Greenhouse gas emissions of India's household food, apparel, mobility and energy consumption: Regional structure and inequality, and scenarios for 1.5°C climate stabilization

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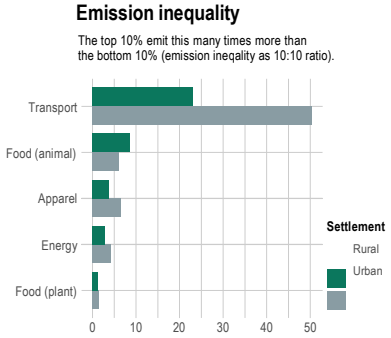

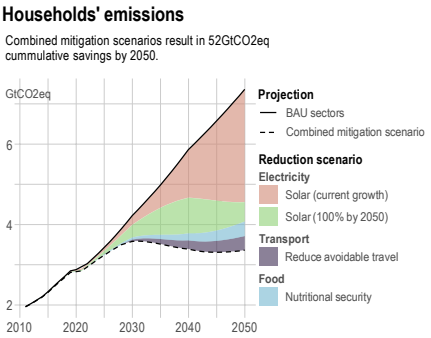

1 Introduction

Like much of the world, India faces two pressing challenges whose solutions seem antithetical: eradicating poverty and combating climate change. In 2012, 48% of India's population earned less than $2 per day, and 98% earned less than $10 per day [1]. India's economic turnover is growing rapidly (although temporarily halted by COVID-19), and the nation is on track to achieving considerable improvements by 2030, especially in economically oriented SDGs [2]. However, this economically minded development would need to continue for another 100 years to eradicate the deepest levels of poverty [3].

Rising economic prosperity is reflected at the individual level in a higher standard of living, translating into higher environmental impacts. Urban India, in particular, is displaying numerous signs of resource-intensive lifestyles,

through increasing consumption of dairy and meat products, rising mobility (due to the expansion of transport infrastructure), increasing use of material goods (cars, smart gadgets, etc.), and services (entertainment and health) [4-7]. This suggests that, with ongoing urbanization, demand for resources and associated impacts will increase as well [8-11].

In terms of GHG impacts, India became the fourth largest carbon emitter in the world, emitting 2.6 $GtCO_2eq$ in 2018 [12-14], even though the average Indian emitted only 1.9 $GtCO_2eq$, a low figure in global context. However, with economic development targeted for a growing population, GHG emissions are expected to increase, threatening climate targets that seek to stabilize global warming at 2°C or below. This raises the question of how to increase materially dependent welfare, particularly of the poor, while reducing GHG emissions, possibly to a net-zero level in 2050.

The range of differences in living standards and consumption patterns ofIndian households is vast, perhaps greater than any other country in the world.The living realities of the 1.3 billion inhabitants range from partial or full sub-sistence agriculture [15] in rural areas to extreme poverty and hyper-modernaffluent consumption in metropolitan areas [7, 16-18]. These differences are reflected in large price differentials across regions and expenditure groups [19].

Research on sustainable consumption (SDG 12 [20]) focuses on estimation of environmental impacts of products and services produced and consumed, including those arising from households [5, 10, 21-33]. These assessments used approaches of environmentally-extended input-output models (EEIOs) mod- els, life cycle assessment (LCA) [34] using life cycle inventories, and resource specific databases such as those provided by the Water Footprint Network [32] to assess single (example, EEIO or WFN) or multi-dimensional footprint assessments (example LCA). As these databases provide commodity or sector- specific environmental impacts only, thus to capture household impacts, these are usually linked with household expenditure databases with the assump- tion that all households buy and consume same quality of commodities and are equally located from production sites (this implies same transportation distances, equal resource use, storage, capital and labor requirements, etc., among others costs for all commodities), with EEIO models being the domi- nant approach to capture indirect impacts. More details on methodologies in Section 2.1.

As indicated above, living conditions within India vary vastly, thus, regional economic structure (due to the differences in the scale of agriculture, indus- tries, maining, etc. sectors located in specific states) also differs. This implies that from the regional household's perspective, supply chain emissions cannot be equally allocated between rural and urban regions, and neither between different expenditure strata, considering retail commodity prices also vary across states [19]. The EEIO-models based on national input-output tables (IOTs) assume sectorally homogeneous prices [35] and are therefore unable to capture the differences across regions and expenditure groups. Similarly, non-monetized goods and services, such as biomass from local forests [36, 37],

do not appear in the monetary national input-output balances.However, as EEIO-models estimate indirect impacts associated with supply chains, thus neglecting above considerations, revised, and aggregated representations based on national IO models of India are being actively deployed to estimate GHG impacts, even for the regional studies [28, 35]. Over the years, such EEIO-based studies using global and national input-output tables have reported per capita GHG footprint between 0.56-1.8tCO_2eq (see additional details in Appendix-01, S.3.4.1).

In this study, we make an attempt to assess regional and expenditure-stratified environmental-impacts of India's household-consumption. Specifi- cally, we estimate GHG emissions of the main consumption categories of Indian households, namely, food, clothing, transport, and energy, using physi- cal consumption data and emission-coefficients given in the literature, (details given in Section 2.2.2). Thus, our study captures household-based impacts while regional and inter-regional aspects of supply chains (because neither regional carbon emissions inventories nor physically-based regional IO models exist for India). That is, we focus on "bottom-up" structure of consumer- survey numbers while excluding the impacts of "supporting" supply-chains as extracted from in EEIO-models. The resulting losses in terms of complete- ness and consistency seem justified to us by the better resolution of regional and expenditure-based price differences [19, 38] for our specific question. Such an approach also differentiates our study from "top-down" and "sector-wise" assessments reported in literature [39, 40].

In summary, by providing a high-resolution consumption-oriented carbon- emissions analysis of both regions and expenditure segments of India, our study offers a unique insight into the regional structure of India's householdconsumption.

Additionally, to explore the capabilities of developed regional commod- ity and carbon-database of 2011-12, we model scenarios aimed at net-zero emissions by 2050 for specific products identified through this "bottom-up" assessment, with the exclusion of rebound effects. The explored scenarios are in alignment with *#SDGinPB* framework [2], and demonstrate the poten- tial reduction of "direct" households emissions from both supply-side [40] and demand-side [41, 42] actions, considering per capita-based share of global carbon-budgets [11, 43] in view of planetary-boundaries [44]. Further, the transitions explored in these scenarios are interpreted and justified under the "Avoid-Shift-Improve" framework [45, 46]. These scenarios highlight other opportunities of GHG reduction from household's perspective, excluding the already advocated "Electric Vehicles" and "Clean cooking" solutions from socio-economic perspective, but also the limits of demand-side transitions con- sistent with climate change stabilization target aimed at 1.5°C. Successive sections on methodology 2, results 3, and discussion 4, provide details this research.

2 Methods and data

2.1 Background

Addressing the objectives of SDG12 [20], the field of Industrial Ecology (IE) is geared towards assessment of environmental impact undertaking a life cycle perspective. From consumption perspective, the environmental impacts of households are mostly estimated as environmental footprints using environmentally-extended input-output models (EEIOs) models [23, 28, 31], however process-based life cycle assessments that outline all environmental impacts (carbon, water, biodiversity, resource depletion, etc.) [31, 47-49] are also gaining traction. The Water Footprint Network's methodology [32] offer another approach to estimate production or consumption footprints [33]; how- ever, it assess only direct water-impacts of operations and thereby misses the impacts associated with indirect uses. For instance, it fails to assess water-pollution impacts of materials required for information infrastructure [50]. In general, pollution impacts of mining and industrial operations are largely missing in this approach [51]. Thus, though pioneering in the field of quan- titative water-based impact assessments, the WFN's-based assessments are usually constrained to scarcity impacts and fail to quantify end-point indica- tors (impacts on human-heath, resource scarcity, biodiversity) that make LCIA approach more comprehensive for impact assessments [34].

The life cycle impact assessment of products or commodities or processes (considered as systems) in life cycle assessments (LCA) approach, usually suffer from boundary truncation problems, however offer multi-dimensional aspect of environment sustainability of individual products and services. In the context of GHG, the above inference can be stated as LCA studies fail to assess Scope 3 impacts or indirect impacts due to the boundary-truncation issues.

As the methodological workings of environmentally-extended input-output (EEIO)-framework follows the life cycle assessment methodology, the IE com- munity frequently employs monetary-based EEIO models to specifically assess Scope 3 impacts which are aggregated under sectors and industries definition in monetary-IO tables usually under the 'Industry-Technology' assumption. Thus, by mapping the impacts of extended suply-chains, EEIO models are capable of providing a comprehensive (and agggregated) estimate of impacts that are truncated in life cycle assessments (LCA) from either a production or a consumption perspective [8, 52]. Furthermore, territorial, demand-driven, or sector-wise indirect (along with direct) impacts are easily outlined using EEIOmodeling.

Thus, in comparison to LCA-based assessments, the EEIO-based assess- ments have the advantage that they allocate environmental impacts along the entire input chain to final household consumption in a consistent and complete manner. However, EEIO-assessments fail to capture product or process-specific impacts mostly due to aggregation of sectors or industries. Further, most EEIO-based assessments have focussed on carbon-emissions owing to following reasons: (i) key determinant of crucial planetary boundary of climate change

(ii) lesser developed regional inventories for other environmental impacts (for instance, regional, gray water [53], biodiversity [54, 55], material [56], etc. input-output models do not exist for India). That said, regional environmental extensions (biodiversity [57], water [8, 9], material [56], etc.) and development of physical input-output models [58] is an active area of research in IE.

As stated earlier, both global and national EEIO models have been utilized to estimate the GHG impacts of India from territorial, national and house- hold perspective [28, 59, 60]. However, most global and national EEIO-models are not well-suited for regional impact assessments due to (i) significant struc- tural difference bewtween regional and national economies [61] (ii) owing to lack of supply-use data of regional and inter-regional economic-flows [8, 9, 62]. Additionally, the use of different approaches of analysis (demand-pull versus supply-push) [8, 9, 27, 28] for global and national EEIO models can present different values of supply-chain responsibilities [63] and of consumers versus producers [64]. The household's perspective in particular demands that con- sumption data is aligned with sector-wise defination given in the IO tables, thus missing the differentiation seen across regions and households.

Substantiating the last point in the context of India, a recent study attempting a regional and racial analyses utilized the global EEIO model, EORA, and the same expenditure accounts (year 2011-12) as used in this study [28]. It explored regional-emission inequality with aggregated expen-diture categories and excluded gender-based inequalities among others. Itreported 0.56tCO_2eq per capita for households at the national level, withoutmaking appropriate considerations for regional supply chain impacts for prod-ucts and different expenditure or income-categories. The main caveat of thisstudy is that their reported per capita estimate is far lower than those reportedby the earlier studies (1.8 tCO_2, [59], 1.6 tCO_2 [60], 0.8 tCO_2 [23]), and GHGemissions by other reports [12-14] even though it is undertook a more recent year for assessment (2011-12). Such a low estimate warrants a necessity toassess and understand the importance of underlying assumptions used in theEORA model and consumer expenditure accounts, from a regional perspective.Considering that the EORA model was used in this assessment ([28]), reasons for the gap with previous IO-based estimates could be either dueto sector-wise aggregations attempted in EORA database or aggregationof consumer expenditure data (more details in next paragraph) of 347 commodity-categories to correspond with EORA database. The EORA modelfollows different sector aggregation (116 sectors for 2011) compared to India'snational IOTs (130 sectors for 2011-12). Such differentiation in global MRIOsare undertaken streamline sectorwise classification at global scale and ease bur-den of massive computational requirements for running these databases (forexample, latest version [65] of EXIOBASE has 139 sectors compared to 130 innational IO tables of 2011 of India). However, due to changes in different sec-tor classification and use of monetary expenditure values (reorganized as perIO structure), the study's [28] per capita estimate was far lower than reported in previous studies.

Additionally, such discrepancy may also be due to substantial variation observed in regional consumer-prices reported in expenditure-survey data [19, 38], even though equal value of carbon-intensities (in monetary-terms due to homogeneous pricing) are derived from the EORA. It is to be noted that the consumption expenditures were observed to be higher for urban areas (proba- bly due to higher disposable income) in the reported statistics[38]; whereas, per unit commodities-prices for consumers, except for fuels, were seen to be lower in rural areas (see Tables 4U/R-a/b in [19]). This aspect can be crucial for regional expenditure-based consumption assessment, since actual consumption can vary a lot in physical units if prices at consumer level differ from IO-based prices, which is usually the case (especially for rural versus urban distinction). The latter statement of varying commodity-prices further implies the same emission-intensity (in price-based terms) derived from EEIO models would undermine consumption for regions with lower per commodity prices and over- state it for regions with higher per commodity prices if equal commodity-prices are assumed.

Further, when commodities such as biofuels (firewood, chips, etc. harvested from local forest-reserves [36, 37]) do not enter the market-system, EEIO- models cannot map impacts of such consumption. That is, EEIOs such EORA or EXIOBASE or national monetary-based emission models cannot estimate true impacts of consumption for the transactions that are based on different prices or those that are not recorded in the national IO tables. With such lim- itations posed by national EEIO models for regional assessments, it is highly imperative that either regional emissions input-output models be used for regional consumption-based assessments or appropriate measures are taken to quantify consumption using regional price differences mentioned earlier.

Acknowledging the competence of the IO-framework along with limitations posed by aggregation, homoneous pricing, and lack of regional scope, EEIO community is moving towards development of physical accounts to assess true impacts from environmental accounting perspective. The move towards devel- opment of hybrid-IO models [8] and physical input-output models (PIOTs) [66, 67] for accounting of the impacts [58] outlines the current trend in IE- dominated EEIO community. Further, PIOTs are being actively pursued to map physical (material, energy or resources) accounts and impacts of economic activities with the broader objective to manage imapcts and resource-use, espe- cially at regional landscape [68]. From the perspective of consumption-based accounting, we can state that EEIOs are best suited to identify sector-wise drivers of emissions (or environmental impacts). Thus, caution is warranted when using national and global datasets to interpret regional household-basedenvironmental results and issues.

Considering that 'environmental-extensions' of regional and multi-regional input-output models are not developed by Indian economic agencies, this rules out the possibility of using them for environmental footprinting accounting. Further, as LCA databases accounting for regional (state-wise) information are also not available for India, thus LCA assessment of products is also

not possible currently. However, estimating actual consumption of regional expenditure-deciles is possible from available regional level data.

As regional carbon and environmental (water, biodiversity, emissions-bio- genic versus fossil, etc.) accounts are difficult to develop, analytical approaches are applied on lower-resolution national models to serve as proxy for estimat- ing impacts of regional production structure. Providing an example a recent MRIO application,transformed the 2015 national IO model of India into a MRIO model, aggregating sectors in states at different levels based on statistics of state GDP and value-added. The aforecited study analyzed consumption- based and not from household-based emissions focusing on different categories of final demand as driving factors. Further, the study included only fossil- based products (coal, petroleum, and gas) at state-level, and thus was able to account for regional structure of fossil-based emissions only. The other GHG gases especially methane associated with food-based products were excluded in the study. Owing to rising affluence, the household consumption of meat and milk is rising over decades. Thus, the GHG (specifically, methane-based) emissions of these commodities are unaccounted in the study. The differences in regional consumer prices (Tables 4U/R-a/b in[19]) are also unaccounted and consumption categories are aggregated according to the IO structure. In summary, the study offers reflections based on sectoral contributions to statewise-GDP in the backdrop of national IO accounts. It does not develop the regional physical-emission inventory of states and evades the social aspects of households' responsibility which is the focus of our study. Thereby, theirresults differ from our assessment.

As our analysis is geared towards understanding the regional structure of emission-impacts, we required the regional expenditure data to stay as it is. Therefore, we did not aggregated the consumption-categories to align with the sector-wise categories reported in the IO databases. Further, the com- modities included is this assessment capture all the categories reported in the expenditure database for all expenditure-categories. Thus, our study illus- trates the emissions differences across the states and expenditure-categories of India, by focusing on consumption-expenditure data and not on background IO model. Thereby, we explicitly differ in our methodological approach from the previous emission studies providing national level estimates [23, 28, 59, 60]. Furthermore, we also differ from food [30] or energy-use[5] studies by captur- ing what these product-systems actually contribute each expenditure categoryat regional scale.

2.2 Method

We rely on a hybrid survey and emission footprinting data [5, 30] to calculate region and expenditure-group specific partial carbon footprints, using those, in turn, to construct household-focused scenarios for India up to 2050 (Figure 1). The information on the data used is given in Section 2.2.2 along with Section
S.1 of the Appendix-01. Details of data processing, data quality, and scenario building are given as follows.

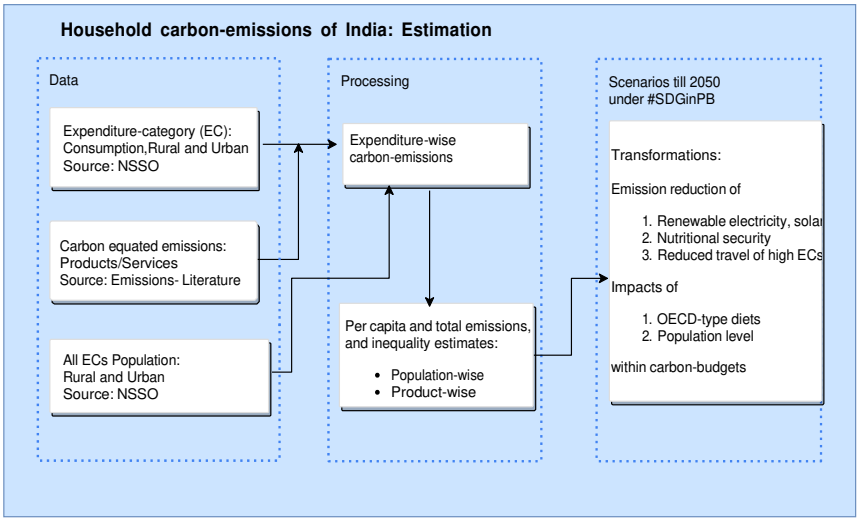

Fig. 1 Conceptual overview of the methodology to estimate regionalized and expenditure- stratified household emissions in India.

2.2.1 Estimates of 2011-12 emissions

We estimate the total per capita emissions (GHG^{pc}) by state (s), settlement profile (p) and expenditure-category (i) as the sum of the per capita emissions of all commodities (c) considered. The emissions per commodity are the prod- uct of the specific greenhouse gas intensity (int^{GHG}), measured in kgCO_2eq per kg commodity, and the quantity (q) consumed (in kg), as shown in Equation 1 below:

$$GHG^{pc}_{s,p,i} = \sum_{c=1}^{n} int^{GHG}_{c} * q_{s,p,i,c} \quad (1)$$

where s is one of 35 Indian states and union territories, settlement profile p can either be rural or urban and expenditure classes i are given as deciles, with the bottom and top 10% further disaggregated into 5% fractiles. We consider a total of eight commodity categories c (fuels and light, transport, dairy, meat, rice, other foods, footwear, and clothing). The total emissions (GHG^{total}) are estimated by multiplying the per capita emissions with the population P specific to the state, settlement profile, and expenditure class.

$$GHG^{total}_{s,p,i} = GHG^{pc}_{s,p,i} * P_{s,p,i} \quad (2)$$

Total emissions by region, settlement type or expenditure class can then be obtained by summing over s, p, i, or a combination thereof.

When reporting expenditure-stratified emissions at the national level, separately for rural and urban conglomerations, we re-estimate national expen- diture deciles (and 5% fractiles at the top and bottom) based on state-level expenditure-data reported for each expenditure class in the NSS to reflect the

absolute national expenditure distribution rather than aggregating over rela- tive spending levels as in the original NSS data [19]. For example, the lowest 10% of rural-population reported at the national-level consists of the people in all states whose consumer expenditure belongs to the lowest 10% category. See Appendix-01, Section S.1.6 for details of expenditure-categories.

Many inequality-measures such as the Lorentz curve, Gini index, Theil index, Atkinson measures, Hoover index, and other ratios [69, 70] exist to quantify inequality, we use the 10:10 ratio [70] as a measure of inequality due to its intuitive interpretation. The 10:10 (also referred to as 90:10) ratio is calculated by dividing the emissions of the top 10% of the expenditure distribution (the 10th decile) by those of the bottom 10%. The resulting index represents how many times more the top 10% emit compared to the bottom 10%. We report 10:10 ratios for commodities, states, and settlement profiles. Additionally, we provide emissions-based Gini Coefficients and Lorentz Curves (using total emissions at national scale) for rural and urban conglomerations in Section S.3.3.3.

2.2.2 Data and limitations

The consumer expenditure data was retrieved from the National Sample Sur- vey (NSS) reports, period 2011-12 [19, 38]. The commodities considered areindicated in Table 1

Table 1 Consumption data in MRP category

Commodities available	
physical units (Kg)	price units *(Rupees)
rice	milk & milk products
wheat	sugar
jowar	salt
bajra	edible oil
maize	egg, fish & meat
barley	vegetables
small millets	fruits (fresh)
ragi	fruits (dry)
gram	spices
cereal subst.	beverages etc.
arahar	fuel and light
gram (split)	clothing
moong	footwear
masur	conveyance/ transportation
urd	
peas	
khesari	
other pulses	
pulse products	

and details on transformation from monetary to physical units (wher- ever required) are given in Appendix-01, Section S.1.1. The commodity-wise emission-intensities with respective data sources are reported in Table 2 The

emissions of different commodities, categorized under different scopes (details indicated in Appendix-01, Section S.1.1.2), capture only direct emissions asso- ciated with production or consumption. That is, indirect emissions of all "supporting" supply-chains of these products/services are excluded [71]. Thus, fuel and transport-use capture embodied-emissions only at the household-site, whereas food and apparel capture emissions at the production-site.

Table 2 Commodity-wise emission factors

Commodity	kg CO2eq. per kg (Range)	Source and notes
rice	1.752	[30]
wheat	0.29	[30]
jowar	0.347	[30]
bajra	0.156	[30]
maize	0.21	[30]
barley	0.048	[30]
small millets	0.156	[30]
ragi	0.156	[30]
gram	0.282	[30]
cereal subst.	0.221	[30]
arahar	0.601	[30]
gram (split)	0.282	[30]
moong	0.541	[30]
masur	0.541	[30]
urd	0.541	[30]
peas	0.362	[30]
khesari	0.541	[30] [1]
other pulses	0.362	[30]
pulse products	0.362	[30]
milk and milk products[2]	8.775 (4.5 - 90)	[30] milk - 95% others - 5%
sugar	0.148	[30]
sugar	0.194	[30]
edible oil	2.402	[30]
egg, fish & meat[2]	16.608 (1.507-75.556)	[30]
vegetables [2]	0.044	[30]
fruits (fresh) [2]	0.043	[30]
fruits (dry) [2]	0.210	[30]
spices [2]	0.000	[30] - consumption in grams
beverages etc. [2]	0.004	[30] - wine, beer, toddy etc.
fuel and light[2]	2.303 (1.22-3.13)	[5] dung cake to L.P.G.
clothing	0.843	[72] - cotton yarn
footwear	30.506	estimated from [73, 74] - rubber emissions
	3256.266	2009 -data [73], KtCO2eq
	106.743	2009 -data [74], Kt
conveyance/transport [2]	2.480 (2.3-2.66)	[5] - petrol and diesel

[1] Same as moong
[2] Multiple commodities are combined

The term "footprint" as used in this manuscript excludes emissions from sequestration (due to natural and engineered technologies [75]) as well

as upstream supply-chains other than indicated above. As equal emission-intensities are used within this study, a lack of variability arising from regional product emission factors and those due to "supporting" supply-chains are the critical limitations of this assessment. The role of gender [76, 77] and contri- bution of high income-categories in internationally traded goods and services is also not investigated explicitly herein owing to data limitations.

2.3 Scenarios

In this section, we offer a summary of the modelled scenarios, with additional details given in Appendix-01, Section S.2. These scenarios are meant to high- light how the "bottom-up" regional data can be used to explore reduction in household emissions, while focusing on specific categories of consumption identified through this assessment.

Identifying the "hotspot" categories (Sections 3.1, 3.2), the transformation scenarios are focused on the commodities that contribute about 89% (Section 3.2) to total households' emissions, namely, fuels and electricity, transportation (reported as 'conveyance' in the survey), dairy, and meat. However, compared to BAU state-level numbers, the transformations are explored at national level, for two reasons (i) state- and profile (urban vs rural)-wise mitigation strategies may differ in actual implementation, (ii) the effect is seen through the com- modities and not the spatial context, and (iii) for the ease of presenting results at national level. That said, spatial, expenditure-based, and also gender-based, analyses can be undertaken in future assessments using the same inventory and regional overshoots can be evaluated using regional carbon-budgets.

Referring to above stated perspective, the electricity transformation sce- nario explores the impact of supply-side intervention of low-carbon electricity infrastructure on households electricity emissions, whereas, behavioral changes of demand-side changes (see next paragraph) focus on reduction of cur- rently increasing animal-based diets while meeting the nutritional requirements proven in the literature. Another demand side intervention focuses on reduced travel of the top 30% expenditure-categories that are found to be dominant emitter as per the analysis.

2.3.1 Business As Usual

The baseline or business as usual (BAU) total emissions scenario is evalu- ated using current [78] and expected future population [79] (see Appendix-01, Section S.2.1), and expected growth of per capita emissions, both estimated at state level. The population projections at state level include rural to urban migration but excludes inter-state and international immigration. The per capita emissions are derived from estimating (a) commodity-based carbon- intensities growth-rate per unit of Gross Domestic Product (GDP), and (b) potential state-level GDP-growth rates till 2050 [80] using the national-level projections given by government of India's energy model outlook [81]. From the estimated emission growth-rate (from [80]), emissions intensity of fuel and

transportation (0.88% of every % of GDP growth) is taken higher than carbon- intensity of GDP (0.626%), whereas that of food and apparel is considered lower (0.20% for every unit of GDP growth) than the GDP emission intensity. That is, the commodities-based emission-intensity growth estimated at state level is further divided across expenditure categories to obtain per capita emis- sions, thereafter per capita emissions are used with population projections to arrive at state level total emissions. The details of all these calculations are given in Appendix-01, Sections S. 2.1 and S.2.2). The results of these BAU emissions at state, profile, and expenditure level are given in Section 3.4.1. It is to be noted that we are presenting scenarios and not projections, based on data and projections reported elsewhere. Hence, all scenarios are subject to changes in underlying parameters defined elsewhere as well as the ferocity of both production and behavioral changes over time. For instance, if fertility rates drop post COVID phase or due to economic uncertainties, the BAU andconsumption trends would change as well.

2.3.2 Electricity transition

The baseline emission scenario for electricity, E BAU, at the national-level, is estimated by summing the integration of expenditure-stratified per capita increase in electricity-emissions with the projected population growth (rural and urban with migration) [79, 82] at the state-level. The per capita increase in emissions is estimated by extrapolating state-GDPs derived from projected national-GDP (pg10- [81]) and electricity emission-intensity per unit of GDP using The World Bank's emission and GDP data [80].

With households electricity-emissions of 3349 $MtCO_2eq$ in 2050, required RE-based capacity translates into 2184 GW (at 0.926 $KgCO_2eq$ per KWhr and 1.656 KWhr per Watt capacity installed). Assuming 58% of electricity- consumption is by households, this translates into total RE-based capacity requirement of 3765 GW. This estimated capacity is nearly equal to 3755 GW (2050) projected by [83] (see Appendix, Table 4-1) with 3217 GW contributed by solar-capacity, 222 GW by wind and hydro, 316 GW by biomass, and therest by other carbon-based systems.

Considering aforementioned data, 2184 GW solar-capacity (68% of 3217 GW [83]) required by households' electricity-consumption is achievable and is considered as 100% threshold in this study. The transformation scenar- ios, E S1 and E S2, determine the potential reduction in emissions by adding solar-sources to electricity-grid from 2021 onwards, after the inclusion of other sources (wind, hydro, etc.) of non-fossil energy. The first transformation- scenario, E S1, captures potential reduction by pursuing current-rate of solar-capacity investments. However, as it fails to achieve 100% solar-capacity by 2050, a higher-rate, E S2, is explored that nearly reaches 100% level of the threshold. Both transitions are explored using logistic functions. For additional details on computation, see Appendix-01, Sections S.2.3 and S.3.5.

2.3.3 Food transition

The baseline emissions scenario for food, F_BAU, is estimated by multiplying the projected population with expected growth in expenditure-stratified per capita food-based emissions (details given in Appendix-01, Section S.2.3). Targetting nutritional-security (1.29 tCO_2eq per capita [84]), transformation scenario, F_S1, follows the growth of the F_BAU scenario until per capita emissions reach the lower bound for nutritional-security and tracks population growth thereafter. The counter-factual scenario, F_S2, models exponential growth in per capita emissions until emissions of OECD-type diets (2.89 tCO_2eq per capita [84]) are reached in 2050. As average food-emissions of top 20% are above $2tCO_2eq$ per capita (see Appendix-04, tabs "per capita" for dairy and meat), and these categories comprise of major international-travellers), the F_S2 scenario is explored to understand how preference towards animal-based diets can increase total emissions.

2.3.4 Transport transition

The baseline transportation scenario, T_BAU (all), is obtained by multiplying expected growth in per-capita transportation-emissions of different expenditure-categories with their respective projected population (Appendix-01, Section S.2.3); whereas, scenario, T_BAU (top 30%), represents transport emissions of top 30% (results indicate 69% contribution) of the expenditure-distribution (national-scale). The transformation-scenario, T_S1, models a 1% annual reduction of emissions due to reduced travel of the top 30%. The contribution and transformation for other expenditure-categories and regions [85-87] can be explored in future studies in conjunction with suggested transportation-policies [88].

Interpreting the above transformation-scenarios in the context of the "Avoid-Shift-Improve" framework [45], renewable-energy transformations (E_S1, E_S2) reflect possible reduction by "shifting" to low-carbon infrastructure. The food-based transformations capture how shifts in diets can reduce (F_S1) or increase (F_S2) emissions; whereas, reduced travel of high expenditure-categories illustrates how altering travel-behaviour can decrease or 'avoid' emissions. Thus, these transformations [2] cumulatively explore the potential of both supply-side and demand-side solutions for mitigating future emissions of India at the household-level.

2.3.5 Scenarios limitations

The above defined scenarios are explored to quantify potential and definite emission reductions that can be achieved through both production-system (electricity) and behavioral changes, however the defined scenarios are not exhaustive. Other scenarios others such as those focusing on expenditure- and age-stratified behavioural-changes [85, 86], regional-densification [87], fueling-behaviour [42] in conjunction with adoption of electricity-vehicles, can be

explored as well. Further, we excluded assessment of vehicle electrification (bat- tery electricity-vehicles (BEVs) or hydrogen-based vehicles(HbVs) [88, 89]) impacts since it is already been proven that without greener grid GHG reduc- tion would not happen [90]. Second, both types of vehicles if produced using current electricity-mix supply chains would imply substantial embodied GHG impacts. Thus, it is advocated that system-wide consequential life-cycle costs or environmental-rebounds [91, 92] of such EV transformations should be explored further for better evaluation of the impacts.

We are also not exploring the impact of clean cooking fuel policy because (i) the GHG intensity of LPG cylinders is more than biofuels (see Table S1 of Appendix of [5]) (ii) the traditional stoves or "chulas" are found to be climate neutral under operational conditions [93]. Last, we hopefully assume in all scenarios that the current CoVID-19 pandemic will not cost millions of lives during 2020-21 [94, 95] and so exclude the potential impact of the current pandemic on domestic electricity use, food consumption, rural to urban migration, and population-growth for the period under consideration.

Further, though we model emissions-reductions due to solar-transitions, it should be noted that these transformations may incur substantial environmen- tal rebound effects [91] on land and related socio-economic-ecological systems (food, water, material-requirements, etc.). From land perspective, owing to conflicting requirements for food and animal-feed especially [96], these "mod- elled" scenarios also do not imply such transitions social-feasibility as well. Further, the life cycle impacts of materials used in developing this infras- tructure, including panels, batteries, grid-connectivity, among others, may be substantial. As the embodied material use implies scope 3 emissions along with other life cycle impacts (water-toxicity, biodiversity loss for extraction of mate- rials). Thus, life cycle environmental impacts of energy transition should be explored further for better understanding of potential environmental benefitsfor future.

3 Results

The category-wise results are summarized in Sections 3.1, 3.2, and 3.3, whereas detailed results with high resolution on regions and expenditures, are given in Appendix-01, Section S.3 and Appendix-02. Comparison, limitations, and differences with other studies are indicated in Appendix-01, Section S.3.4.

3.1 Per capita emissions

Per capita emissions equal 2.72tCO_2 for urban-households and 2.20 tCO_2 for rural-households, translating into national average of 2.35 tCO_2 compared to
0.56 tCO_2 reported by [28] (additional details on differences in methods isgiven in the Appendix-01, Section S.3.4.1) for 2011-12.

The results of Figure 2(a) highlights per capita emissions vary multifold across states. This figure excludes the results of UT of Lakshadweep, which dis- plays very high numbers (discussed in Appendix-01, Section S.3.1.1). Average

emissions of the highest per capita emitting state, Goa (5.58 tCO_2eq -urban, 5.45 tCO_2eq -rural), is nearly four times those of the lowest per capita emitting state of Bihar (1.54 tCO_2eq -urban, 1.3 tCO_2eq -rural). Nearly all populous states tend to have higher per capita emissions in urban-setting, except for the north-eastern states (Tripura, Mizoram, Nagaland, Arunachal Pradesh, and Manipur), the northern state of Uttrakhand, and the UTs of Daman-Diu and Chandigarh. The prominent reason for this disparity in state-level and rural versus urban emissions is on account of differences in consumption-expenditure and price of commodities observed across the states and urban areas. The consumption expenditures tend to be higher in urban areas due to higher dis- posable income [38], whereas, per unit price of commodities, except for fuels, is lower in rural areas since most goods consumed are produced locally. To see difference in per unit prices across rural versus urban, refer to Tables 4U/R-a/bin [19].

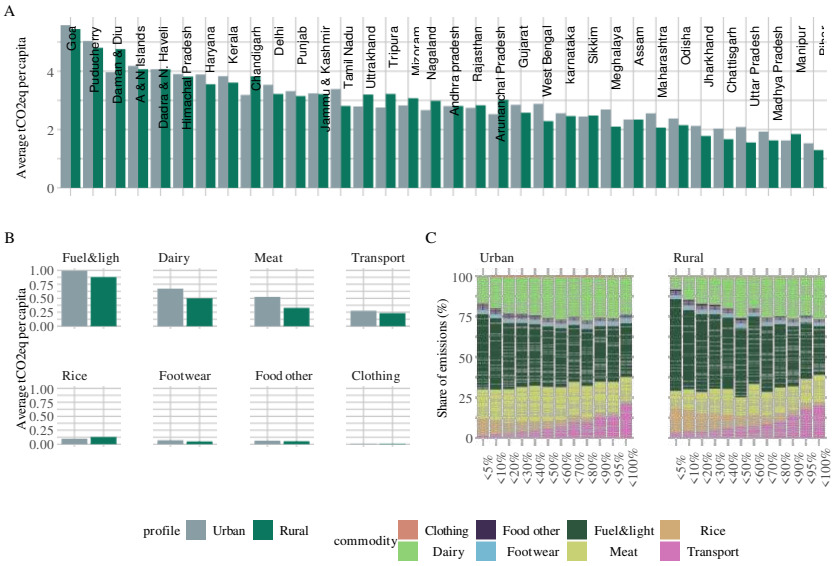

Fig. 2 Per capita emissions: (a) State-wise, (b) Commodity-wise, (c) Expenditure-wise

Commodity-wise, per capita emissions are dominated by fuel and food demand (Figure 2(b)). Average emissions of urban India are, 0.991 tCO_2eq for 'fuel and light', 0.279 tCO_2eq for 'transportation', 0.673 tCO_2eq for 'dairy-products', and 0.528 tCO_2eq for 'meat and eggs' consumption. For rural India, average estimates are, 0.813 tCO_2eq for 'fuel and light', 0.217 tCO_2eq for 'transportation', 0.459 tCO_2eq for 'milk and products', and 0.305 tCO_2eq for 'meat and egg' consumption. This figure confirms the dominance of energy-based products key drivers of emissions are fuels for domestic-cooking, residential electricity-use, and transportation [5]. The figure also highlights

that nutrition-oriented animal-based diets are predominant driver of carbon emissions and not food-security (rice and other plant-based products).

Figure 2(c) indicates both scale and pattern of emissions differ considerably across expenditure-groups. For lowest expenditure-quantiles, significant impacts are created by food-consumption (dairy, meat, rice, other food); whereas, highest expenditure-quantiles display striking dominance over transport-based emissions. The higher transportation-emissions of topmost expenditure-groups in urban-areas is easily justified through private owner- ship of high-end vehicles, available wealth and time for international travel; whereas, for rural-areas, the higher share could be due to the need for travelling larger distances by private transport or due to the lack of public infrastructure. For additional details on per capita numbers, see Appendix-01, Section S.3.1 and Appendix-02, tabs: 'PA U PCinT' and 'PA R PCinT', and Appendix-04, tabs 'Fig3a', 'Fig3b', and 'Fig3c'.

3.2 Total emissions

Amongst 36 states and union territories, only 6 states are responsible for 50% of total emissions (Figure 3(a)). The total households' emissions of India were 2605 million tCO_2eq ($MtCO_2eq$), with two-third share (1743 $MtCO_2eq$) con- tributed by rural population. The maximum emissions were contributed by the most populous states, namely, Uttar Pradesh (≈307 $MtCO_2eq$) and Maha- rashtra (242 $MtCO_2eq$); whereas, least households' emissions are from least populated north-eastern states and Union Territories of India [19, 38]. Due to higher populations, the state of Assam in the north-east contributed 66 $MtCO_2eq$ (rural population and share at 90%) whereas the national capital region of Delhi (nearly 92% urban population) emitted around 45 $MtCO_2eq$ (urban share 93%) emissions. Even with highest per capita emissions, the state of Goa (Fig 2(a), 5.5 tCO_2eq) recorded only 7 $MtCO_2eq$ in total emissions due to a lower level of population (1.27 million only). In comparison, with a population of 94 million, Bihar generated about 124 $MtCO_2eq$ (though it has the lowest per capita, see Fig 2(a)). These regional differences suggest that both high level of expenditure (or income) and socio-cultural drivers (size and distribution of population, education, values, etc.) can contribute to higher environmental-impacts. For additional results, see Appendix-01, Section S.3.2.1.

Figure 3(b) indicate emissions from 'fuel and electricity-use (lighting)' (≈1020 $MtCO_2eq$, urban share 31%) exceeded those from 'milk & dairy prod- ucts' (≈610 $MtCO_2eq$, urban share 35%), 'egg & meat' (≈430 $MTCO_2eq$, urban share 39%), 'transportation' (≈280 $MtCO_2eq$, urban share 32%), and 'rice' consumption (≈130 $MtCO_2eq$, urban share 23%). The total emissions of 'footwear' were nearly 66 $MtCO_2eq$, with the urban share of 36%. Whereas, other food-commodities, 'edible oils' and 'wheat' had negligible emissions. An equal share of rural and urban expenditure for lighting and other uses (50% fuel-expenditure is for electricity-use, urban -pg 9 [97]), translates into electricity-emissions of 507 $MtCO_2eq$. This estimate is lower than 795

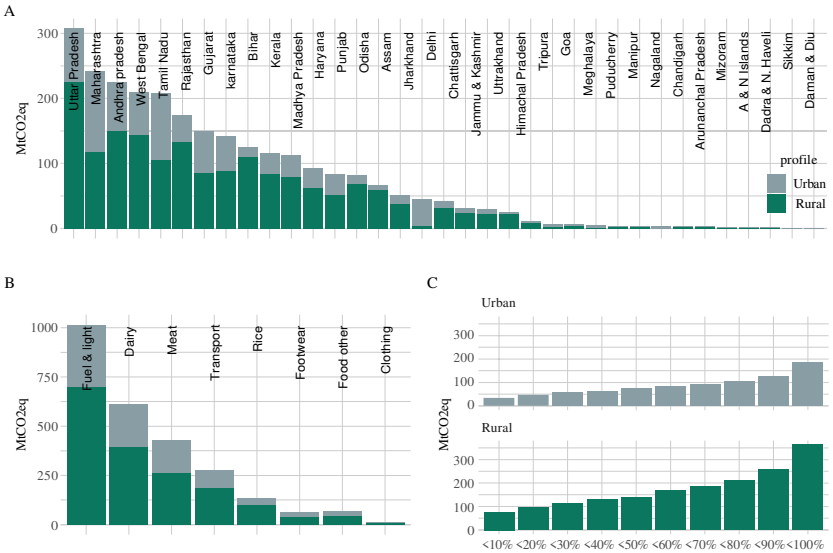

Fig. 3 Total emissions: (a) State-wise, (b) Commodity-wise, (c) Expenditure-wise

$MtCO_2eq$ [98], owing to different assumptions used (additional information in Appendix-01, Section S.3.4).

Summing, results show that only four commodities (fuel & electricity, transportation, milk, and meat) contributed nearly 89% to total households' emissions. Further, nearly 46% emissions of rural-India arise due to food consumption (rice, meat, milk and other products) compared to 50% of urban- India. Other major impact results from transportation (10.3% urban and 10.7% rural) and fuel-use for domestic purposes and electricity for lighting (36% urban and 40% rural). Further, as a large fraction of poor households do not buy fuels (firewood, chips, etc.) from the markets [36, 37], we estimate such households to accrue between 325 to 505 $MtCO_2eq$ emissions for fuel-use (with emission-intensity of 1.5 $kgCO_2eq$ per kg- Table S.1 [5]). The estimated range is subject to limitations stated in other studies [13, 14, 99]; and thus needs verification through additional state-level assessments.

At the national level, expenditure differences translate into highly diver- gent GHG emissions (Figure 3(c)) with key observation being that emissions increase with affluence. For instance, it was observed that the total emissions of the highest urban and rural decile were nearly 5 times than 110 $MtCO_2eq$ recorded for the lowest expenditure-decile. The top 30% emitted nearly 49% of the total national emissions, whereas the bottom 30% emitted about 16%. Further, considering Figure 2(c), upper-expenditure categories are dominant users of transportation-systems; whereas, food-based emissions dominate the lower expenditure categories. Quantitatively, the top 30% (rural+urban) cause nearly 69% of transportation-emissions; whereas, the bottom 30% induce only

6% - see Appendix-04, Tab 'Totals'. These numbers confirm that affluence leads to conspicuous consumption with detrimental impacts on the environment [7]. For specific expenditure-wise numbers at the state-level, refer to Appendix-02, Tabs:'RCF MT' and 'UCF MT', and Appendix-04, Tabs 'Fig4a', 'Fig4b', and 'Fig4c'.

3.3 Inequality analysis

Emission inequality, measured as the ratio of emissions between the highest 10% to lowest 10% expenditure group, varies 3-fold between states (Figure 4(a)). Lakshadweep is the most unequal state. The island state's economy is dominated by high-end tourism. This provides a large capital influx for some that do not reach the low-paid service workers or the traditional fishing workers. Other affluent residents are senior government employees who handle defence and other important services for the nation [100, 101]. In comparison, in mainland urban-India, ratios are much lower. For example, Haryana has a ratio of 6.5, followed by Uttar Pradesh at 6.2. For rural-India, the highest ratio is observed for Arunanchal Pradesh at 6.0, followed by Haryana at 5.6.

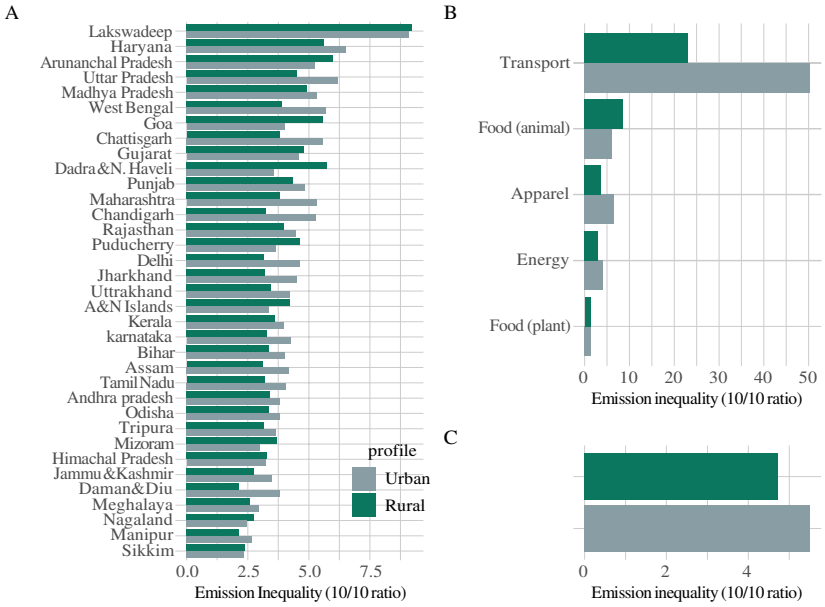

Fig. 4 Inequality as 10:10 ratio (emissions of top 10% divided by bottom 10%) (a) by stateand territory, (b) by commodity, and (c) by urban or rural settlement profile.

Commodity-wise, inequality varies considerably (Figure 4(b)). Transporta- tion displays the highest inequality, followed by meat consumption; whereas, plant-based food consumption is fairly equal in emission footprints. The

transportation-inequality highlights that both expenditure (or incomes) and spatial characteristics [102] determine conspicuous consumption.

Inequality differs slightly between urban and rural areas (Figure 4(c)). The inequality ratio of urban-India is 5.5, whereas that of rural-India is 4.7. The estimated values of the Gini coefficient (using total emissions of expenditure- categories) for rural and urban areas (obtained from Lorentz curves using total emissions of rural and urban populations) are 0.626 and 0.631, respec- tively (the Lorentz Curves are given in Appendix-01, S.3.3.3). These results imply that urban-India has a more inequitable division of emissions than rural-India. Since carbon-Gini's are higher than expenditure-Gini's (urban and rural income-Ginis's are 0.385 and 0.307 respectively, pg 9-[38]), it implies resource-appropriation is far more unequal than money-based distribution [27]. For detailed numbers, see Appendix-02, Tabs 'Inequal PC', 'LCnGC U', and 'LCnGC R'; and, Appendix-04, Tabs 'Fig5a', 'Fig5b', and 'Fig5c'.

3.4 Scenario analysis

Referring to Section 2.3, commodity-wise, BAU scenarios are indicated in Section 3.4.1, whereas transformation scenarios are indicated in Section . Fur- ther, in the latter section, the BAU emissions (Section 3.4.1) are aggregated at level along with transformation scenarios are depicted in Figures 7(a) to (c). The households' total emissions and cumulative impact of all transformations is indicated in Figure 7(d).

3.4.1 BAU scenarios

The BAU projections are based on the assumptions indicated in the Methodol- ogy Section 2.3. Reiterating, the per capita emissions (Figure 5) are estimated using state GDP , and commodity-specific emissions growth rate, whereas total emissions (Figure 6) are estimated by multiplying per capita emissions with state and profile (rural and urban) population. Referring to Figure 5, it offers an insight on how per capita emissions are expected to evolve at both state and national level, for both food and non-food categories within the rural and urban distinctions. Figure 6, on the other hand, indicates how total emissions are expected to evolve at individual state level, for both food and non-food categories within the rural and urban distinctions. As stated earlier, sum of these state-level commodity-emissions are used in transformation scenarios of Section 3.4.2 explored at national level. However, an analysis at regional level can be explored in future works.

Per capita emissions

The urban results for food (Figures 5 (a) and (b)) indicate that the state of Haryana (above 3 tCO_2eq) would have the substantial growth of per capita food emissions if economic growth continued along the projected growth rate by Indian and international agencies, however, the results of urban Mizoram would see the highest per capita emissions in 2050 (slightly less than 4 tCO_2eq). The results of either of the states is hardly surprising considering Mizoram is a dominant meat-consumer, however its daily consumption (2500 kg) is far lower than its demand (6000 kg) [103]. On the other hand, whereas Haryana is likely to increase its emissions due to changing lifestyles. Further, as per the given statistics the state of Mizoram registered one of highest GDP growth in India (see Tab "SW-GDP" in Sheet Appendix-03 and pg 5 of [104, 105]), thus results take higher base level GDP growth rate for projections too. The state of Kerala follows Haryana in both rural and urban categories. The lowest food emissions are expected to be in Chattisgarh in both rural and urban areas, whereas the average urban food emissions is likely to be 2.06 tCO_2eq and rural would be 1.55 tCO_2eq at national level.

In the non-food category, the results Figures 5 (c)(inset only include Mizo- ram numbers) and (d) indicate that the state of Mizoram (above 20 tCO_2eq) would have the substantial growth of per capita non-food emissions considering highest GDP growth continues till 2050. However, the results of rural Mizoram

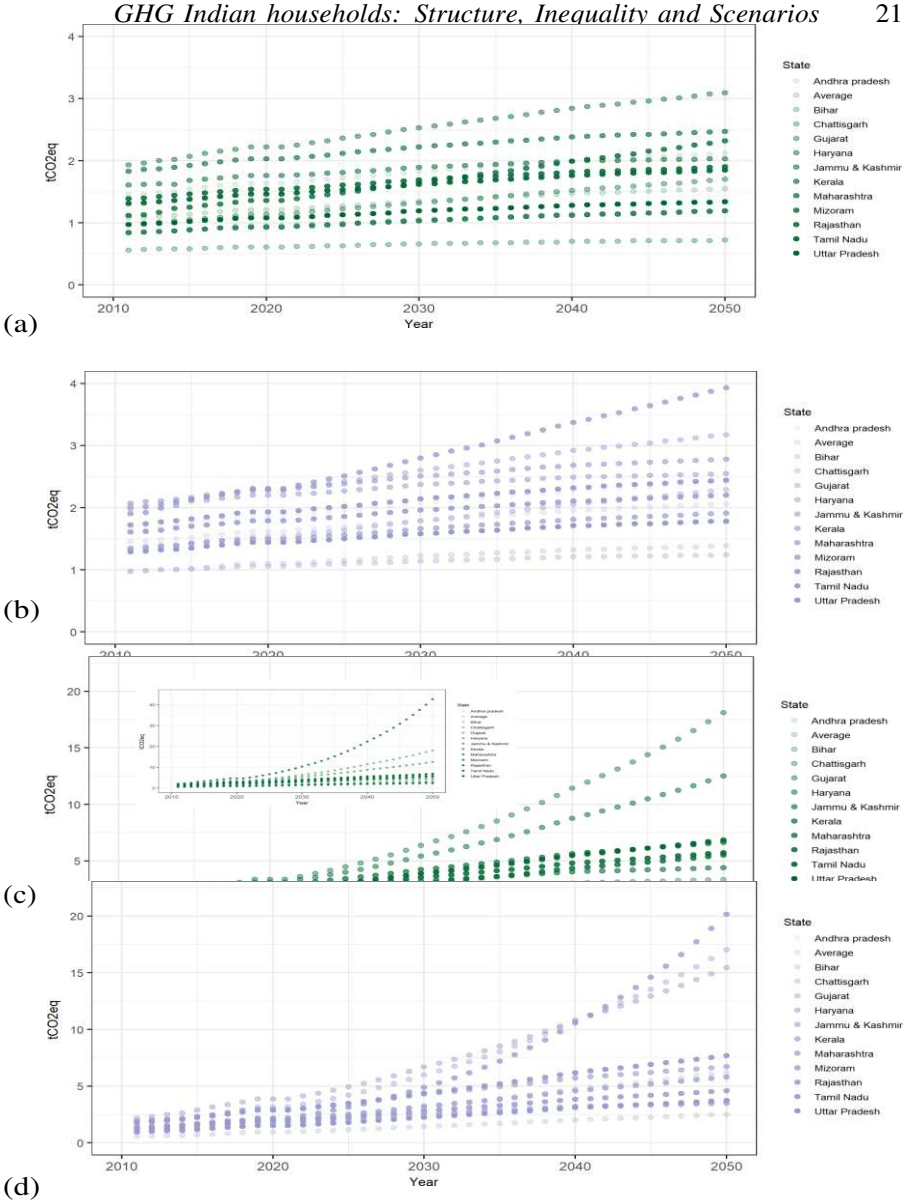

Fig. 5 Baseline per capita emissions for few states and average at national level for (a) Rural: food and apparel, (b) Urban: food and apparel, (c) Rural: non-food, and (d) Urban: non-food. The values indicated on Y asis are in tonnes CO_2 equivalent (tCO_2eq) for per capita impact and X-axis indicates the time period.

are expected to be double than urban per capita non-food emissions in 2050 (around 43 tCO_2eq). Reason could be due to higher use of electricity and per- sonal mobility, considering rural infrastructure wouldlack behind urban, due to hilly terrain of the region. Following Mizoram, rural Gujarat would have around 18 tCO_2eq while urban Gujarat would have 17 tCO_2eq). The state of Haryana is likely to have 15.5 tCO_2eq in urban area and 12.5 tCO_2eq in rural areas. The results of either of the states is hardly surprising considering both are displaying growing economies (see [104]) transforming into higher personal vehicle use and electricity consumption. The higher personal vehilce usage can also be attributed to lack of last minute connectivity in predominantly sub- urban growth, along with bigger houses occupied by growing middle income groups. Thus, if such trend continues, both electricity and mobility emissions are expected to increase under BAU conditions. That said, the national aver- age would be around 6.3 tCO_2eq for urban and 5.7 tCO_2eq for rural areas. The detailed data of other states can be seen in Tab "Scenr BAU SW" of the Appendix-04.

Total emissions

Figures 6 (a) and (b) indicate the total food and apparel emissions of states (see Tab"TF P EG FOwM" in Appendix-03) based on expected per capita food emissions and population growth over the years. Both the figures indi- cate that due to higher populations, Uttar Pradesh, West Bengal, and Bihar would have the highest food emissions, if per capita food emissions con- tinue with associated economic growth. The lowest total rural food emissions are expected in UTs and states with lowest rural population (Delhi, Goa, Arunachal Pradesh, etc.). The lowest total urban food emissions would be seen in UTs and north-eastern states in general.

Figures 6 (c) and (d) indicate the total non-food emissions of states based on expected per capita non-food emissions and population growth over the years. Figures 6 (c) indicate highest emissions in 2050 would be seen for rural Gujarat (553 $MtCO_2eq$) and rural Karnataka (468 $MtCO_2eq$) under BAU. These would be followed by Andhra Pradesh with 353 $MtCO_2eq$, Uttar Pradesh 352 $MtCO_2eq$ and Maharashtra with 296 $MtCO_2eq$. The rural Haryana is expected to generate around 204 $MtCO_2eq$ in 2050. In the con- text of urban India, Gujarat would lead with 641 $MtCO_2eq$, followed by Maharashtra (431 $MtCO_2eq$) Karnataka (413 $MtCO_2eq$), Tamil Nadu (369 $MtCO_2eq$) and Uttar Pradesh (324 $MtCO_2eq$). The lowest total non-food emis- sions would be seen in UTs and north-eastern states in general. For details see Tab "TF P EG NFwM" in Appendix-03.

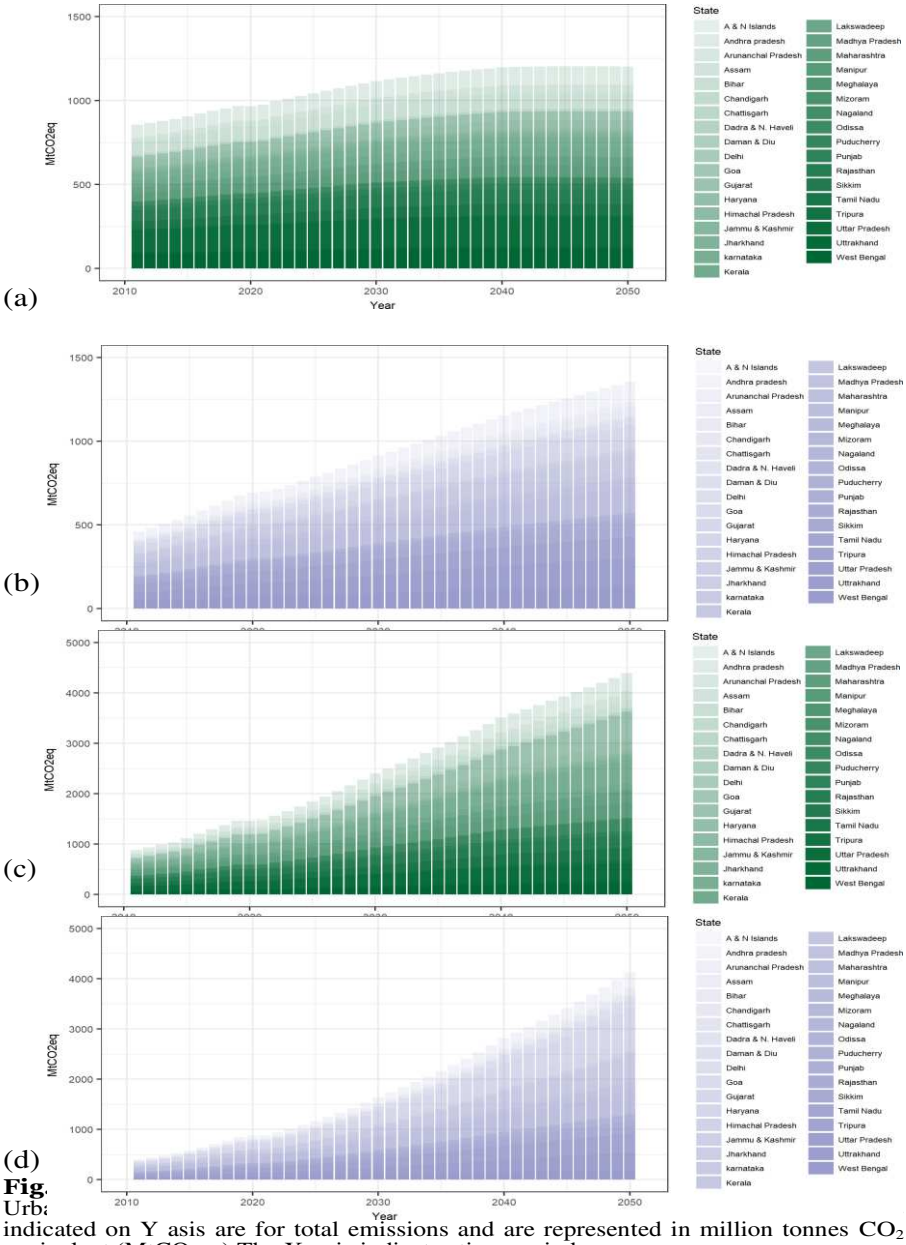

Fig.
Urb
indicated on Y asis are for total emissions and are represented in million tonnes CO_2 equivalent ($MtCO_2eq$).The X-axis indicates time period.

3.4.2 Transformation scenarios

The above estimated total emissions were regrouped in commodity-categories at the national level (combining rural plus urban all states) to derive com- modity based total emissions projections till 2050. As stated earlier, these commodity-specific estimates are used in this section to explore the specific transformations described in the Section 2.3. The following results highlight the potential impact of explored possibilities.

Electricity emissions:

The reference scenario of electricity, E BAU, in Figure 7(a), indicates emissions could rise above 3300 $MtCO_2eq$ in 2050 from 507 $MtCO_2eq$ in 2011. Scenario E S1 estimate potential decrease to 547 $MtCO_2eq$ by 2050 with achieved capac- ity 1827GW, whereas E S2 estimate net emissions of 64 $MtCO_2eq$ in 2050 with achieved capacity 2142GW (which translates into 3693 GW for the whole econ- omy), which is about 42GW lower than required target of 2184 GW. With total wind and hydro capacity of about 200 GW [83] (58% allocated to households), this gap could be easily fulfilled. Thus, households electricity-consumption can be made entirely emission-free if such a capacity is installed and allocated to the domestic-consumption. The IESS's estimate 3258 $MtCO_2eq$ emissions with 479 GW of solar-capacity installation by 2047 [39]. Assuming 58% of electricity is used by households, IESS's numbers differ from ours by a margin of 1.2%. Additional details of this comparison are given in Appendix-01, S.2.3.

Food emissions:

Baseline food-based scenario F BAU in Figure 7(b) indicates emissions of milk, meat, and rice (with a stabilized per capita rice consumption [106]) could increase from 1172 $MtCO_2eq$ in 2011 to 2194 $MtCO_2eq$ in 2050 under current trajectory. Addressing nutritional-security with 1.287 tCO_2eq per capita [84], transformation scenario, F S1 emerges from F BAU after 2028. It indicates that India could be nutritionally secure by 2028 pursuing the F BAU path. Further, under F S1, food-emissions would be about 1844 $MtCO_2eq$ in 2050, or nearly 350 $MtCO_2eq$ lower than those under BAU. Thus, Scenario F S1 trans- lates into fulfilling and meeting the currently insufficient nutritional quality of diets for all. However, if India were to adopt a diet similar to the OECD-level (2.89 tCO_2eq per capita [84]) starting 2011, as indicated by 'Counter-factual' scenario F S2, its emissions could rise above 4100 $MtCO_2eq$ in 2050. This pathway implies an increase of nearly 2000 $MtCO_2eq$ in 2050 from the current trajectory, F BAU. It would then be, similar to OECD countries, far higher than food-based per-capita carbon-budget of 822.5 $MtCO_2eq$ (global carbon- budget of food per annum is 4.7 $GtCO_2eq$ [11], and India's population is 17.5%of the world).

Transport emissions:

Scenario T_BAU in Figure 7(c), captures transportation emissions of all expenditure-categories. This scenario indicates emissions could reach around

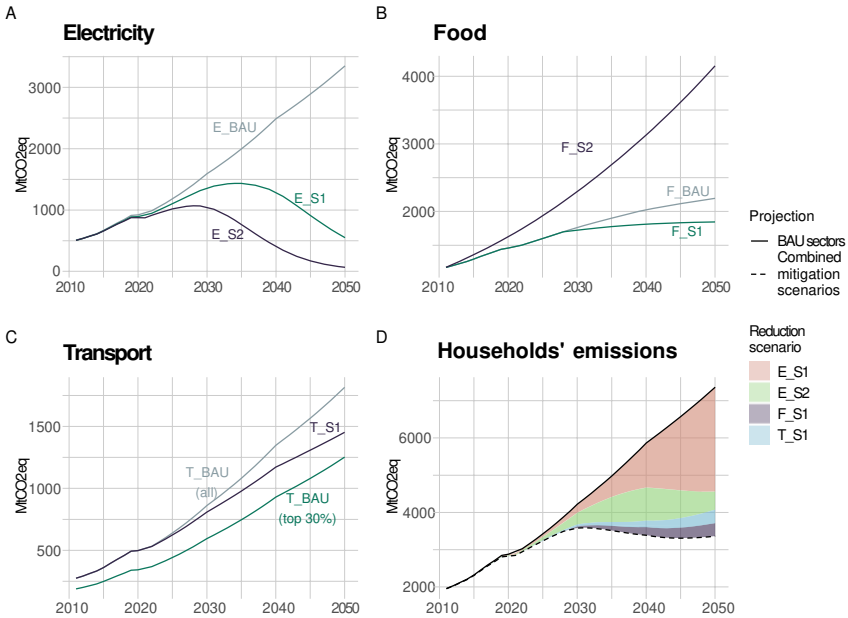

Fig. 7 Baseline emissions (a) Electricity, SE BAU (b) Milk and meat, F BAU (c) Trans- portation, T BAU and T BAU$_{top30\%}$ for all expenditure-categories and top 30% high expenditure-categories, respectively, and (d) Comprehensive impact of respective mitiga- tion strategies on total baseline emissions of these categories. E S1, E S2 - low-carbon electricity transition at current and higher rates; F S1- nutrition-based scenario and F S2- OECD-diet counterfactual. T S1- transportation-emissions reduction of top 30% high expenditure-categories. All indicated in million tonnes CO_2 equivalent ($MtCO_2eq$).

1800 $MtCO_2eq$ in 2050 from 275 $MtCO_2eq$ in 2011. In comparison, IESS's model [39] projects transportation-emissions of 1474 $MtCO_2eq$ in 2047 under least effort scenario, or 1580 $MtCO_2eq$ with linear-extrapolation by 2050. Thus, our transporation-emissions are 14% higher than IESS's. Scenario T BAU$_{top-30\%}$, captures share of the top 30% expenditure segment. It reveals that the emissions of this group could increase from 190 $MtCO_2eq$ to nearly 1300 $MtCO_2eq$ in 2050. The transformation scenario, T S1 indicates 'if' this group reduces its emissions by 1% per annum (starting 2022) by 'Avoiding' unnecessary travel, its total impact could be lowered to 890 $MtCO_2eq$ by 2050. Such a scale clearly reveals that both this group and other expenditure-categories need to adopt low-carbon transportation solutions and change in travel-behaviors.

Further, it is to be noted that the currently pursued vehicle-electrification policy, with or without high-end gadgets (GPS systems for computer-driven mobility to built-in TVs, ACs, etc.) targeting the higher classes(Section 2.3), may not serve as an adequate solution due to increased material and electricity- costs associated with these vehicles [107]. Furthermore, without transforming

the electricity-grid, electric-vehicles, in all likelihood, would transfer emissions from oil to coal (for both high and low-end vehicles). Thus, system-wide reduction of environmental-impacts [91] may not be the real outcome of vehicle-electrification policy.

Total emissions, all transformations and the carbon-budget:

Representing cumulative impact under BAU, Figure 7(d) indicates total household-emissions of India could increase to 11074 $MtCO_2eq$ in 2050 from 2605 $MtCO_2eq$ in 2011. This estimate is higher than projections by integrated assessment models (8 $GtCO_2eq$ by 2050) [108], and energy security scenarios [39], owing to differences in modelling frameworks and values of parameters involved.

The transformation scenarios reveal that by transforming electricity-grid, the maximum reduction possible for households in 2050 is 3300 $MtCO_2eq$ (E S2 scenario). Further, if households followed 'nutritional-security' diets, food-emissions would be lesser by 350 $MtCO_2eq$ comparison to BAU. A per- centage reduction in travel by top 30% expenditure groups can led to a possible reduction of 400 $MtCO_2eq$ in 2050. Thus, by greening the grid, following nutri- tional diets, and by reducing travel of top expenditure-categories, about 4000 $MtCO_2eq$ of household's emissions can be neutralized in 2050 leaving remain- ing emissions of 7 $GtCO_2eq$. In other words, a cumulative reduction of 52 $GtCO_2eq$ (or, 20%) can be achieved by above transitions till 2050.

In the context of annual carbon-budgets, above scenarios highlight that even after successful implementation of above pathways, India's households' emissions would still be 3 times higher than India's annual carbon-budget under 1.5°C (420 $GtCO_2$ [43, 109], i.e., 2.23 $GtCO_2eq$ (allocated by population assumed - 17.5% of world) or about 1.6 tCO_2eq per capita (2020 population). This estimate is also larger than carbon-budget of 6.2 $GtCO_2$ per annum under 2°C [43, 109] (1170 $GtCO_2$, 33 years). Thus, additional actions would be required to reduce emissions of domestic-fuels, mitigating travel-impacts of other income-groups, among others.

Targeting specifically 1.5°C scenario's food-based carbon-budget, 822.5 $MtCO_2$ (4.2 $GtCO_2$[11], 17.5% population, 33 years, 2017) the current car- bon expenditure, required to guarantee nutritional security (1.287 tCO_2eq per capita) reveals how extremely daunting the challenge is for India. It also points to the importance of transitioning to a low-carbon food-system.

4 Discussion and Conclusions

Considering the divergence of India's regional household-consumption, herein we quantify regional emissions of household consumption. First we derive a commodity database in "physical units" using regional household expenditure accounts of India for 2011-12, followed by estimation of emissions associated with consumption using emission intensities reported in the literature. Further, scenarios of future emissions under current trajectory (BAU) and under specific transformations are based on the derived 2011-12 emission database.

Our households-oriented analyses reveals that carbon emissions in India are highly unequal across states and expenditure-categories. Though rural areas and in particular, six states dominate the total emissions of India, per capita footprints are highest in cities. Across commodities, emissions of food consumption, fuel and electricity, are considerably higher than those from transport; whereas, the cumulative impact of households' consumption of these commodities represent 74% (2605/3504- see total emissions calcula- tion in Appendix-01, S.3.4) of India's total GHG emissions. In contrast to the high-expenditure segments with disproportionate GHG emissions from animal-based diets, low-expenditure groups continue to struggle with food security.

These results, particularly, inequalities in carbon footprints, align with those observed for China [110] and Europe [24]. The urban-rich, represent- ing the top 5% income-earners of China's population, induced nearly 19% of emissions with per capita of 6.4tCO_2eq, whereas our study indicates top 5% expenditure-categories in urban-India emitted around 7.48 tCO_2eq. Further, the top 5% of rural India had an impact of about 6.91 tCO_2eq. The lowest 5% emitted around 1.37 tCO_2eq in rural-India and 1.30 tCO_2eq in urban-India. The top 10% of Europe account for 27% of emissions; our study shows that the same group in India contributes about 21%. For India, we estimate that the top 10% (rural plus urban) emitted about 38% of travel-emissions; whereas the top 30% (rural plus urban) had a share of 69% (see total transport emis- sions in Appendix-04). In comparison, [24] report 30% of land-travel emissions by top 10% high-income earners. Our analysis also confirms that resource- based inequality exceeds income-based inequality [27]. Remarkably, inequality in GHG emissions is much higher in the transport sector, especially in cities, than in other emission segments.

Analyzed through the 'Avoid-Shift-Improve' framework, scenarios reveal the importance of shifting to low-carbon infrastructure and adopting low- carbon lifestyles for food and transportation. Particularly, the explored strategies reveal that the biggest reduction in households-emissions would be indirect and through supply-side transition adopting a low-carbon electricity- infrastructure, with solar power playing a formidable role owing to technical and financial feasibility [111, 112]. Low-carbon lifestyles would offer additional benefits. Food-consumption trajectories reveal following high meat and dairy- based diet will invariably double food consumption-based emissions. However, nutritional security-based diets have the potential for stabilizing GHG emis- sions. Nonetheless, the large amount of remaining emissions points to the importance of finding new management strategies in the agriculture sector consistent with the net-zero target. Finally, the transportation-scenario reveals that the current pathway of personal vehicles would steeply increase mobility- based emissions. Specifically, the most affluent 30% would be contributing a lot more than others (nearly 69%, assuming the same level of inequality persists in the society [3, 27]). Thus, transportation-analysis points to the relevance

of exploring alternate transportation-infrastructure, including those of long-distance, mass-mobility for low- and middle-income groups. Additionally, the impact of reduced travel of middle-income groups, especially in the context of transitions such as "teleworking" and increase usage of bicycles with apt changes in spatial-typology [102] should also be explored in future.

From a policy-perspective, promotion of electric-vehicles without grid-transformation (70% of India's grid is coal-based -Figure 9.1 of [113]), may not be an adequate solution for low-carbon future [114] since production also uses electricity [115] (same is also confrimed by [90] though for single urban cen- ter only). Neither does hydrogen-based mobility guarantee such a low-carbon state for all [116]. Thus from a demand-side emission-reduction perspective, apt changes in consumer-behavior [42], increasing material-efficiency [117], reduc- tion in residential-energy demand [118] from fair building space distribution [119], etc. should also be foreseen as possible solutions.

Methodologically, we have shown how estimating household emissions based on physical consumption data can be a promising approach to resolve regional and income-based price differences [38, 97] that cannot typically be represented in national monetary input-output based methods[28]. This approach can capture more within-country heterogeneity than an approach based on national emission intensities could and so is a useful complement, especially when the focus of analysis is on differences in environmental foot- prints within individual countries. However, referring to the issue of accounting of supply chain impacts in Section 2.1, regional, physical input-output mod- els (PIOTs) should be developed in the field of IE for better assessments. The regional PIOTs would not only offer scope 3 accounting of impacts but would outline the differences across regional supply chains, which are paramount for assessment of regional differences in consumption-based accounting. That said, the currently developed inventory of physical consumption could be readily extended to calculate water footprints [8], nexus behaviours [85], etc., among others. Further, if, physical, regional and multi-regional environmentally- extended input output models are developed in future for India, our method and possibly, our, database could be easily deployed for such EEIO-based assessments.

Last, on the limited assessment of sector-specific transformations, the supply-side scenario fails to quantify the life cycle impacts of low-carbon energy infrastructure (Section 2.3.5). That is, the environmental rebound effects are excluded for panels, batteries, grid-connectivity, among others. Thus, we suggest future studies be undertaken to address this issue more concretely, probably through regional integrated assessments [120] or regional input-output analysis [121]. The integrated assessments may also capture the additional social (employment) benefits and costs of these transitions [121].

Associated Content

Appendix. Detailed data used and evaluated used in this work (Appendix 02, 03, and 04) is available free of charge via the Internet at https://doi.org/10.5281/zenodo.5806450.

Conflict of interest statement. Nothing declared.

Contributions

Author 1 conceptualized the study, collated the data, and performed the anal- yses. Author 3 handled the visualization (Figures 2, 3, 4, 7 and abstract) and
data-presentation (Appendix-04) and Author 1 handled Figures 1, 5 and 6. Author 2 and Author 3 supervised the scenarios. All wrote the manuscript.

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