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NO SILVER BULLET II

Land-Use Dynamics in India's Net-Zero Journey

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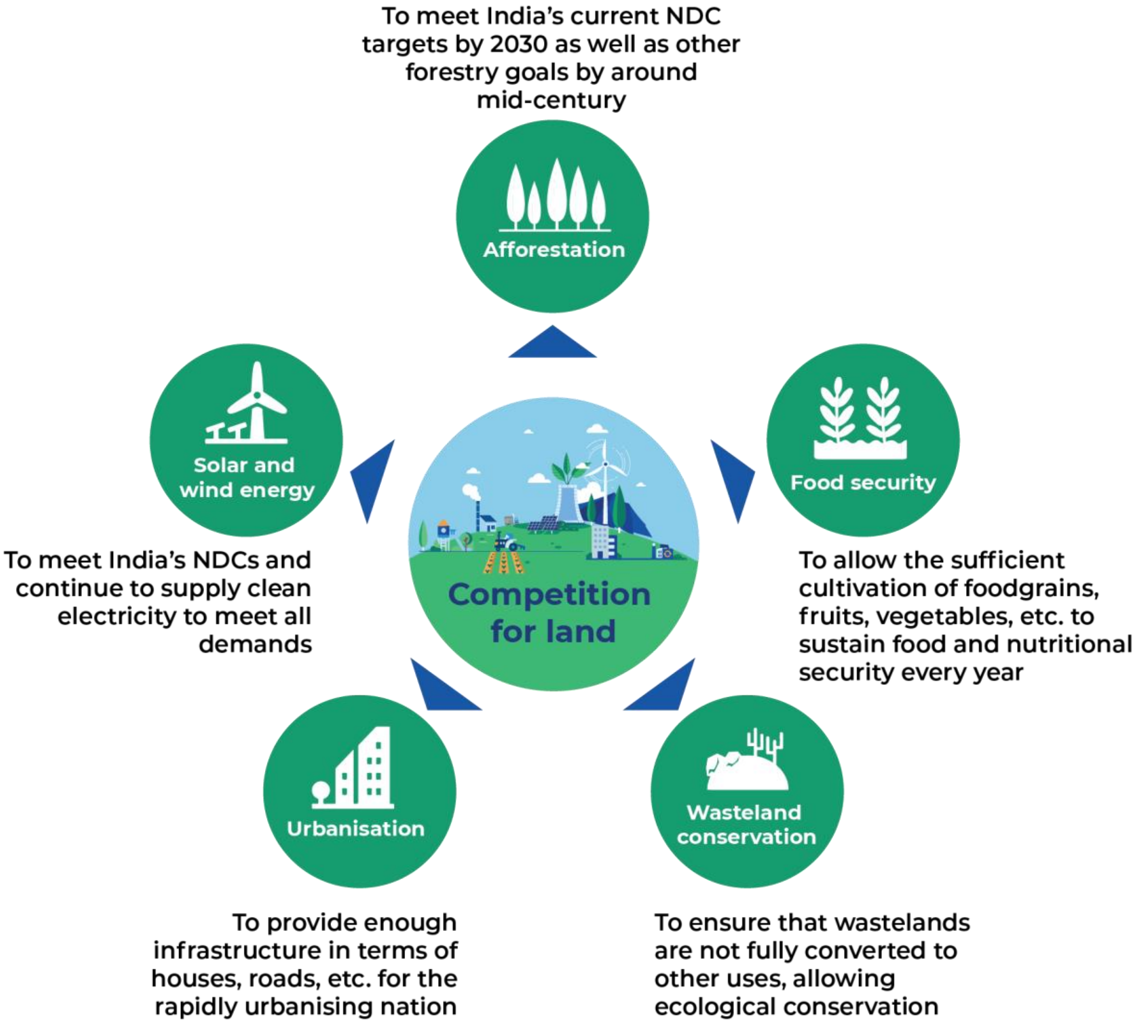
Executive Summary

No Silver Bullet, now a series

The series explores various potential pathways for India's transition to net-zero emissions, discusses the challenges and constraints, and provides directional insights based on long-term modelling using system dynamics. To complement the findings from cost-optimisation models, simulation modelling based on systems thinking was used to determine the impact of competition for natural (and other) resources and the ensuing non-linear feedback dynamics.

As a developing and climate-vulnerable country with a large growing population, India has several climate objectives for the coming decades, going beyond its Nationally Determined Contribution targets. Many of these goals have a considerable land footprint. Figure ES1 indicates these land-intensive competing goals including food security, urbanisation, preservation of forests and wastelands, and provision of clean electricity via solar and wind power.

Figure ES1: India's land-relevant goals for the coming decades



Existing studies estimate only the total requirement of land for renewable energy (RE) or bioenergy for carbon capture and storage (BECCS), typically using or calculating potentials under the current land-use conditions. Future trade-offs arising from competing uses for land and the 'dynamics' of land-use change are often overlooked in these analyses. Further, most 1.5°C-compliant (or net-zero) scenarios cited globally focus on end-use sector electrification combined with the heavy deployment of RE without due consideration of future land availability. To better understand the impact of different net-zero pathways in India on land, a novel dynamic land-use change module was developed within the Sustainable Alternative Futures for India (SAFARI) modelling framework. This approach aimed to help answer the following questions:

i) Will there be sufficient land for afforestation and agriculture under a high-RE scenario?

ii) If agricultural land is prioritised for crop cultivation, will a high-RE scenario use all available wasteland, leaving none for other priorities such as afforestation?

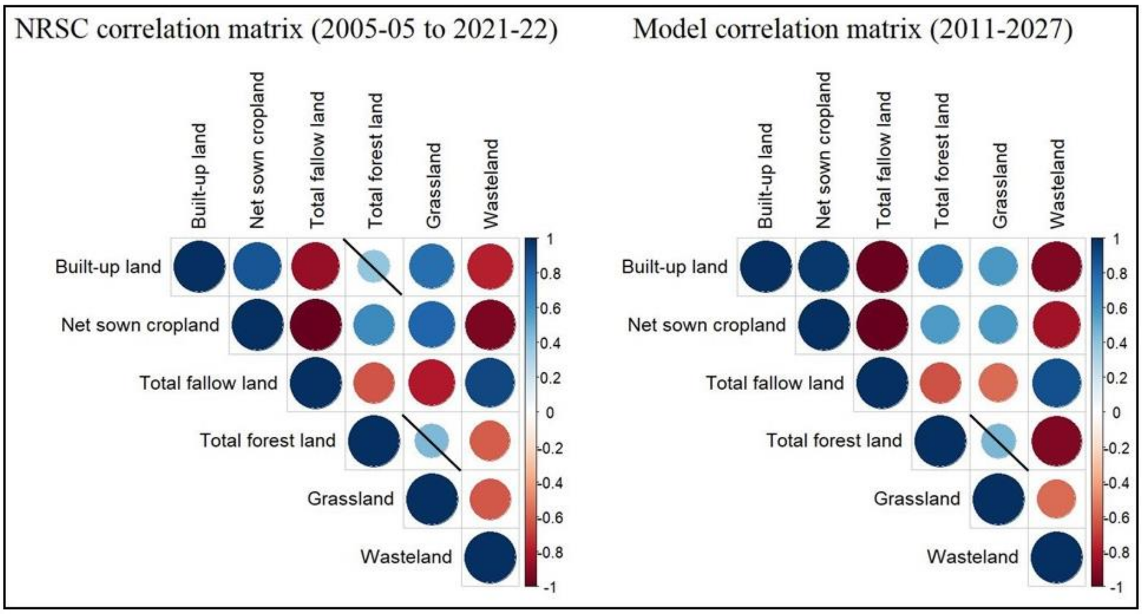
iii) What limitations and constraints should be considered while planning for India's net-zero transition?

Data analysis and model development

The two official sources for the annual land-use data in India are the Land-Use Statistics (LUS) reports from the Ministry of Agriculture and Farmer Welfare and the land use and land-cover maps from the National Remote Sensing Centre (NRSC). These reports follow different land classification taxonomies, often resulting in data discrepancies. To harmonise these datasets, we identified land-use classes with similar definitions and aggregated them into six types—forests, net sown area, fallow land, grassland, wasteland, and built-up area—in alignment with the land classification followed by national greenhouse gas inventories. Although the total area reported under agricultural land (fallow land + net sown area) and forestland is similar between the two datasets, there is a large variation in the wasteland, grassland, and built-up area, the reasons for which are analysed and discussed in this report.

After harmonising the data discrepancies, we performed a trend series analysis using NRSC data (1 : 2,50,000 resolution) to understand the historical land-use change dynamics for future simulations. The correlation matrix is shown on the left-hand side in Figure ES2. These findings, along with expert consultations, led us to develop the basic 'rules' governing future land-use change dynamics in India (an input for the model).

Figure ES2: Comparative correlation matrices (left) of the NRSC data used to build the model and the SAFARI model-generated data (right) to check model validity



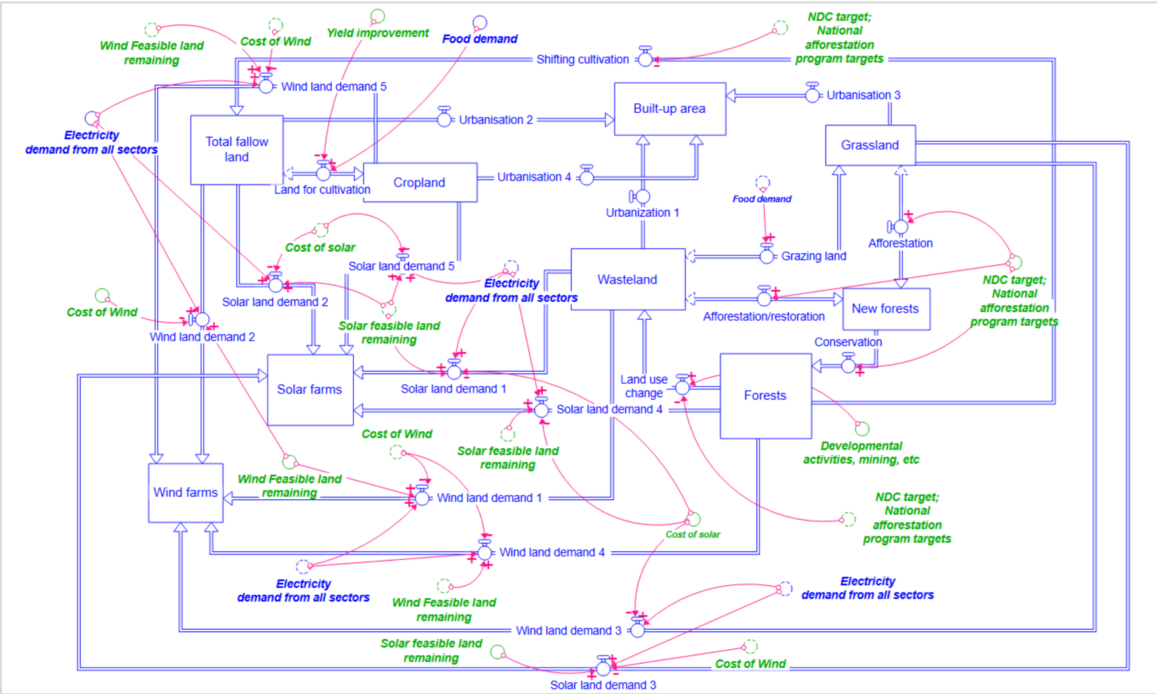
Note: -1 signifies maximum interaction between the corresponding land types.

From 2006–2007 to 2021–2022, the net sown area in India grew by 23.7%, whereas fallow land decreased by 45.7%, indicating shifts between land classes. Wasteland also reduced by 27.9%, and built-up land increased by 23.7%, reflecting urbanisation. Forest cover expanded by 5.42% from 2005 to 2021. Correlation analysis revealed strong interactions, particularly between cropland and fallow land (r = -0.99), forest and wasteland (r = -0.61), and built-up land with both cropland and wasteland. The findings emphasise the competition for land in future development pathways, supporting the need to understand national-level land-use budgeting for sustainable planning.

Based on the trend analysis, expert consultations, and scenario narratives, the 'rules' of land-use change were inputted into the model, and the simplified model structure is shown in Figure ES3. Before simulating scenarios, we validated the model using standard methods used for system dynamics models, including extreme condition tests, behaviour pattern tests, and statistical significance tests. Figure ES2 shows the results of the behaviour pattern test, wherein the correlation matrices from model-generated data (right) and NRSC data (left) are consistent with each other. Comparing the stock values generated by the model with the actual NRSC data for historical years shows an average disparity of around 2.7%, with some land types showing more disparity than others. This is discussed in detail in the report.

Before proceeding to scenario insights, it is important to keep in mind that all modelled pathways for the long term (including ours) are hypothetical and in the realm of the modeller's imagination, and thus, their feasibility remains uncertain. Least-cost optimised scenarios give an illusion of being the most feasible, but cost is only one of the many risks or trade-offs of a chosen pathway, besides the uncertainties in future cost assumptions. Here, we unpacked the potential land-related trade-offs of different net-zero strategies.

Figure ES3: Simplified model structure of land use in the SAFARI model



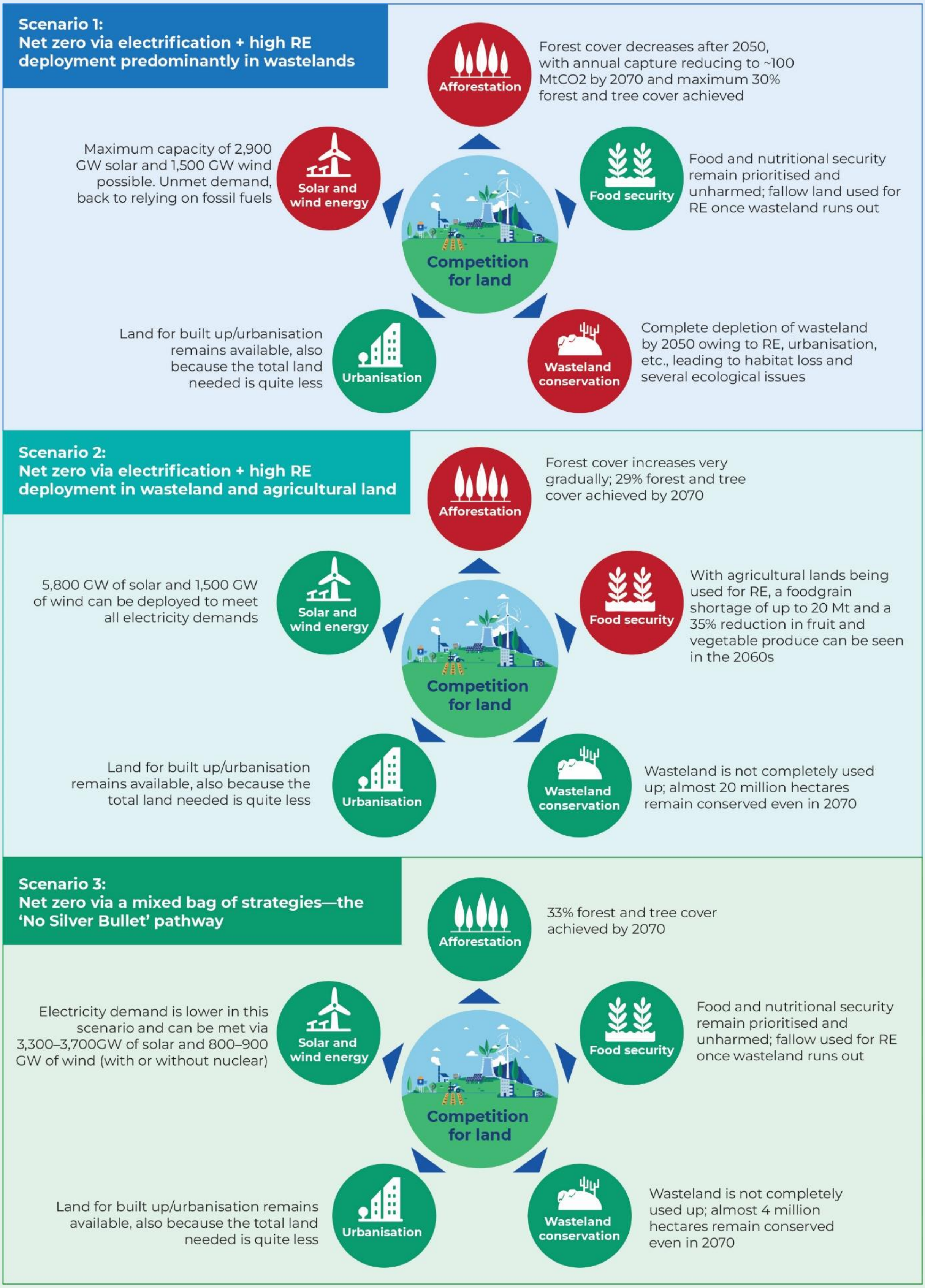
Note: Rectangles are stocks (one for each land type) that are connected to each other by flows, which are in turn determined by drivers and constraints. Key data sources: Forest Survey of India, Indian State of Forests Report, Land-Use Statistics, and National Remote Sensing Centre (NRSC).

Scenario insights

First, we simulated a scenario wherein India embarks on a high-electrification pathway to net zero with a strong focus on RE (Scenario 1). In this scenario, the per capita electricity consumption in 2070 reaches over 8,000 kWh (still lower than the current demands of countries such as the United States, Australia, and France). To meet these demands entirely by fossil fuel-free sources, the amount of solar and wind power needed by 2070 could be as high as 5,800 GW and 1,500 GW, respectively. This is consistent with other similar studies in India. However, our analysis shows that when future land availability is taken into account (feedback), solar power gets constrained at around 2,900 GW and coal and gas will have to be used to meet the remaining demands. In this scenario, wasteland is completely utilised for various purposes, including RE deployment, urbanisation (built-up area), and forestry, and runs out by 2050. This, in turn, affects forest expansion plans, leading to a stagnation in forest cover beyond 2050. This could impact carbon sequestration, biodiversity, livelihoods, and local climates. Wasteland depletion has consequences not only for ecological conservation but also for the livelihoods of thousands of people. This scenario is depicted in Figure ES4 (top panel) and is discussed further under 'land-aware net-zero scenarios' in the report.

Next, we explored the conditions under which this demand from Scenario 1 could be met with RE. We adjusted the rules and priorities in the model to equally prioritise wastelands and agricultural lands for RE deployment (Scenario 2). In this scenario, while RE goals and wasteland conservation are met, food security and forestry goals are negatively impacted, as shown in Figure ES4 (middle panel). Under this scenario, we may have to depend on imports to meet our demand for food grains, fruits, and vegetables.

Figure ES4: Summary of the key scenarios modelled



From Scenarios 1 and 2, we concluded that the path to net zero focussing purely on end-use electrification and RE deployment will have several trade-offs. Thus, in the next scenario, we simulated various strategies wherein electrification and RE were only a part of the mix. This scenario, termed the 'No Silver Bullet' scenario, includes demand-side interventions such as dietary shifts, efficient irrigation and crop yield improvements, the use of better construction materials and passive cooling solutions, and the use of public transport and railways. In addition, on the supply side, this scenario entails increased adoption of decentralised solar photovoltaic (rooftop and solar pumps) and nuclear energy at the grid level via the three-stage thorium programme. The per capita electricity consumption in this scenario reaches around 6,300 kWh in 2070 and can be met with 3,300 GW of solar and 800 GW of wind (and 382 GW of nuclear). Even without the three-stage thorium programme (limited nuclear energy in the mix), this demand can be met with slightly more solar and wind capacities of 3,700 GW and 900 GW, respectively. This scenario poses no trade-offs with respect to the other land-competing goals (Figure ES4, bottom panel).

Limitations and way forward

Our model explores historical land-use trends in India, but owing to limited data, it lacks local- or state-level details. Although these finer nuances could add value, this study provides a broader view of the national-level resource constraints. Further, this study does not focus on the drivers of land-use change but recognises that factors such as demographics, policies, and environmental conditions significantly influence these shifts, impacting water and energy cycles. Understanding these drivers will help inform better policy decisions and resource management. As we work towards overcoming these limitations, we hope that our findings contribute to a more holistic conversation on the net-zero transition, encouraging the inclusion of all types of trade-offs in the discussion.

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Abbreviations

BAU	Business as usual
GHG	Greenhouse gas
GVA	Gross value added
IAMs	Integrated assessment models
IPCC AR6	Sixth Assessment Report of the Intergovernmental Panel on Climate Change
IPPU	Industrial Processes and Product Use
LDN	Land Degradation Neutrality
LULUCF	Land-use, land-use change, and forestry
LUS	Land-use statistics
Mha	Million hectares
$MtCO_2e$	Million tonnes of carbon dioxide equivalent
NDC	Nationally Determined Contributions
NRSC	National Remote Sensing Centre
ONEs	Open natural ecosystems
PV	Photovoltaic
RE	Renewable energy
SAFARI	Sustainable Alternative Futures for India
SDGs	Sustainable Development Goals
WWR	Window-to-wall ratio

1. Introduction

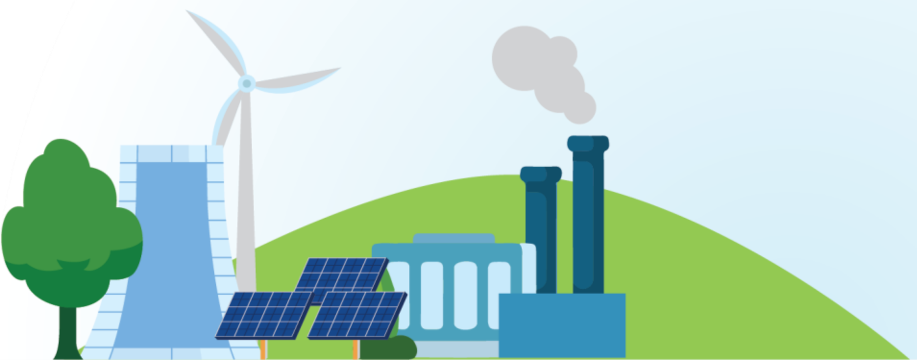
In the previous edition of the No Silver Bullet (CSTEP, 2022), we explored the distinctive aspects of the net-zero transition based on scenarios created using our system dynamics simulation model—the Sustainable Alternative Futures for India (SAFARI). We discussed how the use of renewables in the power sector might not be the 'low-hanging fruit' for decarbonisation because while renewable energy (RE) costs have declined, challenges of intermittency, grid stability, import dependence (for solar cells, lithium-ion batteries, etc.), and land availability may continue to worsen. We also reviewed the uncertainties or the large error bars in estimating future demands based on the historical relationship with parameters such as gross domestic product. We also analysed the extent of industrial decarbonisation and the impact of behavioural change. Using a social accounting matrix-based multiplier model, we examined the spillover effects of a potential carbon pricing policy for the country. Our findings across these various streams indicated that there is no silver bullet solution to the net-zero puzzle but only a balanced mix of diverse semi-optimal solutions.

In this second edition of the No Silver Bullet, we will explore the land dynamics expected to unfold as we strive to meet and sustain our land-intensive goals of food security, urbanisation, RE expansion, and carbon sequestration in forests. Further, the fundamental question addressed in this report is whether there is enough land in India to meet all our developmental and climate goals.

1.1. Rationale for the study

Studies so far have estimated the land requirements or land availability for one or two of the aforementioned goals. For instance, integrated assessment models (IAMs) typically focus on land requirements for biomass cultivation for bioenergy with carbon capture and storage. Towards India's net-zero target, McKinsey and Company (2022) estimated that an additional 45 million hectares (Mha) of land will be needed to achieve net-zero emissions, with 10 Mha likely allocated to the RE sector. Worringham (2021) found that solar and wind power would require approximately 1.7%–2.5% of the country's total land area. However, these studies do not address the trade-offs of this land demand in the future—will there be sufficient wasteland available, or will there be agricultural land conversion or deforestation?

In contrast, studies have estimated the potential for RE siting (Jain et al., 2020a; Kiesecker et al., 2020), typically focussing on the feasibility of various land parcels for RE development based on current land use and resource (solar or wind) availability. For example, the SiteRight tool (Negandhi & Kiesecker, 2020) helps identify areas with resource potential but low social and ecological risks for RE development, i.e. low-impact RE siting (Kiesecker et al., 2019). However, the temporal land-use dynamics arising from competing land demands and the potential feasibility constraints remain unclear.



To build on this comprehensive knowledge base, without reinventing the wheel, we applied the findings of previous studies and performed a trend analysis covering the past 40 years to inform land-use conversions simulated in our system dynamics model, SAFARI. As the demand for different land parcels increases (cropland to meet food security, forestland to meet Nationally Determined Contribution [NDC] goals, or built-up area to meet housing for all and urbanisation), the SAFARI model simulates land conversions to meet competing demands based on historical trends and feasibility constraints. We also examined different data sources, critical challenges in reconciliation, and other open-ended questions on future land use in India.

1.2. Why net-zero?

Climate change and its impacts on natural resources such as land and water, biodiversity, and human life have never been more evident. To reduce the risk of devastating and irreversible consequences, we must prevent the global average temperature from exceeding the threshold of 1.5°C above pre-industrial levels. Towards this goal, the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC AR6) estimated that from 2020 onwards, the remaining global carbon budget for a 50%–67% likelihood of limiting global warming to 1.5°C is between 400 and 500 $GtCO_2$ (Intergovernmental Panel on Climate Change (IPCC), 2023). This means that the global net CO_2 released annually must decline rapidly and reach net zero by the middle of this century. The developed world, being the main driver of climate change, should ideally lead this transition and achieve net-zero emissions before 2050, allowing more time for developing countries to balance their development goals with climate action. The inaction of developed countries may be more iniquitous, considering the impacts of climate change disproportionately affect the economically weaker sections of the population, with a greater concentration in developing countries.

At the 26th Conference of the Parties in 2021, India declared its ambition to achieve net-zero emissions by 2070. Given that India's historical contribution to cumulative emissions has been only 4% and its per capita emissions are among the lowest at 1.6 tCO_2, an argument often made invoking principles of equity is that India's priority should be development and not climate action. However, in its current emission trajectory (or business-as-usual without climate action), India alone will exceed almost half of the remaining global carbon budget by 2060. If this is accompanied by global inaction, the 1.5°C threshold will be breached in the coming decade, leading to unprecedented impacts on the poor and vulnerable. Thus, ironically, not prioritising climate action because it is iniquitous could, in fact, lead to a more iniquitous future.

Nevertheless, reaching the net-zero target for a country like India is no easy feat. India has unveiled a series of policies and initiatives focussed on RE expansion, energy efficiency improvements, and sustainable development practices. Key measures being promoted include the ambitious target of reaching 450 GW of RE capacity by 2030, the implementation of energy efficiency standards across industries, and the promotion of electric mobility (Ministry of Environment, Forest and Climate Change, 2022). However, achieving these targets while pursuing its developmental priorities, including eradicating hunger and ensuring adequate housing for all, presents a complex and multifaceted challenge, including the competition for land.

1.3. Brief history of India's land-use sector

A critical aspect of the net-zero challenge revolves around the use and management of land, a resource that is integral to both development and decarbonisation objectives. The land-use, land-use change, and forestry (LULUCF) sector in India, with a net sink of 485 million tonnes of carbon dioxide equivalent ($MtCO_2e$), offset the net emissions of the country by 15% in 2019 (Ministry of Environment, Forest and Climate Change, 2023). Although it is a limited resource, the sequestration potential of the sector is large, and thus, it must be considered while formulating mitigation pathways.

India's arable land availability per person is already limited, and projections indicate an increase in demand due to urbanisation and development needs (Press Information Bureau, 2019). Moreover, India aims to sequester an additional 2.5–3 billion tonnes of CO_2e by 2030 through forest and tree cover expansion (Press Information Bureau, 2022). Further, with increasing land demand from the power sector for wind and solar farm expansion, the importance of managing land resources to achieve multiple societal goals, including food security, energy needs, and carbon sequestration, cannot be undermined. Thus, a comprehensive understanding of various land-use change drivers and how land use intersects with different sectors and emission reduction strategies is essential.

Historically, land-use and land-management practices in India have been driven by demographic changes, economic development, policy shifts, and environmental factors. The pre-colonial period saw diverse cropping patterns (Gadgil, 1990; Morrison & Sinopoli, 1992); good irrigation systems using wells and canals; and healthy maintenance of forestland for timber, fodder, and other non-timber products (Gadgil, 1990). However, in the colonial period, new forest laws prevented local communities from using forestland (Bhukya, 2013; Washbrook, 1994) and forests were mostly commercialised and converted to large-scale plantation lands (Gadgil, 1990; Tian et al., 2014). Further, large-scale deforestation for developing roadways and railways (Tian et al., 2014); major changes in cropping patterns with increasing areas under cash crops such as tea, coffee, cotton, and indigo (Gadgil, 1990); and land-ownership changes led to land degradation (Roy, 2020).

During the post-independence era, the Green Revolution led to the introduction of high-yielding crop varieties and an increase in the use of chemical fertilisers (Tian et al., 2014). This enhanced agricultural productivity but led to the loss of soil fertility, groundwater, and biodiversity and increased land degradation. Large-scale urbanisation during this period also led to increased industrial and urban expansion into cropland and forestland, resulting in increased deforestation (Tian et al., 2014). Eventually, the Forest Conservation Act of 1980 was introduced, with the aim of preventing the conversion of forestland for non-forest purposes and for boosting community-based forest management via joint forest management (Bhat et al., 2001; Tian et al., 2014). Evidently, human activities result in drastic changes in land use, and for a developing country like India with a large population and limited per capita land availability, it is vital to understand and strategise land use for ensuring the adoption of sustainable mitigation pathways.

1.4. Report preview

To contribute towards the improved understanding of land use in India and to identify sustainable mitigation pathways, we performed a comprehensive analysis of the land-use pattern in the country over the past two decades. This enabled us to formalise the modelling methodology and framework for the LULUCF sector of India within the SAFARI modelling initiative developed at the Center for Study of Science, Technology and Policy (CSTEP). SAFARI adopts a holistic approach, considering development goals beyond economic growth, making it a valuable tool for understanding the complex interplay between land use and carbon emission reduction in India.

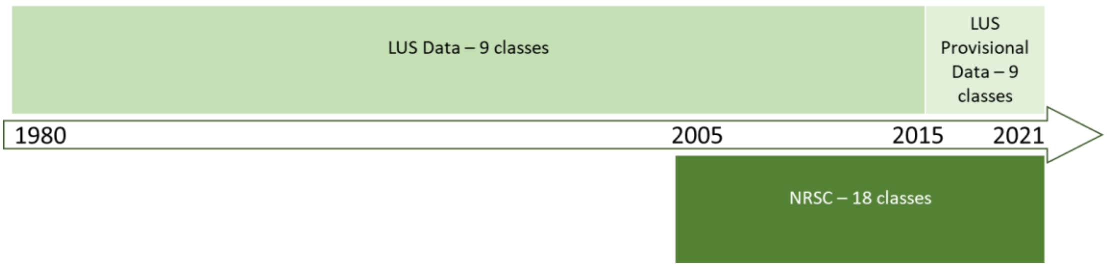
Chapter 2 of this report delves into the details of various land-use categories, compares multiple databases, and analyses historical trends for each land category and their interactions. Chapter 3 describes the modelling approach for the sector, along with the data assumptions and modelling logic. Chapter 4 explores the results of various scenario simulations, and Chapter 5 summarises the main learnings.

2. Land Classification Systems in India: Ramifications and Challenges

There are two official databases for the land-use sector in India:

1. Land-use statistics (LUS): LUS reports (Ministry of Agriculture and Farmers Welfare, 2023) include nine land classes (Figure 1, Figure 2b), among which agricultural land is further divided into different crop types. These reports provide land-use data since 1980, providing insights into the historical land-use trends. The data sources for LUS include the agricultural census, State Directorate of Economics and Statistics, and Forest Survey of India (FSI).
2. Land-use and land-cover maps: The National Remote Sensing Centre (NRSC) at the Indian Space Research Organization started releasing land-use and land-cover maps from 2005–2006[1] onwards (Figure 1). They provide spatial land-use data at two resolutions: 1 : 50,000 scale and 1 : 2,50,000 scale (National Remote Sensing Center, 2024). However, owing to the processing involved in generating the finer 1 : 50,000 resolution data, it is released only once every 5 years, whereas the coarser resolution of 1 : 2,50,000 is released annually. This annual map has 18 land classes (Figure 2a).

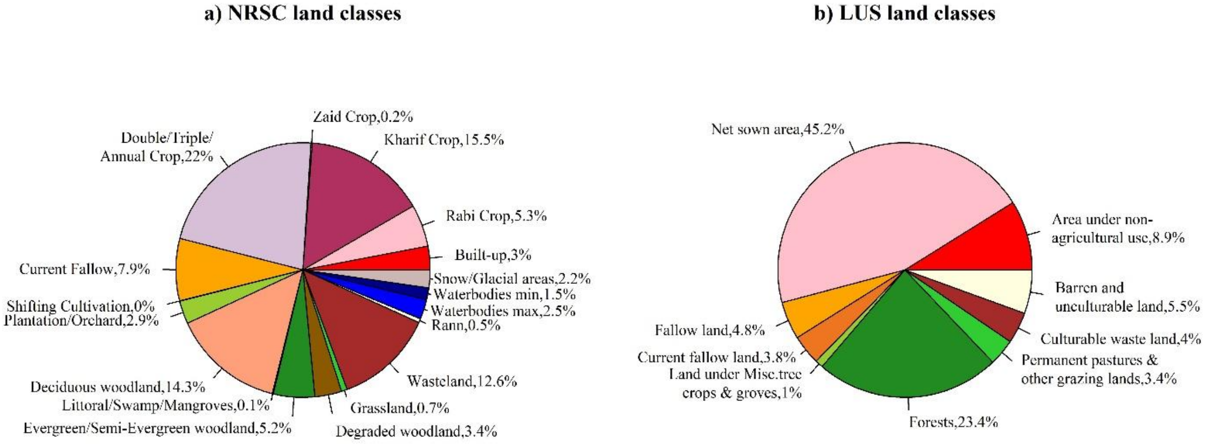
Figure 1: Timeline of data from land-use statistics and National Remote Sensing Centre reports



Because of the granularity of the NRSC data compared with LUS, the land-use change insights from NRSC are more nuanced. LUS primarily uses survey results from the agriculture ministry to compile data, whereas NRSC uses remote sensing satellite data to generate maps. Owing to the fundamental difference in the approach of data collection, there are multiple definitions and classifications across the LUS and NRSC land-use datasets (Figure 2). Further, the total reported area is also different in the two datasets. In LUS, the reported area is based on the information provided by the states, whereas the geographical area is based on the data provided by the Directorate of Map Publication, Survey of India, Dehradun. In NRSC, almost all geographical areas in the country are imaged using remote sensing.

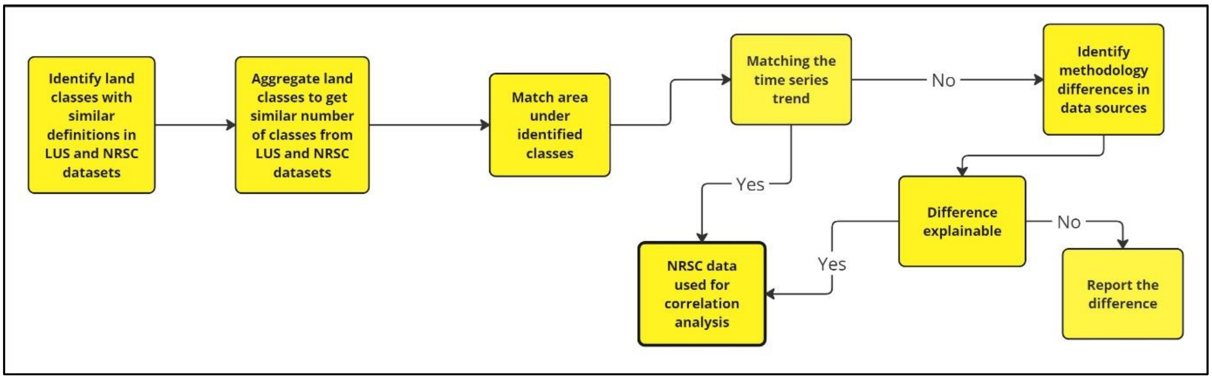
[1]NRSC provides data in accordance with the agriculture year of the country, which starts in July with the harvesting Rabi season and ends in June during the subsequent year with the end of the Kharif season.

Figure 2: Land-use classes and areas in 2021 based on a) land-use statistics (LUS) and b) National Remote Sensing Centre (NRSC) reports



Harmonising these two datasets (one based on ground truthing and the other based on remote sensing) is essential for analysing the land-use pattern and using the data effectively to model the land-use sector in India. The approach adopted in this study for harmonising the two datasets is captured in the flowchart given in Figure 3.

Figure 3: Flowchart on the steps for harmonising land-use statistics (LUS) and National Remote Sensing Centre (NRSC) datasets



As a first step, we identified land classes with similar definitions in both datasets and aggregated them individually into six relevant classes: forests, net sown cropland and fallow land, grassland, built-up area or area under non-agricultural uses, and wasteland (Table 1). These six land classes also represent the land classification reported in the national greenhouse gas (GHG) inventory, i.e. forestland, cropland (includes both net sown area and fallow land), grassland, settlements, and other land. The time series data for these land-use classes, as reported by NRSC and LUS, are provided in Figure 4.

Table 1: Details of land classes, aggregations used in this study, and their definitions as per LUS and NRSC reports

Classification used in this study	LUS classification	Definition	NRSC classification	Definition
Forestland	Forests	It includes all land classified either as forest under any legal enactment or administered as forest, whether state-owned or private and whether wooded or maintained as potential forestland. The area of crops raised in the forest and grazing lands or areas open for grazing within the forests remain included under the 'forest area'.	Woodland	The term woodland is used to refer to land with a tree canopy cover of more than 10% and an area of more than 0.5 ha. It is determined both by the presence of trees and the absence of other predominant land uses. It consists of three woodland classes: evergreen/semi-evergreen woodland, deciduous woodland, and degraded woodland.
			Littoral/Swamp/Mangroves	Mangroves include shrubs and trees growing along the coastal saline and brackish waters. Swamps include wetlands dominated by woody plants.
Built-up area	Area under non-agricultural uses	It includes all land occupied by buildings, roads, and railways or under water, e.g. rivers and canals, as well as other land used for non-agricultural purposes.	Built-up area	It refers to an area with buildings (roofed structures), paved surfaces (roads and parking lots), commercial and industrial sites (ports, landfills, quarries, and runways), and urban green areas (parks and gardens).
Wasteland	Barren and unculturable land	It includes all land covered by mountains, deserts, etc. Land that cannot be brought under cultivation, except at an exorbitant cost, is classified as unculturable, irrespective of whether such land is in isolated blocks or within cultivated holdings.	Wasteland	It covers degraded land that can be brought under vegetative cover with reasonable efforts and is currently underutilised. It also covers land that is deteriorating owing to the lack of appropriate water and soil management or natural causes. It includes rocky areas, scrub lands, mining dumps, gullied lands, and sand dunes.

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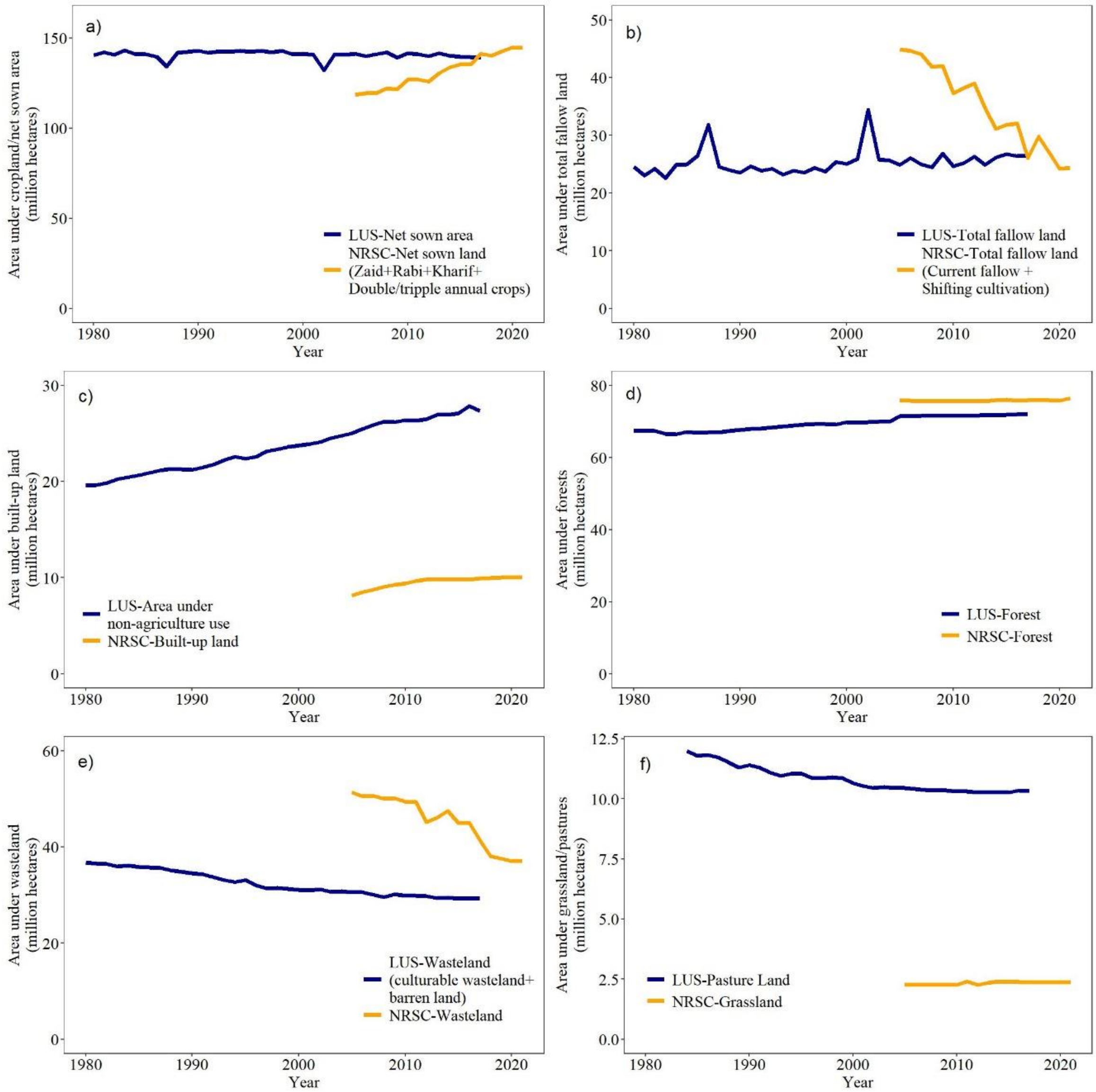
Classification used in this study	LUS classification	Definition	NRSC classification	Definition
	Culturable wasteland	It includes land available for cultivation, regardless of whether it is used for cultivation once but not cultivated during the last 5 years or more in succession, including the current year, for any reason. Such land may either be fallow or covered with shrubs and jungles, which remain unused. They may be accessible or inaccessible and may lie in isolated blocks or within cultivated holdings.	Rann	A large area of salt marsh located in western India between the Gulf of Kutch and the Indus River Delta.
Grassland	Permanent pastures and other grazing land	It includes all grazing lands regardless of whether they are permanent pastures or meadows. Village common grazing land is included under this category.	Grassland	It includes areas of natural grass along with other vegetation, predominantly grass-like plants (monocots) and non-grass-like herbs (except Lantana species, which are classified as scrubs). It includes natural or semi-natural grass and grazing lands of alpine/sub-alpine, temperate, or tropical/sub-tropical zones and deserted areas.
	Land under miscellaneous tree crops, etc.*	It includes all cultivable land that is not included under 'net area sown' but is used for agricultural purposes. Land used for plantation trees, thatching grasses, bamboo bushes, and other groves for fuel, etc., that are not included under 'orchards' are classified under this category.	Plantations/Orchards*	It covers regions where tree crops have been planted on agricultural land using agricultural management methods.

Classification used in this study	LUS classification	Definition	NRSC classification	Definition
Fallow land	Fallow lands other than current fallows	It includes all land that is used for cultivation but is temporarily out of cultivation for a period of not less than 1 year and not more than 5 years.	Shifting cultivation	It covers areas where woodland plots are cleared, cultivated temporarily, and then abandoned, allowing post-disturbance fallow vegetation to grow freely as the cultivator moves on to another plot.
	Current fallows	It represents cropped areas that are kept fallow during the current year.	Current fallow land	It covers land that is taken up for cultivation but is temporarily uncultivated and remains uncropped for one or more seasons.
Net sown cropland	Net area sown	It represents the total area sown with crops and orchards. Area sown more than once during the same year is counted only once.	Cropland	It is primarily used for the production of different types of crops for commercial purposes and consumption. In this classification system, four classes belong to the cropland, i.e. Kharif, Rabi, Zaid, and double/triple/annual cropland.

**These land classes were not used in any aggregation but only if reconciliation was required to explain the differences.*

LUS: Land-use statistics; NRSC: National Remote Sensing Centre

Figure 4: Comparison of data from LUS (blue) and NRSC (orange) for different land classes



LUS: Land-use statistics; NRSC: National Remote Sensing Centre

Although the areas under each land-use class do not match, the trends in land use over the common timeframe of analysis match for most land categories, with the exception of net sown area and fallow land. In the LUS data, the net sown area and fallow land have plateaued, showing slight annual variations, where they clearly interact with each other. Although this interaction between the two land classes is corroborated with the NRSC dataset, the time series trend is not similar; the NRSC dataset shows a reduction in fallow land and an increase in net sown cropland. Interestingly, the total agricultural land in both datasets converge over the common timeframe (Figure 4a,b). The forestland in both datasets matched both in terms of area and time series trends (Figure 4d).

Wasteland in NRSC data includes multiple other land categories, including scrubland, rocky and barren land, sandy area, salt-affected land, Rann of Kutch (extensive salt marsh in western Gujarat), and gullied and ravenous land. Therefore, to compare wasteland across the two datasets, the culturable wasteland and barren land from the LUS data were combined to represent wasteland, as the definitions of these classes matched the definition of wasteland from NRSC. Despite this reconciliation, a significant difference was observed in the two datasets, with the area under wasteland in LUS data being 45% less than the area under wasteland in NRSC data on average (Figure 4e). This could be partly attributed to areas outside the survey boundaries for LUS, which are captured through remote sensing.

Likewise, we used the area under 'permanent pastures and grazing land' from LUS data to compare with the grassland area reported by NRSC. This comparison also showed a huge average difference of 347% (Figure 4f). It can be inferred that a significant area of permanent pasture in the LUS could be accounted for as part of the wasteland by the satellite data. The NRSC only includes alpine/sub-alpine, tropical/sub-tropical, temperate, and desert grasslands in their grassland category, which does not necessarily include all grazing and pasture lands as reported in the LUS dataset. If we assume that only 22% of the 'permanent pastures and grassland' category fits the definition of grassland as per the NRSC database with the remaining allocated to wasteland, the previously observed difference of 347% reduces to -2% for grassland and the difference in wasteland reduces to an average of -30% from the earlier -45%. Further, some of the grazing lands might be accounted for as 'plantations' in the NRSC data, which is another way of reconciling this huge difference.

The misclassification of grasslands as wasteland carries significant land management and ecological ramifications. India hosts numerous faunal species endemic to grasslands, such as the critically endangered great Indian bustard and one-horned rhinoceros. Misclassification exposes these areas to potential land-use changes for afforestation, bioenergy uses, or other developmental projects, such as infrastructure expansion or RE farm installations. This poses a threat to biodiversity and may compromise the long-term carbon stocks of newly planted forests, rendering them vulnerable to the impacts of climate change.

Having reconciled the two datasets on the key land-use categories, the next step involved decoding the dynamics among the different land uses. The NRSC data were used for this analysis as they were relatively up-to-date and granular. As mentioned earlier, a few classes were combined to represent broader land classifications (Table 2), with respect to our research objectives and based on land classes for the LULUCF sector as per the national GHG inventory reports, the Third Biennial Update Report to the United Nations Framework Convention on Climate Change (Ministry of Environment, Forest and Climate Change, 2021) and the Third National Communication and Initial Adaptation Communication (Ministry of Environment, Forest and Climate Change, 2023). India has five major land categories: wasteland, agricultural land (fallow land and net sown cropland), built-up land (settlements), forestland, and grassland. The LULUCF sector in national GHG inventory reports does not include wetlands owing to data paucity and a very small area under this category. Accordingly, wetlands have been excluded from this analysis.

Table 2: Combinations of NRSC land classes to form new land classes

NRSC land classification	Land classification used in the model
Built-up area	Built-up area
Rabi crop	Net sown cropland
Double/triple/annual crop	
Kharif crop	
Zaid crop	
Current fallow	Fallow land
Shifting cultivation	
Deciduous woodland	Forestland
Littoral/swamp/mangroves	
Evergreen/semi-evergreen woodland	
Degraded woodland	
Grassland	Grassland
Wasteland	Wasteland

Note: Forestland data used in this study were obtained from the India State of Forest Reports. Explained in subsequent sections.

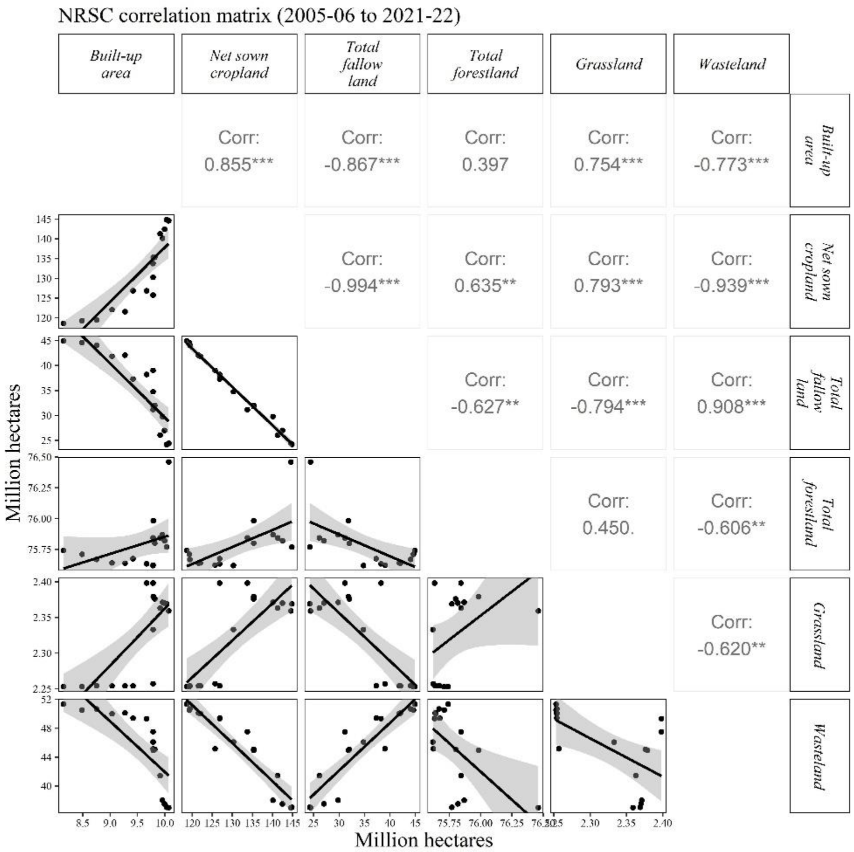
NRSC: National Remote Sensing Centre

For each land class, a detailed time series analysis was performed to understand the historical trends of land-use change. According to the NRSC dataset, the net sown cropland in the country has grown substantially by 23.7% at a growth rate of 1.34% annually, from 119 Mha in 2006–2007 to 144 Mha in 2021–2022. Correspondingly, the total fallow land has decreased by 45.7%. However, this decrease is greater than the growth in the net sown cropland, indicating interactions of fallow land with other land classes as well. Wasteland has also decreased by 27.9%, from 50 Mha in 2006–2007 to 37 Mha in 2021–2022. The built-up area, which includes both urban and rural built-up land along with land used for mining activity, has increased by 23.7%. This is an expected trend, considering growing urbanisation and other developmental activities, along with an increase in population. Land under forest cover, as per the India State of Forest Reports (ISFRs), has increased from 67.7 Mha in 2005 to 71.3 Mha in 2021, indicating an increase of 5.42% in the last two decades. Correlation analyses were performed using the NRSC time series data to gain insights into whether and how these land types get converted to each other (Table 2). Domain experts were also extensively consulted to better understand these interactions. The 2011–2012 NRSC 1 : 250,000 annual land-cover data were used as the base year data for each land class to match the base year for SAFARI.

Both the time series analysis and correlation matrix showed a clear interaction between net sown cropland and fallow land (Figure 5, $r = -0.99$, $p < 0.001$). A significant negative correlation was observed between forestland and wasteland, indicating an interaction between the two land classes. The slightly lower r value ($r = -0.61$, $p < 0.01$) indicated that not all wasteland might be available/feasible for afforestation. A significant area of wasteland is used for urban expansion and other developmental projects, as seen from the relationship between built-up area and wasteland ($r = -0.77$, $p < 0.001$). The negative correlation between forestland and total fallow land ($r = -0.63$, $p < 0.01$) mainly occurs through shifting cultivation, wherein forest area is cleared for agricultural and plantation purposes. Once the harvest is completed, the land is left fallow for forest regrowth (NITI Aayog, 2018). The positive correlation between built-up land and net sown cropland (r =

0.85, $p < 0.001$) can be attributed to population growth, which increases the demand for both food grains and buildings. Further interactions and assumptions are explained in the model description below.

Figure 5: Correlation matrix of aggregated land classes used in this study (from 2005–06 to 2021–2022)



*Note: The asterisk (*) indicates a significant relationship (** = p < 0.01, *** = p < 0.001).*

Notably, in our interactions with senior experts, agricultural land conversion into the built-up area and for urban expansion was a common narrative based on anecdotal evidence. The matrix also reflected this trend (both fallow land and net sown cropland were correlated to the built-up area [$r = -0.86$ and 0.85, respectively; $p < 0.001$]). Currently, the built-up area is only 7% of the total geographical area, and the agricultural area conversion could have happened in pockets. However, because we work in the realm of prospective modelling and mainly provide modelling support for decision-making at a national scale, we did not assume this conversion in our model reference scenario. This value judgement was made after several rounds of stakeholder interactions.

This exercise in deep data analysis helped us further shape the use case for such a model. Although the model resolution may be national, the trends captured are consistent with the 1 : 2,50,000 pixel resolution data. Further, this study did not aim to provide insights on RE siting or any such geographically relevant aspects. Instead, this study focussed on understanding land as a finite resource essential for several competing demands that may arise in sustainable developmental pathways. The use case for this model is to assist with ‘budgeting’ for land under various future scenarios to help identify the most robust, least risky, or most feasible transition pathways. The next chapter explains the modelling approach for the land-use sector in SAFARI, building on this data analysis.

3. Integrating land-use dynamics in SAFARI

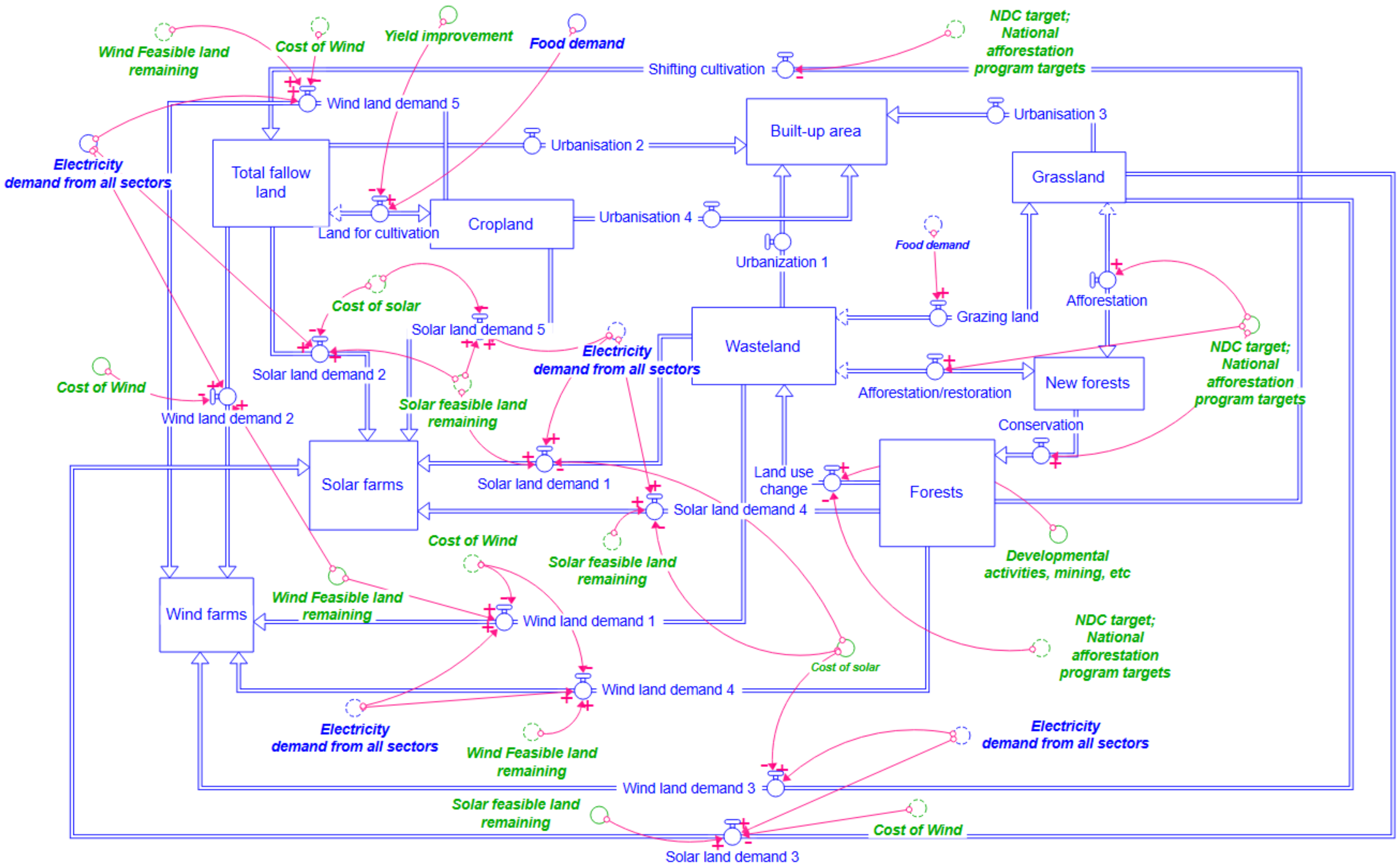
One of the objectives of this study was to build a model to simulate and project land-use changes in India, especially under deep decarbonisation or net-zero scenarios. The land-use information from different data sources, definitions of land-use categories, and historical trends in land use presented in the previous chapter informed the development of the land-use module for SAFARI. The analysis helped establish the 'rules' of how the land-use types interact with one another.

The causal loop diagram representing these interactions is provided in Figure 6. Each land-use type is modelled as a stock of land available, to or from which land 'flows' to other stocks of land use representing land-use change.

The sectors that create land demand in this module are mentioned as follows. However, the land interactions are not restricted to these demands alone and include wasteland, grassland and forest clearance interactions.

1. Agriculture sector
    a) Total fallow land
    b) Foodgrains
    c) Other crops
2. Power sector
    a) Solar power
    b) Wind power
3. Built environment
4. Forest sector
    a) Afforested land

Figure 6: Causal loop diagram of the modelled system depicting modelling logic and causal relationships



Note: The rectangular boxes indicate various land category stocks, and the arrows connecting the stocks indicate flows. The double-headed arrows are 'bi-flows': the solid arrow represents the demand-driven direction of the flows, and the dashed arrow represents the constraint-driven direction. The numbers on flows represent the priority of land conversion for that demand. The circles represent the drivers of the interactions: blue circles are as modelled in SAFARI, and the green circles represent the policy/user-driven levers that can be adjusted to dictate the flows.

3.1. Agricultural land

SAFARI has an agricultural module, in which the cropped area for agriculture is estimated bottom-up, driven by specific goals. The food grain area (for rice, wheat, nutri-cereals, and pulses) is driven by food security goals, and sugarcane and maize areas are driven by ethanol demand, in addition to the need for direct and indirect consumption. All other crops are considered based on the business-as-usual (BAU) cropping pattern and macroeconomic elasticities (Appendix A, Ashok et al., 2021). The area estimated by the agriculture module (gross cropped area) includes all instances of land being cultivated more than once in a given year and is adjusted to interact with the land module. This adjustment converts the gross cropped area into the net sown cropland by accounting for the cropping intensity. Cropping intensity is calculated as the ratio of the gross cropped area to the net sown cropland. This conversion is necessary because the net sown cropland represents the actual land area cultivated, wherein multiple cropping cycles on the same land are counted only once. This way, cropping intensity is a lever with which net sown cropland can be managed to an extent. From Figure 5 and Figure 6, the historical interaction between net sown cropland and fallow land is evident—the cropland has expanded by the conversion of fallow lands exclusively. This is reflected as follows:

$$\begin{gathered} Annual\ fallow\ land\ diverted = \\ MIN\left(\sum Annual\ net\ sown\ cropland\ required_c\ , Total\ fallow\ land\right), \end{gathered} \tag{1}$$

3.2. Land for solar and wind plants

SAFARI has a power module that simulates capacity planning and electricity generation by different sources, such as coal, nuclear, gas, solar, and wind, to meet the demand for electricity from various sectors (Appendix B). As mentioned earlier, previous studies focussing on RE siting aimed to assess the technical potential available per unit land area; the metric in this case is MW/km^2. A comprehensive literature review suggested the following range: 70–23 MW/km^2 for solar and 2–6 MW/km^2 for wind (Deshmukh et al., 2019; Jain et al., 2020b; Kiesecker et al., 2020; TERI, 2017; von Krauland & Jacobson, 2024; Worringham, 2021). This range depends on the principal question driving the respective study and the technical assumptions. For example, Kiesecker et al. (2019) estimate 2 MW/km^2 for wind, which is on the lower spectrum of the scale compared with other studies. They explored the low-impact siting of wind plants that requires large buffer zones due to high vibrational and noise disturbances, thereby separating them from forests, urban or residential areas, airports, and other sensitive regions. Studies with various levels of assumptions of buffer zones will, thus, have different potential estimations. Notably, owing to the increasing difficulty of land acquisition for wind plants, developers are currently acquiring land on a turbine-footprint basis, which will drastically lower the footprint. MW/km^2 is a parameter that depends on many assumptions, which can be consolidated to the extent of multi-land-use possibilities within and around a wind farm.

For our line of enquiry to look at the dynamic annual requirement of land resulting from RE projections, the parameter of interest is hectare (ha/GW). Considering the huge range in literature, this parameter was kept as a scenario lever, especially for wind, to examine scenarios that explore RE siting with varying degrees of buffer and multi-land-use possibilities.

To model the land-use changes resulting from establishing solar and wind plants, understanding the land suitability in terms of the resource potential of different land-use types is essential. For this, we employed the Assessment Module of the SiteRight tool (Negandhi & Kiesecker, 2020), which is designed to assess RE siting, avoiding potential socio-ecological conflicts and maximising resource potential. It provides the area feasible for solar and wind power separately in land-use types identified as 'converted land' (wasteland and fallow land together), agriculture, forests, and grassland.

For converted lands, which are already altered by human activities and thus present fewer ecological and social conflicts, we utilised the feasible land identified under the low-conflict scenario within the SiteRight Assessment Module (Negandhi & Kiesecker, 2020). This scenario considers any land with potential for solar, wind, or both as viable land for RE development. In SAFARI, the feasible area for converted land was apportioned between wasteland and fallow land, following the proportions calculated from the NRSC dataset (wasteland: 56%, fallow land: 44%). This is a geographically consistent assumption, given the significant overlap between the two land-use types.

The 'rules' of land-use change for solar and wind plants cannot be appraised from the analysis of historical data for 1980–2011 because of the lack of data. Therefore, we relied on policy documents (Ministry of Rural Development, 2011) and consultations with experts to establish the 'rules' in SAFARI with respect to the land-use changes for solar and wind plants. Our model prioritises the area required for the expansion of RE initially from wasteland (Wind land demand 1 and Solar land demand 1 flows in Figure 6) followed by fallow land (Wind land demand 2 and Solar land demand 2 flows in Figure 6).

The land identified as feasible for RE by the SiteRight tool, encompassing both wasteland and fallow land, was utilised as a threshold to govern the extent of annual changes in land use within SAFARI. The land-use change was obtained using the following equation:

$$\begin{aligned} Annual\ land\ diverted_{RE,i} &= IF\ (\text{Total land converted}_{RE,i} < Land\ feasible_{RE,i}) \\ &THEN\ MIN(Annual\ land\ required_{RE}, Total\ land\ available_i)\ ELSE\ 0, \end{aligned} \tag{2}$$

where i is the land category (wasteland and fallow land) and RE represents solar/wind.

Once the threshold was attained and the land identified as feasible by the SiteRight tool was exhausted, the model was set up to start allocating land from forestland, grassland, and net sown cropland with equal priority to cater to further RE expansion needs (Wind and Solar land demands 3, 4, and 5 flows in Figure 6), as they have comparable ecological and social impacts (Kiesecker et al., 2019). This additional land requirement was estimated as a 'gap' and calculated as follows:

$$Gap_{RE} = Annual\ land\ required_{RE} - \sum Annual\ land\ diverted_{RE,i}, \tag{3}$$

where i is the land category (wasteland and fallow land) and RE represents solar/wind.

A threshold was also applied on land that could be converted for RE from these three land categories based on the feasibility estimates of SiteRight (Negandhi & Kiesecker, 2020). The change in land use from grassland and net sown cropland to the RE sector was calculated as follows:

$$\begin{gathered} Annual\ land\ diverted_{RE,i} = IF\ Annual\ land\ required_{RE}\ <\ 0\ THEN\ 0 \\ ELSE\ IF\ Land\ converted_{RE,i}\ <\ Land\ feasible_{RE,i} \\ THEN\ MIN(\frac{Annual\ land\ required_{RE}}{3}, Total\ land\ required_i)\ ELSE\ 0, \end{gathered} \tag{4}$$

where i is the land category (grassland and net sown cropland).

In the model, forestland was further divided into three classes based on canopy density as defined by the FSI: very dense forests (VDFs), moderately dense forests (MDFs), and open forests (OFs). The extent of feasible land for the RE sector from the three density classes of forestland and consequently the total land diverted from these classes for RE expansion were based on the proportion of each class to the total forestland (CSTEP, 2023). Based on this, forestland was calculated as follows:

$$\begin{gathered} Land\ diverted_{RE,i,j} = IF\ Annual\ land\ required_{RE}\ <\ 0\ THEN\ 0 \\ ELSE\ IF\ Land\ converted_{RE,i,j}\ <\ (Land\ feasible_{RE,i} \times Proportion_j) \\ THEN\ MIN(\left(\frac{Annual\ land\ required_{RE}}{3}\right) \times Proportion\ forest\ class_j, Total\ land\ available_j)\ ELSE\ 0, \end{gathered} \tag{5}$$

where i is the land category (forestland) and j is the class of forest (VDF, MDF, or OF).

The final gap in solar and wind farms, which could not be met by any land parcel, was calculated as follows:

$$Gap_{RE} = Annual\ land\ required_{RE} - \sum Land\ diverted_{RE,i}, \tag{6}$$

where i is the land category (wasteland, fallow land, grassland, forestland, and net sown cropland).

The total land available for RE expansion ($\sum Land\ diverted_{RE,i}$) is linked back to the power sector in the SAFARI model, which informs the model regarding the total energy that can be generated.

For land categories with higher ecological and social values, such as agriculture, forests, and grasslands, we relied on the feasible land identified under the BAU maximum potential scenario within the SiteRight Assessment Module. This scenario includes only land with the highest resource potential for solar and wind power, thus ensuring that the socio-ecological impacts are minimised.

3.3. Built-up area

Our analysis of the NRSC dataset revealed that the expansion of the built-up area draws from diverse land categories (Figure 6). The demand for land required for built-up area expansion is based on an average growth rate of 12 Mha per annum, as seen in the NRSC data on built-up area. Similar to the RE sector expansion, the growth of the built-up area predominantly commences with the utilisation of wasteland (Urbanisation 1 flow in Figure 6). However, unlike the expansion of the RE sector, the growth of the built-up area lacks a predefined threshold on the area that may be allocated from individual categories.

The land allocated for built-up area expansion from wasteland was calculated using the following equation:

$$Land\ diverted_B = MIN\left(\sum Land\ required_B\ , Wasteland\right), \tag{7}$$

where *Land required*$_B$ is the annual built-up area expansion as observed in the NRSC dataset. Subsequently, if additional land is required for housing, the transition extends to include fallow land, grassland, and net sown cropland in the same order of priority (Urbanisation 2, 3, and 4 flows in Figure 6). The land required for built-up area expansion from other land categories was calculated using the following equation:

$$Land\ diverted_{B,i} = MIN\left(\sum Land\ required_B\ , Land\ category_i\right), \tag{8}$$

where i is the land category (grassland, fallow land, and net sown cropland).

This transition did not include forestland, as the total forest loss modelled in the forest sector already accounts for developmental projects, such as housing and industrial expansion.

The total forest loss was classified into two categories (Figure 6): 1) shifting cultivation/planned harvest (30% of total loss), wherein the forest area cleared is flowed into the fallow land for agricultural purposes, and 2) land-use change (70% of total loss), which included developmental activities, mining activities, and encroachment. The proportion of these two categories of forest loss was derived from the ISFRs, which offer state-wise analyses of changes in forest cover, providing insights into both increases and decreases in forested areas. To estimate the proportions, we assigned equal weightage to the various factors driving negative changes in forest cover across the different states. The overall proportion of different forest loss purposes was then calculated based on the frequency of these factors at the national level (CSTEP, 2023). In case of forest loss attributed to land-use change, the forestland cleared flowed into the wasteland from where it was allocated for other purposes.

The final gap in land required for built-up area expansion was calculated as follows:

$$Gap_H = \sum Land\ required_B - \sum Land\ diverted_{B,i}, \tag{9}$$

where i is the land category (wasteland, grassland, fallow land, and net sown cropland).

3.4. Afforested land

Forestland expansion occurs mainly via the wasteland (Afforestation/Restoration bi-flow in Figure 6) and to a certain degree via the grassland (Afforestation bi-flow in Figure 6). In the land model, we derived the data for historical afforested area from the ISFRs for 2011–2020, and then, the average land requirement for afforestation was calculated based on the historical afforestation. The land diverted for afforestation from wasteland was capped based on the percentage of wasteland (30%) indicated as available for forest expansion, as mentioned in the technical report for NDC projections by FSI (Forest Survey of India, 2021) and calculated as follows:

$$Wasteland_F = IF(TIME < 2021)\ THEN(Aff_{hist}) \\ ELSE\left(MIN\left(\left(Wasteland \times \frac{Percentage_{W,F}}{100}\right), Aff_{Avg}\right)\right), \tag{10}$$

where Aff_{hist} is the historical land required for afforestation and is the area of non-forestland converted to forestland (Box 1), $Percentage_{W,F}$ is the percentage wasteland that is allocated for forest expansion via afforestation (default value at 20%), and Aff_{Avg} is the average land required for afforestation (CSTEP, 2023).

Land for afforestation that is diverted from grassland depends on the additional land required for afforestation based on the demand, in case it cannot be met through wasteland alone. This is calculated using the following equation:

$$Grassland_F = IF\ (TIME < 2020) THEN\ 0\ ELSE\ IF\ (Gap_{Aff} < 0) THEN\ 0 \\ ELSE\ \left(MIN\left(Gap_{Aff}, Grassland \times \frac{Percentage_{G,F}}{100}\right)\right), \tag{11}$$

where $Percentage_{G,F}$ (default value assumed at 5%) is the percentage of grassland that is made available to be diverted for forest expansion via afforestation and Gap_{Aff} is the difference between Aff_{avg} and $Wasteland_F$. Lastly, the final gap in land required for afforestation was calculated as follows:

$$Final\_gap_{Aff} = Aff_{Avg} - (Wasteland_F + Grassland_F). \tag{12}$$

The total land available for afforestation (sum of $Wasteland_{aff}$ and $Grassland_{aff}$) was then classified into the area available for afforestation for VDFs, MDFs, and OFs based on the historical proportions (Box 1). Thus, for each forest type, the available land for afforestation was derived as follows:

$$IF(TIME < 2021)\ THEN\left(Aff_{hist,j}\right) \\ ELSE\left(MIN\left((Wasteland_F + Grassland_F) \times Proportions_j, Aff_{Avg,j}\right)\right), \tag{13}$$

where j is the forest type (VDF, MDF, and OF), Aff_{hist} is the historical afforestation land requirement, and Aff_{Avg} is the average afforestation land requirement.

Box 1: Estimating changes in area under forest cover using the change matrix from ISFR

Historical data for areas under different density classes are provided by the biennial India State of Forest Reports (ISFRs) published by the Forest Survey of India (FSI). These reports also provide land-use change matrices, which help understand land conversions between non-forest and forestland as well as within forestland, across density classes. Based on these change matrices, we assumed the afforested area as any non-forestland that is converted to forestland. Within our modelling framework, afforested areas are considered young forests until 20 years, beyond which they are considered old-growth forests. This creates two age classes: less than 20 years and greater than 20 years. Based on this assumption and the forest cover change matrix over the years, we calculated the average historical afforestation proportion for each density class. These proportions were used to apportion the area available for afforestation from wasteland to the different density classes.

Forest class	Proportion
Very dense forests	0.01
Moderately dense forests	0.11
Open forests	0.88

3.5. Model validation

As highlighted by Barlas (1996), for system dynamics models, statistical significance testing is only appropriate for behaviour validation once the structural validity is established. In this context, the focus is on determining whether the model's behaviour predictions are sufficiently accurate through statistical calibration methods.

Pattern-oriented testing: System dynamics models require statistical tests that are pattern-oriented rather than data point-oriented. This is because system dynamics typically seek to capture long-term trends, oscillations, or other behavioural patterns in the system, rather than individual data points. Following the recommendations on statistical procedures for behaviour validation by Kleijnen (1995), we evaluated the accuracy of the model's predictions by comparing simulated and actual system behaviour. Figure 7 shows the trend analysis of projected values by the structure captured in the model versus the NRSC data for a period of 18 years. The results validate the 'rules' followed by the model to project land-use dynamics.

Figure 7: Model validation

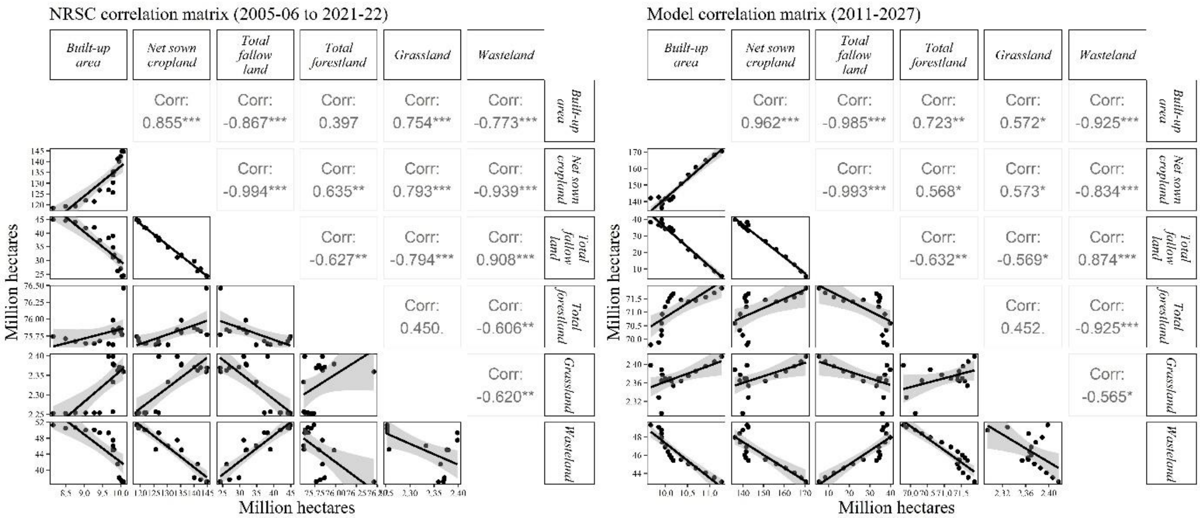


Table 3 shows the mean absolute percentage error of the model-generated values with the historical NRSC data (2011–2021).

Forest and agricultural area: The forest and agriculture modules were initialised and calibrated to FSI and LUS data, respectively, and these land categories projected in SAFARI calibrated well with the NRSC data. Although the correlation of fallow land and net sown cropland has been captured in the structural behaviour of the model (Figure 7), the projected values show a high degree of variance. This is because the rate of decline observed in reality is higher, indicating the possibility of non-agricultural land-use change occurring on fallow land (National Remote Sensing Center, 2024). This is not captured in the model, as described earlier in Section 2.

Build-up area: Built-up area from the NRSC dataset amounts to 9.8 Mha and includes land covered by roofed structures; paved surfaces such as roads and parking lots; commercial and industrial sites including ports, landfills, quarries, and runways; and urban green areas such as parks and gardens. Combining all built-up land (residential and commercial buildings) based on the floor space index/sprawl assumptions and the land required for RE plants, the model estimates the built-up area to be 2.25 Mha using a bottom-up approach. In case the actual urbanisation was more 'sprawling' than our assumptions, this area could be as high as 6 Mha. Adding pockets of land that were not considered in the model, such as mining (0.3 Mha), industrial land (0.7 Mha), government land (2 Mha), and roads (6 Mha), an additional built-up area of 9–10 Mha could be estimated. Refining the model to capture all built-up areas in a bottom-up manner as effectively as a satellite is not possible. Therefore, this data gap was plugged using the NRSC data, and the model projected this land category based on the current trends. Bottom-up estimates of the built-up area were used, mainly as a validation measure for the future. The land required for RE was segregated from the built-up land, as it is a crucial element of net zero and is central to our objective.

It is noteworthy that the current version of our model included a select subset of land categories (water bodies, snow cover, and glacial areas), and the Rann was not included. In particular, these land categories in the NRSC dataset showed variations across years, indicating potential interaction with other land categories. The model structure was validated using forest and tree cover data procured from ISFRs and cropland data procured from the LUS report. The above considerations lend to the differences in areas across different land classes, contributing to an overall difference (weighted average of the differences in different land classes) of 1.26% between the model-generated and NRSC-reported geographical areas (Table 3). The difference in the total geographical area was 1.05%. This validation process underscores the robustness of our model's predictions while acknowledging the differentials ascribed to methodological and data-specific considerations.

Table 3: Mean absolute percentage error

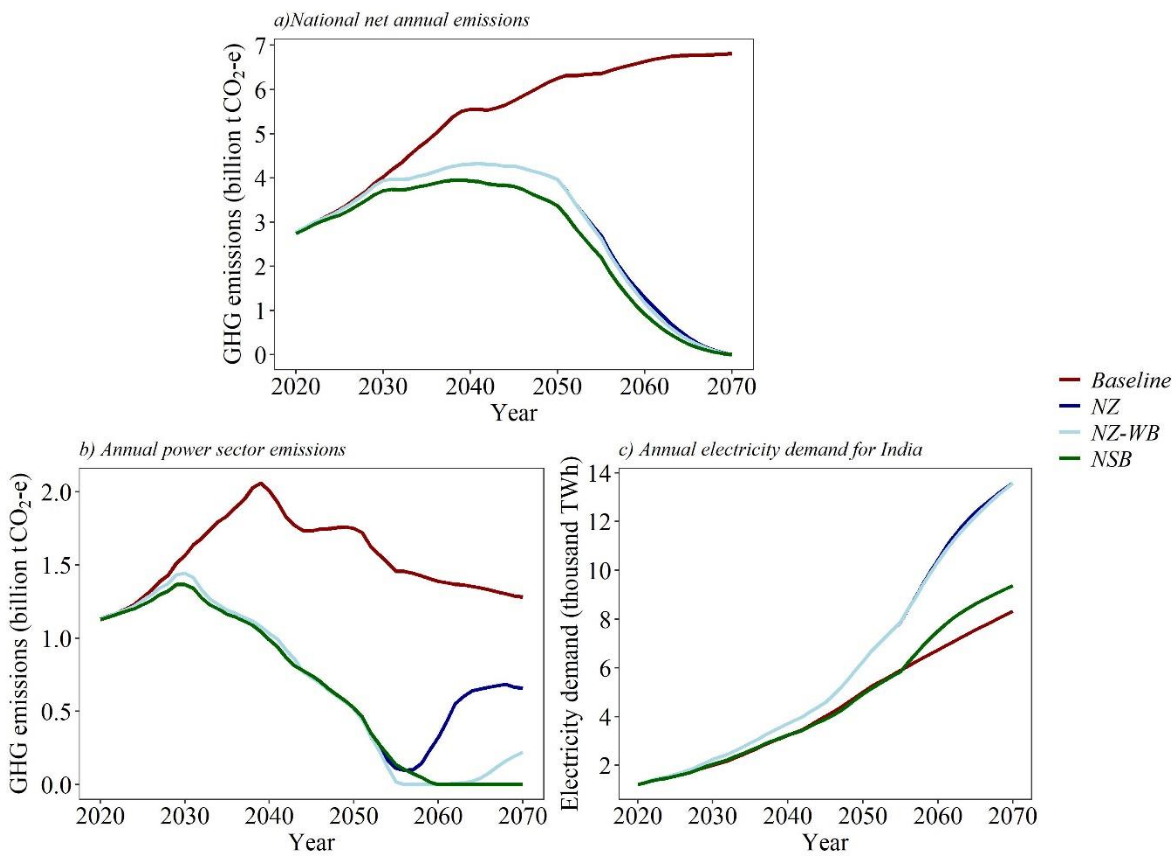
Land class used in the model	Percentage difference
Wasteland	12.3
Fallow land	16.5
Net sown cropland	3.0
Grassland	0.03
Forestland	6.6
Total geographical area	1.05

4. Long-term land-use dynamics: Model insights

The land-use dynamics until 2070 across sectors were modelled as described in Chapter 3. This chapter discusses the insights gained from the model based on scenario constructs. These scenarios include (i) baseline, (ii) land-agnostic (NZ-LA), (iii) land-aware (NZ), and (iv) no silver bullet (NSB) scenarios.

In the baseline scenario, driven by development aspirations and population growth, India's electricity demand is expected to reach around 8,300 TWh by 2070 (a five-fold increase from the current demand). Assuming minimal decarbonisation efforts beyond meeting NDCs, India's net emissions will continue to increase till at least 2070 (Figure 8), without peaking. The power sector emissions, however, are likely to peak in the 2040s even in the baseline scenario, assuming current cost trends.

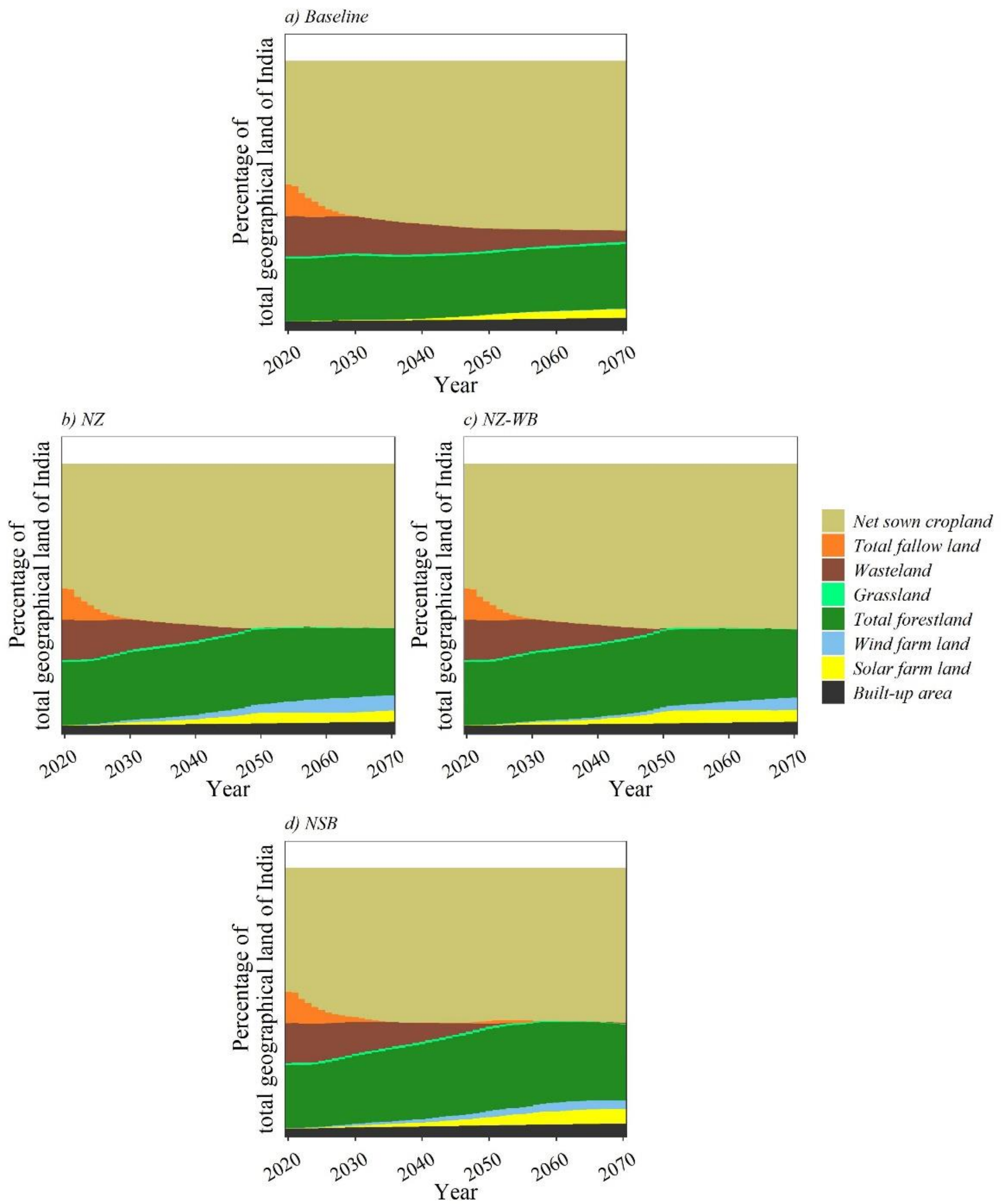
Figure 8: India's electricity demand and emissions under different scenarios



Note: Baseline: Business-as-usual scenario; NZ: Net-zero scenario with high electrification of end-use sectors and decarbonised power sector as the mitigation pathway; NZ-WB: NZ scenario with multiple land-use possibilities in wind farms; and NSB: No silver bullet scenario focussing on multiple demand-side interventions as the mitigation pathway.

The land-use dynamics of all simulated scenarios are captured in Figure 9. The trends in the actual land areas are given in Appendix C. As expected, the largest land-use type occupying an average of 61% of the total land is agricultural land, which captures the interaction among net sown cropland, fallow land, and shifting cultivation. A substantial reduction in fallow land is observed between 2020 and 2030, corresponding with an increase in net sown cropland, driven by the food demand due to population growth. However, by 2060, as the population growth stabilises and crop yields improve, the interaction between net sown cropland and fallow land stabilises. Wasteland depletes to provide land for multiple purposes (built-up area, land for solar and wind power plants, and afforestation). Correspondingly, forestland increases by an average of 0.65 Mha annually, continuing historical afforestation trends. These trends highlight the ongoing competition for land, particularly wasteland, driven by urbanisation, RE expansion, and afforestation.

Figure 9: Land-use dynamics under the considered scenarios



As discussed in Section 1.1, the modelling studies so far have mainly captured the land footprint of RE for a deep decarbonisation scenario or defined a constraint, based on technical potential studies. To recreate the most commonly modelled pathway to net zero, which is the extensive electrification of end-use sectors and high deployment of RE to provide electricity, a 'land-agnostic' scenario (NZ_LA scenario, explained in Appendix D) was constructed. Here, we assume that there are no land constraints, i.e. the feedback from land availability on RE deployment was disabled. Comparing this with the results from the land-integrated scenarios can help provide a better understanding of the annual land-use dynamics and related constraints as well as the risks/trade-offs for achieving deep decarbonisation or net zero.

4.1. NZ_LA scenario

The rampant electrification of transport and industrial sectors, along with the adoption of green hydrogen fuel and carbon capture systems to reach net-zero emissions, can significantly increase the electricity demand to over 12,500 TWh in 2070, i.e. an 8-fold increase from the current demand (Figure 8). India-specific studies have estimated a similar increase (10,000–20,000 TWh) in electricity generation in net-zero pathways in 2070 (Chaturvedi & Malyan, 2022; Das et al., 2023). This translates to a per capita electricity demand of over 8,000 kWh in 2070, which is still lower than the current demand in several countries; for comparison, as per the 'Our World in Data' database (https://ourworldindata.org/), the per capita electricity generation in the United States in 2023 was 12,497 kWh.

Assuming that this power requirement will be increasingly met by RE sources, the total RE requirement in 2070 will be 7,470 GW, majorly driven by solar (5,800 GW) and wind (1,500 GW), along with a storage capacity of 11,240 GWh (details are provided in Figure 14). This is consistent with other studies. Out of the 150 vetted 1.5°C-compliant scenarios available in the IPCC AR6 scenario database with results for solar and wind capacity projections for India, 60 showed solar capacities ranging from 5,500 GW to 13,000 GW and 95 showed wind capacities ranging from 1,500 GW to 6,000 GW (Byers et al., 2022). Net-zero analyses specific to India suggest similar projections of solar and wind capacities for 2070 (Chaturvedi & Malyan, 2022; McKinsey and Company, 2022).

To support the RE generation of 7,470 GW, about 30–40 Mha of land is required, which amounts to 10%–12% of India's total geographical area (equivalent to the area of Rajasthan state). We explored this possibility further in the land-aware net-zero scenarios, considering required changes in land use and exploring potential risks for this pathway.

4.2. NZ scenario

In this scenario, the land-use feedback was activated. With this feedback, the land with technical potential for solar energy was found to be constrained at 2,900 GW in the NZ scenario, signified by the depletion of wasteland by 2050 Figure 9. The constraints remained even after accounting for the additional land that becomes available due to the retirement of existing plants. Wind energy could partially compensate by expanding slightly more to reach 1,550 GW (Figure 9b), until all land with wind potential (with a minimum capacity utilisation factor of 15%) runs out. In this scenario, we will have to rely on fossil fuel to meet the electricity demand from 2050 onwards, when RE gets constrained due to land. This results in increased emissions from the power sector (Figure 8), which reinforces the need for electricity-intensive carbon capture and thus fossil fuel for achieving net zero. The model shows that to adequately meet the electricity demand for net-zero emissions in this scenario, the gas operating capacity has to be enhanced during 2060–2070 to reach 386 GW (due to the 'no new coal' constraint), and the existing coal plants that remain viable will have to continue running at full capacity, starting at 2050 till the end of the plant lifetime.

If we assume lower buffer considerations for wind energy, more wind energy capacity of up to 2,430–3,020 GW can be operationalised with the same land-use dynamics as NZ. This scenario (NZ_WB) was considered to explore the possibility of higher wind potential reported in the literature (Deshmukh et al., 2018; Hossain et al., 2011). In this case, the risk of falling back to fossil fuel in the later decades may be minimised. However, the following risks may prevail:

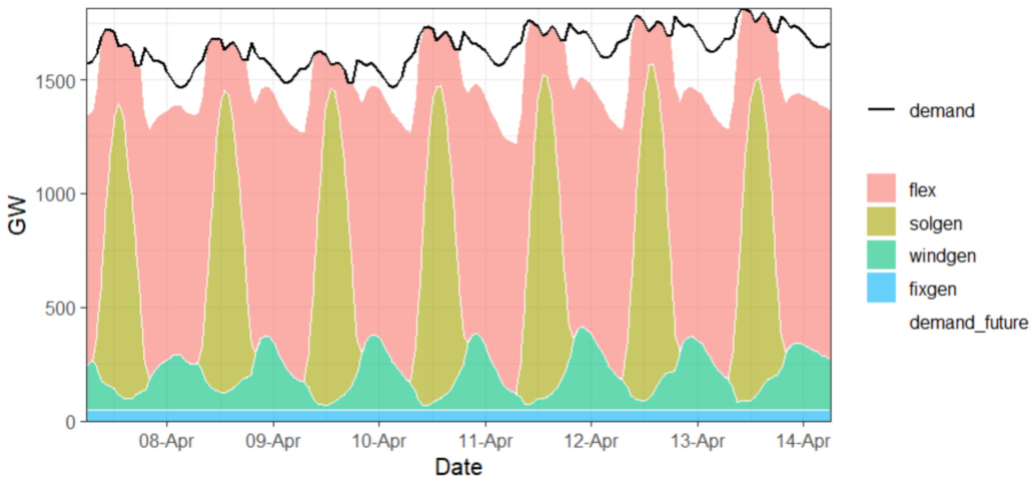
- There is a risk of unmet demand because of the extreme reliance of the power supply system on a highly seasonally variable, climate-sensitive source (See Box 2 for details).
- The case for multi-use of land with wind turbines is weak. High vibrational noise and other socio-ecological concerns leave very few choices of land use that can co-locate with wind plants (Msigwa et al., 2022; Teff-Sekar et al., 2022). The land buffer may not reduce enough for wind energy to augment as much as required (Abbassi et al., 2014; Haggett, 2012).

Box 2: Testing for robustness using hourly demand–supply profiles

To further investigate the possible issues because of increasing variability in the power supply due to RE, we analysed the SAFARI power sector results using R code. The code is designed to simulate hourly demand and generation for a given year based on scenario-specific annual power sector results from SAFARI (solar, wind, coal, gas, nuclear, hydro, and storage: capacity and generation). Coal and nuclear sources were assumed to be baseload/fixed generation, whereas gas, hydro, and storage were assumed to be flexible generation. The profiles for solar irradiance and wind speed at a hub height (100-m above ground) were obtained from the ERA5 database (Copernicus Climate Change Service (C3S), 2017). The energy generation from solar and wind was estimated using the solar panel datasheet and the turbine power curve provided by manufacturers. Further, the hourly electricity demand profile was based on the NITI Aayog dataset for 2023 (NITI Aayog, n.d.). A comparison of the hourly demand–supply profiles enabled us to check any mismatches, such as unmet demand and curtailed generation in a given year. Despite various uncertainties involved in the supply and demand profiles, the simulation results can be seen as a crucial indicator for assessing the scenario-specific, hourly scale supply–demand balance.

All scenarios show robust results until 2050. Beyond 2050, scenarios that are more reliant on wind energy (NZ_WB) indicate an aggregate unmet demand of 0.7%–2.8% in 2060 and 5.2%–6.2% in 2070. A representative supply–demand curve for summer in 2070 is shown in Figure 10. Unmet demand can have huge implications for all sectors. Further, these are national level assumptions and state-specific generation can have more uncertainties.

Figure 10: Representative supply–demand load profiles for a typical summer week in 2070

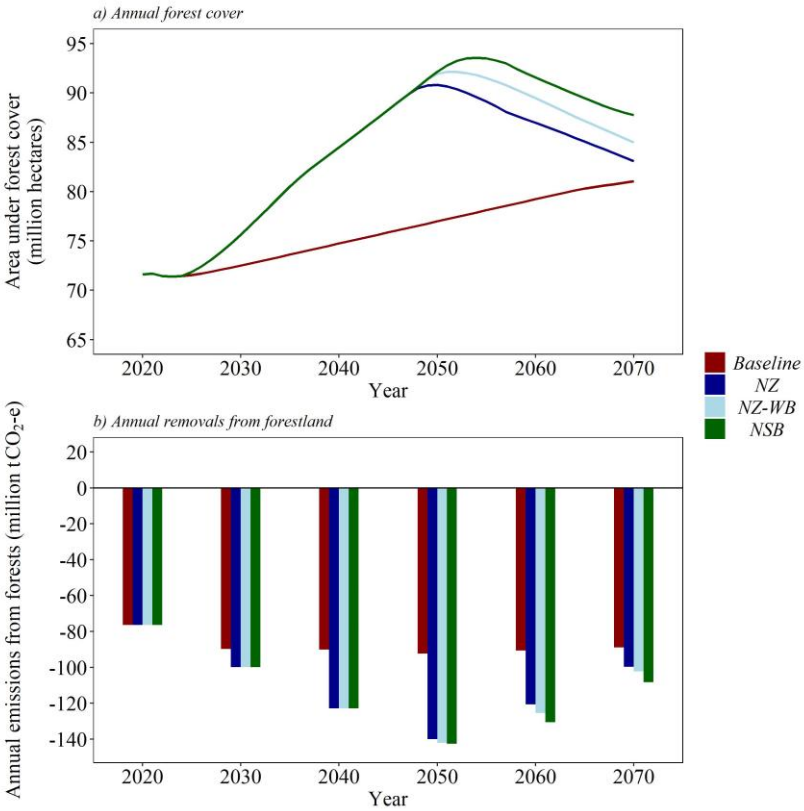


The demand for land for RE expansion is met primarily by wasteland and caters to the need for expansion of built-up area and afforestation. The model shows the possibility of near-complete depletion of wasteland in this scenario by 2049 (Figure 9). Wasteland constitutes very diverse ecosystems both in terms of structure and composition and hosts a large number of endemic and often endangered flora and fauna (Madhusudan & Vanak, 2022). Loss of this land category directly impacts biodiversity and the livelihood of thousands of people dependent on it for livestock fodder resources. Moreover, a reduction in wasteland could lead to increased pressure on other land use types, such as agricultural land including both net sown cropland and fallow land, grassland, and forestland for further expansion of RE and built-up land and afforestation. The land-use constraints also result in reduced annual carbon capture by forestland beyond 2050 owing to constraints in cultivable wasteland available for afforestation. This means that with more land demand for RE, land availability for afforestation reduces. See Box 3 for details.

Box 3: RE versus forestry

SAFARI has multiple levers for increasing the net carbon sink of forestland, such as increasing afforestation and tree cover, decreasing deforestation, increasing restoration of forests (improving forest density class or quality to increase their sequestration potential), and decreasing degradation of forests through conservation activities. The rate of afforestation historically averages at 0.66 Mha. For the NZ scenario, in line with National Forest Policy and Green India Mission, we assumed the doubling of afforestation efforts for both forest (additional 0.36–0.49 Mha from 2025 to 2030) and tree cover, doubling restoration and conservation activities, and decreasing deforestation by 30% compared with baseline levels (annual reduction of 0.5–0.4 Mha). This helps realise a net carbon sink of 36.6–37.3 $GtCO_{2e}$ and a forest and tree cover of 30% by 2043. As the wasteland depletes by 2050 owing to competing demands, the total forest area also plateaus along with the land demand for RE (Figure 11). A reduction in the annual carbon removal by forests associated with this land constraint can be observed (Figure 11). Further, studies have shown that forest type selection based on carbon capture ability for afforestation has implications for land-use competition. The selection of native forest types, which have a lower per hectare carbon capture potential, versus carbon-intensive forest types at a large scale for afforestation could worsen the economy and food and land systems because of a decrease in land efficiency (Hasegawa et al., 2018, 2024). However, the fact that native forest types demonstrate greater resilience to long-term climate change impacts and foster richer and more diverse ecosystems (Osuri et al., 2020) further highlights the land-use optimisation complexity and the trade-offs among different Sustainable Development Goals.

Figure 11: Impact of forest interventions on a) annual forest cover and b) annual carbon removals by forestland



To further understand this trade-off between land for RE and land for afforestation, we ran the NZ scenario with the historical afforestation rate continuing till 2070. The land constraint on RE was eased, resulting in the solar operating capacity reaching 3,480 GW (from the earlier 2,900 GW) and wind capacity reaching 1,560 GW. Correspondingly, the net carbon sink realised due to the increase in forest and tree cover reduces to 34.4 $BtCO_{2e}$. Notably, purely in terms of the net reduction in emissions or carbon sequestration, both scenarios are comparable. In fact, the 'no additional afforestation' scenario is marginally better. However, forests provide innumerable additional natural and cultural ecosystem services that cannot be provided by RE.

Some interesting literature discusses this trade-off from different perspectives. Jayakrishnan and Bala (2023) showed that reducing fossil fuel emissions is relatively more effective than afforestation for the same amount of carbon removed from the atmosphere. van de Ven et al. (2021) argued that the net land-cover changes due to RE deployment may cause a net release of carbon. Stern et al. (2023) quantified the climate change mitigation potential of afforestation and solar photovoltaic (PV), considering reduced atmospheric carbon, surface energy balance, and land area required, and found that in drylands, PV fields are over 50 times more efficient than afforestation.

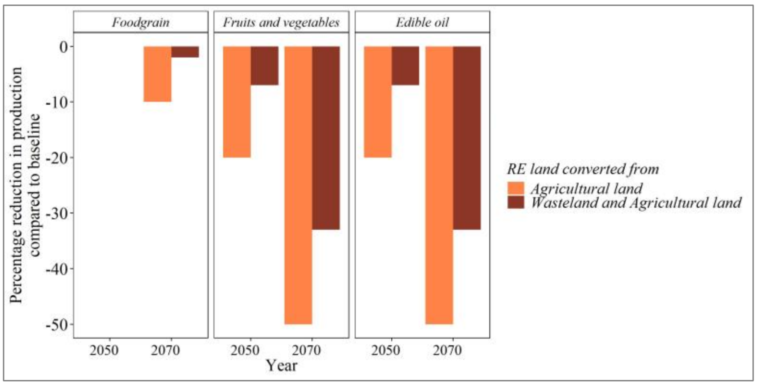
With RE transition at the cusp, plans for managing this trade-off with 'techno-ecological' multi land-use solutions that minimise habitat fragmentation and biodiversity loss are much needed in the NZ discourse.

As detailed in Chapter 2, the choice of wasteland as the primary land category for conversion was based on detailed historical data analysis and stakeholder consultations. Further, most of the technical potential estimations, including the government estimates (Worringham, 2021), are based on wasteland conversion. In contrast, several studies highlight the socioecological prominence of wasteland and the risks of misclassification of ecological niche, grazing land, or commons as wasteland, exposing it to conversion. RE developers often cite difficulty in the acquisition of wasteland, which can be at least partly attributed to the high socioecological significance of wasteland. According to Ortiz et al., (2022), over 74% of the land for RE siting in India includes agricultural land. Therefore, a scenario that equally prioritises agricultural land and wasteland for siting RE was explored. Although this resolves the land constraint on RE, it has significant impacts on food security and other agricultural produce. See Box 4 for details.

Box 4: Impact of converting agricultural land for RE development

Assigning increased priority for the conversion of agricultural land for RE development leads to a reduction of 32–58 Mha of net sown cropland. This indicates the possibility of severe food and nutritional security impacts during 2050–2070 and beyond. Figure 12 shows the normalised impact of converting agricultural land for RE development on food production for an extreme scenario wherein only agricultural land continues to be converted and one scenario wherein wasteland and agricultural land are given equal priority. The SAFARI model framework prioritises food grain production over other crops; thus, the impact on fruits, vegetables, and edible oil can be observed from 2050 onwards. Without this model-specific prioritisation, food grain security issues could emerge earlier than indicated.

Figure 12: Normalised impact of land priority change for RE



Thus, for a net-zero pathway that is dependent on electrification and RE for mitigation, land poses a significant constraint. Further, there are several risks/trade-offs involved in strategies that may help in easing the land constraint, which have already been discussed in this report. Therefore, for a sustainable transition to net zero, demand-side measures and a diversified and clean power supply are crucial.

4.3. NSB scenario

This brings us to an illustrative NSB scenario that achieves net zero with reduced reliance on land and associated risks. With the understanding of the risks posed by net-zero development that relies on high electricity consumption, this scenario focusses on a slew of demand-side measures, which help reduce the demand for electricity without compromising end services. The power supply portfolio is also assumed to be more diversified.

Figure 13 shows the high-level sectoral assumptions and their impacts. For emission savings, cumulative emissions mitigated till NZ year (2024–2070) were selected as the impact parameter because it can provide a sense of impact on the remaining carbon budget and shows the impact of early or late action. For electricity savings, as our main finding from the previous scenario was on the constraints of RE power infrastructure, we chose 'avoided additional power infrastructure' that would have been otherwise required or alternatively 'avoided solar operating capacity' in GW.

Figure 13: Illustrative 'No Silver Bullet' scenario: Summary of key assumptions and impacts

Energy demand side		Cumulative (2024–2070) emissions mitigated (MtCO2e)	Avoided power infrastructure (TWh/Solar GW)
Buildings	• 100% of the households to adopt 4-5 star-rated electrical appliances by 2060 • 100% of the new construction to adopt passive design by 2070	118	530/318
Transport	• 30% share of inter-city travel to be via rail mode by 2070 • 65% share of urban transport to be PT+NMT by 2070 with transit-oriented development • 100% of passenger transport modes to be electrified by 2070	8,800	40/24
Food and agriculture	• 33% of cereal requirements in the diet to be met by millets by 2050 • 67% of the cropped area to be precise irrigated, and 33% to be organically farmed by 2070	4,490	429/258
Industry	• Implementing measures such as waste heat recovery to unlock greater efficiency, especially in small- and medium-scale industries • 40% steel production using scrap by 2070 • 50% clinker substitution by 2070 • Use of alternative fuels in addition to electricity and hydrogen	39,082	751/451

Power supply side

- Increasing adoption of RTPV in buildings to support decentralised solar energy capacity of 435 GW by 2070
- Dedicated agricultural feeders powered by solar energy capacity of 120 GW by 2070 to cater to irrigation energy
- Utility-scale solar capacity of 3,370 GW and onshore and offshore wind capacity of 825 GW supported by battery capacity of 6,560 GWh by 2070
- Nuclear energy to reach 380 GW in 2070 with the implementation of a three-stage thorium programme

Households opting for efficient appliances and consuming consciously have a significant impact on reducing grid electricity demand. Rising temperatures and increasing affluence can exponentially increase the cooling demand from buildings. Given that most of India's building stock that will exist in the long term is yet to be built, the choice of construction material and design will considerably shape the cooling energy demand. Design choices that increase insulation and window-to-wall ratio (WWR) and alternative construction materials with a low U-value can help decrease the cooling electricity load (CSTEP, 2024).

Assumptions and impacts of this lever in the illustrative NSB scenario are as follows:

- With a 10% diffusion of 4–5 star-rated appliances in households, in addition to progressive adoption with increased awareness and peer effects, 90% of households are assumed to utilise high-efficiency appliances by 2055. This lever results in net savings of 356 TWh power infrastructure (equivalent to a solar energy capacity of 214 GW).
- Construction material choices for new building stock considered in the scenario include complete phasing out of clay bricks by 2070 and replacement with materials such as autoclaved aerated concrete blocks with a low U-value, 100% adoption of progressive cool green roofs for houses by 2070, and progressively increased adoption of effective insulating materials and Energy Conservation Building Code-recommended WWR. Together, these passive design aspects reduce the net cooling electricity demand from the grid by 95 TWh (in terms of an additional solar energy capacity of 57 GW).
- The combined effect of both these levers considered shows a net saving of grid infrastructure equivalent to 530 TWh (an additional solar capacity of 318 GW). Interestingly, this effect is higher than the sum, given the reinforcing impact of passive design reducing the demand for electricity, which is then assumed to be provided by energy-efficient appliances.

Incentivising the adoption of public transport modes through sustained investments in infrastructure for reliable and convenient options can not only help unlock additional emission savings but also save grid electricity demand.

Assumptions and impacts of this lever in the illustrative NSB scenario are as follows:

- The share of railways for inter-city passenger transport is increased (from 15% at present to 30% in 2070), instead of road-based modes (from 78% at present to 65% in 2070).
- The urban transport mode trends of increasing individual vehicle ownership accommodated till mid-term or 2050 are set to reach reasonable levels of per capita vehicle ownership. From 2040 and beyond, increasing the shares of bus, metro-rail, and non-motorised transport is set to reach 65% of the urban transport requirements.
- The model results show that this can cumulatively mitigate 655 $MtCO_2e$, adding to the 8.2 $BtCO_2e$ that passenger transport electrification with the current modal share trends would have cumulatively mitigated. This trajectory also results in power infrastructure savings of 40 TWh/24 GW solar capacity requirement.

A dietary shift to include more millet instead of rice helps reduce water withdrawal, irrigation energy requirement, and methane emissions.

Assumptions and impacts of this lever in the illustrative NSB scenario are as follows:

- Currently, the cereal preference in the average Indian diet is predominantly rice or wheat-based, with millets only constituting 3%–5%. Here, we assumed an increasing preference for millet over time to reach 33% of cereals by 2050.
- This saves 40 $MtCO_2e$ of methane emissions, which are hard to abate, and progressively reduces annual groundwater withdrawal, saving an average of 135 billion cubic metres per year from 2050 to 2070. This lever also has the co-benefit of reducing the net grid power infrastructure equivalent by 46 TWh/28 GW additional solar capacity.

Groundwater withdrawal and electricity can be reduced by the increased adoption of precise irrigation options such as drips and sprinklers. Efficient water application also positively impacts crop yields, which also saves energy, water, land, and fertiliser required.

Assumptions and impacts of this lever in the illustrative NSB scenario are as follows:

- Assuming the share of cropped area with precise irrigation linearly increases to cover 2/3 of the net sown cropland, cumulative emission savings of 1,550 $MtCO_2e$ and electricity infra savings of 213 TWh/128 GW solar.

The fertiliser industry is driven by agricultural practices, which are currently disproportionately dependent on urea (Ashok, 2019). Increased adoption of natural farming can reduce the Industrial Processes and Product Use (IPPU) emissions from the fertiliser industry and the demand for hydrogen and therefore electricity.

Assumptions and impacts of this lever in the illustrative NSB scenario are as follows:

- The NZ scenario considered (a) fuel/feedstock shift from natural gas to electrolytic hydrogen and (b) meeting the electricity demand from the grid. Cumulative emissions of 2.3 $BtCO_2e$ were mitigated in this scenario, with an additional electricity infrastructure requirement of 300 TWh/180 GW solar.
- Assuming that the increasing adoption of natural farming covers 1/3 of the total cropped area in 2070 significantly reduces the emission and energy demand. The model shows that this results in the mitigation of increased cumulative emissions (4 $BtCO_2e$) and a decrease in additional electricity infrastructure demand (130 TWh/78 GW solar), compared with the NZ scenario.

The cement industry in India is well known to operate efficiently in terms of energy consumption. The cement industry, therefore, is not the biggest emitter in terms of energy emissions. However, the process emissions from this industry during clinker production constitute over 50% of the IPPU emissions and are hard to abate. Clinker substitution with the currently commercially and structurally viable options can help reduce the net emissions from the cement industry by 20% and therefore the carbon capture requirement (CSTEP, 2022).

Assumptions and impacts of this lever in the illustrative NSB scenario are as follows:

- The NZ scenario considered emission-mitigating levers that focussed on fuel shift to electricity and hydrogen and assumed a shift in the electricity demand to be provided by cleaner grid electricity rather than coal-based captive power plants. This resulted in a cumulative emission mitigation of 1,033 $MtCO_2e$, at the cost of additional equivalent power infrastructure of 600 TWh/360 GW solar energy.

- In addition to the above, the following levers were also considered:
    - Clinker substitution to reduce the current clinker : cement ratio of 0.7 to 0.5 over time by 2070
    - Enhanced waste heat recovery of 33% by 2050
- The additional levers in the NSB scenario result in twin benefits of increased net emission savings of 2,082 $MtCO_2e$ and reduced requirement of additional equivalent power infrastructure to 511 TWh/307 GW solar.

The steel industry is a major electricity consumer. Therefore, measures such as enhanced efficiency, especially in medium- and small-scale electric arc furnace-based industries, and increased use of scrap to produce steel can unlock deeper energy and emission reductions.

Assumptions and impacts of this lever in the illustrative NSB scenario include the following:

- Similar to fertiliser and cement industries, for the steel industry, the NZ scenario considered mitigation levers focussing on shifting fuel and production processes away from coal-based blast furnace and electric arc furnace towards hydrogen and natural gas-based arc furnaces. Cumulative emissions thus mitigated amount to 19 $BtCO_2e$, with an additional power infrastructure requirement equivalent to 2,200 TWh/1,322 GW solar capacity.
- With increased use of scrap in steel production in the long term (40% by 2070 linearly increasing from 10% in 2040), cumulative emission savings increase by 521 $MtCO_2e$ and electricity infrastructure requirement reduces to 1,876 TWh/1,127 GW solar capacity.
- Increased efficiency, especially in electric arc furnaces, reduces coal and gas burning, leading to further mitigation. This leads to cumulative emission savings of 21.5 $BtCO_2e$, with the same power requirements.

Despite being individually insignificant emitters, numerous medium- and small-scale industries can have high aggregate energy demands and energy emissions. The adoption of low-carbon alternative fuels can help reduce the electricity demand and emissions.

Assumptions and impacts of this lever in the illustrative NSB scenario include the following:

- The NZ scenario assumes extensive electrification of micro, small, and medium enterprises towards the reduction of emissions. This helps achieve cumulative emission mitigation of 16 $BtCO_2e$, with additional electricity infrastructure equivalent to 338 TWh/203 GW of solar capacity.
- With the adoption of alternative fuels and waste heat recovery, the same emission reduction can be achieved with no additional power infrastructure.

Because the NSB scenario clearly mitigates more emissions than the NZ scenario in terms of industries, the corresponding carbon capture requirement for industries is lower. The additional power infrastructure required for carbon capture systems is equivalent to 770 TWh/463 GW solar capacity in the NZ scenario versus 462 TWh/278 GW solar capacity in the NSB scenario.

Rooftop PV and agrivoltaics can help reduce the grid electricity demand with significantly less land requirement.

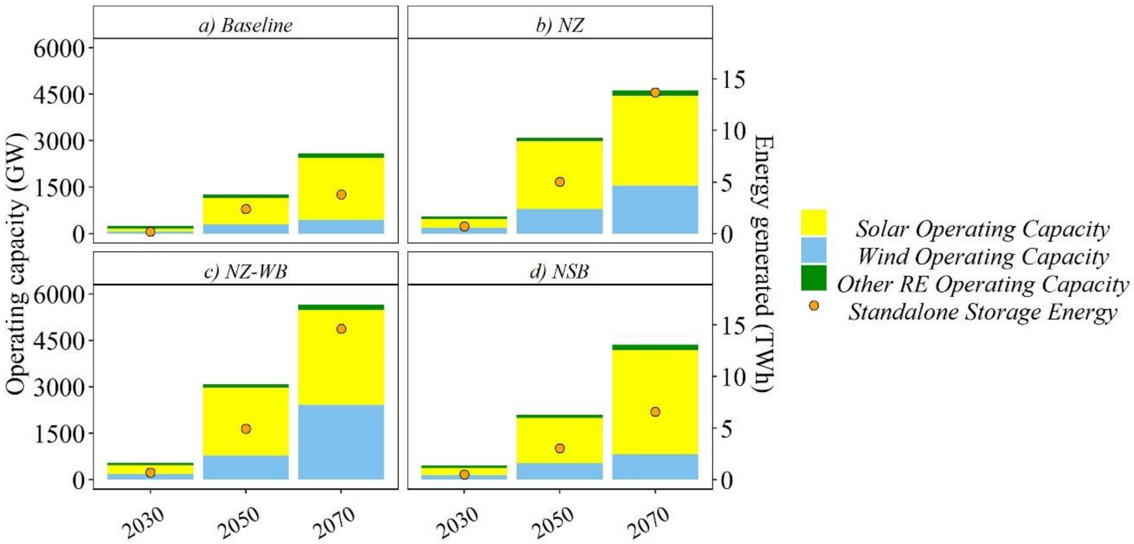
Assumptions and impacts of this lever in the illustrative NSB scenario are as follows:

- The share of residential buildings and commercial buildings adopting RTPV was assumed to linearly increase to 20% and 5%, respectively, by 2070.
- Increased adoption of dedicated solar-based agri-feeders cater to the irrigation demand.
- This leads to overall savings of at least 500 GW of additional solar capacity (without accounting for the additional gains due to the absence of transmission and distribution losses in decentralised plants).

A combination of these demand-side measures, therefore, reduces the net grid electricity demand by more than 30% compared with the net-zero scenario with the co-benefit of further reducing emissions and other resources. The illustrative zero-carbon power sector scenario that is capable of reliably catering to this demand without any land constraints is described below:

- The solar operating capacity reaches 3,370 GW and the wind capacity reaches 825 GW by 2070 without any land constraints. A total battery capacity of 6,560 GWh ensures no unmet demand due to variability (Figure 14d).
- The scenario considers an enhanced role for nuclear energy, which reaches 380 GW in 2070. This helps meet the baseload comfortably without any risk of falling back to fossil fuel. See Box 5 for details.
- Overall, no unmet demand is observed in the daily load analysis and a robust and zero-carbon power supply scenario is ensured, with no land constraint.

Figure 14: RE power supply operating capacity and generation under the considered scenarios



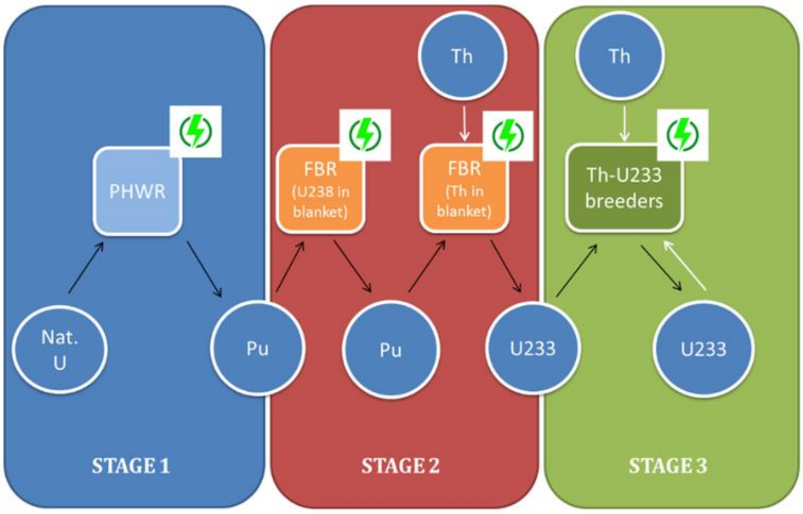
With respect to land-use dynamics, in this scenario, we assumed an increased focus on millet instead of rice, along with an incremental yield improvement sufficient to bridge the current average yield gap by 30%. This frees up more agricultural land for RE, which means that wasteland never really depletes and there is no land constraint for RE (See Box 6).

Box 5: Augmenting India's nuclear energy trajectory

India's nuclear energy strategy is based on the three-stage programme envisioned by Dr Homi J Bhabha in 1954. The main aim of this programme was to utilise the vast thorium reserves and provide energy security to the country (Figure 15) (Bhabha, 1957).

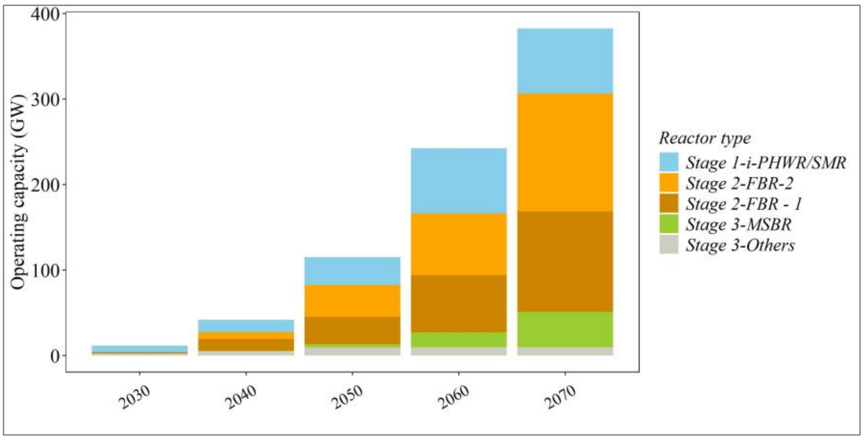
Recently, some momentum was regained around nuclear energy, particularly on indigenous small modular reactors, after the announcement of the Union Budget 2024–2025. With higher degrees of standardisation, the rapid deployment of indigenous pressurised heavy-water reactors of 220 MWe is a possibility. A corresponding increase in spent fuel reprocessing facilities can put India on track for the three-stage nuclear programme. After a detailed analysis (Appendix B) of fissile material flows and reactor parameters, we arrived at a possible trajectory for nuclear energy (Figure 16). This is the trajectory of nuclear energy assumed in the NSB scenario.

Figure 15: Schematic of the material flow and reactor technology under the three-stage nuclear programme



PHWR: Pressurized heavy-water reactor; FBR: Fast breeder reactor

Figure 16: India's nuclear energy trajectory as per the three-stage programme



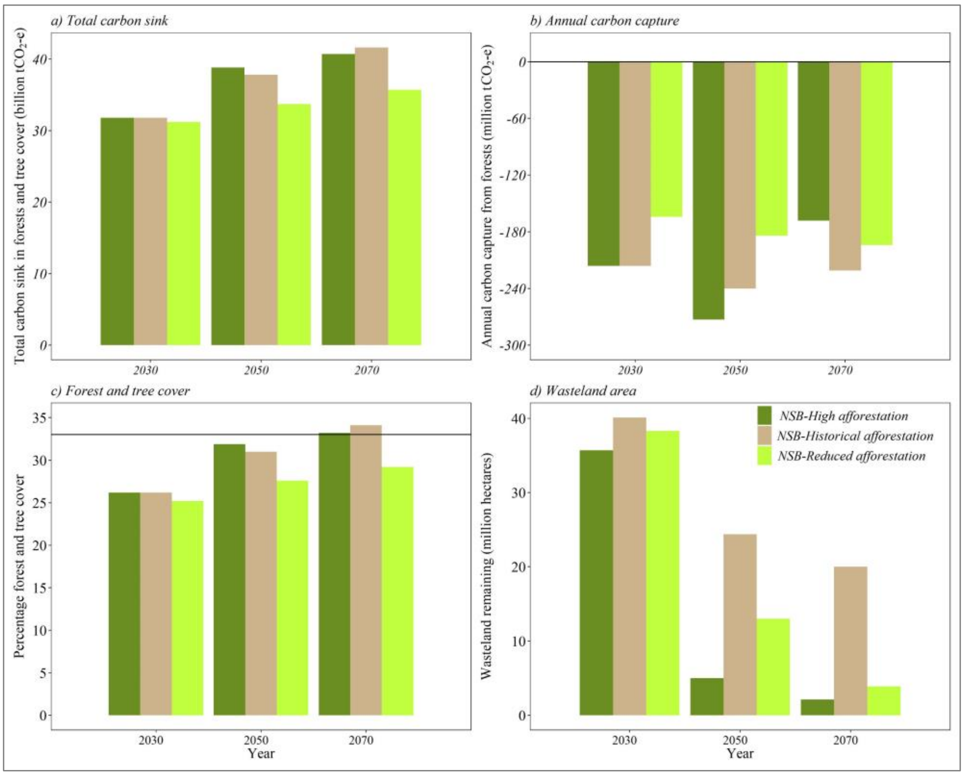
Box 6: Conservation of open natural ecosystems

About 32 Mha of wasteland can be reclassified into open natural ecosystems (ONEs), which are ecologically unique ecosystems inhabited by large populations of endemic flora and fauna (Sankaran & Ratnam, 2013). These ecosystems primarily support the livelihood of livestock owners. ONEs are frequently chosen for tree-based restoration, as the ecological importance of scrubland and other wastelands tends to be underappreciated. In our model, we explored a scenario to understand the extent of trade-offs between afforestation and conserving wastelands.

By reducing the rate of afforestation from 1.02–1.32 Mha during 2025–2070 (NSB-high afforestation scenario) to the historical average rate of 0.66 Mha annually (NSB-historical afforestation scenario), the wasteland depletion is curtailed, saving around 20 Mha of wasteland, which are **potentially ONEs** (Figure 17d). The annual carbon capture in the NSB-historical afforestation scenario is affected, with the value reaching a maximum of 199 GgCO_2e in 2070, compared with the NSB-high afforestation scenario (273 GgCO_2e) in 2049. However, if afforestation efforts are increased to 1.15 Mha initially, keeping in mind the NDC target and the national forest policy target, and then gradually reduced to 0.78 Mha till 2070 (Figure 17d) to conserve **ONEs, classified as wasteland** (NSB-reduced afforestation scenario), the annual carbon capture can reach a maximum of 242 GgCO_2e in 2045 and can be maintained between 240 and 220 GgCO_2e till 2070 (Figure 17b). Moreover, with lower land demands due to afforestation, almost 4 Mha of ONEs can be conserved (Figure 17d), with the demand-side mitigation interventions in other sectors (NSB).

Furthermore, in the NSB-reduced afforestation scenario, with reduced land demand for afforestation activities and RE expansion, competition for wasteland is reduced, curtailing its depletion. With a sustained increase in the total forestland in this scenario, the total CO_2e sink in 2070 can increase by 0.9 billion tonnes (40.7 billion tonnes in the NSB-high afforestation scenario versus 41.6 billion tonnes in the NSB-low but sustained afforestation scenario).

Figure 17: Impact of afforestation activities on total forest carbon sink, annual carbon capture, forestland, and wasteland



Many of the levers discussed in this illustrative scenario may be atypical in the context of energy system models or climate change mitigation modelling studies. However, as demonstrated, they have a significant impact on power sector emissions and overall emissions, along with co-benefits on land and other resources. Although there are policies supporting many of these levers, they are seldom discussed in climate change mitigation or net-zero narratives. This could be because they are not included in the mainstream, mostly global-scale IAMs that dominate this space. As illustrated in the previous scenario, models like SAFARI can offer complementary perspectives. Processes or requirements to add scenarios and models to the IPCC database are often in favour of these giant models, which overlook the ‘forests for trees’ efforts. More discussions on these issues are needed to generate robust, actionable pathways from IPCC reports and 1.5°C scenarios.

5. Conclusion

This study explored the various trade-offs with respect to land use to achieve the net-zero target. It addressed the question 'What are the land consequences considering the projected demand for electricity, food security, and mitigation requirements?'. As illustrated in the report, there is no easy answer. We attempted to find a comprehensive and feasible solution while uncovering more questions in this complex landscape.

Mitigation measures mainly aim at decarbonising the power sector alone, a popularly discussed pathway towards net zero. However, these can lead to several consequences on food security, carbon capture potentials, and conservation of important and endangered ecosystems while being unreliable with respect to the seasonal supply of electricity, as observed in multiple NZ scenarios in this study. Without demand-side management strategies, as shown in the NSB scenario, these trade-offs will arise and be impossible to avoid. The NSB scenario demonstrated that optimising land utilisation and appropriate land allocation should be prioritised. Despite the mixed interventions across various sectors, there are still unavoidable trade-offs that should be considered while designing net-zero pathways. There is no 'one-size-fits-all' approach. However, our study can help not only understand these trade-offs but also design pathways to minimise the trade-offs.

In our attempt to uncover the historical trends of land use and land-use change in India, multiple assumptions were made in our model. Further, owing to data paucity, the model lacks a local and/or state-level dimension. Although such fine-scale nuances can add value to this work, our findings provide a holistic view of land resource constraints at the national level.

Our study also sheds light on the lack of consensus on land-use classification across databases that leads to inconsistencies, highlighting the need for a standardised system and collaboration among government agencies. Diverse methodologies driven by varying objectives and regional targets fragment the data, making it difficult to understand land-use trends. A uniform classification system could address these issues, improving policy-making, land management, and data reliability for researchers and stakeholders involved in environmental planning, agriculture, and urbanisation. The digitisation of records, proposed during the Union Budget 2024–2025 announcement (Government of India, 2024), is a concrete step towards this standardisation.

Adding to the complexity, India's land-use challenges are deeply influenced by local contexts. Factors such as diverse topographies, varying climatic conditions, and different socio-economic priorities impact land-use practices across the country. Furthermore, state governments play a crucial role in land administration, including the allocation, regulation, and monitoring of land resources (Ministry of Rural Development, 2013). For example, the siting of RE projects such as wind farms and solar parks is a highly localised process. The land rent or purchase price can vary dramatically based on regional land-use classifications, local regulations, and the specific socio-economic context of the area. In the states of Punjab and Rajasthan, agricultural land can be used for setting up RE projects without any payment for land-use change (Department of Science, Technology, Environment and Non-conventional Energy, 2012; Energy Department, Government of Rajasthan, 2014). However, under the Andhra Pradesh Solar Power Policy, 2015 (Energy Infrastructure and Investment Department, 2015), solar projects in the state are deemed to have a non-agriculture status on the payment of applicable fees. Thus, land acquisition for these projects heavily depends on the land-use management practices and policies of a state.

An important aspect not explicitly examined in this study is the drivers of land-use change. India has encountered a diverse set of land use and land-management practices driven by demographic shifts, policies, and environmental factors. These drivers not only influence land-use change but also alter local climatic conditions by affecting the water and energy fluxes between terrestrial ecosystems and the atmosphere (Assennato et al., 2022; Ceccarelli et al., 2013; Jones et al., 2015; United Nations Human Settlements Programme, 2016). Consequently, these changes inform and shape land-use management practices over time. The United Nation Convention to Combat Desertification has proposed the concept of Land Degradation Neutrality (LDN), which has been adopted under the Sustainable Development Goals (SDG 15.3). India has also raised its LDN target, which now aims to restore 26 Mha of degraded land by 2030 (Ministry of External Affairs, 2021). A potential solution to address the intricacies of land-use optimisation lies in strategic formulation and implementation of policies pertaining to land-management practices. The emergence of agrivoltaics encourages the coexistence of agricultural activities and solar energy generation (Barron-Gafford et al., 2019). Other land-management practices in solar and wind farms, such as maintaining various types of natural vegetation, enhancing the soil carbon capacity, and increasing carbon capture, can also be implemented (van de Ven et al., 2021). Analysing the drivers of land-use change and their interactions and impacts on land quality and viability can offer a clearer view of how demographics, policies, and environmental factors shape land use. It would also help assess policy impacts, enabling better management of this limited resource.

In this study, we unpacked the consequences of land resource constraints. The study scenarios have been designed to explore the subtleties of trade-offs among different sectors. We endeavour to continue exploring India's long-term pathways from a systemic perspective and engage meaningfully with fellow modellers and policymakers.

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7. Appendices

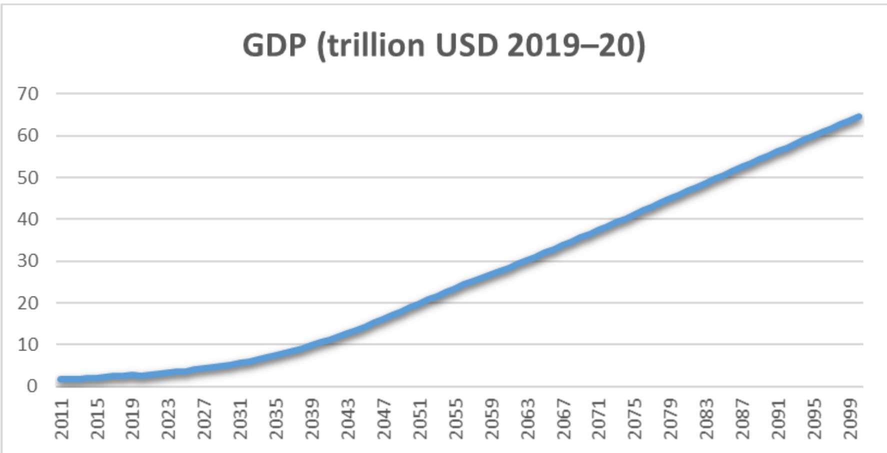
Appendix A. Gross domestic product (GDP) and population

The SAFARI model requires a GDP trajectory from 2011 to 2100 as an exogenous input. For this, we gathered data from numerous sources based on the time span covered by each source. We used real GDP data (calculated at 2011–12 prices) from the National Accounts Statistics (Ministry of Statistics and Programme Implementation, 2021) up to the most recent available year (2021). We used GDP growth rate projections provided by the International Monetary Fund for 2021–2023 (IMF, 2022). GDP growth rate projections from the India Energy Security Scenarios database are available up to 2047 (NITI Aayog, 2015). These have been used for the period from 2023 to 2047. Beyond 2047, the GDP trajectory provided by the Organisation for Economic Co-operation and Development's Shared Socio-economic Pathways (SSP2) database has been used (Dellink et al., 2017) up to the most recent available year (2021), as it describes a middle-of-the-road scenario. We used 10-year moving averages to smoothen the available growth rate estimates post-2032 to ensure that the growth pathway is not erratic. The growth rates assumed and absolute GDP are shown in Table A1 and Figure A1, respectively.

Table A1: Annual GDP growth rate assumptions

2023–2040	2040–2050	2050–2070	2070–2100
7.22%	6.08%	3.34%	1.92%

Figure A1: GDP assumption



Once the GDP growth trajectory was finalised, we employed regression analysis to obtain the estimates of the GDP elasticity of sectoral growth, using gross value added (GVA) data from the KLEMS database (Reserve Bank of India, 2021). Using the obtained estimates for each sector, we projected sectoral growth rates up to the year 2100. These elasticity parameters are based on the historical relationships between the GDP and each sector's GVA. However, in sectors for which per capita demand is expected to saturate (i.e. deviate from historical trends), we used a combination of elasticity estimates from regression analysis and assumptions regarding saturation levels based on the available literature (Millard-Ball & Schipper, 2011; Singh, 2006; Dhar & Shukla, 2015; van Ruijven et al., 2016).

Population projections have been taken from the UN World Population Prospects (https://population.un.org/wpp/).

Appendix B. Power sector methodology

The power sector portion of the Sustainable Alternative Futures for India (SAFARI) model uses energy demand as an input to project future growth in installed capacity and generation in this sector. SAFARI's electrical supply module is designed to adapt to changing conditions and meet the total demand. It records the relationships between the supply and demand for energy and other resources. Thermal, nuclear, big hydro, solar photovoltaic, wind, biomass, micro-hydro, and firmed-up renewable energy using grid-scale storage are some of the supply sources under consideration. The model operates at an annual timestep and treats India as a single spatial unit.

The energy mix planning or capacity planning is based on the levelised cost of electricity generated from various resources and accounts for variations in supply at seasonal and diurnal timescales. However, considering the daily and seasonal variations in solar and wind generation, to ensure electricity grid stability, solar and wind generations are designed to meet up to 53% of the future demand gap.

The available resources such as land, water, and potential are interconnected with the power sector within the model. This allows the availability of land, water, and resource potential (solar and wind) to restrict the extent of capacity that can be added. Being one of the major contributors towards greenhouse gases, the power sector plays a pivotal role in the estimation of scenario-specific greenhouse gas emissions from the SAFARI model.

Appendix C. Area in million hectares under each land category modelled for different scenarios

Scenario	Year	Net sown cropland	Total fallow land	Wasteland	Grassland	Total forestland	Wind farm land	Solar farm land	Built-up area
Baseline	2030	175.28	0.56	41.64	2.45	72.51	0.06	0.80	10.94
	2050	209.21	0.15	27.76	2.66	76.99	0.38	5.83	13.35
	2070	213.05	0.15	14.10	2.87	81.05	0.55	10.79	15.76
NZ	2030	173.21	0.75	34.59	2.45	75.64	2.56	2.59	10.94
	2050	199.59	0.06	0.01	2.01	90.82	10.61	12.84	13.35
	2070	205.05	0.04	0.02	0.31	83.08	19.13	14.24	15.79
NZ-WB	2030	173.21	0.75	35.87	2.45	75.64	1.28	2.59	10.94
	2050	199.81	0.13	0.93	2.40	91.95	5.32	14.41	13.35
	2070	205.96	0.05	0.03	0.25	84.99	15.24	14.80	15.81
NSB	2030	167.03	5.31	35.66	2.45	75.64	2.00	2.08	10.94
	2050	172.07	3.07	3.62	2.51	92.17	6.88	9.29	13.35
	2070	178.15	0.12	1.28	0.52	87.76	9.71	16.65	15.78

Appendix D. Key levers and sectoral assumptions for NZ scenarios

Sector	Intervention	Assumption
Transport	Passenger transport	100% Electric by 2070
	Freight transport	100% Electric by 2070
	Fuel efficiencies	High
Industry	Cement fuel share	40% Green hydrogen and 20% electric by 2070
	Steel fuel share	60% Hydrogen-based by 2070
	Fertilizer fuel share	100% electric by 2070
Buildings	Cooking fuel	100% Electric in Urban and 50% electric in rural by 2070
	Appliance efficiency	Medium
Power	No new coal	No new coal sanctioned beyond 2025

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