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Spatio-temporal patterns and hierarchical determinants of hypertension, diabetes and obesity in South India: a narrative review of survey evidence and Bayesian small-area approaches to forecasting

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ABSTRACT:

Background: Hypertension, diabetes and overweight make up a growing share of ill health in India, and the southern states are furthest along this path. Yet most published estimates stop at the national or state level, whereas programmes are planned and delivered in districts. In this review we bring together what is known about how common these three conditions are in South India, where they are concentrated and what drives them, and we look at the statistical tools that could be used to map and forecast them district by district.

Methods: We reviewed peer-reviewed articles, national survey reports and methodological texts available up to October 2026. The main sources were the National Family Health Survey (NFHS), the ICMR-INDIAB study, the Longitudinal Ageing Study in India and the Global Burden of Disease analyses. We included work that reported prevalence, spatial patterns, multilevel determinants or projections of hypertension, diabetes or overweight/obesity in India or its southern states, together with methodological papers on small-area estimation and spatio-temporal modelling of survey data.

Findings: Whichever source one looks at, Kerala, Tamil Nadu and Puducherry rank among the highest-burden settings in the country, and Karnataka, Andhra Pradesh and Telangana are not far behind. The provisional NFHS-6 fact sheets for 2023–24 show steep rises in raised blood glucose and overweight since NFHS-5; measured hypertension, by contrast, has not risen evenly. District studies repeatedly find positive spatial autocorrelation, with hotspots in the south. Risk is shaped at more than one level: age, adiposity and household wealth matter for individuals, while urbanisation, the reach of the health system and state policy act higher up. The gap between rural and urban areas is closing, most visibly in Kerala. Most district work still depends on exploratory statistics or single-level regression, and very few studies handle spatial smoothing, time trends and the survey design in a single model.

Conclusions: For district estimates up to 2030, the strongest option is a Bayesian hierarchical spatio-temporal model that takes the NFHS sampling design into account, draws on information from neighbouring districts and carries uncertainty through to the projections. How useful such estimates turn out to be will depend just as much on careful

harmonisation across survey rounds, on handling changes in district boundaries and biomarker definitions, and on being open about how uncertain the forecasts are.

1. INTRODUCTION

India did not pass through its epidemiological transition all at once. According to the India State-Level Disease Burden Initiative, the country as a whole began losing more disability-adjusted life-years (DALYs) to non-communicable diseases and injuries than to communicable, maternal, neonatal and nutritional conditions around 2003, but individual groups of states crossed that line as much as 24 years apart [1]. Kerala and Tamil Nadu got there first. By 2016, high systolic blood pressure and high fasting plasma glucose were already among the five leading risk factors for lost health in India [1]. None of this is surprising if one recalls the original description of the epidemiological transition [2] and the changes in diet that tend to follow higher incomes and city life [3]. Worldwide, non-communicable diseases now cause most deaths, and premature deaths from them fall disproportionately on low- and middle-income countries [4].

Hypertension, diabetes and obesity lie at the heart of this change. Of all modifiable causes of cardiovascular and kidney disease, raised blood pressure is the largest [5]. Type 2 diabetes is rising in nearly every Indian state, and India has one of the largest numbers of people living with diabetes anywhere [6,7]. Overweight and obesity, which contribute to both, have climbed sharply since the 1990s [6,8]. Because the three conditions tend to occur in the same people and in the same places, and because they share many upstream causes, we think there is more to be gained by studying them together than by treating each as a separate programme.

South India is a natural place to start. In this review the term covers Kerala, Tamil Nadu, Karnataka, Andhra Pradesh and Telangana, along with the Union Territories of Puducherry, Lakshadweep and the Andaman and Nicobar Islands. The region is demographically the most advanced part of the country. Literacy is high, the population is older, and primary care networks are well developed. These advantages delivered large gains in maternal and child health. They have also come with the highest recorded diabetes prevalence in India [6,9] and, in the latest national survey, some of the highest levels of adult overweight [10]. The rest of the country may well follow where the south is now.

One problem keeps coming up in this area. Evidence is usually produced at one level and decisions are taken at another. Health is a state subject in India, and the National Programme for Prevention and Control of Non-Communicable Diseases is run through district NCD cells and population-based screening in primary care [11]. Even so, the figures most often quoted are national or state averages, which can conceal sharp differences between districts of the same state and even between villages of the same district [12,13]. NFHS fact sheets do report district values, but direct survey estimates for small areas are noisy. This is especially true for men, who are interviewed in only a subsample of households [14]. Forecasts are rarer still, and the few that exist for India are national [8,15].

We wrote this review as groundwork for a doctoral study that will map the district-level burden of hypertension, diabetes and obesity in South India across three NFHS rounds and project it to 2030. We had three goals. The first was to summarise what is currently known about how common these conditions are in the southern states and how they have changed. The second was to pull together the evidence on where they cluster and on the factors behind them at the individual, household, community and district levels. The third was to weigh up the statistical options, from simple spatial statistics to Bayesian spatio-temporal small-area models, for turning repeated cross-sectional surveys into district maps and forecasts that can be relied on.

2. METHODS OF THE REVIEW

We opted for a narrative rather than a systematic review. The question cuts across epidemiology, survey methods and spatial statistics, and the relevant work is scattered across fields that use different language and seldom cite each other. A systematic search confined to clinical databases would have missed most of the methods literature; one confined to statistics journals would have missed most of the Indian epidemiology.

PubMed, Scopus and Google Scholar were searched for material published from January 2010 to October 2026. Search terms combined the conditions (hypertension, blood pressure, diabetes, blood glucose, overweight, obesity, body mass index), the setting (India, South India and each southern state and Union Territory by name), the data sources (National Family Health Survey, NFHS, Demographic and Health Survey, ICMR-INDIAB, LASI, District Level Household Survey) and the methods (spatial, geospatial, Moran, hotspot, multilevel, small area, Bayesian, conditional autoregressive, forecasting, projection). We

also went through the reference lists of key papers by hand. Survey reports and fact sheets came from the International Institute for Population Sciences and the Ministry of Health and Family Welfare. Older methodological papers were included when they define methods still in use today.

Preference was given to studies that were representative at national or state level and used measured biomarkers, to district-level spatial analyses, to multilevel analyses that split variance across levels, and to methods papers on small-area estimation from complex surveys. We set aside facility-based studies and small convenience samples unless they filled a particular gap. The findings are organised by theme rather than pooled; definitions, age ranges and measurement protocols vary too much between sources for a meta-analysis to mean much.

3. THE BURDEN AND ITS TRAJECTORY

3.1 Data sources that define the evidence base

Most of what is known about metabolic NCDs in India comes from four kinds of data, and many of the apparent contradictions between published figures go back to differences in how these sources were designed. The first is the NFHS, a household survey carried out for the Ministry of Health and Family Welfare, with the International Institute for Population Sciences as nodal agency. NFHS-4 (2015–16) interviewed 699,686 women and 112,122 men in 601,509 households [16]. NFHS-5 (2019–21) reached 636,699 households, 724,115 women and 101,839 men in 707 districts [14]. NFHS-6 (2023–24) covered 679,238 households, and its India and state fact sheets came out as provisional results in May 2026 [10]. In every round, field teams record height, weight, blood pressure and a random capillary glucose reading, and the sample is built to give district estimates for most indicators. No other source offers repeated biomarker data that are representative at district level.

ICMR-INDIAB was designed differently. It sampled adults aged 20 years and over, state by state, and measured fasting and post-load glucose, which brings its diabetes estimates nearer to a clinical diagnosis [9,17]. By its final phase it had enrolled 113,043 people from every state and Union Territory, with fieldwork running from 2008 to 2020 [9]. The Longitudinal Ageing Study in India (LASI) adds a sample of more than 72,000 adults aged 45 and over, representative at national and state level, with measured blood pressure and anthropometry [18]. That helps with the older age groups that NFHS modules, built around women of reproductive age, largely leave out. The National NCD Monitoring Survey of 2017–18, with 10,659 adults aged 18–69, gives national risk factor estimates under the WHO STEPS approach [19]. Lastly, the Global Burden of Disease (GBD) study and the NCD Risk Factor Collaboration (NCD-RisC) combine these and other inputs into modelled, internally consistent time series [6,20–22].

No single source can stand in for the others. The NFHS has breadth and district detail but relies on random glucose and, for many indicators, a narrow age band. ICMR-INDIAB is clinically more precise but has neither district estimates nor repeated rounds. LASI is strong for older adults but has completed only one wave. Anyone trying to project district burden has to work within these constraints.

3.2 Hypertension

How common hypertension appears to be in India depends a great deal on the age range studied and the definition used. That is why published figures anywhere between about 18% and 35% can all be right. In NFHS-4, roughly 18% of adults aged 15–49 had hypertension. Three in four of them had had their blood pressure checked at some point, yet fewer than half knew they had the condition, 13% were being treated and only 8% had it under control [23]. Puducherry and Tamil Nadu were among the places with the highest share of all adults living with uncontrolled hypertension [23]. When data on 1.3 million adults from the District Level Household Survey-4 and the Annual Health Survey (2012–14) were pooled, crude prevalence across all adult ages came to 25.3%, and state values ranged from 18.0% to 41.6% [24]. The national NCD monitoring survey put raised blood pressure at 28.5% among those aged 18–69 [19]. ICMR-INDIAB, which took in every adult aged 20 and over, found that about 35% had hypertension [9,25].

With NFHS-5, blood pressure was measured in all household members aged 15 and above. Around 21% of women and 24% of men met the survey definition [26]. An analysis of the full adult sample of 1.7 million people found that 28.1% had hypertension. Only about a third of these had ever been diagnosed, fewer than one in five were on treatment, and roughly one in twelve had their blood pressure controlled [27]. Much of the variation in diagnosis, treatment and control lay within states rather than between them [27], which in itself is a strong case for working at district level. Another NFHS-5 analysis found

raised blood pressure in 15.9% of those aged 18–54, higher in the southern region than nationally. The same study showed that the share of adults who had ever had their blood pressure measured ranged from about 30% to 98% across districts [26].

The southern picture holds together well. On district maps from NFHS-5, Kerala has the heaviest burden of raised blood pressure, and the coastal districts of the peninsula form one of the country's two main high-prevalence belts [28]. A Bayesian spatial analysis of 304,420 adults from the southern states and Puducherry estimated hypertension at 31.8% and pre-hypertension at 28.9%, with Kerala again at the top [29]. In a state-wide STEPS survey in Kerala, 30.4% of adults aged 18–69 had raised blood pressure; rural and urban figures were much the same, and control was poor [30]. Comparing NFHS-4 with NFHS-5, prevalence went up at most ages, and age and male sex stayed the strongest correlates [31,32].

3.3 Diabetes

GBD estimates for Indian states suggest that the number of adults with diabetes went from 26.0 million in 1990 to 65.0 million in 2016, and that age-standardised prevalence climbed in every state [6]. In 2016 Tamil Nadu and Kerala had the highest prevalence, followed by Delhi, Punjab, Goa and Karnataka. The same work found 38 adults with diabetes for every 100 overweight adults in India, about double the global ratio [6]. This fits the well-known observation that South Asians develop diabetes at lower body-mass index than many other populations [33,34].

ICMR-INDIAB-17 put diabetes prevalence at 11.4% and prediabetes at roughly 15% among adults aged 20 and over, well above earlier estimates [9]. The authors also noted that the epidemic seemed to be flattening in the more developed states while still growing in most of the rest [9]. Earlier rounds of the same study had already shown higher prevalence in towns and cities and in states further along the economic transition [35]. Random glucose measured in DLHS-4 and the Annual Health Survey gave a crude adult prevalence of 7.5%, with states ranging from 3.2% to 19.9% [24]. In the national NCD monitoring survey, 9.3% of adults had raised fasting glucose [19], and many of them were unaware of it or poorly controlled [36]. Across the world, NCD-RisC estimates that more than 800 million adults had diabetes in 2022, and treatment coverage in south Asia was among the lowest anywhere [21].

Self-reported or previously diagnosed diabetes runs well below measured prevalence, which matters for anyone using the NFHS self-report questions. In the southern states in 2012–13, the prevalence of diagnosed diabetes was about three times that of self-reported diabetes [37]. A projection that uses self-report as a stand-in for true prevalence will therefore understate the burden, and more so in districts where screening is weak.

3.4 Overweight, obesity and central adiposity

Adult overweight in India approximately doubled between 1990 and 2016 [6]. By 2021 the country had an estimated 180 million adults with overweight or obesity, a number exceeded only by China [8]. Underweight, however, has not gone away. NCD-RisC data show that south Asia still carries one of the heaviest combined loads of underweight and obesity [22], and Bayesian quantile models fitted to NFHS-4 picked out 66 districts where high risks of both exist side by side [38]. Using Asian cut-offs, ICMR-INDIAB estimated generalised obesity at 28.6% and abdominal obesity at 39.5% [9,39]. These Asian thresholds, a body-mass index of 23 kg/m² for overweight and lower waist circumference limits [34,40], give much higher figures than the WHO global cut-offs used in NFHS fact sheets. Whichever is used, the choice needs to be stated clearly.

Women in the south are hit particularly hard. A state-wide survey in Kerala found abdominal obesity in close to three-quarters of women aged 18–69 [30]. Spatial analysis of NFHS-4 gave a Moran's I of 0.64 for overweight or obesity among women of reproductive age. High-high clusters were concentrated in Kerala, Tamil Nadu, Karnataka and Andhra Pradesh, and also in Punjab, Haryana, Gujarat and Maharashtra [41]. NFHS-5 confirmed that the southern states, along with parts of the north-west, were the main hotspots [42]. Forecasts built on multistate life tables suggest that, among Indians aged 20–69, overweight will more than double and obesity will triple between 2010 and 2040, with the biggest relative rises in rural areas and among older people [15].

3.5 What the NFHS-6 fact sheets add

The provisional NFHS-6 fact sheets give us the first national biomarker data since the pandemic. Nationally, the share of women aged 15–49 who were overweight or obese went from 24.0% in NFHS-5 to 30.7%; for men it went from 22.9% to 27.3% [10]. Among adults aged 15 and over, the proportion with high blood glucose (above 140 mg/dl) or on treatment rose

from 13.5% to 17.8% in women and from 15.6% to 20.9% in men [10]. Raised blood pressure or use of medication was reported for 19.4% of women and 22.1% of men, a little below the NFHS-5 values [10,26].

Once again the south stands apart. Among the large states, Kerala had the highest prevalence of raised glucose, at 31.9% in men and 28.9% in women, with Tamil Nadu and Karnataka next [10]. Overweight or obesity among women reached 46.3% in Puducherry, 46.7% in Kerala and 44.2% in Tamil Nadu, and passed 40% in Karnataka and Andhra Pradesh [10]. In Kerala the urban–rural gap in raised glucose has all but disappeared [10]. Glucose and adiposity going up while measured blood pressure holds steady or falls is not easy to read. It could be a real change, perhaps because more people are now being treated after wider screening. It could equally come from differences in field procedures, device calibration or when the fieldwork took place. The full NFHS-6 report and unit-level data had not been released when we wrote this, so these comparisons should be read as provisional. It is also worth keeping in mind that the fact sheets leave out several indicators that NFHS-5 reported [10].

4. SPATIAL STRUCTURE: WHAT DISTRICT-LEVEL STUDIES SHOW

In population health, spatial dependence is the norm. Districts that border one another share climate, food systems, job markets, cultural habits and administrative arrangements, so they tend to look more like each other than like districts far away. Geographers often call this Tobler's first law [43]. Global Moran's I measures the tendency across a whole map [44]. Local indicators of spatial association (LISA) go further and show where significant high-high clusters (hotspots), low-low clusters (cold spots) and outliers lie [45], and the Getis–Ord Gi* statistic is a close cousin [46]. All of these are easy to run in GeoDa [47], which goes a long way towards explaining why they appear in so many Indian district studies.

For diabetes, different data sources and different periods tell much the same story. In DLHS-4, district prevalence of diagnosed diabetes across the southern states ran from about 5% in Telangana to over 10% in Goa, with moderate positive spatial autocorrelation [37]. National analyses of NFHS-4 found the highest prevalence in coastal districts [48] and, among women aged 35–49, a concentration in the south and east [49]. Work limited to southern districts confirmed significant clustering among women of reproductive age [50]. A study that used both NFHS-4 and LASI found a positive and significant Moran's I for men and women in each survey. The largest hotspots were in districts of Kerala, Tamil Nadu, Karnataka and Andhra Pradesh, and the cold spots were in central India [51].

The district picture for hypertension is more mixed. In NFHS-5 maps, the main high-prevalence zones were the coastal districts of the peninsula and parts of the north-east, and Kerala carried the largest burden. Moran's I was positive but modest, and close to a third of the hotspot districts were in the south [28]. The same authors found only a weak positive link between district health insurance coverage and raised blood pressure, and they suggested that insurance aimed at inpatient care does little for detection [28]. When a Bayesian spatial model was fitted to southern districts, hypertension clustered together with diabetes, while most other comorbidities and behavioural risks showed no significant spatial association once these two were accounted for [29]. District maps from NFHS-5 also show that the share of adults who had ever had their blood pressure measured varied several-fold from one district to the next [26]. Some of what looks like a geography of diagnosed hypertension is, in part, a geography of screening.

The same shortcomings turn up again and again in this body of work. Most studies are single-round snapshots, so they cannot say whether clusters are growing, shrinking or shifting. Many treat district prevalence as an ecological outcome and then read district-level associations as though they held for individuals, which invites the ecological fallacy [52]. Results also depend on the spatial unit and weights matrix chosen, the so-called modifiable areal unit problem [53], yet few authors check how sensitive their findings are to other neighbourhood definitions. Most importantly, Moran's I and LISA are usually applied to raw direct estimates whose sampling variance differs a lot from district to district. A district with only a handful of men in the sample can show up as a hotspot by chance alone. This is the main reason for turning to the model-based methods discussed in Section 6.

5. HIERARCHICAL DETERMINANTS

The risk of metabolic disease is shaped by influences working at several levels at the same time. People live in households; households sit within villages or urban wards; these make up districts; and districts belong to states, each with its own health system and policies. Analyses that take this structure seriously ask not only which factors matter, but at which level they operate and how much of the total variation each level explains [54,55].

5.1 Individual level

Age is by far the strongest and most consistent determinant of all three conditions. In NFHS-4 and NFHS-5, the odds of hypertension and diabetes rose steeply with each age group, and the odds of having both were many times higher in the oldest group than among adolescents [31]. At most ages men have more hypertension and more measured hyperglycaemia, whereas women have more obesity, central obesity in particular [9,10,30]. Excess body fat is the main proximal cause of diabetes. In India, overweight was responsible for an estimated 36% of diabetes DALYs in 2016 [6], and globally high body-mass index accounts for roughly half of type 2 diabetes DALYs [7].

Behavioural risks are common and only loosely linked to socioeconomic position. In 2017–18 more than 40% of Indian adults were physically inactive, hardly anyone ate the recommended amount of fruit and vegetables, and average salt intake was about 8 g a day [19]. ICMR-INDIAB found little recreational physical activity in any state [56]. Tobacco and alcohol use have dropped a little in recent rounds but are still common among men [10,19].

Early life adds yet another layer. Indian newborns tend to be small, but for their size they carry relatively more fat [57]. Undernutrition early in life followed by overnutrition later is thought to explain part of why Indians are so prone to diabetes at modest body weights [33]. Cross-sectional surveys cannot capture this intergenerational effect, but it is worth bearing in mind when interpreting cohort-like shifts from one survey round to the next.

5.2 Household and community

In India, socioeconomic gradients do not always run the way they do in high-income countries. In NFHS-3, adults in the richest wealth quintile had more than two and a half times the odds of self-reported diabetes compared with those in the poorest, even after allowing for body-mass index [58]. Positive gradients with wealth and education have also been reported for overweight [41,42] and, less strongly, for hypertension [24]. Part of this gradient, though, reflects better diagnosis among the well-off rather than more disease, a point argued firmly in a critique of the Indian literature on socioeconomic status and cardiovascular risk [59]. When diabetes and hypertension are actually measured instead of self-reported, the gradient becomes flatter, and prevalence among middle-aged adults in the poorest rural households turns out to be high already [24].

The household is itself a level that matters. Chronic conditions tend to cluster among people living under the same roof, reflecting shared diet, activity and surroundings [60]. A multilevel analysis of more than a million adults in DLHS-4 found that variation in measured hypertension and diabetes was substantial at the village level and, after that, at the household level. Individual sociodemographic characteristics explained almost none of the variation at the higher levels [12]. Context, in other words, appears to matter over and above who happens to live in a place.

The rural–urban divide is shrinking. A STEPS survey in Punjab found no rural–urban difference in diet or overweight [61], and in Kerala raised blood pressure and fasting glucose were no more common in towns than in villages [30]. NFHS-6 shows the same convergence for glucose in the southern states [10], and forecasts point to the largest relative increases in overweight in rural areas over the coming decades [15]. For district analysis, this means that the urban share of a district now tells us less about its metabolic risk than it did ten years ago.

5.3 District and state context

States differ in income, in when they went through the epidemiological transition and in how strong their primary care systems are [1]. These differences affect both how much disease occurs and how likely it is to be picked up and treated. The fact that most variation in hypertension care lies within states [27] suggests that district administration and local service delivery count for something as well. Village-level mapping of child undernutrition in India found that villages accounted for most of the geographic variation and states for a smaller share, with districts adding fairly little once the other two were included [13]. Whether the same is true of adult metabolic risk is not yet known, but the finding warns against simply assuming that the district is the most informative unit.

District-level contextual variables that have been tried in the literature include the urban share of the population, poverty, female literacy, health insurance coverage, density of health facilities, and patterns of food production or consumption [28,48,51]. Very few studies have looked at the built environment, food prices or air pollution, even though all three plausibly vary between districts. Just as few have asked whether the effect of an individual factor such as wealth differs from district to district, something a random-slopes model or geographically weighted regression [62] would make possible.

6. ANALYTICAL APPROACHES AND THEIR LIMITS

6.1 From single-level regression to multilevel models

The early NFHS analyses used single-level logistic regression with survey weights. They identified the main individual correlates, but because every geographic unit was treated as independent, they could not tell individual effects apart from contextual ones. Multilevel models deal with the nesting of individuals within clusters, districts and states. They let the total variance be divided up, and summary measures such as the median odds ratio put between-area variance on a scale that can be compared directly with fixed-effect odds ratios [54,55]. Several Indian studies have taken this route with NFHS, DLHS and LASI data [12,31,58].

Standard multilevel models still treat districts as exchangeable, though. Every district estimate is pulled towards the overall mean in the same way, no matter where the district sits on the map. If neighbouring districts really do resemble one another, useful information is thrown away, and the leftover spatial autocorrelation can distort the standard errors.

6.2 Exploratory spatial statistics

Global and local measures of spatial autocorrelation are a sensible first step. They tell us whether clustering exists and where it is strongest [44–46]. Spatial lag and spatial error regressions build on this by modelling district prevalence as a function of covariates and of neighbouring values, and several Indian studies report lag coefficients that put a number on spillover between neighbours [37,41]. Geographically weighted regression goes one step further and lets the coefficients themselves change across space [62].

For our purposes, these methods have two weak points. They treat district prevalence as if it were known exactly, when it is really an estimate whose error differs from district to district. And they offer no natural way of projecting forward in time. They are better seen as descriptive tools that point towards a formal model than as the analysis itself.

6.3 Bayesian hierarchical spatial and spatio-temporal models

Disease mapping has long relied on pulling unstable small-area estimates towards something more stable [63]. The Besag–York–Mollié (BYM) model brought space into this by splitting area-level variation into two parts: a structured part with an intrinsic conditional autoregressive (ICAR) prior, under which each area's effect is centred on the average of its neighbours, and an unstructured part that treats areas as exchangeable [64]. The Leroux version uses a single mixing parameter to balance the two [65]. In the BYM2 reparameterisation, the structured part is scaled so that its variance means the same thing across different neighbourhood graphs, and the mixing parameter can be read directly as the share of variance that is spatially structured. It also works well with penalised-complexity priors [66]. South India includes island territories with no land neighbours and enclaves such as the districts of Puducherry, so how a model handles disconnected parts of the graph is a real practical concern here, and BYM2's scaling copes with it more neatly than the older forms.

Space-time extensions bring in a temporal trend and allow it to differ between areas. Bernardinelli and colleagues proposed area-specific linear trends [67]. Knorr-Held set out four types of space-time interaction, from fully independent to fully structured in both space and time [68], and these have become the usual menu of options. With only three NFHS rounds, area-specific trends are weakly identified, and which interaction type is chosen will make a visible difference to the projected maps. This choice should be explored and reported, not simply settled by habit.

Fitting such models once meant long Markov chain Monte Carlo runs. The integrated nested Laplace approximation (INLA) now gives fast and accurate approximate Bayesian inference for latent Gaussian models, a class that covers the BYM, BYM2, Leroux and Knorr-Held specifications [69]. Where cluster coordinates are available, the stochastic partial differential equation approach makes it practical to fit continuous spatial surfaces [70]. When more flexibility is needed, full Hamiltonian Monte Carlo in Stan is a workable alternative [71,72]. The standard textbooks cover all of these in detail [73,74].

For the problem at hand the benefits are tangible. Districts with small samples can draw on their neighbours and on earlier rounds. Uncertainty flows through to every derived quantity, so instead of simply labelling a district a hotspot, we can say how likely it is to be above a given threshold. These posterior exceedance probabilities are a sounder basis for choosing priority districts than LISA run on raw estimates. Global modelling groups already rely on Bayesian hierarchical models for national estimates of hypertension, diabetes and body-mass index [20–22], and the same reasoning carries over to districts.

The protocol behind this review calls these models a gold standard, and that claim needs some qualification. Smoothing lowers variance but adds a degree of bias, and a district that genuinely differs from its neighbours, say an urban district ringed by rural ones, can end up over-smoothed. Checking the model against held-out data, and looking at where shrinkage is greatest, cannot be skipped.

6.4 Small-area estimation with complex survey data

The NFHS uses a stratified two-stage cluster design with unequal selection probabilities, and ignoring this can bias the estimates. There are two broad ways to square Bayesian smoothing with the survey design. The first grows out of the Fay–Herriot area-level model [75,76]. It begins with weighted, design-based direct estimates for each district and their design-based variances, and then smooths these with a hierarchical model. Mercer and colleagues extended this idea to space and time by building a working likelihood for the direct estimates and placing a space-time prior on the area effects, fitted with INLA [77]. The second way models individual or cluster-level responses directly and includes design variables, such as the urban–rural stratum, as covariates. Wakefield and colleagues lay out the trade-offs between the two clearly [78], and the wider difficulty of combining survey weights with model-based inference has been well described [79].

With NFHS data, the area-level route has real practical appeal. It respects the sampling design, it stands up well if the individual-level model is wrong, and it is easy to explain to programme managers, since it starts from the same weighted figures they see in the fact sheets. Its weak point is that districts with very few respondents, which is common for men, give unstable variance estimates that have to be smoothed or pooled before modelling. A unit-level model makes better use of individual covariates but has to deal with the design in other ways. Running both, at least as a sensitivity analysis, would make any district-level study more convincing.

6.5 Forecasting to 2030

To project prevalence forward, one has to make assumptions about how the drivers of disease will change. Simply extending the trend from three survey rounds is risky: with three points almost any curve will fit, and the direction one ends up with leans heavily on the most recent value. Demographic forecasting has better tools to offer. The Lee–Carter model splits age-specific rates into an age pattern and a time index that can be carried forward [80]. Multistate life-table models have been used to forecast overweight and obesity in India, modelling incidence, mortality and urbanisation explicitly [15]. GBD forecasts link future prevalence to projected sociodemographic development and risk factor exposure [7,8,81]. And averaging across several plausible Bayesian models has been shown to give better-calibrated life expectancy projections than relying on any one of them [82].

For district projections in South India, one practical approach is to separate two things: the effect of population ageing, which demographic projections can predict fairly well, and the change in age-specific prevalence, which is much less certain. The second can be projected from the posterior distribution of the space-time model, with explicit scenarios for how body-mass index and urbanisation might evolve. Forecast skill should be tested out of sample, for example by fitting the model to NFHS-4 and NFHS-5 and seeing how well it predicts NFHS-6 [83]. The results should then be judged with proper scoring rules, which reward both accuracy and honest statements of uncertainty [84]. Comparing models with the deviance information criterion or the widely applicable information criterion is helpful [85,86], but it is no substitute for predictive checks.

7. MEASUREMENT AND DATA ISSUES SPECIFIC TO THE NFHS

A number of NFHS features bear directly on spatio-temporal modelling, and they are easy to overlook.

Glucose is measured from a random capillary blood sample. The fact sheets class readings above 140 mg/dl as high and combine this with self-reported medication to form the main glucose indicator [10]. That threshold is not a diagnostic criterion for diabetes, and the time since the person last ate is not controlled. Studies that used stricter cut-offs, such as 126 mg/dl for people who had fasted and 200 mg/dl for those who had not [24], arrive at lower figures. Whatever definition is used, it has to be the same in every round, and the results should be described as raised glucose, not diabetes.

Blood pressure is taken three times with an automated device, and analysts usually average the last two readings [26]. A single visit overstates sustained hypertension compared with repeated clinical measurement. Since this bias is probably much the same across rounds and districts, though, it matters less for trends and relative patterns than for the absolute size of the burden.

Age coverage varies by module and round. Anthropometry has traditionally been collected for women aged 15–49 and men aged 15–54, while blood pressure and glucose were extended to all adults aged 15 and above from NFHS-5 onwards [14,27]. Limiting an analysis to ages 15–49 so as to match NFHS-4 means leaving out the very age groups in which most hypertension and diabetes occur. Bringing in LASI data for older adults, or reporting age-standardised estimates over a wider age range from NFHS-5 and NFHS-6, would help.

Men are interviewed in only a subsample of households, which leaves small district samples and wide confidence intervals [14]. This is exactly the situation in which model-based small-area estimation earns its keep, but it also means male district estimates will rely more heavily on the model than female ones.

District boundaries keep changing. NFHS-4 reported on about 640 districts, NFHS-5 on 707 and NFHS-6 on 715 [10,14,16]. In the south, Telangana and Andhra Pradesh have each redrawn their districts more than once since 2014. A time-series analysis needs a fixed geography, which means either rolling new districts back up to the older boundaries or dividing older estimates among the new districts using population weights or cluster locations. DHS cluster coordinates are deliberately displaced to protect confidentiality, by up to 2 km in urban areas and up to 5 km (occasionally 10 km) in rural areas [87], so placing clusters near a boundary in the right district involves some error.

Finally, the COVID-19 pandemic split NFHS-5 fieldwork into two phases that covered different states [14]. Comparisons between states surveyed in different phases, and comparisons across rounds that involve them, should allow for possible period effects.

8. RESEARCH GAPS AND AN AGENDA FOR SOUTH INDIA

Looking across the evidence, we see several gaps that a district-level study in South India is in a good position to address.

To our knowledge, nobody has yet published a district-level spatio-temporal analysis of the southern states that uses all three NFHS rounds. The spatial studies we found are snapshots, and the trend analyses work at national or state level. Bringing the two together is the main contribution such a study can make.

Joint modelling of the three conditions is also rare. Hypertension, diabetes and obesity share determinants and cluster in the same places [29]. Multivariate or shared-component spatial models, which estimate a common spatial field alongside condition-specific ones, could reveal where risk comes from a shared underlying process and where one condition breaks away from the others. That distinction has real consequences for how programmes are designed.

We still understand little about how health-system factors shape measured prevalence. As screening coverage rises, more people know their diagnosis and are treated, and this in turn changes measured blood pressure and glucose. The small fall in measured hypertension in NFHS-6 [10] may be partly due to this. Telling apart changes in how often disease occurs from changes in how well it is detected and controlled would mean linking survey data with district-level programme data on screening and treatment.

Uncertainty is seldom passed on to decision-makers. District rankings and hotspot maps usually come with no indication of how much confidence they deserve. Reporting the posterior probability that a district is above a policy-relevant threshold, or that its rank falls in the top tenth, would make these maps more useful and less likely to mislead.

The validation plan in the protocol, which compares NFHS-based estimates with ICMR-INDIAB and LASI and uses earlier rounds to predict later ones, is sound and ought to be routine. Because age ranges and biomarker definitions differ, external comparison should concentrate on relative patterns and rankings rather than absolute levels.

Once NFHS-6 unit-level data are released, the region will have its first three-point district time series. There will be a temptation to read too much into district-level change from samples that, in many districts, are small. A model that pools information across space and time is the right tool for this, and its outputs should always be shown with uncertainty intervals.

9. CONCLUSIONS

South India has the highest burden of diabetes and overweight in the country, and both are still rising; hypertension remains common and poorly controlled. These conditions cluster in space, are shaped by influences at several levels, and are becoming as common in rural areas as in urban ones. The NFHS gives an unusually rich basis for district-level work, but its direct district estimates are too noisy, on their own, to support reliable rankings or projections. Bayesian hierarchical spatio-temporal models that respect the survey design, draw on neighbouring districts and earlier rounds, and carry uncertainty into the forecasts are

the most defensible way to arrive at district estimates for 2030. In the end, how useful those estimates prove for planning will depend as much on careful harmonisation of definitions, age ranges and boundaries, and on frank reporting of uncertainty, as on how sophisticated the model is.

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