variables against NFHS. Arguably, the introduction of access to surgical care index is the most novel contribution of the study. We synthesized ZV-ASCI to be computationally simple, non-compensatory, and robust to outliers. It can improve communication with policymakers and help bring surgical care on the national health agenda. Estimation of surgical care access dimensions and index at the district level is a major study strength. Typically, subnational studies for India focus on states. However, within-state variations identified in this study demonstrate the need and usefulness of high-resolution estimates. Our inequality in ZV-ASCI findings points to specific districts 'low' access clusters of districts that need urgent policy attention. Finally, accompanying the primary index value for a given state or district, we provide a library of 200 index estimates per region that researchers, policymakers, and planners can choose from.

We acknowledge that the study has several limitations. First, like any secondary data analysis, our estimates inherit the known limitations of the parent datasets. For instance, any known limitations of the MAP motorized friction-surface raster (72) and the global URCA raster (69) apply to timeliness analysis. HMIS analytical reports have shown greater estimates for generic health system variables such as immunizations, institutional deliveries, child and maternal mortality rates, etc. when compared to sample surveys such as Annual Health Survey and District-Level Household Survey, etc. (120) In this study, we compared the c-section proportions against NFHS-4 for a similar time window. While the agreement was classified to be ‘poor’, the value of Lin’s concordance correlation was quite large, particularly after removing the outliers. The limited agreement could be due to exclusion of several districts in Telangana that did not match with GADM, inexact matching of the periods (i.e. 20th January 2015 to 4th December 2016 in case of NFHS-4 (121) was matched with January 2015 to November 2016 from HMIS due to presence of only monthly data), differences in the definition of births in case of population proportion (presumably all births were considered for NFHS-4 (63) while only live births were considered for HMIS), etc. Even so, data quality as measured by completeness, actual vs. reported coverage, etc. for other non-surgical variables has been studied for HMIS (122,123). Regardless, we promote the use of HMIS data as it is relevant for local health planning in LMICs and increased use in academic research can provide feedback on potential data issues. In the case of NSS, the under-reporting and under-sampling issues are known for consumption expenditure (64). Hence, our estimates for CHE and IHE should be considered cautiously, particularly for small regions with sparse data. State or district-wise differences in underlying datasets can further impact our subnational estimates. Second, our geocoded surgical care facilities database is not exhaustive. We focused on creating a well-characterized database in which all the included facilities certainly provide surgical care. This database will continue to expand in the future. Third, despite our best efforts, some misplaced coordinate points (see **Appendix H**) were present in the geocoded surgical facility dataset generated in the study. These were most likely due to the incomprehensibility of Indian language names while locating places using Google Maps API. In the future, such errors can be manually corrected. However, the current findings are robust to a handful of such 'nuisance' points. In the future, a validation step for the address string can be added to improve the geocoding procedure. Fourth, our analysis of surgical volumes, rates, or needs did not consider the classification of surgical operations by underlying conditions or patient demographics since we used the district-level aggregates from HMIS. For similar reasons, we also could not directly link the SSI to the surgical OPs and hence did not account for follow-up. Such an analysis would be possible with more extensive and transparent data sharing from HMIS. Fifth, the current HMIS dataset was inflated with NA (not available) and zero values for SSI. We included the zero values to avoid investigators' bias. However, these data issues make the SSI proportion estimates unreliable. Hence, the observed low values could be erroneous. In the future, data imputation techniques can be used to model SSI relative to surgical volumes to correct bias due to excess zeros. Sixth, our CHE definition differs from that used in studies conducted recently in Brazil (13) and Colombia (14). We used consumption expenditures and not household incomes and did not account for food subsistence due to lack of available data. While the current approach might differ from other surgical care studies, it matches the approach of the global surgical care studies (32,92) and other Indian studies focusing on health expenditures (47,48,93,124). The advantages of using expenditure over income for CHE calculations particularly in LMICs are previously known (92). Seventh, our analysis only includes surgical hospitalizations and not outpatient surgical procedures due to differences in the recall periods (last 365 days for hospitalizations vs. 15 days for non-hospitalizations). Eighth, for IHE calculations, the underlying value of the Indian National Rupee was not standardized for a given year between poverty lines and expenses. While the poverty lines were drawn in 2011-12, the reference year for INR valuation was unclear in the RBI source data (83). We could not adjust for inflation and hence, the IHE values might also be underestimated. Ninth, we did not undertake an uncertainty analysis. While this may not be necessary for timeliness estimates and those reliant on HMIS data, it is critical for estimates based on sample survey data. Uncertainty propagated for affordability proxies will also generate uncertainty data for the index values making findings robust. Finally, a complete validation of the index was beyond the scope of the current study. Our aim here was to introduce ZV-ASCI, provide an instance of its application, and advocate for the use of indices in global surgery research to raise surgery on health agenda. Except for SSI, we used the existing notions of global surgery access dimensions and indicators with known content and construct validity (125). However, criterion and other validity measures are needed for ZV-ASCI's greater uptake.

4.4 Implications for future research

The current study could inspire research along multiple lines. For India, ZV-ASCI estimates should be generated for urban areas. Our current approach can be extended for urban India for all dimensions except safety due to lacking SSI data from HMIS. Modeled estimates generated through meta-analyses, the release of new data from HMIS, or using other data sources such as the PMJAY insurance claims database could help. Creating dis-aggregated estimates for public vs. private surgical facilities, adult and pediatric populations, socio-economic status of surgical care seekers and facilities in rural vs. urban regions is critical for comprehensive understanding. Creating annual surgical care access dimensions and ZV-ASCI estimates to study trends is vital. The resolution of can be enhanced to the sub-regional surgical facility-level if relevant data are available by HMIS. For CHE calculations, the use of modeled income distributions (64,126) instead of consumption expenditure can improve the comparability of subnational Indian estimates with those of other countries. The inequality analysis conducted here for ZV-ASCI should be conducted for various surgical care variables to better understand the distributional and spatial patterns for directing policy interventions. Uncertainty analysis (127) accompanying small area estimation or population microsimulations (see (128) for methodological review) can enhance the robustness of estimates.

The current estimates should be validated by facility-level randomized assessments in select Indian districts collecting data on surgical care access dimensions similar to those conducted in Ghana (111) and Uganda (15).

Beyond India, the methods and tools proposed in the current study have high translational value for global surgery research. Our methodological approach relies on household surveys and HMIS that is common across LMICs and hence can be easily adopted in similar settings such as the neighboring South-Asian countries or those beyond. We also plan to develop an application interface for our analytical pipelines to improve access to research tools. ZV-ASCI can be extended to incorporate other proxy variables for access dimensions. For instance, the met need for the SAO workforce can be used for surgical capacity while POMR could be a more suitable safety indicator (125,129). Regional and country-level ZV-ASCI could enhance a global comparison of accessibility and depict the association of index with other indices such as UHC effective coverage index (130), human development index (8), etc.

5. Conclusion

We present the first-ever high-resolution surgical care access data generated in the current study that can inspire the initiation of national surgical plan development for India. The novel index can help draw attention from high-level policymakers and political leaders of the country. We developed methods that have high translational value for synthesizing similar surgical care access estimates at subnational resolution in other low-and-middle-income countries. The Indian estimates can be further improved by overcoming the limitations of our study and with the availability of more data. Future studies should extend our findings to include other surgical care indicators and assess the validity of the proposed ZV-ASCI.

Appendix A

Summary of studies on c-section (CS) proportions in recent years based on nationally representative surveys

Authors	**Study description**	**Estimate**
Ologunde et al. (2014) (131)	Cross-sectional analysis of facility-based data on LMICs under WHO Situational Analysis Tool to Assess Emergency and Essential Surgical Care, including 171 Indian facilities, of which 110 provided data on CS deliveries.	% CS births of total births in 2008- 8.1%
Neuman et al. (2014) (132)	Cross-sectional analysis of data collected during cluster-randomized controlled trials (c-RCTs) in Asian countries, including India (rural - Jharkhand and Orissa, 2005-08; urban - Mumbai slums, 2006-09) assessing CS prevalence and determinants in private and public facilities.	Cluster-level estimates of % CS births of total live births for 2011- Rural-Public: 15% Rural-Private/Charitable: 5% Urban-Public: 15% Urban-Private/Charitable: 18%
Singh et al. (2018) (133)	Secondary analysis of DLHS-4 for comparing CS births across public and	National-level estimates of % CS births of facility-based

	private facilities. Authors present analysis of trends and sociodemographic and health service utilization correlates but do not depict inter-state or district differences.	deliveries- Private facilities: 13.7% Public facilities: 37.9% Urban areas: 28.6% Rural areas: 19.5%
Guilmoto et al. (2019) (63)	Secondary analysis of NFHS-4 for CS births w.r.t institutional deliveries and population-level births. The authors present an analysis of trends, state and district differences, and sociodemographic correlates.	National-level estimates of % CS births of- Population sampled births: 17.2% Institutional deliveries: 21.8% District and state-level estimates are given.
Bhatia et al. (2020) (134)	Secondary analysis of NFHS-3 and -4 for CS births in public and private facilities. Authors present analysis of trends, state-level differences, and sociodemographic and health service utilization correlates but do not depict district-level differences.	National-level estimates of % CS births of institutional births- NFHS-3 (2005-06) Public facilities: 15.2% Private facilities: 27.9% NFHS-4 (2015-16)

		Public facilities: 11.9% Private facilities: 40.9% State-level estimates are presented.

Appendix B

Summary of studies on surgical site infections (SSI) in India in recent years.

Authors	**Study description**	**Estimate**
Lilani et al. (2005) (135)	A prospective study (May 2001 - July 2002) with 30-days postoperative follow-up in the general surgery unit of a tertiary care teaching hospital in Mumbai, Maharashtra. Surgical wounds were classified by the Center for Disease Control (CDC) criteria with SSI considerations specified in the study.	SSI: 17/190 (8.95%)
Kamat et al. (2008) (136)	A prospective observational study (June 2005 - July 2005) in General Surgery wards of an apex medical teaching hospital in Goa state. SSI was determined and classified as per CDC criteria.	SSI: 35/114 (30.7%)
Shahane et al. (2012) (137)	A prospective study (one-year duration - period not specified) in Surgery and Obstetrics and Gynecology wards of a tertiary care center in Pune, Maharashtra.	SSI: 18/300 (6%)

Rana et al. (2013) (138)	A prospective, observational study (June 2010 - May 2011) in the General Surgery ward of a tertiary care teaching hospital in Ahmedabad, Gujarat. SSI was determined by the CDC criteria.	Suspected SSI: 28/220 (12.72%) Confirmed SSI: 19/220 (8.63%)
Setty et al. (2014) (139)	A prospective study (July 2007 - August 2007) in the General Surgery department of a tertiary care teaching hospital in Mysore, Karnataka.	SSI: 39/180 (21.66%)
Pathak et al. (2014) (140)	A prospective study (October 2010 - August 2011) with 30 days postoperative follow-up in the General Surgery ward of teaching hospital in Ujjain, Madhya Pradesh. SSI was determined and classified as per CDC criteria.	SSI: 36/720 (5%)
Lindsjö et al. (2015) (141)	Intervention (alcohol-based hand rub) study with 1-group pretest-posttest design (pre-intervention period: October 2010 - August 2011 and intervention period: September 2011 - August 2013) with 30 days post-operative follow-up in the department of surgery of a rural teaching tertiary care hospital in Ujjain, Madhya Pradesh. SSI was determined and classified as per CDC criteria.	SSI: Pre-intervention period - 36/720 (5%) Intervention period - 103/1,581 (6.5%)

Negi et al. (2015) (142)	Cross-sectional study (January 2013 - June 2013) in various surgical wards of a resource-constrained, rural tertiary care hospital in Uttarakhand state.	SSI: 137/768 (17.8%)
Shah et al. (2015) (143)	Prospective observational cohort study (April 2009 - March 2013) with 30 days post-operative follow-up in various surgical wards of a private tertiary care hospital in Mumbai, Maharashtra. SSI was determined and classified as per CDC criteria.	SSI: 389/24,355 (1.6%)
Singh et al. (2015) (144)	Prospective cohort multi-center surveillance study (January 2005 - December 2011) with 30 days post-operative follow-up (12 months follow-up for prosthesis SSIs) in 10 hospitals in 6 Indian cities.	SSI: 1189/28340 (4.2%)
Akhter et al. (2016) (145)	A prospective observational study (June 2011 - March 2013) with 30 days post-operative follow-up in the general surgery and surgical intensive care unit (ICU) wards at a tertiary care center in Mumbai, Maharashtra. SSI was classified by CDC definitions.	SSI: 131/1196 (11%)

Mekhla et al. (2019) (146)	Prospective abdominal surgery cohort study (April 2016 - May 2017) in the department of surgery of a rural teaching hospital in Wardha, Maharashtra. SSI was determined and classified as per CDC criteria.	SSI: 39/100 (39%)
Narula et al. (2020) (147)	Prospective descriptive cross-sectional study (April 2014 - August 2014) in General Surgery department of a government tertiary care teaching hospital in Jodhpur, Rajasthan. SSI was determined and classified as per CDC criteria.	Suspected SSI: 102/609 (16.75%) Confirmed SSI: 88/609 (14.45%)

Appendix C

Tabular summary for R packages used in the current study with links.

Package name	Link to documentation
tidyverse	https://www.tidyverse.org/
ggplot2	https://ggplot2.tidyverse.org/
ggstatsplot	https://indrajeetpatil.github.io/ggstatsplot/
rgeos	http://rgeos.r-forge.r-project.org/index.html
scales	https://cran.r-project.org/web/packages/scales/scales.pdf
gdistance	https://cran.r-project.org/web/packages/gdistance/index.html
raster	https://cran.r-project.org/web/packages/raster/raster.pdf
sf	https://r-spatial.github.io/sf/
sp	https://github.com/edzer/sp/
tmap	https://cran.r-project.org/web/packages/tmap/vignettes/tmap-getstarted.html
cowplot	https://cran.r-project.org/web/packages/cowplot/vignettes/introduction.html
RColorBrewer	https://cran.r-project.org/web/packages/RColorBrewer/index.html
janitor	https://github.com/sfirke/janitor
pastecs	https://github.com/phgrosjean/pastecs
stars	https://r-spatial.github.io/stars/
DescTools	https://andrisignorell.github.io/DescTools/
data.table	https://rdatatable.gitlab.io/data.table/

matrixStats	https://github.com/HenrikBengtsson/matrixStats
IC2	https://cran.r-project.org/web/packages/IC2/IC2.pdf
spdep	https://github.com/r-spatial/spdep/
rgdal	http://rgdal.r-forge.r-project.org/
gglorenz	https://github.com/jjchern/gglorenz
ggpubr	https://rpkgs.datanovia.com/ggpubr/
reshape2	https://github.com/hadley/reshape
xlsx	https://github.com/colearendt/xlsx
rstatix	https://rpkgs.datanovia.com/rstatix/
flextable	https://davidgohel.github.io/flextable/
summarytools	https://cran.r-project.org/web/packages/summarytools/vignettes/Introduction.html
ggrepel	https://github.com/slowkow/ggrepel
smoothr	https://cran.r-project.org/web/packages/smoothr/vignettes/smoothr.html
units	https://github.com/r-quantities/units/
exactextractr	https://isciences.gitlab.io/exactextractr/
tibble	https://tibble.tidyverse.org/
DT	https://rstudio.github.io/DT/
maptools	http://maptools.r-forge.r-project.org/
mapproj	https://cran.r-project.org/web/packages/mapproj/index.html
ggmap	https://github.com/dkahle/ggmap

dplyr	https://dplyr.tidyverse.org/

Appendix D

The folder

https://drive.google.com/file/d/1umpnYchAZEIIExQzA093bMMuM9YXy6rZ/view?usp=sharing contains:

1. Input data used in the current study
2. R Markdown notebooks and analysis scripts
3. District-level estimates generated in the study
4. State-level estimates generated in the study
5. ZV-ASCI sensitivity estimates
6. High-resolution images
7. GADM-HMIS-NSS name matching file

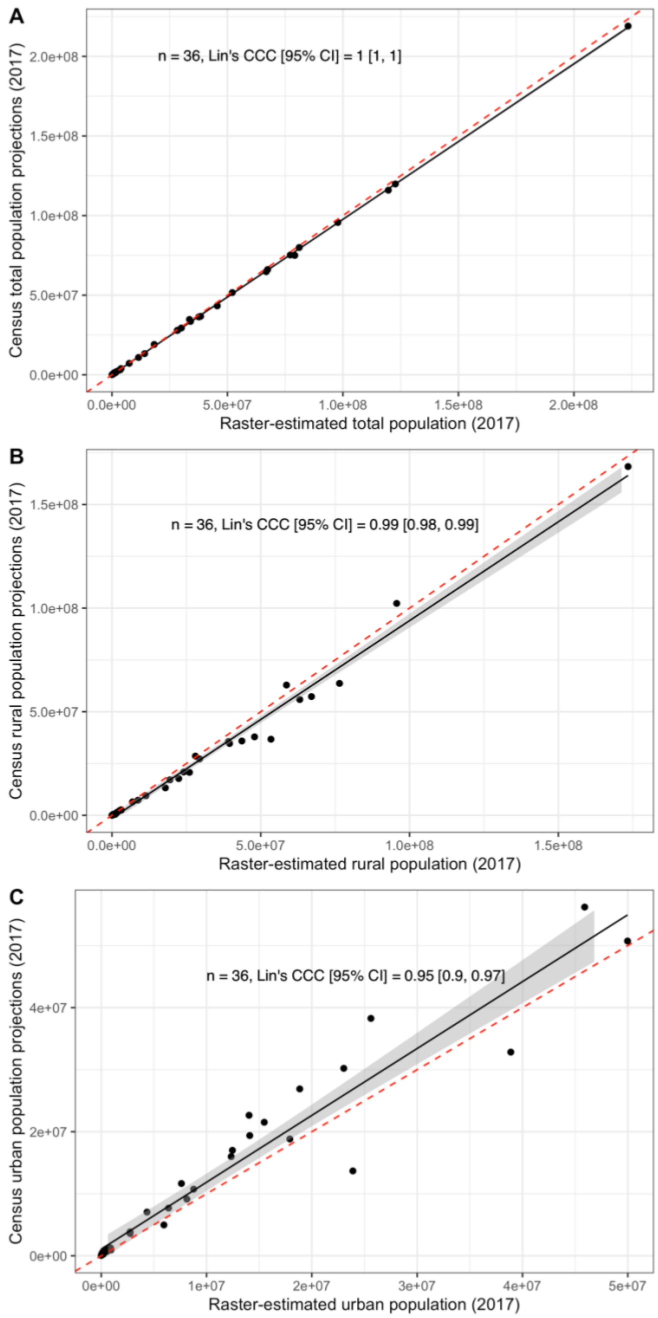
Appendix E

Notations for proxies used in ZV-ASCI sensitivity analyses.

Notation	Variable
T_0	% population within 120 mins. of the nearest surgical facility
T_1	% population within 30 mins. of the nearest surgical facility
T_2	% population within 60 mins. of the nearest surgical facility
T_3	% population within 240 mins. of the nearest surgical facility
T_4	% population within 120 mins. of the nearest NIN/NHP surgical facility
C_0	Met surgical need – major OPs (requiring general or spinal anesthesia)
C_1	Met surgical need – total (all) OPs (minor + major)
C_2	Met surgical need - select major OPs (excluding gynecology and ophthalmic procedures)
C_3	Met C-section need at 10% institutional deliveries
S_0	% SSI relative to total surgical Ops
S_1	% SSI relative to major surgical Ops
A_0	% CHE in surgery-seeking households at 10% threshold (i.e. CHE when OOPE > 10% household consumption expenditure)
A_1	% CHE in surgery-seeking households at 25% threshold
A_2	% CHE in surgery-seeking households at 40% threshold
A_3	% CHE in surgery-seeking households at 60% threshold
A_4	% IHE in surgery-seeking households

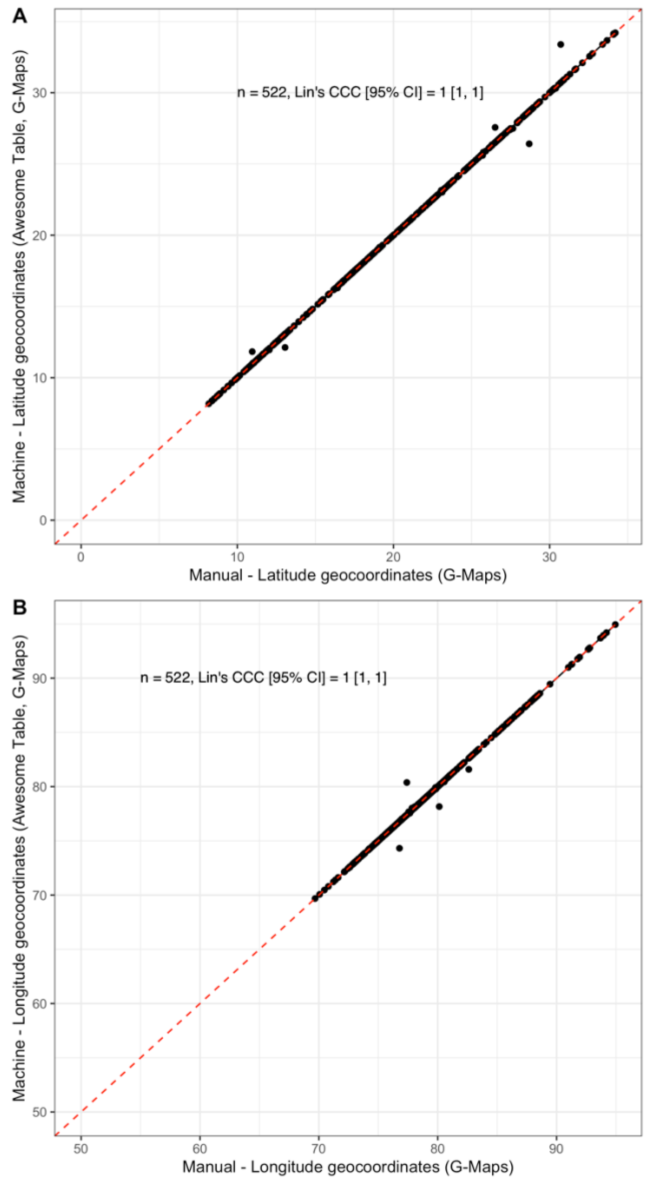
Note: Primary ZV-ASCI is defined as the combination – $T_0C_0S_0A_0$. These proxies can lead to 200 (5*4*2*5) index values including the primary value.

Appendix F



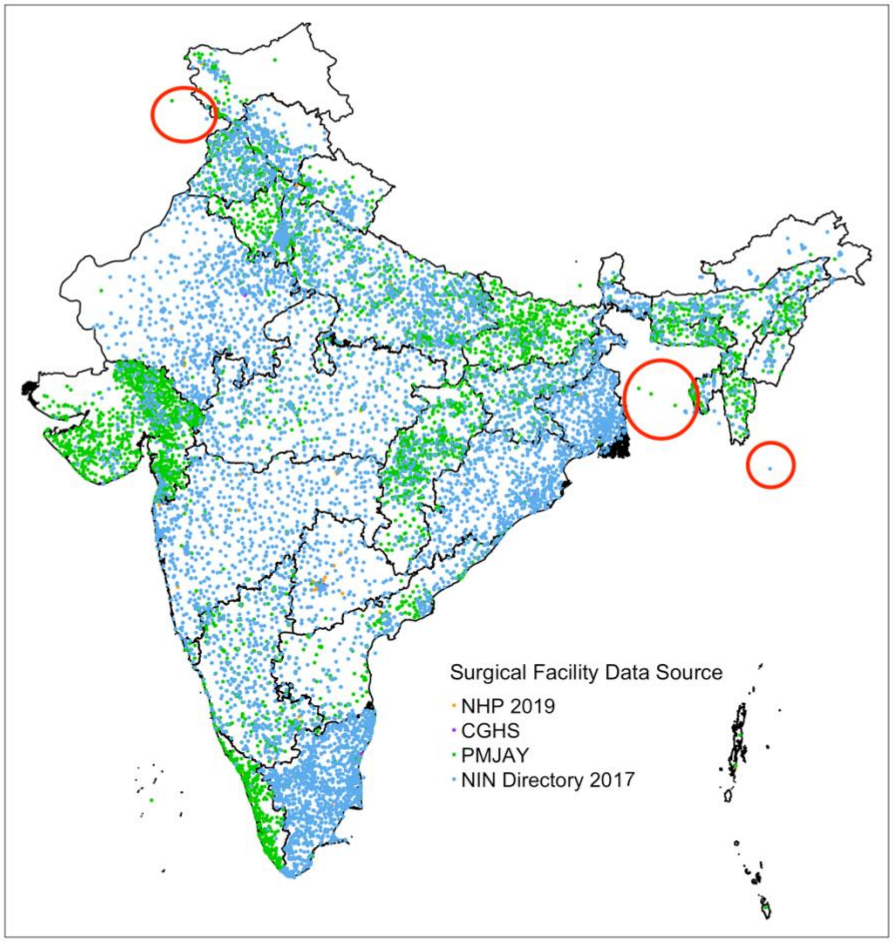
Agreement analysis to validate 2017 state-level estimates for A) total, B) rural, and C) urban populations.

Appendix G



Agreement analysis to validate machine/API-based geocoding against manual geocoding for NHP-2019 teaching hospitals for A) Latitude coordinates, B) Longitude coordinates.

Appendix H



Integrated geocoded database of 20802 surgical care facilities.
Note: Red ellipses mark the erroneous points that lie beyond the realistic geographical country boundaries.

Appendix I

State-level rural-urban differences for surgical care variables.

	Rural regions			Urban regions			Pair-wise adjusted comparison	
Variable	**No. of states**	**Mean (SD)**	**Median (IQR)**	**No. of states**	**Mean (SD)**	**Median (IQR)**	**test statistic (p-value)**	**Effect size (interpretation)**
% population within 30 mins. of nearest surgical facility	36	78.798 (20.999)	83.512 (20.815)	35	98.183 (3.858)	99.546 (1.022)	137 **(<0.001)**	0.673 (large)
% population within 60 mins. of nearest	36	88.802 (19.238)	95.661 (7.35)	35	98.925 (3.168)	99.953 (0.63)	197 **(<0.001)**	0.593 (large)

surgical facility								
% population within 120 mins. of nearest surgical facility	36	93.135 (16.657)	99.184 (4.09)	35	99.131 (2.758)	99.987 (0.229)	262 **(<0.001)**	0.508 (large)
% population within 240 mins. of nearest surgical facility	36	94.948 (15.815)	99.568 (2.324)	35	99.138 (2.759)	99.998 (0.184)	355.5 **(0.001)**	0.38 (moderate)
% population within 120 mins. of nearest NIN/NH	36	93.135 (16.657)	99.184 (4.09)	35	99.131 (2.758)	99.987 (0.229)	262 **(<0.001)**	0.508 (large)

P surgical facility								
Surgical rate - all OPs	35	76531.847 (437619.682)	1697.726 (1789.995)	34	2004.539 (4518.617)	509.685 (1317.716)	855 **(0.002)**	0.376 (moderate)
Surgical rate - major OPs	35	18031.358 (102762.522)	379.452 (631.909)	34	572.995 (1111.624)	194.443 (359.114)	808 **(0.011)**	0.308 (moderate)
% C-sections out of institutional deliveries	35	21.249 (11.556)	20.335 (15.978)	32	35.089 (20.303)	36.181 (26.617)	309 **(0.002)**	0.385 (moderate)
Met surgical need (relative) - major	35	3.606 (20.553)	0.076 (0.126)	34	0.115 (0.222)	0.039 (0.072)	808 **(0.011)**	0.308 (moderate)

OPs								
Met surgical need (relative) - all OPs	35	15.306 (87.524)	0.34 (0.358)	34	0.401 (0.904)	0.102 (0.264)	855 **(0.002)**	0.376 (moderate)
Surgical need gap (absolute) - major OPs	35	-13031.358 (102762.522)	4620.548 (631.909)	34	4427.005 (1111.624)	4805.557 (359.114)	382 **(0.011)**	0.308 (moderate)
Surgical need gap (absolute) - all OPs	35	-71531.847 (437619.682)	3302.274 (1789.995)	34	2995.461 (4518.617)	4490.315 (1317.716)	335 **(0.002)**	0.376 (moderate)
Met C-section need at 10% threshold (relative)	35	2.125 (1.156)	2.034 (1.598)	32	3.509 (2.03)	3.618 (2.662)	309 **(0.002)**	0.385 (moderate)

Met C-section need at 15% threshold (relative)	35	1.417 (0.77)	1.356 (1.065)	32	2.339 (1.354)	2.412 (1.774)	309 **(0.002)**	0.385 (mode rate)
C-section need gap at 10% threshold (absolute)	35	-11.249 (11.556)	-10.335 (15.978)	32	-25.089 (20.303)	-26.181 (26.617)	811 **(0.002)**	0.385 (mode rate)
C-section need gap at 15% threshold (absolute)	35	-6.249 (11.556)	-5.335 (15.978)	32	-20.089 (20.303)	-21.181 (26.617)	811 **(0.002)**	0.385 (mode rate)
Per case surgical OOPE (INR)	36	25615.33 (11641.907)	25272.423 (14342.969)	36	37703.121 (18628.457)	34521.25 (15276.271)	359 **(0.001)**	0.384 (mode rate)

Per capita surgical OOPE (INR)	36	268.582 (239.104)	211.319 (246.97)	36	493.365 (340.41)	444.698 (290.467)	313 **(<0.001)**	0.445 (moderate)
% CHE in surgery-seeking households at 10% threshold	36	46.388 (19.027)	49.968 (25.46)	36	50.272 (13.447)	51.73 (17.739)	610 (0.675)	0.05 (small)
% CHE in surgery-seeking households at 25% threshold	36	23.934 (12.501)	26.269 (22.064)	36	23.666 (11.076)	23.734 (15.194)	683 (0.699)	0.046 (small)
% CHE in surgery-	36	14.852 (9.622)	14.887 (14.711)	36	14.565 (9.549)	13.751 (12.593)	676 (0.757)	0.037 (small)

seeking households at 40% threshold								
% CHE in surgery-seeking households at 60% threshold	36	9.168 (6.607)	8.821 (10.292)	36	8.355 (7.221)	7.514 (7.64)	717.5 (0.437)	0.092 (small)
% IHE in surgery-seeking households	36	4.623 (4.246)	4.046 (8.015)	36	3.85 (2.949)	3.625 (4.423)	684 (0.689)	0.048 (small)
% CHE out of all households at 10% threshold	36	1.945 (1.352)	1.759 (1.782)	36	2.405 (1.239)	2.542 (1.47)	493 (0.082)	0.206 (small)
% CHE	36	1.015	0.944	36	1.123	1.028	596	0.069

out of all households at 25% threshold		(0.793)	(1.176)		(0.745)	(0.692)	(0.564)	(small)
% CHE out of all households at 40% threshold	36	0.611 (0.542)	0.545 (0.727)	36	0.71 (0.599)	0.562 (0.51)	592 (0.532)	0.074 (small)
% CHE out of all households at 60% threshold	36	0.384 (0.344)	0.322 (0.507)	36	0.414 (0.414)	0.339 (0.264)	639.5 (0.928)	0.011 (small)
% IHE out of all households	36	0.202 (0.213)	0.134 (0.325)	36	0.189 (0.168)	0.148 (0.178)	630 (0.843)	0.024 (small)

Note: Differences are based on non-parametric Wilcoxon rank-sum tests. The p-values and effect sizes may vary from the corresponding figures for some variables due to different outlier considerations. Significant p-values (<0.05) are presented in bold.

Appendix J

District-level rural-urban differences for surgical care variables.

	Rural regions			Urban regions			Pair-wise adjusted comparison	
Variable	**No. of districts**	**Mean (SD)**	**Median (IQR)**	**No. of districts**	**Mean (SD)**	**Median (IQR)**	**test statistic (p-value)**	**Effect size (interpretation)**
% population within 30 mins. of nearest surgical facility	662	78.883 (20.046)	84.484 (26.058)	637	97.674 (10.056)	100 (0.876)	30216.5 **(<0.001)**	0.748 (large)
% population within 60 mins. of nearest surgical facility	662	91.752 (15.428)	97.234 (7.241)	637	98.998 (7.463)	100 (0)	42405 **(<0.001)**	0.722 (large)

% population within 120 mins. of nearest surgical facility	662	96.293 (11.19)	99.841 (1.359)	637	99.686 (2.147)	100 (0)	87270.5 **(<0.001)**	0.565 (large)
% population within 240 mins. of nearest surgical facility	662	97.903 (8.785)	100 (0.29)	637	99.721 (2.098)	100 (0)	151393 **(<0.001)**	0.321 (moderate)
% population within 120 mins. of nearest NIN/NHP surgical facility	662	96.293 (11.19)	99.841 (1.359)	637	99.686 (2.147)	100 (0)	87270.5 **(<0.001)**	0.565 (large)

Surgical rate - all OPs	660	5912.982 (101199.209)	658.761 (1217.351)	636	8674.509 (169234.698)	16.226 (718.314)	311517 **(<0.001)**	0.422 (moderate)
Surgical rate - major OPs	658	1356.468 (23747.685)	165.659 (329.542)	487	7108.646 (136323.795)	40.301 (312.518)	206015 **(<0.001)**	0.245 (small)
% C-sections out of institutional deliveries	653	14.48 (13.893)	10.408 (19.505)	463	28.654 (24.879)	26.995 (44.757)	110764 **(<0.001)**	0.228 (small)
Met surgical need (relative) - major OPs	658	0.271 (4.75)	0.033 (0.066)	487	1.422 (27.265)	0.008 (0.063)	206015 **(<0.001)**	0.245 (small)
Met surgical need	660	1.183 (20.24)	0.132 (0.243)	636	1.735 (33.847)	0.003 (0.144)	311517 **(<0.001)**	0.422 (moderate)

(relative) - all OPs								
Surgical need gap (absolute) - major OPs	658	3643.532 (23747.685)	4834.341 (329.542)	487	-2108.646 (136323.795)	4959.699 (312.518)	114431 **(<0.001)**	0.245 (small)
Surgical need gap (absolute) - all OPs	660	-912.982 (101199.209)	4341.239 (1217.351)	636	-3674.509 (169234.698)	4983.774 (718.314)	108243 **(<0.001)**	0.422 (moderate)
Met C-section need at 10% threshold (relative)	653	1.448 (1.389)	1.041 (1.951)	463	2.865 (2.488)	2.7 (4.476)	110764 **(<0.001)**	0.228 (small)
Met C-section need at 15% threshold	653	0.965 (0.926)	0.694 (1.3)	463	1.91 (1.659)	1.8 (2.984)	110764 **(<0.001)**	0.228 (small)

(relative)								
C-section need gap at 10% threshold (absolute)	653	-4.48 (13.893)	-0.408 (19.505)	463	-18.654 (24.879)	-16.995 (44.757)	191575 **(<0.001)**	0.228 (small)
C-section need gap at 15% threshold (absolute)	653	0.52 (13.893)	4.592 (19.505)	463	-13.654 (24.879)	-11.995 (44.757)	191575 **(<0.001)**	0.228 (small)
Per case surgical OOPE (INR)	627	27190.664 (31613.38)	22169.536 (20136.104)	631	36504.936 (28468.177)	29977.078 (25040.583)	145597.5 **(<0.001)**	0.229 (small)
Per capita surgical OOPE (INR)	627	283.783 (440.37)	167.234 (233.571)	631	442.74 (455.072)	317.394 (390.257)	132523 **(<0.001)**	0.286 (small)
% CHE in surgery-seeking	627	55.539 (26.66)	57.953 (38.252)	631	55.911 (25.757)	57.119 (35.563)	197306 (0.937)	0.002 (small)

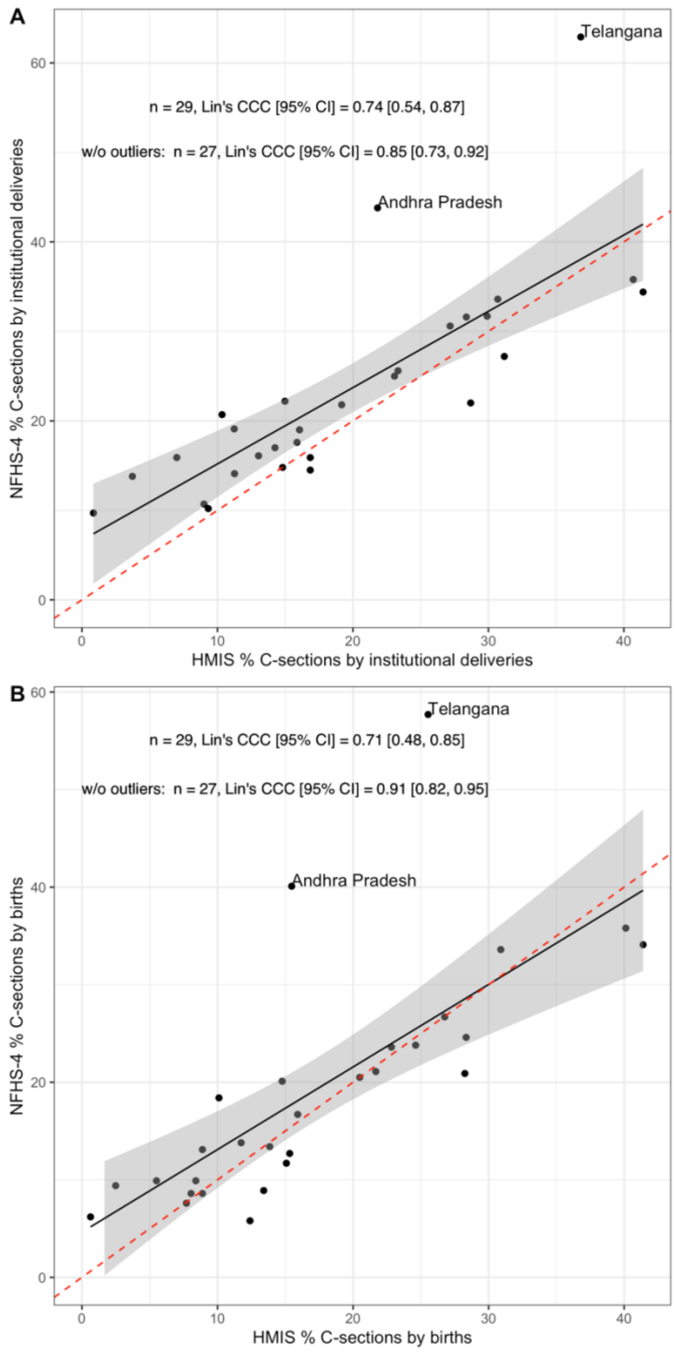
households at 10% threshold								
% CHE in surgery-seeking households at 25% threshold	627	30.102 (23.022)	27.301 (32.052)	631	27.972 (22.521)	24.279 (28.862)	209369 (0.073)	0.051 (small)
% CHE in surgery-seeking households at 40% threshold	627	19.586 (19.412)	14.559 (24.838)	631	16.572 (17.906)	12.147 (24.475)	217678.5 **(0.002)**	0.087 (small)
% CHE in surgery-seeking households at 60% threshold	627	11.797 (15.354)	6.667 (17.157)	631	10.139 (14.762)	5.021 (14.77)	220239.5 **(<0.001)**	0.1 (small)
% IHE in	627	6.294	1.431	631	5.452	0 (7.238)	218589.5	0.097

surgery-seeking households		(11.948)	(8.443)		(10.278)		**(0.001)**	(small)
% CHE out of all households at 10% threshold	635	2.217 (2.032)	1.824 (2.11)	635	2.617 (2.307)	2.138 (2.215)	176080 **(<0.001)**	0.11 (small)
% CHE out of all households at 25% threshold	635	1.224 (1.533)	0.78 (1.244)	635	1.299 (1.561)	0.936 (1.382)	190925.5 (0.102)	0.046 (small)
% CHE out of all households at 40% threshold	635	0.802 (1.3)	0.459 (0.876)	635	0.783 (1.257)	0.489 (0.99)	202726 (0.864)	0.005 (small)
% CHE out of all househol	635	0.496 (1.037)	0.206 (0.53)	635	0.461 (0.865)	0.213 (0.619)	212005 (0.105)	0.045 (small)

ds at 60% threshold								
% IHE out of all households	635	0.28 (0.88)	0.053 (0.306)	635	0.241 (0.549)	0 (0.32)	217188.5 **(0.011)**	0.071 (small)

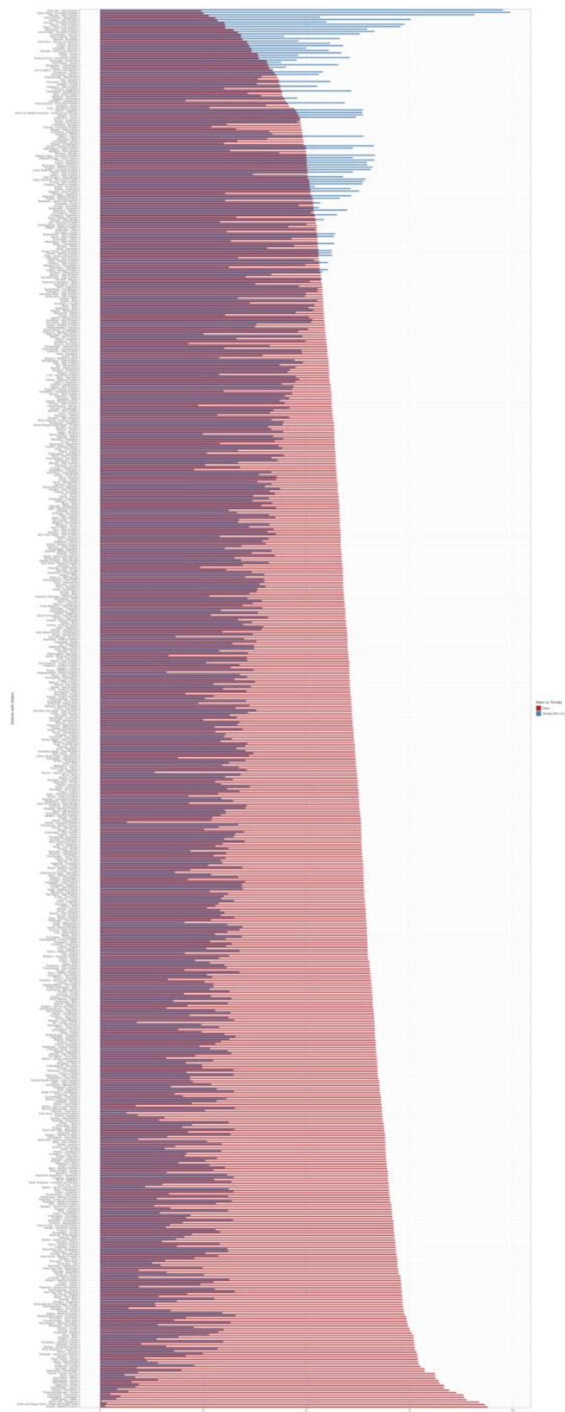
Note: Differences are based on non-parametric Wilcoxon rank-sum tests. The p-values and effect sizes may vary from the corresponding figures for some variables due to different outlier considerations. Significant p-values (<0.05) are presented in bold.

Appendix K



Agreement analysis to validate state-level HMIS values against corresponding NFHS-4 based estimates for c-sections as A) % institutional deliveries, B) % births.

Appendix L



Scissor diagram showing the relationship between the mean and penalty terms of ZV-ASCI for districts.

Appendix M

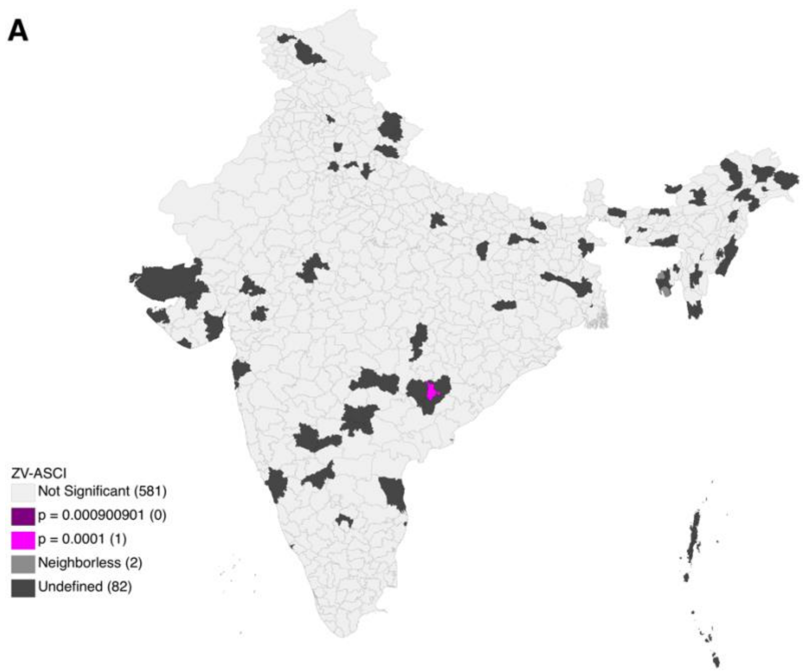
State-wise inequalities in ZV-ASCI and contributions to total inequality.

State	Subgroup Theil Index	Subgroup contribution to Theil	Subgroup Extn. Gini Index	Subgroup contribution to Gini
Andaman and Nicobar	0.000e+00	0.000e+00	0.000e+00	0.000e+00
Andhra Pradesh	3.576e-02	8.082e-04	1.461e-01	7.693e-05
Arunachal Pradesh	7.391e-02	7.433e-04	2.002e-01	1.563e-05
Assam	1.176e-01	4.207e-03	2.533e-01	3.166e-04
Bihar	2.188e-01	1.264e-02	3.480e-01	1.367e-03
Chandigarh	0.000e+00	0.000e+00	0.000e+00	0.000e+00
Chhattisgarh	1.526e-01	5.357e-03	2.591e-01	3.709e-04
Dadra and Nagar Haveli	0.000e+00	0.000e+00	0.000e+00	0.000e+00
Daman and Diu	6.064e-03	4.678e-05	5.501e-02	1.648e-06
Goa	8.190e-04	5.576e-06	2.023e-02	5.350e-07
Gujarat	8.440e-02	4.872e-03	2.267e-01	6.098e-04
Haryana	1.353e-01	4.414e-03	2.875e-01	3.277e-04
Himachal Pradesh	6.887e-02	1.569e-03	2.073e-01	9.171e-05
Jammu and Kashmir	4.578e-02	1.889e-03	1.343e-01	1.506e-04
Jharkhand	1.194e-01	4.012e-03	2.344e-01	2.753e-04

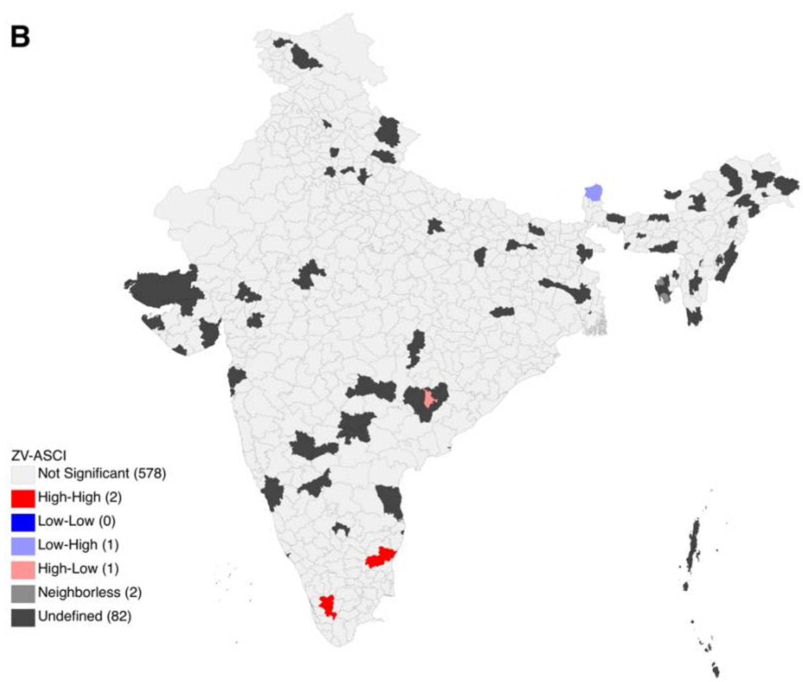
Karnataka	1.751e-01	7.414e-03	3.141e-01	5.939e-04
Kerala	5.305e-02	2.296e-03	1.806e-01	2.125e-04
Lakshadweep	0.000e+00	0.000e+00	0.000e+00	0.000e+00
Madhya Pradesh	1.612e-01	1.146e-02	2.949e-01	1.710e-03
Maharashtra	1.445e-01	7.821e-03	2.919e-01	9.510e-04
Manipur	2.411e-01	5.589e-04	3.324e-01	2.992e-06
Meghalaya	8.420e-02	1.421e-03	2.101e-01	4.131e-05
Mizoram	1.247e-01	6.298e-04	2.573e-01	7.571e-06
Nagaland	1.270e-01	2.316e-03	2.700e-01	8.602e-05
Odisha	1.696e-01	6.361e-03	3.151e-01	6.427e-04
Puducherry	4.749e-04	4.700e-06	1.541e-02	5.921e-07
Punjab	6.748e-02	3.184e-03	1.783e-01	3.593e-04
Rajasthan	1.094e-01	4.932e-03	2.491e-01	6.543e-04
Sikkim	7.911e-02	1.211e-03	1.774e-01	2.110e-05
Tamil Nadu	3.985e-02	3.283e-03	1.472e-01	7.301e-04
Telangana	2.879e-02	2.523e-04	1.229e-01	1.045e-05
Tripura	8.925e-02	8.203e-04	2.292e-01	1.636e-05
Uttar Pradesh	1.811e-01	1.312e-02	3.267e-01	2.527e-03
Uttarakhand	1.125e-01	1.504e-03	2.331e-01	4.841e-05
West Bengal	7.402e-02	2.037e-03	2.145e-01	1.605e-04

Note: Abbreviations - Extn. = extended

Appendix N



Significance map of Local Moran's I for district ZV-ASCI values based on FDR-corrected pseudo p threshold (0.000901).



Corresponding cluster map depicting outliers and clusters of districts for ZV-ASCI.

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