India's Low Carbon Electricity Futures

by

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Abstract

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Decarbonizing its electricity sector through ambitious targets for wind and solar is India's major strategy for mitigating its rapidly growing carbon emissions. In this dissertation, I explore the economic, social, and environmental impacts of wind and solar generation on India's future low-carbon electricity system, and strategies to mitigate those impacts. In the first part, I apply the Multi-criteria Analysis for Planning Renewable Energy (MapRE) approach to identify and comprehensively value high-quality wind, solar photovoltaic, and concentrated solar power resources across India in order to support multi-criteria prioritization of development areas through planning processes. In the second part, I use high spatial and temporal resolution models to simulate operations of different electricity system futures for India. In analyzing India's 2022 system, I find that the targets of 100 GW solar and 60 GW wind set by the Government of India that are likely to generate 22% of total annual electricity, can be integrated with very small curtailment (approximately 1%). Further, I find that flexibility strategies that include increasing the size of the balancing area (moving from state level to regionally coordinated scheduling and dispatch), lowering the minimum generation levels of thermal plants, and increasing inter-regional transmission capacity are the most effective in decreasing production costs and renewable energy curtailment. In the final part of this dissertation, I examined the effects of different mixes and targets of wind and solar installed capacities on overall system cost and avoided emissions in 2030. I find that the value of renewable energy decreases with increasing penetration across all mixes of wind and solar, with value of solar decreasing faster with higher penetration than wind. In India, the limited correlation of wind and solar generation profiles with load leads to a relatively small conventional generation capacity being avoided by renewable energy. The data sets, models, and tools developed through these analyses can be used to evaluate future low carbon electricity systems, and develop strategies and policies to ensure that integration of wind and solar is cost-effective and socially and environmentally sustainable.

To Grace, my parents, and Aba

Contents

List of Figures

List of Tables

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Chapter 1

Introduction

Climate change due to anthropogenic greenhouse gas (GHG) emissions is rapidly changing our planet. Global CO_2 concentrations surpassed 400 parts per million in 2016. Limiting global temperature rise to 2 degrees Celsius above pre-industrial levels will require significant actions to mitigate GHG emissions. Just three countries – China, United States, and India – accounted for over 50% of global emissions in 2015 (EU 2016). Although India's emissions were only a fifth of China's, and less than half of the United States' emissions, its emissions continue to increase rapidly. In 2015, carbon emissions (which form the bulk of GHG emissions) increased by 5.1%, making India the largest contributor to global emissions growth in that year (EU 2016). However, India's per capita emissions, 1.8 tonnes-CO_2 per year, were less than half the world's average in 2015 (EU 2016). Its Gross Domestic Product (GDP) per capita was only 14% of the world's average in the same year (World Bank 2016). According to the World Bank's Global Monitoring Report (2015-16), 20% of India's population was below the poverty line. So from a social equity perspective, India needs to grow. However, with its large population of 1.25 billion and an economy growing at 7%, the country has by far the largest potential for growth in carbon emissions. As a result, in a climate-constrained world, India faces a monumental challenge to mitigate its emissions and at the same time increase its GDP, build infrastructure, and pull millions out of poverty.

With a share of 58% of primary energy consumption (BP 2016), coal is the number one contributor to India's carbon emissions. Coal combustion was responsible for 72% of India's total fossil-fuel combustion-based CO_2 emissions, predominantly from the electricity sector. Coal accounted for 70% of electricity generation (CEA 2016). To significantly mitigate its carbon emissions, India will need to decarbonize its electricity sector.

Renewable energy, especially wind and solar, has become a major strategy in most countries to mitigate carbon emissions. In 2015, the world added more renewable energy capacity than that from all fossil fuels combined (REN21 2015). Solar PV and wind accounted for 77% of new renewable energy installations, and hydropower made up the remainder.

India too is relying on large investments in renewables to mitigate its emissions. Over the past couple of decades, the Government of India (GoI) has been promoting renewable energy generation, both wind and more recently, solar, through various policy incentives including feed-in tariffs, tax benefits, and renewable generation targets (Gambhir et al. 2016). By 2016, India had installed 28 GW of wind and 8.7 GW of solar capacity (MNRE 2016). In its Nationally Determined Contributions submitted to the United Nations, the Government of India (GoI) has set a target of 175 GW of renewable energy capacity by 2022 (GoI 2016b). The majority of this target is for solar (100 GW) and wind (60 GW), with the remainder for biomass and small hydropower (GoI 2016b). Further, the GoI also set a goal to meet 40% of its installed generation capacity from non-fossil fuels-based generation sources by 2030.

These ambitious targets for solar and wind will have significant economic, social, and environmental implications. In this thesis, I address three broad questions.

1. How can the economic, social, and environmental impacts of large-scale deployment of wind and solar resources be mitigated by incorporating multiple criteria in planning?

2. What are the impacts of VRE generation on system operations in the medium-term, and what strategies can mitigate these impacts?

3. How do the cost and value of wind and solar resources evolve in the long-term?

Large-scale deployment of wind and solar will require strategic spatial planning that addresses both grid integration and siting barriers. Identifying RE resource areas with high quality potential and low environmental and social impacts can enable rapid yet appropriate deployment of RE power plants and planning of transmission systems. Spatial planning reduces the risk to project developers, utilities, and government agencies by facilitating preemptive transmission planning that encourages socially and environmentally responsible development, thus lowering costs and enabling rapid growth of RE. In Chapter 2, I, along with my co-authors, apply the Multi-criteria Analysis for Planning Renewable Energy (MapRE) approach to identify and comprehensively value high-quality wind, solar photovoltaic (PV), and concentrated solar power (CSP) resources across India in order to support multi-criteria prioritization of development areas through planning processes.

In Chapter 3, my co-authors and I examined the impacts of high shares of VRE generation including the GoI target of 160 GW of solar and wind on India's power system in 2022. Further, we also evaluated strategies to cost-effectively integrate VRE generation into the Indian national grid. As part of this analysis, we developed a suite of models with high spatial and temporal resolution - RE site selection and generation profile model, load forecast model, and a production cost model – that can enable evaluation of alternate energy futures for India.

Although the costs of solar photovoltaic (PV) and wind have declined over the last several years, these variable renewable energy (VRE) sources are still more expensive than some conventional generation sources such as coal and gas. Further, the variability and relative unpredictability of solar and wind pose additional challenges and costs to the overall electricity system. In Chapter 4, I examine a subset of VRE costs and its value to the overall electricity system for different penetrations and mixes of solar and wind in 2030.

The overall objective of my thesis is to mitigate the impacts and accelerate the development of variable renewable energy resources to enable a fast transition to a low carbon electricity grid.

Chapter 2

Multi-criteria analysis for planning renewable energy

2.1 Introduction

With a projected GDP growth rate of 7.5 percent in 2015, India is the world's fastest growing major economy (IMF 2015). India's economic growth is driving rapid increases in its energy demand. By some estimates, the electricity demand in 2032 is expected to be four times greater than that in 2015 (CEA 2012). In order to meet this demand cost-effectively and sustainably, the Government of India has set ambitious targets for grid-connected renewable energy (RE) generation. As of 2016, India has 27,000 MW of installed wind generation capacity and more than 7,800 MW of solar (mostly PV). Current national policies have set a target of 60,000 MW of wind and 100,000 MW of solar capacity by 2022 (GoI, 2016). In its Intended Nationally Determined Contribution (INDC), India has committed to 40% of its installed generation capacity to be from non-fossil sources by 2030 (GoI, 2016).

Achieving the unprecedented scale of energy infrastructure development needed to meet these near-term targets will require strategic spatial planning that addresses both grid integration and siting barriers. Identifying RE resource areas with high quality potential and low environmental and social impacts can enable rapid yet appropriate deployment of RE power plants and planning of transmission systems. Spatial planning reduces the risk to project developers, utilities, and government agencies by facilitating preemptive transmission planning that encourages socially and environmentally responsible development, thus lowering costs and enabling rapid growth of RE. In this study, we apply the Multi-criteria Analysis for Planning Renewable Energy (MapRE) approach to identify and comprehensively value high-quality wind, solar photovoltaic (PV), and concentrated solar power (CSP) resources across India in order to support multi-criteria prioritization of development areas through planning processes.

2.1.1 Renewable energy zones and multi-criteria analysis

Numerous studies have quantified renewable energy resource potential using geographic information systems (GIS) for spatial analysis. Many of these studies have focused on an entire country or its sub-region (Lopez et al. 2012; He and Kammen 2014, 2016), and a few have even analyzed resource potentials at a global scale (Lu, McElroy, and Kiviluoma 2009). In India as well, there have been a few studies on renewable energy resource assessment and site suitability analysis using GIS. Most of these studies have focuses on wind resource assessment, out of which some were restricted to individual states (Ramachandra and Shruthi 2005; TERI 2012; WISE 2012; CSTEP 2013), whereas others have covered the entire country (Hossain, Sinha, and Kishore 2011; Phadke 2012; CSTEP, WFMS, and SSEF 2016). The study by CSTEP, WFMS, and SSEF (2016) provides a comprehensive summary of past wind potential assessment studies in addition to technical estimates of wind potential using two different methodologies.

Resource assessment is only the first step in formulating a cost-effective, socially and environmentally sustainable renewable energy development policy framework. As many of the India-specific studies as well as this study concludes, there are no near-term limits to either wind or solar resources. Identifying high quality RE zones that have low negative environmental and social impacts can enable preemptive transmission planning to evacuate energy to load centers, accelerate environmental clearances, and incentivize project developers to build plants in those zones.

Several significant renewable energy zoning studies for the purposes of transmission planning have been conducted. The most notable studies in the United States include the California Renewable Energy Zones commissioned by the California Public Utilities Commission (CPUC 2009) and the Texas Competitive Renewable Energy Zones (CREZs) commissioned by the Electricity Reliability Council of Texas (Electricity Reliability Council of Texas 2008). Under the Texas CREZ project, transmission lines were built to facilitate transmission of wind power from the northwest areas of the state to the load centers in the southeast. In South Africa, Renewable Energy Development Zones were identified to streamline environmental impact assessment applications and promote a low-environmental impact and more equitable siting process for renewable energy (Department of Environmental Affairs and Council for Scientific and Industrial Research 2014).

Multi-criteria decision analysis (MCDA) or multi-criteria evaluation (MCE) in conjunction with GIS allows for integration of environmental, economic, and social factors that affect land suitability for a certain use (Arán Carrión et al. 2008). Several academic studies have applied variants of a joint GIS-MCDA methodology to address specific siting challenges and whether certain generation technology-specific policy targets can be met by available land (Stoms, Dashiell, and Davis 2013; Kiesecker et al. 2011). Other studies have used site scores based on ranked or weighted criteria to prioritize areas for development (Janke 2010). In this study, we apply an MCDA approach to incorporate a broad spectrum of siting criteria to prioritize RE zones in order to sustainably meet projected energy demand at a national or regional scale.

2.1.2 Objectives and approach

This report aims to achieve the following objectives:

1. Identify and value high-quality wind, solar PV, and solar CSP zones for grid integration based on techno-economic criteria and socio-environmental impacts.
2. Map the abundance and quality of wind and solar zones across India.
3. Identify potential siting challenges due to the predominance of particular land use and land cover types.
4. Examine the extent to which capacity value of wind reinforces or changes the distribution of economically valuable wind zones across the country.
5. Examine opportunities for cost-effective and low-environmental impact wind and solar development.
6. Identify zones suitable for the development of more than one generation technology.

2.1.3 Direct applications in planning and policy-making

In this study, we quantified multiple criteria for each renewable energy zone that policymakers, project developers, and other stakeholders may use to prioritize development through a stakeholder process. To facilitate this process, we integrated the results of this study into a dynamic, multi-criteria zone ranking tool that allows users to select and weigh different criteria to create a supply curve that ranks zones according to criteria weights. We designed this excel-based planning tool to be used in conjunction with an interactive PDF map created for India. The PDF map embeds both the visual content as well as the criteria attribute values of the key spatial inputs and zones. Users are able to rank zones based on country-wide range of scores, which is useful for planning state-wise electricity generation or regional interconnections. Selected zones can then be used to focus efforts on ground measurements. These maps and tools can facilitate preemptive planning of transmission and other infrastructure, which encourage development by reducing project risk in selected zones. Simulated potential generation profiles of identified zones can be used in transmission power flow and production cost models to conduct detailed transmission studies. Input and output datasets are available for public download on `http://mapre.lbl.gov`, for encouraging further research and updates.

The MapRE approach is not a static process. Due to changing infrastructure and availability of improved data, the mapping of renewable energy resources must be dynamic to be useful. Data gathering is a multi-stakeholder effort that can support capacity-building of India's government agencies and organizations and ultimately expand its energy information repositories along with its physical RE infrastructure. We hope that Indian agencies adopt and improve upon the data and methodology presented in this study to meet their needs as they change. Planning and developing energy infrastructure is and should be a stakeholder driven process, informed by structured decision-making tools and a framework.

2.2 Methods

The Multi-criteria Analysis for Planning Renewable Energy (MapRE) approach uses a modeling framework that integrates renewable resource assessment and multi-criteria decision making analysis. We developed this approach to identify and value RE resources in eastern and southern Africa, and adapted it for India. Details of the methodology can be found in *Renewable Energy Zones for the Africa Clean Energy Corridor* (Wu et al. 2015). In this report, we provide an overview of the methods and the India-specific changes to the assumptions and methodology. The following summary briefly describes the methodology flowchart in Figure 2.1.

2.2.1 Methods overview

We first conducted a **(1) resource (potential) assessment** using thresholds (e.g. wind speed and GHI for resource quality, elevation, and slope) and exclusion categories (e.g. protected areas, water bodies) to identify all technically viable land for renewable energy (RE) development. To **(2) create project opportunity areas**, we divided the resource areas into spatial units of analysis referred to as "project opportunity areas" (POAs) with size ranges (after applying a land-use discount factor) representative of utility-scale wind and solar power plants. In order to capture the percentage of projects that could be developed in any given RE potential area, a land use discount factor was applied based on developer experiences reported in previous zoning studies. However, the choice of POA sizes were not meant to suggest that an entire POA must be developed. To **(3) estimate project opportunity area attributes**, we calculated the average values for multiple siting criteria (see Figure 2.1. The resource quality and two of the siting criteria - distances to transmission and road infrastructure - were then used to estimate each POA's generation, transmission, and road components of the levelized cost of energy (LCOE) for each technology. Using a statistical regionalization technique, we clustered POAs on the basis of their resource quality (wind speed or solar radiation) similarity in order to **(4a) create zones** that vary in size from 30 km^2 to 1000 km^2. The actual sizes were determined by the regionalization algorithm based on the extent of spatial homogeneity in resource quality. In order to **(4b) calculate zone attributes**, we calculated the area-weighted average value of attributes of all POAs within a zone.

For wind **(5) capacity value estimates**, 100 locations across the entire study region were selected based on abundance and quality of wind resource and spatial representation across India.[1] Using 10 years of simulated hourly wind speed profiles from 3Tier for each of

[1] Capacity value is the contribution that a given generator makes to overall system adequacy, as determined by the profile of system load.

100 locations and hourly demand profile for the country, we estimated capacity value ratios using the top 10% of annual demand hours and the top three daily demand hours for each of the 100 wind locations. The capacity values for wind zones were estimated using their average annual capacity factors and the capacity value ratios (ratio of capacity value and annual capacity factor) of the nearest location with hourly wind speed data.

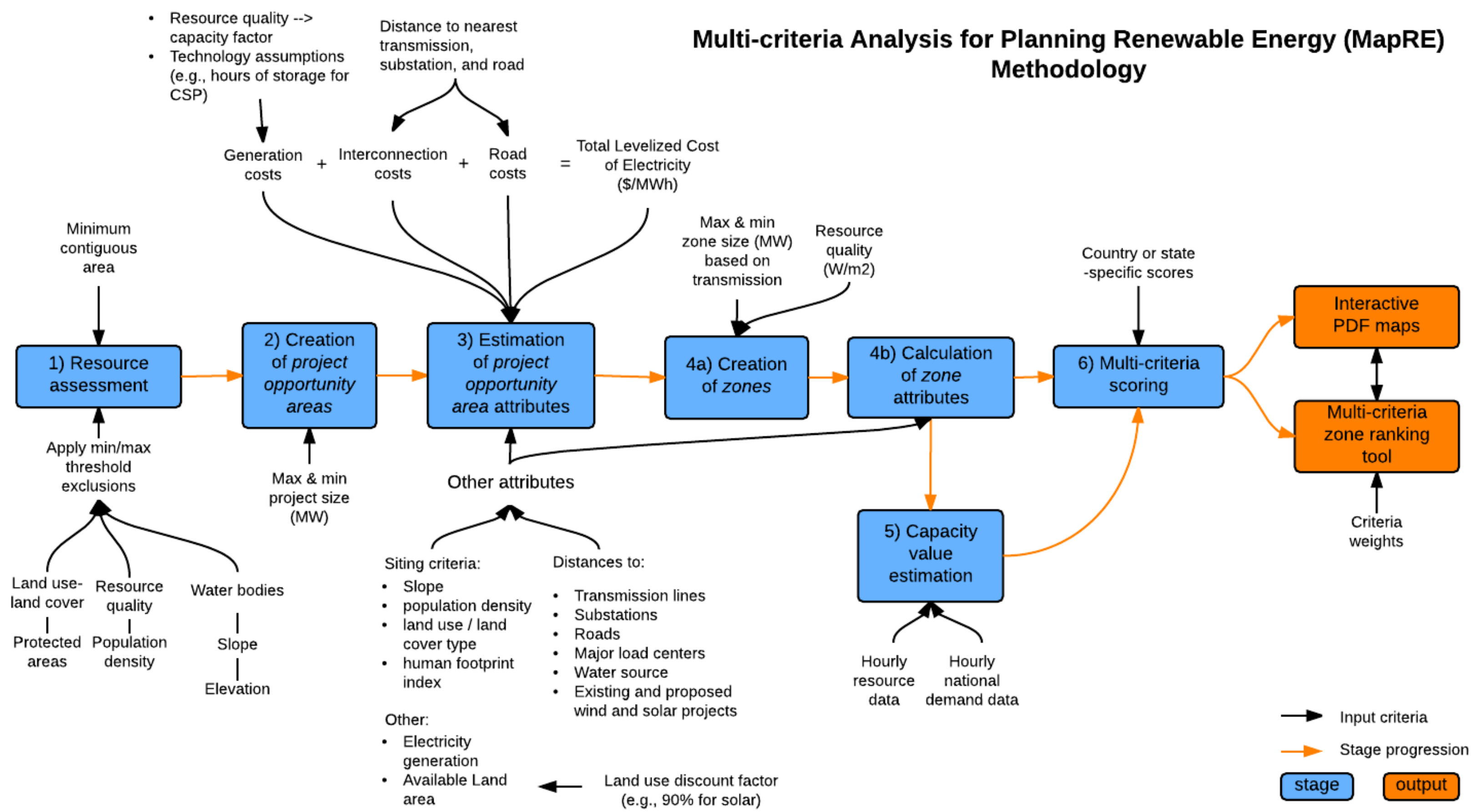


Figure 2.1: **MapRE zoning methodology flow chart.** Reproduced from Wu et al. (2015) with modifications. See section 2.2.1 for descriptions of each stage of the methodology.

For **(6) multi-criteria scoring** of each zone, we assigned every criteria value (e.g., percentage of slope, population density, LCOE, capacity value) a score ranging from 0 (least favorable) and 1 (most favorable) corresponding to the worst and best criteria values within the country. Users of the **multi-criteria zone ranking tool** are able to assign weights to each criteria in order to calculate and rank cumulative zone scores, visualized using zone supply curves. The ranked zones can be geographically located on the **interactive PDF maps** using each zone's unique zone identification.[2]

2.2.2 Data collection

A comprehensive zoning process requires various types of physical, environmental, economic, and energy data in both specific spatial and non-spatial formats. We rely on a combination of global spatial data and India-specific datasets. The preference of India-specific datasets where available ensure consistency with similar past and ongoing national efforts using these datasets, and in some cases, greater accuracy. We collected these data from various Government of India agencies. See Table E.1 for a list of datasets and their sources.

2.2.3 Resource assessment for wind, solar PV, and CSP (stage 1)

Identifying areas that meet baseline technical, environmental, economic, and social suitability criteria for renewable energy development is the first step in any zoning analysis. Using Python and the Arcpy package for spatial analysis, we estimated the resource potential by linearly combining binary exclusion criteria after applying thresholds for the following data types: techno-economic (elevation, slope, renewable resource quality, water bodies), environmental (land-use/land-cover, protected areas), socio-economic (population density) (Table E.1 in Appendix E). Specifications for thresholds and buffer distances for unsuitable areas follow international industry standards and previous studies (Lopez et al. 2012; Phadke 2012; CPUC 2009; Black & Veatch Corp. and RETI Coordinating Committee 2009). We imposed a minimum contiguous area of 2 km^2 for both wind and solar. The technology-specific land-use/land-cover (LULC) categories are listed in Table 2.1. The criteria scores for LULC categories indicate preference for development on an LULC category and were used to estimate LULC attribute scores for POAs. All analyses were performed at 500 m resolution using South Asia Albers Equal Area Conic projection.

We generated potential areas and approximated generation (MWh) using average capacity factors, land use factors, and a land use discount factor of 75% for both wind and solar technologies (Black & Veatch Corp. and RETI Coordinating Committee 2009). The land use discount factor, which is the percentage of land not available for development within a project opportunity area, reflects the uncertainties in ground realities (e.g. land ownership, conflict areas) that are not captured in our geospatial inputs. Because of the significantly

[2]This section is a direct excerpt of the methods overview in Wu et al. (2015), and it is reproduced here for the purposes of contextualizing the remainder of the methods section specific to this study.

Table 2.1: National Remote Sensing Centre's land use/land cover included (In) and excluded (Ex) categories for all technologies.

Code	**Class Name**	**Solar PV and CSP**	**Wind non-agricultural**	**Wind agricultural**	**Criteria score**
1	Built-up (urban)	Ex	Ex	Ex	
2	Kharif (cropland)	Ex	Ex	**In**	4
3	Rabi (cropland)	Ex	Ex	**In**	4
4	Zaid (irrigated cropland)	Ex	Ex	**In**	5
5	Double/Triple (irrigated cropland)	Ex	Ex	**In**	5
6	Current fallow (cropland)	Ex	Ex	**In**	3
7	Plantation/orchard	Ex	Ex	Ex	
8	Evergreen forest	Ex	Ex	Ex	
9	Deciduous forest	Ex	Ex	Ex	
10	Scrub/degenerated forest	Ex	Ex	Ex	
11	Littoral swamp	Ex	Ex	Ex	
12	Grassland	**In**	**In**	**In**	2
13	Other wasteland	**In**	**In**	**In**	1
14	Gullied	Ex	Ex	Ex	
15	Scrubland	**In**	**In**	**In**	2
16	Water bodies	Ex	Ex	Ex	
17	Snow covered	Ex	Ex	Ex	
18	Shifting cultivation	Ex	Ex	**In**	3
19	Rann	**In**	**In**	**In**	2

lower footprint of wind turbines (Denholm et al. 2009) compared to solar PV, and the potential of wind plants to accommodate dual usage of land with other activities like agriculture or grazing, wind development may have lower uncertainties than utility-scale solar development. Note that although our assumption of land use discount factor is the same for wind and solar, the land available for solar development is significantly less than that for wind due to the exclusion of agricultural lands in our analysis. We chose default criteria thresholds that identify economically-viable resource quality by industry standards (5.5 m/s wind speed or 200 W/m^2 power density for wind; 4.9 kWh/m^2/day or 1800 kWh/m^2/y for solar) (CPUC 2009; Black & Veatch Corp. and RETI Coordinating Committee 2009).

Limitations Results and data derived from meso-scale models such as Vaisala's can be inconsistent with ground-based measurements, as well as data from other meso-scale models such as AWS Truepower or CWET's (RISOE) simply due to differences in the numerical model or simulation. The type of analysis applied in this study is a high-level analysis to broadly identify opportunity areas for wind and solar zone development. Appropriate long term ground-level data measurements are essential before embarking on project development.

No physical site reconnaissance has been done to verify the results of this study. These analyses better enable and facilitate detailed feasibility studies by robustly identifying the most suitable sites.

2.2.4 Creation of project opportunity areas (stage 2)

Using resource areas generated under stage 1, we created representative utility-scale "project opportunity areas" (POAs). After applying land use factors and land use discount factors adopted in this analysis (Table 2.5), these steps divide large resource areas into POAs that range from 2 km^2 - 25 km^2 and have the potential to accommodate 15 - 187.5 MW solar power plants and 4.5 - 56.25 MW wind plants. See Wu et al. (2015) for a more detailed explanation of POA creation.

2.2.5 Estimation of project opportunity area attributes (stage 3)

For each POA, we estimated several attributes (Table 2.2) for direct use in multi-criteria scoring of zones or for calculations of capacity factors (section 2.2.5.1) and costs (section 2.2.5.2), which are described in greater detail in subsequent sections. For an explanation of the remainder of the attributes in Table 2.2, please see Wu et al. (2015).

2.2.5.1 Capacity factor estimation

Solar PV: In this study, we estimate the annual average capacity factor for each POA, which is the ratio of the estimated output of a power plant over a whole year, to the potential output of that plant if it were to generate continuously at its rated capacity. In addition to the resource quality, capacity factors for solar PV depend on the type of system. Single and dual axis tracking systems will have higher capacity factors but also greater costs than fixed tilt systems.[3] In this study, we assume that all solar PV systems are south-facing fixed tilt systems, with their tilt equal to the latitude of the location. Because the latitude varies significantly along the length of the country, the relationship between GHI and capacity factor of a fixed tilt system is not linear. As a result, we estimated the annual average capacity factors for locations at the centroids of the 617 solar PV zones that we identified in this study (zone creation described in section 2.2.6). We used simulated hourly solar radiation, temperature, and wind speed data from NREL's National Solar Radiation Database (NSRDB) in the System Advisor Model (SAM) to simulate the solar PV capacity factors (see Table 2.3 for assumptions). We then spatially associated each POA to the nearest location with a simulated capacity factor and resource quality, and estimated each POA's capacity factor

[3]Although single-axis tracking systems dominated the U.S. utility-scale solar market in 2015 (Bolinger and Seel 2016), the Indian market still preferred fixed tilt systems, likely due to reasons such as lower steel and labor costs (IHS and Insider 2015).

Table 2.2: Description of estimated project opportunity area (POA) attributes.

Attribute	**Description**
Area	Total area of the POA in units of square kilometers
Resource quality	Mean resource quality in terms of wind speed (m/s) or solar irradiance (kWh/m^2/day).
Capacity factor(s)	Mean annual capacity factor of the POA for each sub-technology (e.g., Class II turbine and chosen class turbine for wind), estimated using average resource quality.
Electricity generation	Average annual electricity generation (MWh) estimated using each technology's (and sub-technology's) capacity factor, land use discount factor, and land area.
Generation LCOE(s)	Average levelized cost of electricity (in Rs/MWh or USD/MWh) for the generation component. Values were estimated using the location and sub-technology's capacity factor and efficiencies specific to the technology or norms specified by the Central Electricity Regulatory Commission.
Interconnection LCOE(s)	Average levelized cost of electricity (in USD/MWh) for the transmission component for each sub-technology.
Road LCOE	Average levelized cost of electricity (in USD/MWh) for the road component, assuming 50 MW of installed capacity per POA.
Total LCOE(s)	Average total levelized cost of electricity (in Rs/MWh or USD/MWh) estimated by summing the individual component LCOEs for generation, transmission infrastructure (to nearest substation), and road.
Distance to nearest location	Straight-line distance from each POA to the nearest substation (with 1.3 terrain factor applied); road (with 1.3 terrain factor applied); and surface water body.
Slope	Mean slope of the POA in units of percent rise.
Population density	Mean population density of the POA in units of persons/km^2.
Human footprint score	Mean human influence index metric (0 – least human impact; 100 – most human impact)
Land use / land cover score	Mean score for land use/land cover categories in the zone. Scores range from 1 to 5, with 1 being most compatible for energy development and 5 being least compatible. See Table 2 for the score of each LULC type.
Co-location score(s)	A binary score of 0 or 1, with 1 indicating that a POA is suitable for the development of another renewable energy technology. A score was determined for each of the other RE technologies (e.g., wind and solar PV for a solar CSP POA).
Water access score	A binary score of 0 or 1, with 1 indicating that a POA is within 10 km of surface water.

by proportionally adjusting the closest simulated capacity factor using the POA's average resource quality.

CSP: We used NREL's System Advisor Model (NREL 2016b) to simulate the capacity factor (CF) for 19 locations throughout India for two generic CSP plants with the following assumptions: (1) no storage and a solar multiple of 1.2; (2) 6 hours of storage and a solar multiple of 2.1. Solar resource data for India were developed using satellite imagery using a

Table 2.3: Assumptions for solar PV capacity factor simulations in the System Advisor Model

Parameter	**Value**
System DC capacity	1.1 MW_{dc}
DC-to-AC ratio	1.1
Tilt of fixed tilt system	Latitude of location
Azimuth	180^o
Inverter efficiency	96%
Losses	14%
Ground cover ratio	0.4

numerical model developed at the State University of New York (SUNY) with the weather data from the Integrated Surface Database maintained by the U.S. National Oceanic and Atmospheric Administration (NOAA). The combined data for the locations in India were available from NREL. We plotted CF against DNI and chose to fit a logarithmic equation to the data because of known increased efficiency losses at the higher end of the DNI range (Figure 2.2). We used these fitted equations (Figure 2.2) to estimate the CF for the spatially averaged DNI in each project opportunity area for both no-storage and 6-hr-storage CSP power plant design assumptions.

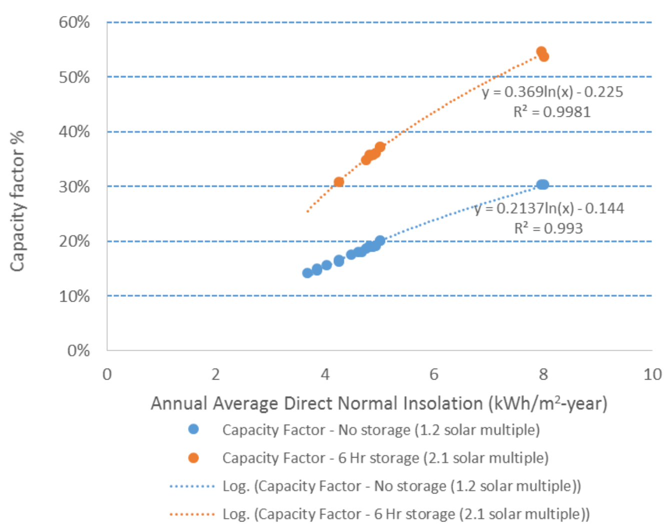


Figure 2.2: **Relationship between capacity factor and Direct Normal Insolation (DNI).** Capacity factors were simulated using the generic CSP plant in NREL's System Advisor Model for 19 locations throughout high quality resource areas in India. Logarithmic equations were fit to the simulated capacity factor data to statistically model the relationship between capacity factor and DNI.

Wind: The capacity factor of a wind turbine installation depends on the wind speed distribution at the wind turbine hub height, the air density at the location, and the power curve of the turbine. We first used a Weibull distribution to generate a wind speed probability distribution per 3.6 km grid cell (the resolution of Vaisala data). To account for the effect of air density on power generation, we first estimated the air density using elevation and average annual temperature for each grid cell, and then applied power curves modified for different air densities to the wind speed distributions. See Wu et al. (2015) for details and thorough discussion.

On-shore wind turbines are generally classified into three International Electrotechnical Commission (IEC) classes depending on the wind speed regimes. We used normalized wind curves for the three IEC classes developed by the National Renewable Energy Laboratory (King, Clifton, and Hodge 2014) and assigned IEC classes based on each grid cell's annual average wind speed (Wiser et al. 2012). For each of the three turbine classes, we adjusted the power curves for a range of air densities by scaling the wind speeds of the standard curves according to the International Standard IEC 61400-12 (IEC 1998; Svenningsen 2010). See Wu et al. (2015) for details.

To compute the capacity factor for each 3.6 km grid cell, we selected the appropriate air-density-adjusted power curve given the average wind speed, which determines the IEC class, and the air density, which determines the air-density adjustment within the IEC class. For each grid cell, we then discretely computed the power output at each wind speed given its probability (using a Weibull distribution with a shape factor of 2) and summed the power output across all wind speeds within the turbine's operational range to calculate the mean wind power output in W ($\overline{P}$). The capacity factor (cf_{wind}) is simply the ratio of the mean wind power output to the rated power output of the turbine (P_r or 2000 kW), accounting for any collection losses (η_a) and outages (η_o) (Eq. 2.1).

$$cf_{wind} = \frac{(1-\eta_a)\cdot(1-\eta_o)\cdot\overline{P}}{P_r} \tag{2.1}$$

2.2.5.2 Levelized Cost of Electricity (LCOE) estimates

Input cost assumptions

Wind, solar PV, and CSP costs. For estimating the LCOE for generation, we used the parameters from the Central Electricity Regulatory Commission regulations (CERC, 2014) and adjusted some of the parameters (e.g. capital costs, O&M costs) for 2016 using norms provided in those regulations (Table 2.4). No costs for CSP with storage are specified. The CERC determines parameters for its regulations through an industry consultation process.

Table 2.4: Parameters for generation cost estimates from the Central Electricity Regulatory Commission (CERC) regulations

	Wind	**Solar PV**	**CSP (no storage)**
Capital cost [INR/kW]	62,000	53,000	120,000
Capital cost [USD/kW]	950	810	1,850
Non - Depreciable Amount	10%	10%	10%
Debt Fraction	70%	70%	70%
Debt [INR/kW]	43,400	37,100	84,000
Equity [INR/kW]	18,600	15,900	36,000
TOTAL [INR/kW]	62,000	53,000	120,000
Interest Rate on Term Loan	12.76%	12.76%	12.76%
Repayment Period [years]	12	12	12
No of installments for Interest on Term Loan	12	12	12
Moratorium Period [years]	0	0	0
Term loan period for principal payment [years]	12	12	12
Depreciation (Straight Line Method,Company Law) - for first 12 years	5.83%	5.83%	5.83%
Depreciation (Straight Line Method,Company Law) - for last 13 years	1.54%	1.54%	1.54%
Discount Rate	10.8%	10.8%	10.8%
O&M and insurance cost [INR/kW]	1,124	700	1,874
O&M and insurance Cost Escalation	5.72%	5.72%	5.72%
Maintenance spares (of yearly O&M costs)	15%	15%	15%
Return on Equity - pretax (1-10 years)	20%	20%	20%
Return on Equity - pretax (11-25 years)	24%	24%	24%
Interest on working capital	13.26%	13.26%	13.26%
Normative capacity factors	22%, 25%, 30%, 32%	19%	23%
Gross generation [kWh/year]	2190	1664	2015
Auxiliary consumption (% of gross generation)	0%	0%	10%
Auxiliary consumption [kWh/year]	0	0	201

Transmission and road costs. For our analysis, we estimated the cost of transmission as a function of its length alone, holding all other cost parameters constant. We added the cost of the substations, which does not vary by distance, to the transmission line costs (see Table 2.5 for parameter values). Additional transmission cost assumptions are explained in detail in the corresponding section in Wu et al. (2015). Road costs can vary widely depending on the type of road, terrain, and region-specific factors such as labor costs and financing. We assumed costs for a two lane bituminous road (Table 2.5).

Table 2.5: Parameters to estimate levelized cost of electricity

Parameters	**W**ind	**S**olar PV	**S**olar CSP **No-storage**	**6 hr storage**
Land use factor [MW/km^2](l)	9[a]	30[b]	30[b]	17[c]
Land use discount factor (f)	75%	75%	75%	
Costs				
Transmission – capital [USD/MW/km] (c_i)	450[d]	450[d]	450[d]	
Transmission – fixed O&M [USD/km] ($o_{f,i}$)	-	-	-	
Substation – capital [USD / 2 substations] (c_s)	35000[d]	35000[d]	35000[d]	
Road – capital [USD/km] (c_r)	407000[e]	407000[e]	407000[e]	
Road – fixed O&M [USD/km] ($o_{f,r}$)	-	-	-	
Economic discount rate (i)	10.8%[f]	10.8%[f]	10.8%[f]	
Outage rate (h_o)	2%[g]	4%[g]	4%[g]	
Inverter efficiency and AC wiring loss (h_i)	-	4%[g]	-	
Array and collection loss (h_a)	15%[h]	-	-	
Lifetime [years] (n)	25[f]	25[f]	25[f]	

[a] Mean of U.S. empirical values (3 MW/km^2) (Ong, Campbell, and Heath 2012) and theoretical land use factors (Black & Veatch Corp. and RETI Coordinating Committee 2009)

[b] (Ong, Campbell, and Heath 2012)

[c] Estimated from no-storage land use factor by multiplying by the ratio of no-storage to 6-hr-storage solar multiples (2.1/1.2)

[d] (PGCIL 2012)

[e] Costs are for two lane bituminous road, and inflation adjusted. (Collier, Kirchberger, and Söderbom 2015)

[f] (CERC 2014)

[g] Default value in the System Adviser Model (SAM) (NREL 2016b)

[h] (Tegen et al. 2013)

Cost Calculations Using the size (km^2) of project opportunity area and its associated land use factor (LF) and land use discount factor (LDF), distance to nearest substation (or transmission line) and road, and economic parameters listed in Tables 2.4 and 2.5, we calculated the generation, interconnection and road components of the levelized cost of electricity (LCOE; USD/MWh). The LCOE is a metric that describes the average cost of electricity for every unit of electricity generated over the lifetime of a project at the point of interconnection.

We estimated the LCOE component of generation using two methods. In the first, we adopted the CERC methodology and used the Renewable Energy Tariff and Financial Analysis Tool developed by the Group (2014) to estimate the LCOE for different capacity factors for each of the technologies (Figure 2.3). For the second method, we used the simple LCOE calculation provided in Equation (6) in Wu et al. (2015).

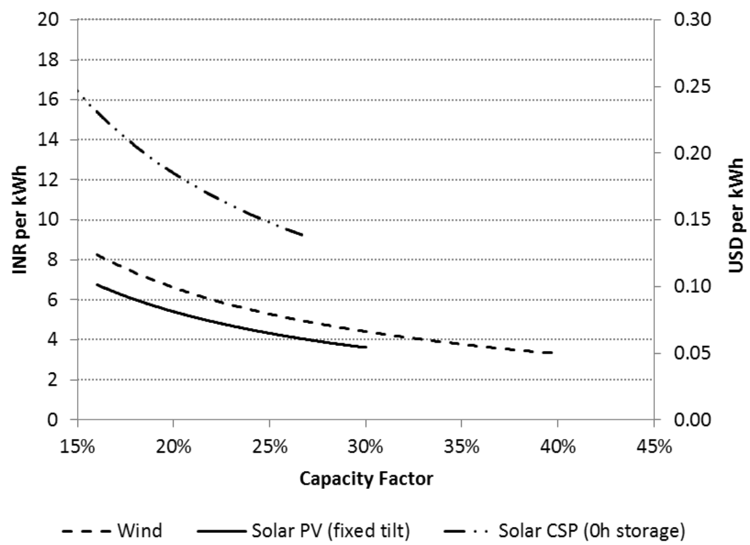


Figure 2.3: Relationship between capacity factors and LCOE estimates for generation based on the Central Electricity Regulatory Commission norms.

We used Equations (7) and (8) from Wu et al. (2015) to estimate the transmission and road LCOEs, respectively. The total LCOE is simply the sum of the generation, transmission, and road cost components. Refer to Table 2.5 for definitions of cost notation that correspond to equations in Wu et al. (2015).

Limitations By adopting the same assumptions as recommended by the Central Electricity Regulatory Commission, we intended for our LCOE estimates to be as representative of current conditions and costs in India as possible. However, note that CERC assumptions of capital costs seem to be significantly lower than in other literature. For example, median installed price for solar PV in the United States in 2015 was USD 2,700/ kWac (INR 175,000/ kWac), more than three times the CERC assumed capital cost (Bolinger and Seel 2016). Less data are available on CSP plants, but installed price of two 250 kWac CSP parabolic trough plants were approximately three times that of CERC assumptions. However, the resulting LCOE estimates, particularly for wind and solar are comparable to those seen in the industry. Utility-scale solar PV prices discovered in several auctions in various states in India are comparable or lower than LCOE estimates in this study. Weighted average prices of 3 solar PV auctions conducted in 2016 for a total of 1,770 MW capacity across 3 states were INR 4.61/kWh or 0.07 USD/kWh, lower than LCOE estimates using CERC norms. Several thousand megawatts of wind capacity are being installed at state feed-in tariffs that are comparable to CERC's norms. This suggests that CERC assumptions about other parameters may be more conservative that industry standards. Given these context-specific cost determinants, we intend for these LCOE estimates to be used to compare development costs across areas suitable for the development of a single technology, and not as estimates of absolute costs. The actual costs for a project will depend on several factors including but not limited to discount rate (or cost of capital), capital costs of the technology available to the developer, ongoing costs, and actual capacity factors.

System integration costs or balancing costs are not included in the analysis. These can vary across states or balancing areas based on their electricity generation mix. For example, hydro capacity with storage is considered more flexible than coal power plants that typically incur a higher penalty for cycling in order to balance both variable RE and load (net load).

LCOE does not account for differences in the value of electricity generated by different technologies in a particular location. Generation at different times of the day or year have different economic value depending on the demand and the available generation at that time. We have addressed this separately using capacity value estimates (section 2.2.7).

LCOE estimates are based on present existing and planned transmission and road infrastructure. In this study, we did not value a project opportunity area sequentially based on the utilization of infrastructure that may be built earlier for another nearby planned project.

2.2.6 Creation of zones (stage 4a) and calculations of zone attributes (stage 4b)

We used three criteria to create zones from project opportunity areas: size, spatial proximity, and resource quality. The outcome of this process were zones created on the basis of spatial proximity as well as similarity in resource quality. This criteria-based spatial clustering of project opportunity areas increases the representativeness of the average zone resource quality, and thus its average capacity factor and generation LCOE, by reducing the intra-zone variability of these criteria. Defining zones along these meaningful criteria allows for the subsequent ranking analysis to distinguish the high potential zones from the low potential zones. See Appendix D for the variability of resource quality across zones for the three technologies. For details of the methodology for zone creation, see Wu et al. (2015).

Zone sizes are not meant to imply that entire zones must be developed, but instead inform the maximum estimated installable capacity in a broad, contiguous suitable area similar in resource quality. After the highest scoring zones have been identified, zones can be further refined to identify candidate sites for on-the-ground surveys by examining POA-level criteria values.

In order to generate area-weighted zone average attribute values, we area-weighted each of the attributes listed in Table 2.2 for each POA within a zone and summed them for each zone. Attributes that were summed across POAs within a zone, rather than averaged, included land area, electricity generation, installed capacity, and water score. The zone water score represents the number of POAs within 10 km of surface water.

2.2.7 Capacity value estimation (stage 5)

Capacity value is a metric that represents the contribution of a generation technology towards supporting the demand of the utility or balancing area. It is one way of valuing variable renewable energy sources, in order to reward or favor those resources that contribute more towards resource adequacy and system reliability due to their higher correlation with system demand. Effective load carrying capability (ELCC) is a metric that is often used to determine capacity value (Keane et al. 2011; Milligan and Porter 2008), but the methods for estimating ELCC are data- and computationally-intensive. Simplified methods can provide useful, approximate results without the computational demand and detailed power systems data. They can also be more transparent and provide direct insights into what is driving the results (Dent, Keane, and Bialek 2010). Since one of the main purposes of this study is to robustly compare zones within India, relative capacity values of zones is more useful than the absolute values. Because these simplified methods lack a power systems model of the national grid, they more reliably discern differences between zones' generation profiles rather than absolute contribution to system reliability. We restrict the capacity value analysis to wind energy, given the limitations of the scope of the study. The choice of wind technology is justifiable since solar PV profiles are more predictable and correlated across the region and solar CSP with a 6 hour storage is less subject to variability. See Wu et al. (2015) for additional details about capacity value.

2.2.7.1 Selection of sites with hourly wind profiles

Estimation of capacity value required both time series data for demand and wind generation. We used simulated hourly wind speed data for 100 sites across India provided by Vaisala. After identifying the wind zones, we selected these 100 sites by considering the highest quality project opportunity areas within zones, spatial representation across a state, amount of resource within a state, and locations of existing project sites.

2.2.7.2 Capacity value ratio

In our simplified approach, we defined the capacity value of the RE generator as a ratio of the expected average generation during the defined peak demand hours to the nameplate capacity of the generator. The units of capacity value are the same as that of capacity factor, usually expressed as a percentage.

Further, we define the capacity value ratio as the ratio of the capacity value to the annual average capacity factor at the site. The capacity value ratio is used in conjunction with the capacity factor of a zone to determine the contribution of the generation profile to meeting demand during peak hours. By estimating the capacity value ratio for a wind zone by extrapolating it from the nearest of the 100 Vaisala wind sites, we assume that the wind zone has a similar hourly generation profile as that site, but it may have a different capacity factor depending on its average wind speed, air density and other factors. The capacity value of any wind zone can then be computed as the product of the capacity factor and the extrapolated capacity value ratio.

We define three metrics for the capacity value and capacity value ratio. For the first metric, we define capacity value as the average capacity factor of a RE generator during the top 10% of peak demand hours in a year (Mills, Phadke, and Wiser 2010). For the second metric, we estimate the capacity value as the average capacity factor during three specific peak demand hours in a day over the course of a year based on their annual demand profile. Figure 2.4 shows the frequency that a particular hour is the daily peak demand hour in 2014. We chose 7, 8, and 9 p.m. as the top three peak hours for this second metric (Fig. 2.4). We repeated the estimation procedure of the second metric for the third metric, but using Vaisala hourly wind data over ten years, as opposed to just one year. We compute the capacity value ratios as the ratio of the capacity value to the capacity factor at the site for all three metrics. Finally, we extrapolate the capacity value ratios of the 100 wind sites to all the wind zones based on proximity.

Limitations These capacity value metrics do not capture the seasonal contribution of wind towards meeting demand. While these metrics provide an indication of the potential annual contribution of the wind zone towards meeting peak demand, we advise conducting a more detailed analysis on the variability of wind with detailed datasets.

We estimated the capacity value for wind based on the load profile only and did not exclude the existing RE generation profile (which is considered must-run, zero marginal cost generation or negative load). Although this simplification is justifiable because RE contributes to only 5% of India's electricity demand, it is a limitation of this study. The capacity value estimates can be interpreted as the contribution of a marginal wind plant to the overall demand. These estimates will change in the future with changes in the net load profiles due to changing electricity consumption patterns and increase in the share of RE resources.

2.2.8 Multi-criteria scoring and decision-making tools

In order to examine how the weighting of different criteria alters the overall suitability of zones, we created a scoring system to evaluate zones within the country. Scoring enables the combination of the component and total LCOEs with other criteria that improve site suitability, but cannot be directly monetized (Table 2.2). See Table 7 in Wu et al. (2015) for details about scoring each criterion.

To allow users to set weights that reflect the relative importance of each criteria and generate a cumulative suitability score, we created a multi-criteria zone ranking tool for each country. Weights are multiplied by the criteria scores to generate a resultant cumulative suitability score for each zone. Users may then identify the location of the highest ranking zones using the unique zone identification letters and the interactive PDF map's analysis tools.

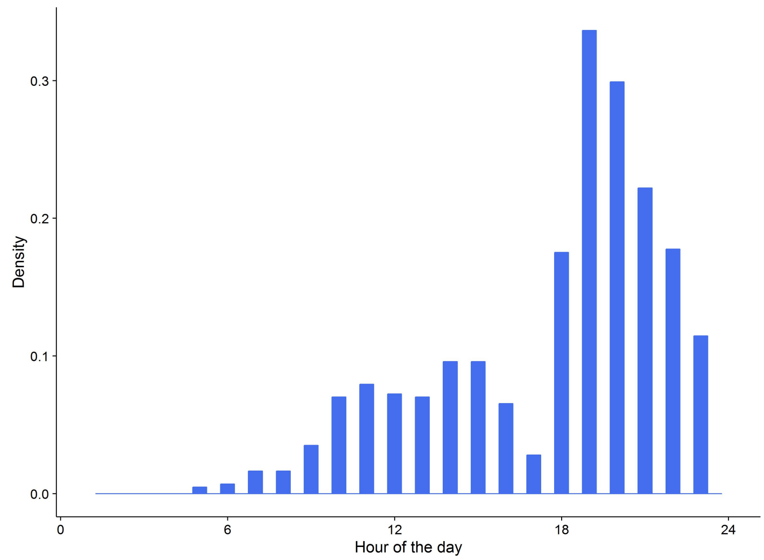


Figure 2.4: Histogram of daily peak demand hours for India in 2014

2.3 Results

2.3.1 Resource assessment

Abundant wind, solar PV, and CSP potential exists within India. These resources, however, are unevenly spatially distributed between the states. We provide the state-wise technical potential for wind, solar PV, and CSP in Table 2.6, Table 2.7, and Table 2.8.

Our estimates for RE resources may differ from other studies because of multiple reasons including but not limited to differences in meso-scale resource input data sets, assumptions about land use and land cover, and land use factors. Further, the choice of technology within a technology category (e.g. fixed tilt, single or dual axis tracking for solar PV; different turbine models for wind; parabolic trough or central tower with or without storage for CSP) also affects the potential estimates. Lastly, the actual developable potential will vary based on ground realities that include land ownership and availability. Therefore, potential numbers are only indicative of the overall resources, which can be useful for policy-making and understanding the distribution of resources across different regions.

To allow comparison with other resource quality maps available for India, maps and stacked bar charts of resource quality are available in Appendix A. Because LCOE calculations relied on CERC cost assumptions that may not be comparable with cost assumptions used in other studies, maps and stacked bar charts of capacity factor are available in Appendix B. A map of India and its state boundaries is provided in Appendix F

Wind. Wind resources are concentrated mainly in the western states (Gujarat, Maharashtra, and Rajasthan) and southern states (Andhra Pradesh, Karnataka, Tamil Nadu, and

Table 2.6: State-wise technical potential for electricity generation and capacity for wind

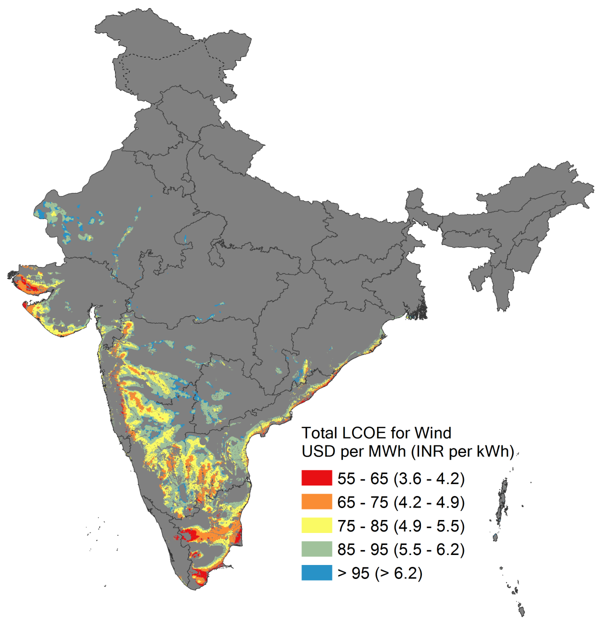
		Land use factor - 9 MW/km^2 (0% discount)		**Land use factor - 2.25 MW/km^2 (75% discount for uncertainty)**	
State	**Area (km^2)**	**Generation Potential (TWh)**	**Capacity Potential (GW)**	**Generation Potential (TWh)**	**Capacity Potential (GW)**
Andhra Pradesh	64,394	1,329	580	332	145
Chhattisgarh	842	16	8	4	2
Gujarat	35,226	762	317	191	79
Karnataka	88,964	1,808	801	452	200
Kerala	908	24	8	6	2
Madhya Pradesh	2,321	42	21	10	5
Maharashtra	76,848	1,560	692	390	173
Odisha	8,007	162	72	40	18
Rajasthan	23,079	427	208	107	52
Tamil Nadu	59,800	1,403	538	351	135
Telangana	14,496	268	130	67	33
Grand Total	375,921	7,824	3,383	1,956	846

Telangana) (Table 2.6, Figures 2.3.1 - 2.3.1). Low estimated LCOE sites are concentrated in Tamil Nadu and Gujarat.

Solar PV. Solar PV resources are distributed across several states, but Rajasthan, Gujarat, Maharashtra, and Madhya Pradesh have the most resource potential (Table 2.7, Figure 2.3.1 - 2.3.1). The relatively few areas of solar PV resources with estimated total LCOE greater than USD 100 per MWh (INR 6.5 per kWh) suggests that solar PV potential is limited by land availability rather than by lower resource quality.

LCOE estimates are based on CERC norms and may be higher than prices discovered in recent solar PV auctions (PVTECH 2016). Estimates of total LCOE include costs for transmission connection to the nearest 220 kV or higher voltage substation. In reality, those transmission costs may not be borne by the project developer. See Appendix C for maps showing LCOE of generation only.

Solar CSP. Solar CSP resources are the most limited amongst the three technologies and naturally closely follow the pattern of solar PV spatial distribution. CSP potential is highest in Rajasthan, Gujarat, Maharashtra, Andhra Pradesh, and Madhya Pradesh (Table 2.8, Figure 2.3.1). While areas in the Ladakh district of Jammu and Kashmir have the highest resource quality (i.e., highest DNI), development potential in this state is limited by protected areas and hilly topography considered unsuitable for CSP development. Because of high capital costs, solar CSP resources remain much more expensive than both wind and solar PV.



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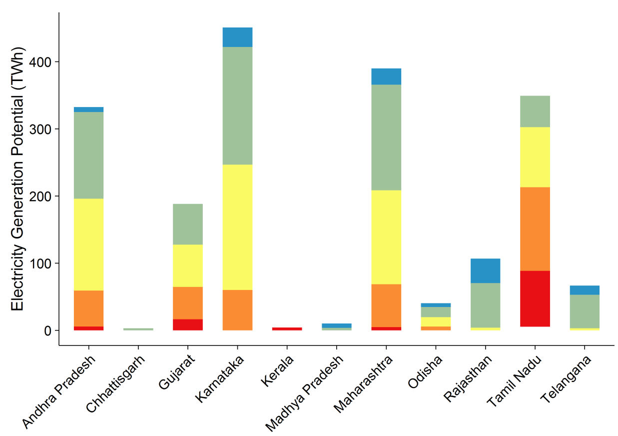

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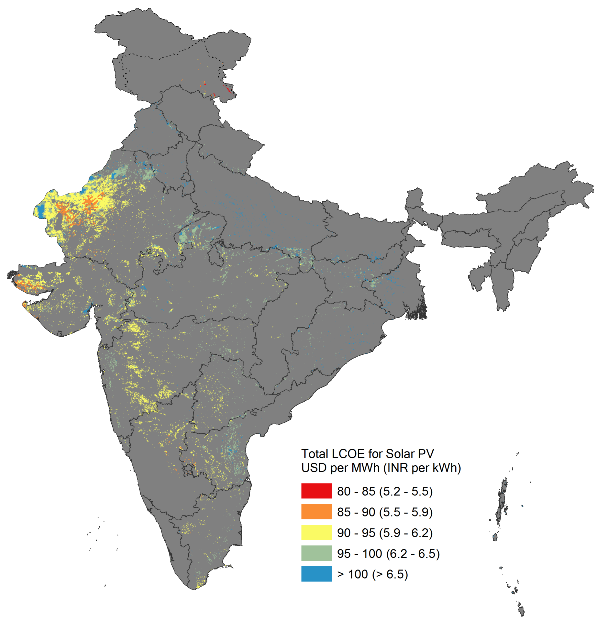
Figure 2.5: Spatial distribution (a) and state-wise potential (b) of wind electricity generation for different ranges of total levelized cost of energy (LCOE) estimates. LCOE for generation is estimated using CERC norms. Wind speeds are simulated at 80m hub heights and resource threshold is 5.5 m/s. Land use factor of 9 MW/km^2 with a 75% discount for uncertainty, equivalent to 2.25 MW/km^2.



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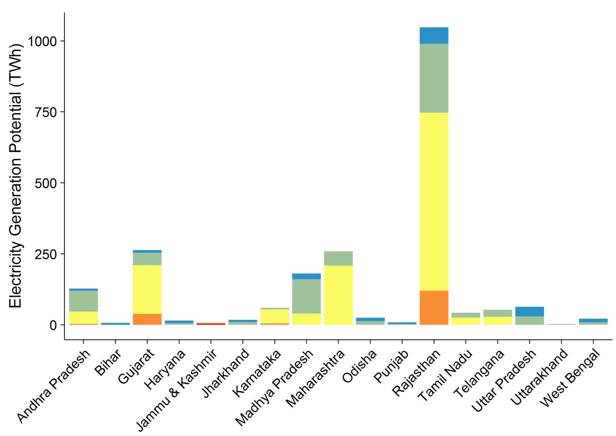

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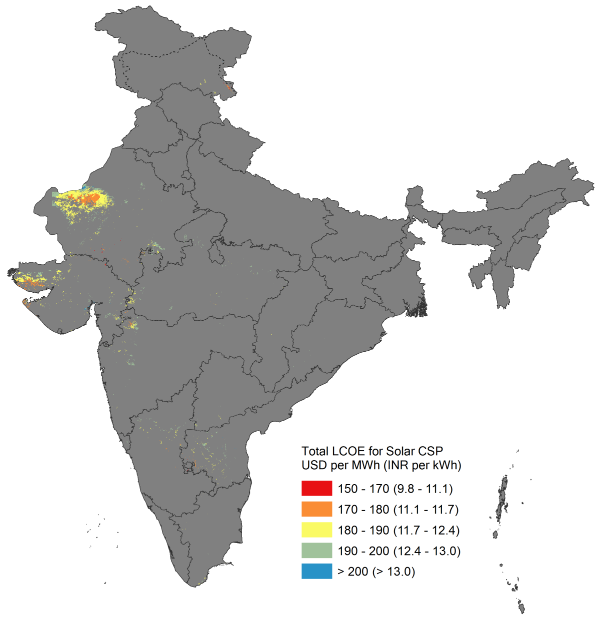
Figure 2.6: Spatial distribution (a) and state-wise potential (b) of solar PV electricity generation for different ranges of total levelized cost of energy (LCOE) estimates. LCOE for generation is estimated using CERC norms and assuming fixed-tilt systems. GHI resource threshold is 4.9 kWh/m^2-day and land use factor of 30 MW/km^2 with a 75% discount for uncertainty, equivalent to 7.5 MW/km^2.



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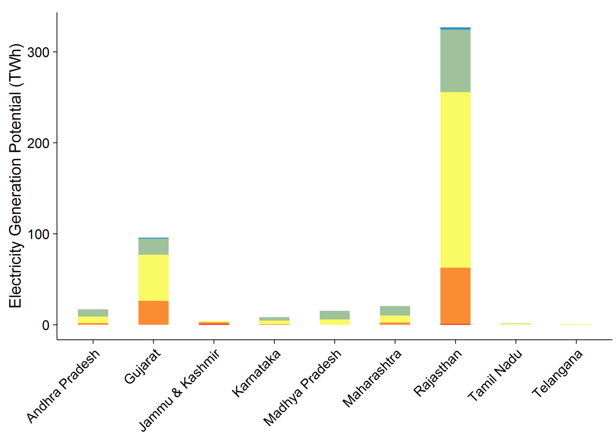

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Figure 2.7: Spatial distribution (a) and state-wise potential (b) of solar CSP electricity generation for different ranges of total levelized cost of energy (LCOE) estimates. LCOE for generation is estimated using CERC norms, and assuming parabolic trough systems with no storage. DNI resource threshold is 4.9 kWh/m^2-day and land use factor of 30 MW/km^2 with a 75% discount for uncertainty, equivalent to 7.5 MW/km^2.

Table 2.7: State-wise technical potential for electricity generation and capacity for solar PV.

		Land use factor - 30 MW/km^2 (0% discount)		**Land use factor - 7.5 MW/km^2 (75% discount for uncertainty)**	
State	**Area (km^2)**	**Generation Potential (TWh)**	**Capacity Potential (GW)**	**Generation Potential (TWh)**	**Capacity Potential (GW)**
Andhra Pradesh	10,120	511	304	128	76
Bihar	746	36	22	9	6
Gujarat	20,227	1,053	607	263	152
Haryana	1,275	61	38	15	10
Jammu & Kashmir	567	33	17	8	4
Jharkhand	1,470	72	44	18	11
Karnataka	4,653	242	140	61	35
Madhya Pradesh	14,426	724	433	181	108
Maharashtra	20,408	1,038	612	259	153
Odisha	2,052	100	62	25	15
Punjab	768	37	23	9	6
Rajasthan	80,255	4,192	2,408	1,048	602
Tamil Nadu	3,457	175	104	44	26
Telangana	4,327	219	130	55	32
Uttar Pradesh	5,371	256	161	64	40
Uttarakhand	297	14	9	4	2
West Bengal	1,840	87	55	22	14
Grand Total	172,817	8,877	5,185	2,219	1,296

2.3.2 Costs

Using the Central Energy Regulatory Commission (CERC) cost assumptions to estimate generation levelized cost of energy (LCOE), wind is still the most cost-competitive renewable energy resource in India. We estimated wind resources above a wind speed threshold of 5.5 m/s to cost USD 49-96 per MWh (mean 80, s.d. 9) or INR 3.2-6.3 per kWh (mean 5.2, s.d. 0.6) for 80 m hub height turbines.

Costs for the two solar technologies have evolved differently in recent years. On the one hand, continuing decline of costs due to technology improvements, and auction-based procurement in India has enabled low prices for solar PV that are comparable to wind. On the other hand, higher capital costs and relatively poor resources makes solar CSP an expensive option for renewable energy generation. Solar PV resources above a threshold of 4.9 kWh/m^2-day for GHI were estimated to cost USD 72-101 per MWh (mean 90, s.d. 3) or INR 4.7-6.6 per kWh (mean 5.9, s.d. 0.2) for fixed tilt systems, whereas the cost of CSP resources above a threshold of 4.9 kWh/m^2-day for DNI were estimated to be USD 148-191 per MWh (mean 181, s.d. 6) or INR 9.7-12.4 per kWh (mean 11.8, s.d. 0.4) for parabolic trough systems. The LCOE estimates show that the distribution of solar PV

Table 2.8: State-wise technical potential for electricity generation and capacity for solar CSP

		Land use factor - 30 MW/km^2 (0% discount)		**Land use factor - 7.5 MW/km^2 (75% discount for uncertainty)**	
State	**Area (km^2)**	**Generation Potential (TWh)**	**Capacity Potential (GW)**	**Generation Potential (TWh)**	**Capacity Potential (GW)**
Andhra Pradesh	1,307	70	39	18	10
Gujarat	7,071	385	212	96	53
Jammu & Kashmir	312	18	9	5	2
Karnataka	635	34	19	8	5
Madhya Pradesh	1,191	63	36	16	9
Maharashtra	1,563	83	47	21	12
Rajasthan	24,016	1,308	720	327	180
Tamil Nadu	141	7	4	2	1
Telangana	100	5	3	1	1
Grand Total	36,387	1,976	1,092	494	273

LCOEs significantly overlaps that of wind, but CSP resources may cost twice as much as solar PV or wind. Further, a comparison between the standard deviations of LCOEs indicates a greater variability in wind quality across the country, whereas quality of solar PV resources varies less.

LCOEs of wind and solar are rapidly evolving. Wind LCOEs may decline as turbines with higher hub heights and larger rotor diameters capture faster and greater wind resources that increase capacity factors and offset the associated higher capital costs (Wiser and Bolinger 2016). Capital costs of solar PV have been rapidly declining over the last decade. Hence, LCOE estimates in this study should be interpreted as only indicative, given the sensitivity of LCOEs to multiple factors. Actual costs depend on project-specific factors including but not limited to on-the-ground measurements of resources, financing rates, and capital costs of equipment. We provide LCOE estimates primarily for comparing zones within a technology.

2.3.3 Transmission expansion

Longer distances from the nearest transmission infrastructure results in higher interconnection costs for renewable energy installations. Further, lack of high voltage transmission infrastructure in a high renewable resource area may lead to a higher number of low voltage transmission lines from installations to pooling substations, because low voltage transmission lines have lower capacity to transmit energy. This may result in greater land fragmentation and environmental impact (Wu, Torn, and Williams 2015). Finally, depending on the number of power plants and loads connected to them, these lines can experience congestion when their transmission limits are violated. During such congestion events, system operators or electric utilities are forced to curtail generation, and in most cases, project developers incur the losses.

Several areas with high quality wind resources in northern Gujarat, Rajasthan and Andhra Pradesh are far from high-voltage (>= 220 kV) substations, which may lead to high transmission costs for project developers (Figure 2.8). If high-voltage transmission infrastructure is extended to these regions, not only will project developers incur lower costs to interconnect over shorter distances, but the overall cost of RE development in those areas will also be lower due to economies of scale achieved through high-voltage transmission and lower probability of congestion.

In Figure 2.8, red and orange areas (in northern and western Gujarat, southern and central Tamil Nadu, Maharashtra, Karnataka, Andhra Pradesh, and Rajasthan) have low wind generation LCOE, but are at a distance of more than 25 km from the nearest high-voltage transmission substation (>= 220 kV). Identifying such areas to preemptively build transmission infrastructure will reduce the risk for project developers and enable rapid development of renewable energy.

2.3.4 Capacity value and wind development

Capacity value is the contribution that a given generator makes to overall system resource adequacy. In the case of wind and solar power plants, it is an indicator of how well the expected generation of a given plant temporally matches with demand. We have limited our capacity value analysis to wind, because solar generators without storage are likely to have similar temporal generation profiles across the country, and as a result, similar capacity values.

The spatial distribution of wind capacity values, estimated using average capacity factors during the top 10% annual peak demand hours, are different than that of annual-average capacity factors (Figure 2.3.4). Wind sites in Rajasthan, which have relatively low annual-average capacity factors (< 25%), have some of the highest capacity values, highlighting the temporal correlation of their potential generation profiles with the country's demand. These zones in Rajasthan can be considered as competitive in terms of their capacity value as those with high annual average capacity factors (>35%) in Gujarat and Tamil Nadu. Capacity values of sites in Tamil Nadu and Gujarat are also high, both due to their correlation of generation with demand, and their overall high annual average capacity factors (Figure 2.3.4). Developing projects in areas with wind profiles better matched to load profiles will reduce the need for conventional, "balancing" generation capacity. Selecting project locations purely based on highest annual-average capacity factors and lowest LCOE may not necessarily provide the highest value to the overall system.

Note that the capacity value attributes are estimated using India's nationally-aggregated load profile. Results may differ if instead, the state load profile is used to calculate capacity value for each zone. However, because India's entire grid is synchronized, correlation with the nationally-aggregated load profile leads to the greatest grid benefits. Also note that capacity values are determined for the marginal generator that is added to the system with-

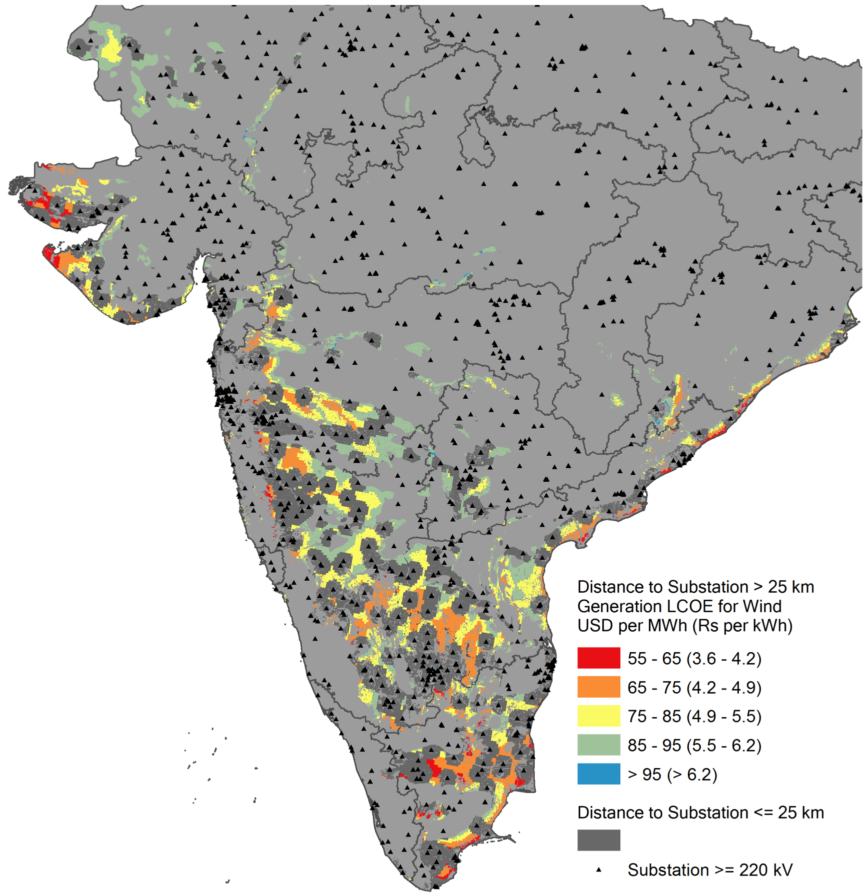
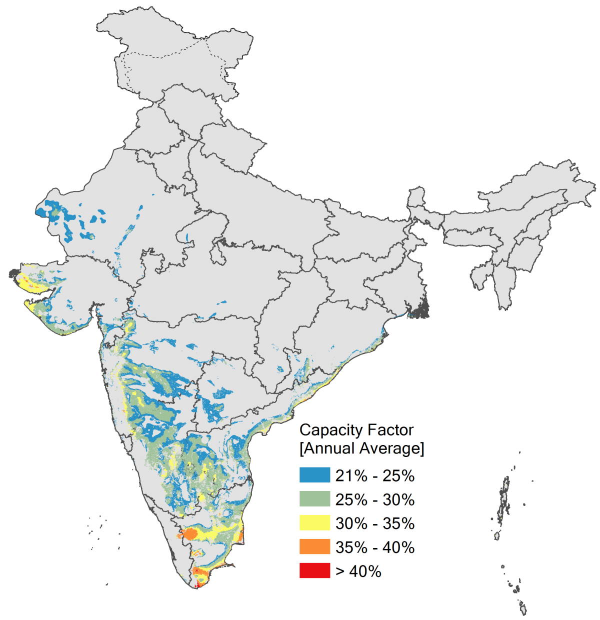


Figure 2.8: Spatial distribution of transmission substations and high quality wind resources. All wind project opportunity areas within 25 km of an existing substation are indicated in dark grey. All wind project opportunity areas more than 25 km from the nearest substation are colored by their generation LCOE. These colored areas show opportunities for wind project development that could be enabled by expanding the substation infrastructure network.

out considering the effect of renewable generation on the net load profile (demand minus renewable energy generation). Increasing renewable energy generation will change the net load profile. Further, changing appliance ownership (e.g. air conditioners) and addition of new types of loads will also influence the overall load profile. As a result, capacity values should be re-estimated on a continual basis as new data on load and actual renewable energy generation becomes available.



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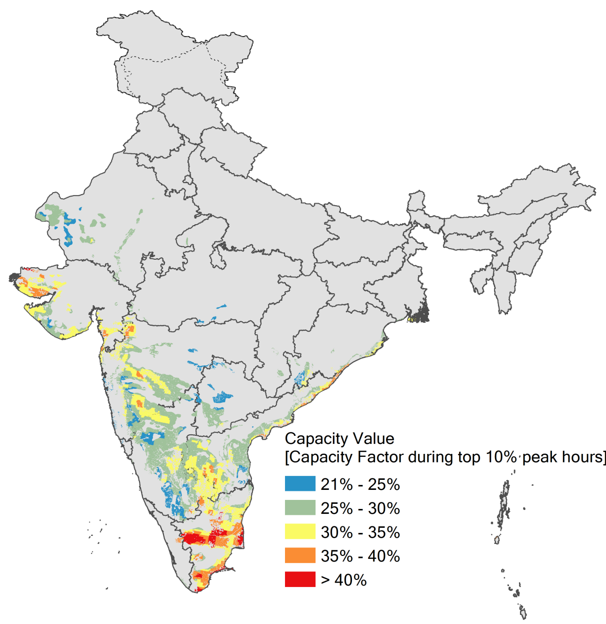

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Figure 2.9: Comparison of annual average capacity factor (a) and adjusted capacity factors (capacity value) for wind estimated using top 10% annual peak hours (b).

2.3.5 Agricultural land and wind development

Most of India's wind energy potential exists on agricultural lands. By our estimates and assumptions, 84% of India's wind resources are found in agricultural areas (Figure 2.10).

These include areas with single and multiple crops, as well as those observed to be fallow and areas under shifting cultivation, as classified by the 2011-12 NRSC land-use/land-cover dataset (See Table 2.1 for land classification). Because the direct land footprint of a wind turbine is small relative to the entire area of a wind farm (Denholm et al. 2009), dual use of the land for farming and wind generation is not only possible, but preferable from a land use efficiency point of view. For India to scale up its wind generation capacity, policies such as land-leasing would be important to ensure socially-equitable wind development.

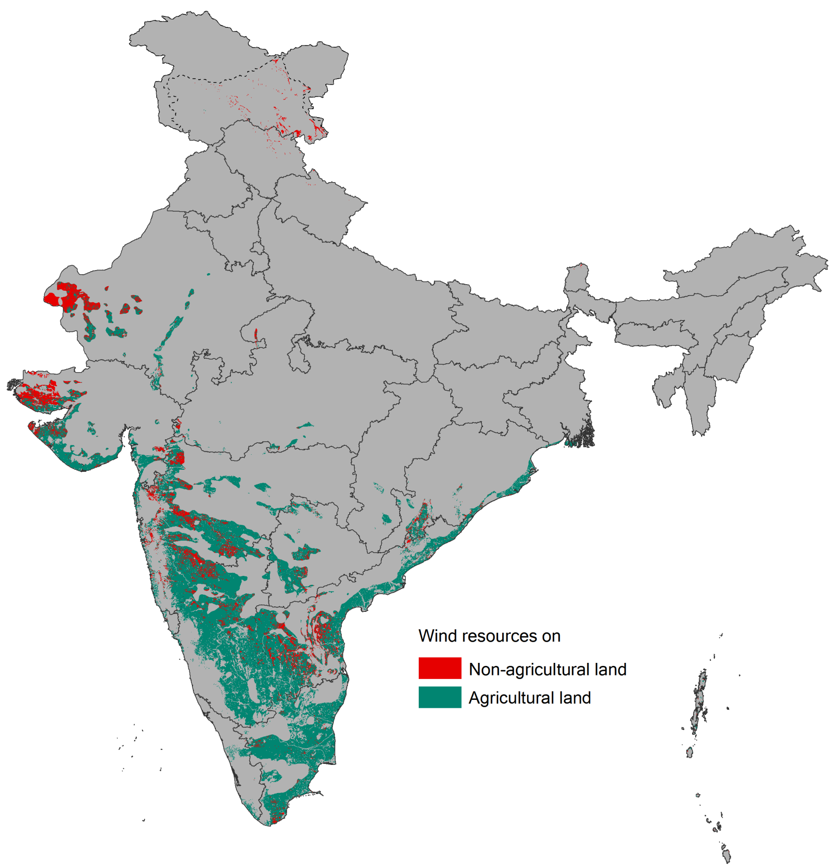


Figure 2.10: Wind resources on agricultural and non-agricultural lands as identified using land-use/land-cover data from India's National Remote Sensing Center.

2.3.6 Water availability for solar projects

Water availability is crucial for solar PV and CSP resources. On average, solar PV plants require 26 gal/MWh for cleaning of panels, and even dry-cooled trough CSP power plants require 78 gal/MWh (Macknick et al. 2012). Previous studies report 10 km as the maximum cost-effective distance to transport water for cooling for solar CSP power plants or washing for solar PV power plants (CPUC 2009). Analysis shows that although Rajasthan contains a large proportion of the country's solar PV potential (Figure 2.3.1 - 2.3.1), only a small fraction of potential project areas within Rajasthan (8% for solar PV and 6% for CSP) are within 10 km of a surface water body (Figure 2.11). Ground water resources were not considered in this study, but may be an additional source of water in areas without surface water.

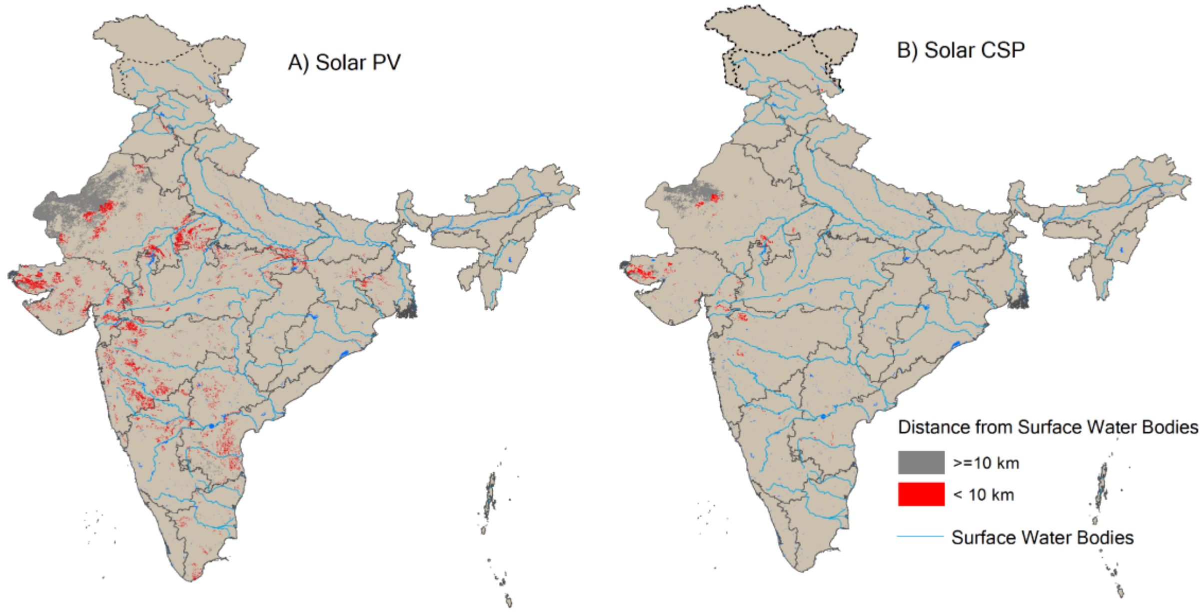


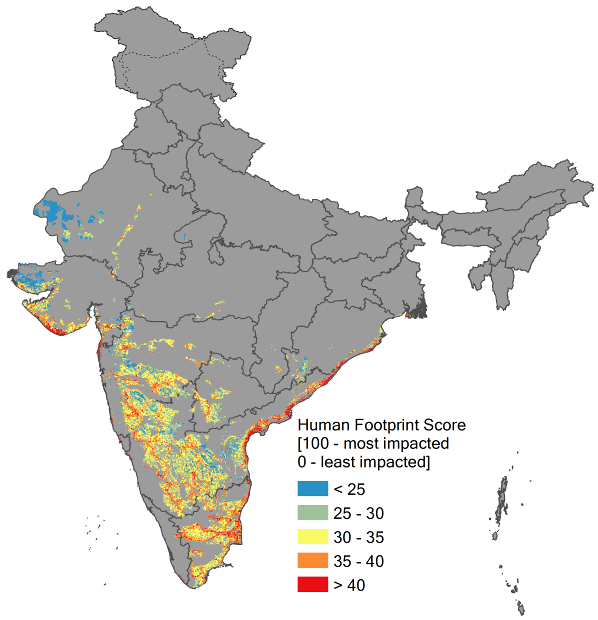
Figure 2.11: Solar PV (A) and solar CSP (B) resources that are within and beyond a distance of 10 km from surface water bodies.

2.3.7 Ecologically sustainable development

A comparison of the spatial distribution of the human footprint score, which is a measure of human impact, with that of total LCOE reveals potential wind project areas that have low ecological impact and low total LCOE (Figure 2.3.7 - 2.3.7). Regions where these two criteria align over larger land areas are in Eastern Tamil Nadu, coastal Andhra Pradesh, and Western Gujarat.

2.3.8 Potential for co-location of wind and solar sites

Co-location of wind and solar PV plants, especially on non-agricultural lands, can enable better land and transmission infrastructure utilization. Our assumptions for land use and land cover, and slope suitable for utility-scale solar PV development are a subset of those



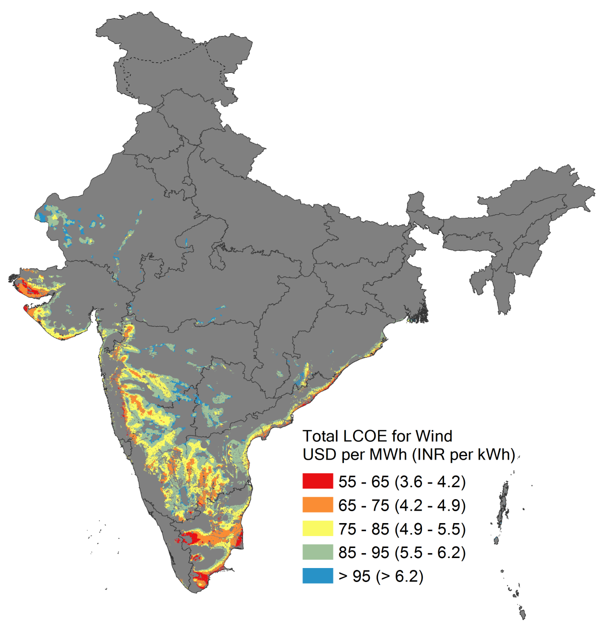


Figure 2.12: Comparison of the human footprint score metric (a) and total LCOE for wind zones (b). Common areas in red, corresponding to higher human footprint score (less ecologically intact) and lower LCOE, are more desirable for development.

considered suitable for wind development. We found approximately 48,000 km^2 to be suitable for co-location of wind and solar PV plants (Figure 2.13). Based on our assumptions of land use factor and land use discount factor, these areas could accommodate 108 GW (or 13% of total) wind potential and 360 GW (or 28% of total) utility-scale solar PV potential.

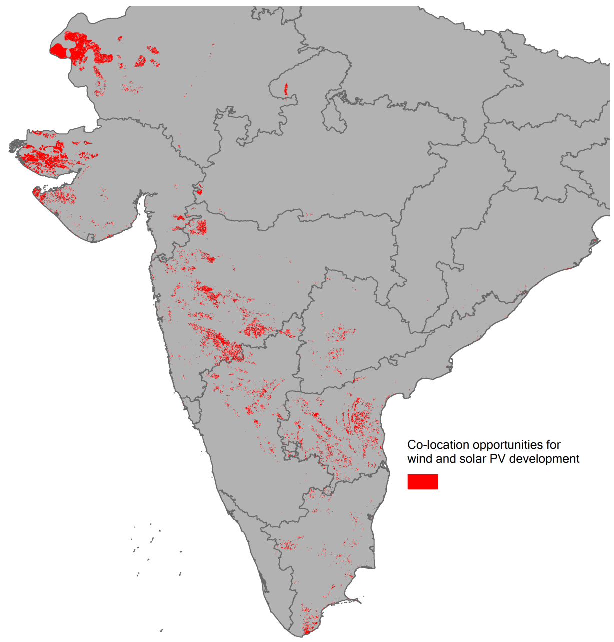


Figure 2.13: Co-location opportunities for wind and solar PV projects.

2.3.9 Multi-criteria analysis for prioritizing zones

Multiple criteria can be used to prioritize RE zones but these criteria could often be divergent in nature. Because different stakeholders have their own points of view and priorities for different criteria, the final decision among multiple stakeholders or decision makers is one of compromise and mutual understanding. Therefore, a flexible tool that can allow different stakeholders to provide their own weights to different criteria is essential to understand the interactions between the criteria and how they affect the ultimate ranking and prioritization, in this case, of renewable energy zones. We demonstrate the value of the MapRE tool by providing a set of weights to zone attributes from a policymaker's perspective.

We incorporated nine criteria for both wind and solar PV (Table 2.9 and Table 2.10). For this exercise, we did not include CSP because of its high costs relative to the other technologies, and consequently, its lower likelihood of development. We included capacity value as a criteria for wind and not for solar PV because the latter's generation profiles are likely to be similar across zones. For solar PV, we included slope, which may be an important factor in terms of installation costs. Attributes of each of the zones have a score depending on the best and worst criteria values. The aggregate score of a zone is the weighted sum of scores of all its attributes, with the weights specified by the stakeholder. The weights in

Table 2.9: Range and weights for wind zone attributes

Zone atribute	**Best criteria value (score=1)**	**Worst criteria value (score=0)**	**Weights (points(%))**
Generation LCOE [USD/MWh]	51.84	95.38	3 (20%)
Transmission LCOE [USD/MWh]	1.3	5.01	2 (13%)
Road LCOE [USD/MWh]	0.01	8.8	1 (7%)
Capacity Value Ratio using Top 10% peak hours	1.78	0.97	2 (13%)
Distance to Load Centers [km]	0	100	2 (13%)
Co-location Potential with other RE [binary]	1	0	1 (7%)
Land use land cover score	1	5	1 (7%)
Population Density [persons/km^2]	0	100	1 (7%)
Human Footprint Score	100	0	2 (13%)
Slope [%]	0	20	- (-)
Total			15 (100%)

Table 2.10: Range and weights for solar PV zone attributes

Zone atribute	**Best criteria value (score=1)**	**Worst criteria value (score=0)**	**Weights (points (%))**
Generation LCOE [USD/MWh]	74.25	100.34	3 (20%)
Transmission LCOE [USD/MWh]	2.47	7.76	2 (13%)
Road LCOE [USD/MWh]	0.02	10.97	1 (7%)
Capacity Value Ratio using Top 10% peak hours	-	-	- (-)
Distance to Load Centers [km]	0	100	2 (13%)
Co-location Potential with other RE [binary]	1	0	1 (7%)
Land use land cover score	1	5	2 (13%)
Population Density [persons/km^2]	0	100	1 (7%)
Human Footprint Score	100	0	2 (13%)
Slope [%]	0	5	1 (7%)
Total			15 (100%)

Tables 2.9 and 2.10 are an example of how a policymaker may prioritize among different zone criteria.

Most policies focus only on the generation costs of wind and solar. From a project developer's perspective, the costs for transmission interconnection and road connectivity are important components of the overall installed costs. Transmission planners may value resources closer to load centers to avoid wheeling energy and siting transmission lines over long distances. Environmental concerns dictate that zones be sited on more disturbed lands, indicated by higher human footprint scores, and on land types that are more environmentally and socially sustainable (Table 2.1). Zones sited in lower population density areas will avoid displacement of people, making population density an important criteria for social equity. Project developers may value co-locating wind and solar plants, especially on non-agricultural land. For wind, electricity system planners prefer sites with higher capacity value to ensure resource adequacy.

Figures 2.14 and 2.15 show the relationship between the various zone attributes and the LCOE for generation. Preferred values of attributes lie in the upper left quadrant of each of the individual attribute plots. These plots indicate that zones with the lowest generation LCOEs may not be the most preferred zones for development.

The selected wind zones show a wide range of generation LCOEs, which suggests that preference for other criteria may lead to higher generation costs. Most of the selected wind zones have low transmission and road costs, and are close to load centers. The LULC scores for wind zones are much lower than those for solar PV, mainly because agricultural lands, which have high LULC scores (less preferred), are included in wind zones. Wind zones with high generation LCOEs are prioritized for their higher capacity values, greater co-location potential, and higher human footprint scores.

Most of the selected solar PV zones have low transmission and road costs, and several of them are close to load centers, have potential for co-locating with wind plants, and have high human footprint scores. Solar PV zones that have some of the lowest generation LCOE but were not selected have high transmission costs, are far from load centers, and have low human footprint scores, which make them undesirable for development. These zones happen to be in Rajasthan's remote desert region.

The multi-criteria analysis can also be applied across individual states or sub-regions to meet their RE targets, and with additional attributes that are not captured in this analysis (e.g. land ownership, groundwater resources).

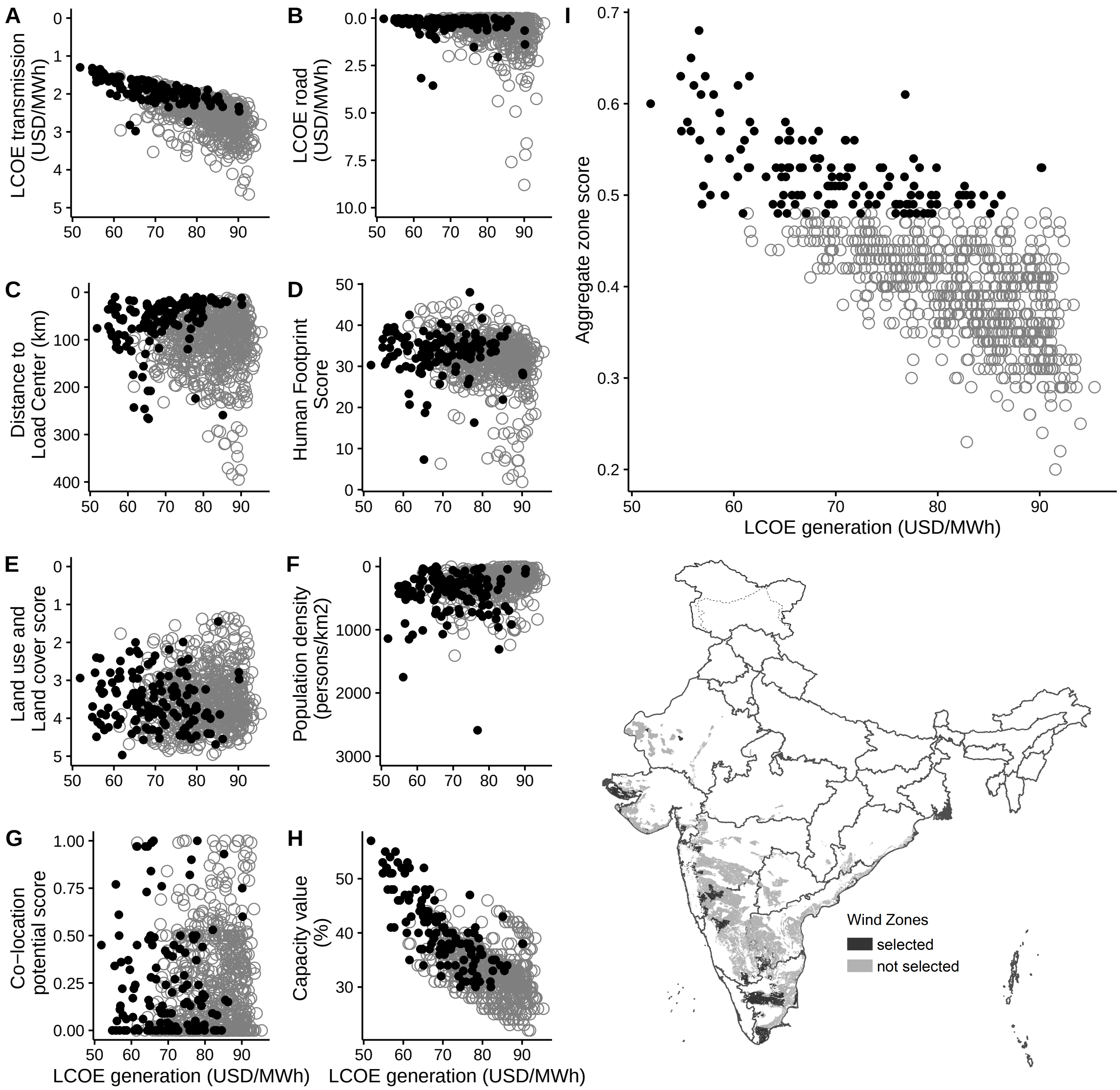


Figure 2.14: **Multi-criteria analysis results for wind energy zones.** Plots A-I show the relationship between levelized cost of generation and various zone attributes - levelized cost of energy for transmission (A), levelized cost of energy for road (B), distance to load center (C), human footprint score (D), land use and land cover type score (E), population density (F), co-location potential score (G), capacity value (H), and aggregate zone scores based on assumed weights (I). Selected zones are in black. Preferred values of attributes should lie in the upper left quadrant of each individual attribute plot. Map shows the spatial distribution of selected (black) and all (grey) wind zones

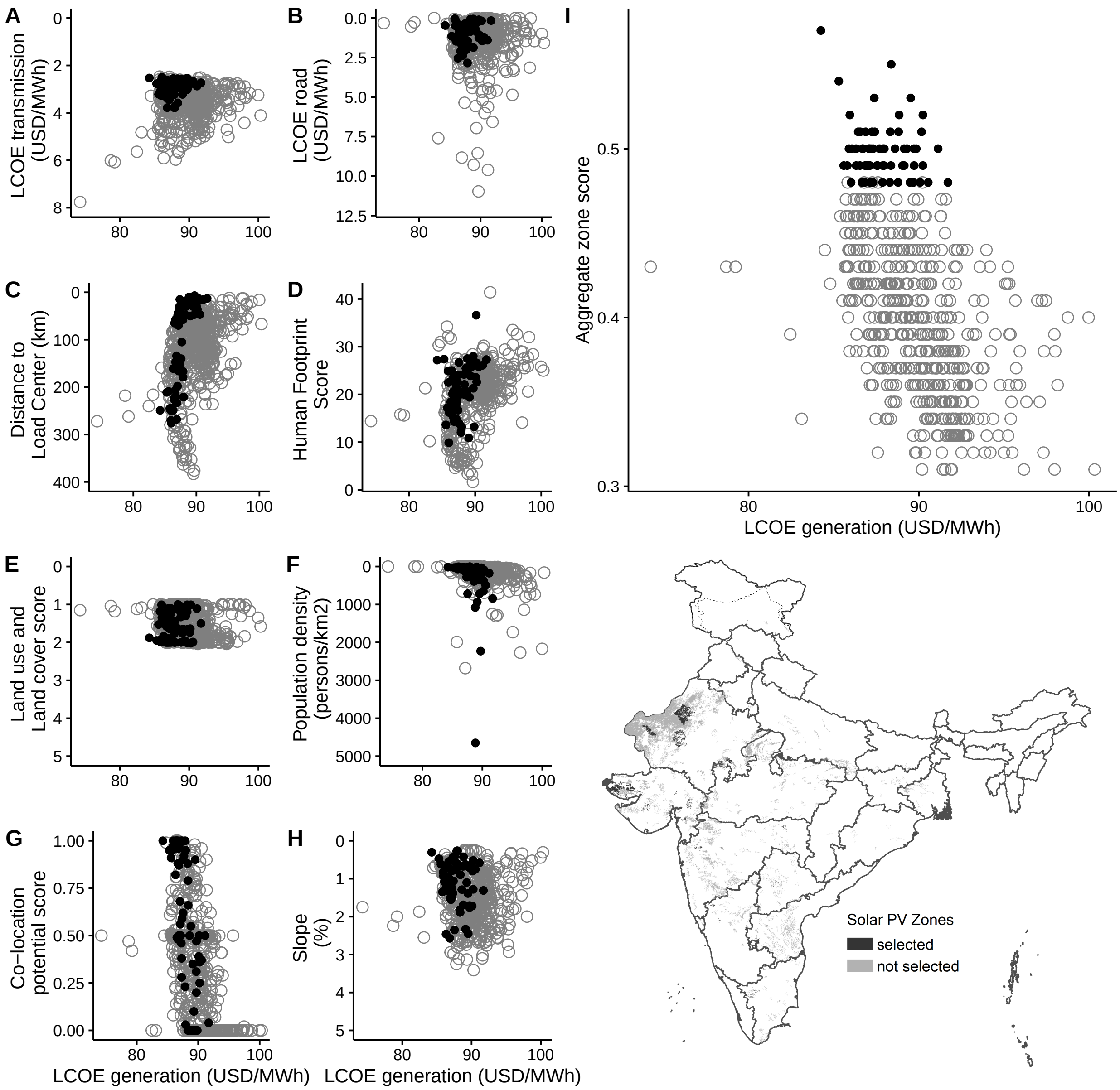


Figure 2.15: **Multi-criteria analysis results for solar PV energy zones.** Plots A-I show the relationship between levelized cost of generation and various zone attributes - levelized cost of energy for transmission (A), levelized cost of energy for road (B), distance to load center (C), human footprint score (D), land use and land cover type score (E), population density (F), co-location potential score (G), slope (H), and aggregate zone scores based on assumed weights (I). Selected zones are in black. Preferred values of attributes should lie in the upper left quadrant of each individual attribute plot. Map shows the spatial distribution of selected (black) and all (grey) solar PV zones

2.4 Discussion and conclusions

1. **Resource distribution.** Abundant resources exist in India for wind and solar PV development but are unevenly distributed, with the best resources available in the western and southern states. Resources for utility-scale solar PV are constrained mainly by the slope threshold and types of land use and land cover that are considered suitable for development. CSP resources exist mainly in Rajasthan and Gujarat. The highest quality solar CSP resources are found in the Ladakh district of Jammu and Kashmir, but few areas are suitable for development because of protected areas and high slopes. The spatial unevenness of RE resources across the country underscores the importance of inter-regional transmission lines and sharing of balancing resources across the entire grid to ensure cost-effective and reliable integration of high shares of variable renewable energy generation.

2. **Cost comparison across technologies.** Using the Central Energy Regulatory Commission (CERC) cost assumptions to estimate generation levelized cost of energy (LCOE), wind is still the most cost-competitive renewable energy resource in India. However, continuing decline of costs due to technology improvements, and auction-based procurement in India has enabled low prices for solar PV that are comparable to wind. In many regions, LCOEs for solar PV based on CERC norms are similar to those of wind. CSP resources, because of high capital costs and relatively poor resources, are estimated to cost twice as much as wind or solar PV.

   LCOE estimates are sensitivity to multiple factors, and actual costs depend on project-specific parameters. We provide LCOE estimates primarily for comparing zones within a technology.

3. **Pre-emptive transmission planning.** Some areas with high quality resources are far from high-voltage transmission substations. Identifying such RE zones for pre-planning of high-voltage transmission infrastructure will encourage development in these areas and avoid long-distance low-voltage transmission interconnections that often result in congestion and land fragmentation (Wu, Torn, and Williams 2015).

4. **Wind development on agricultural land** More than 80% of India's wind resources lie on agricultural lands where dual land use strategies could encourage wind development. Policies such as land leasing and revenue sharing can ensure equitable development and avoid potential land use conflicts.

5. **Land cover and water constraints on solar development.** Solar PV resources are relatively abundant, but can be restricted depending on the type of land that is allowed for its development. Our restrictive selection of land-use and land-cover types based on the National Remote Sensing Center's data shows adequate solar PV resources to meet 30% of 2030 demand. However, water requirements for solar PV plants will restrict their placement to areas with water availability, and could significantly reduce the

amount of developable resources. For example, Rajasthan, the state with the highest solar resources, has only 8% of solar PV resources within 10 km of a water body. Our analysis was restricted to determining zones close to surface water bodies, and did not include ground water bodies. Proximity to water resources also does not guarantee access to adequate water supplies. Ground-truthing of available resources after initial screening of RE zones is therefore important to ensure long-term viability of actual projects.

6. **Co-location of wind and solar sites.** Co-location of wind and solar PV plants, especially on non-agricultural lands, can enable better land and transmission infrastructure utilization. Based on discounted land use factors of 2.25 MW/km^2 for wind and 7.5 MW/km^2 for solar PV, we found 108 GW (or 13% of total) wind potential overlaps with 360 GW (or 28% of total) utility-scale solar PV potential and can be co-located. Actual potential would vary depending on adjustments to land use required for co-located plants.

7. **Planning tools** Finally, given the importance of incorporating such multiple attributes in renewable energy infrastructure planning, the multi-criteria analysis for planning renewable energy (MapRE) tools enable stakeholders to prioritize RE zones within a multi-criteria decision analysis framework. The zone ranking tool allows stakeholders to set different weights for these criteria or zone attributes, many of which that cannot be quantified in monetary terms, and derive aggregate scores for zones. These scores can then be used to compare and prioritize zones. The interactive pdf and online maps enable visualization of RE zones, as well as geospatial layers of transmission and road infrastructure, existing and planned RE plants, co-location potential, and exclusion areas (e.g. water bodies, protected areas, high elevation and slope areas). The ArcGIS tools allow users to conduct their own site-suitability analysis with their own data sets, add new geospatial layers, update input parameters, and recalculate project opportunity area and zone attributes. The MapRE tools and maps will enable a more informed, stakeholder-driven process for prioritizing and selecting RE zones for cost-effective, and environmentally and socially sustainable development.

Chapter 3

Grid Integration of Renewable Energy

3.1 Introduction

Grid-connected renewable energy (RE), mainly wind and solar, is one of the main strategies to mitigate carbon emissions. Although both wind and solar are relatively abundant, these resources are weather dependent, and as a consequence, have variability and uncertainty associated with their outputs. Variability is the change in output of wind and solar generation based on resource availability, and uncertainty is the reduced accuracy in the prediction of generation. System operators, whose task is to keep electricity supply and demand in balance at all times to maintain reliability of the electric grid, find it increasingly difficult to manage this variability and uncertainty with rising shares of wind and solar penetration. The complexity of operations increases for large electricity systems that are predominantly dependent on relatively inflexible coal generators. Predicting and understanding the impacts of high shares of wind and solar (also referred to as variable RE or VRE) on future electricity systems is essential to prepare and modify these systems to mitigate the potential adverse impacts of variable RE. In this study, we analyze the impacts of high shares of wind and solar on the large coal-based electricity system of India, and analyze different strategies that can be used for the cost-effective and reliable integration of variable RE.

India has one of largest synchronous grids in the world with an installed generation capacity of 250 GW in 2016 (CEA 2016). 60% of this capacity is coal-based, supplying 70% of the country's annual demand (CEA 2016). Over the past couple of decades, the Government of India (GoI) has been promoting renewable energy generation, both wind and more recently, solar, through various policy incentives including feed-in tariffs, tax benefits, and renewable generation targets (Gambhir et al. 2016). By 2016, India had installed 28 GW of wind and 8.7 GW of solar capacity (MNRE 2016). The GoI has set an installed capacity target of 175 GW for RE, which includes 60 GW of wind and 100 GW of solar (GoI 2016b). Further, in its Nationally Determined Contribution, India has committed to 40% non-fossil fuels-based generation capacity by 2030.

3.1.1 Objective of the study

The objective of this study is to analyze the impacts of the 160 GW of wind and solar on the rest of India's electricity system, and analyze different strategies to mitigate the adverse effects of the variability and uncertainty of these resources. We developed a detailed high spatial and temporal resolution modeling framework that includes an RE site selection and generation profile model, a load forecast model, and a production cost model. We used the RE site selection and generation profile model to select sites around the country to meet existing and future installed capacity targets. We created temporal profiles of future demand using the load forecast model. We then used the RE and load profiles along with existing and planned conventional generation and transmission infrastructure in a production cost model, which we used to optimize scheduling and dispatch of available generation by minimizing production costs, subject to physical, operational, and market constraints. Through these set of models, we evaluated RE generation variability, system costs of scheduling and dispatch, RE curtailment, periods of stress, and emissions. Further, we analyzed the effect of different integration strategies that include market coordination, increasing transmission capacity, and increasing conventional generation flexibility on key parameters such as system cost, RE curtailment, and emissions.

The results of the analysis are intended to inform regulatory and policy decisions, including actions to improve system flexibility, which is the ability of the system to cost-effectively and reliably absorb the variability and uncertainty of RE, and maintain balance between supply and demand. The analysis presented here is part of a larger grid integration study under the Greening-the-Grid initiative supported by the US Agency for International Development.

3.1.2 Previous studies

There have been several VRE grid integration studies since the 2000s. The Western Wind and Solar Integration Study (WWSIS) was one of the first major studies of VRE grid integration in a large electricity grid (NREL 2010). The WWSIS analyzed the impacts of 35% VRE penetration in the Western Interconnection of the US. The Eastern Wind Integration Study (EWITS) examined the impacts of 20% wind in the Eastern Interconnection of the US (NREL 2011). A followup study, the Eastern Renewable Generation Integration Study (ERGIS), used a unit commitment and economic dispatch model to simulate four different VRE build-out scenarios to understand the impacts of and evaluate strategies to integrate up to 30% VRE generation in the Eastern Interconnection (Bloom et al. 2016).

Nelson and Wisland (2015) analyzed the role of flexibility of non-fossil generators in integrating 50% renewable electricity in California's 2030 grid. Another study on California's 2030 system by Brinkman et al. (2016) looked at the operational impacts of VRE build-out scenarios to reduce GHG emissions in the state's electricity sector by 50%. Milligan et al. (2013) examined and quantified the benefits of an Energy Imbalance Market in the Western Interconnection. Other grid integration studies have focused on electricity systems in countries and regions other than the US including the European Union and China (Winter 2010, Davidson et al. 2016).

While the broader conclusions of these grid integration studies are similar - larger balancing areas, increased flexibility in conventional generators, and increased transmission capacity reduce production costs and VRE curtailment - the actual cost savings, impacts of VRE generation at different penetration levels, and the most effective strategies to mitigate those impacts vary across electricity systems. These differences arise from varying flexibility in conventional generation fleets (e.g. a coal dominated system is less flexible than one with large hydro and gas generation), spatial and temporal profiles of wind and solar generation as well as load, and transmission infrastructure. Non-technical aspects such as institutional structures, regulations, and contracts also play a significant role.

A few recent studies in India have identified key issues that a high VRE penetration can introduce to the power system. A technical committee formed by the GoI's Ministry of Power came up with several recommendations to manage the additional variability and uncertainty introduced by VRE generation (GoI 2016c). These recommendations include an increase in transmission capacity both within and across states for evacuating VRE generation and trading across balancing areas, regulatory frameworks to handle inter-state imbalances and operationalize reserves, improved forecasting and scheduling of VRE generators, and a wholesale market design with multiple intra-day clearing opportunities. A study by the Prayas Energy Group (Gambhir, Sarode, and Dixit 2016) has similar recommendations. None of these studies simulate system operations of India's future electricity grid, but rely on empirical data of the current system and results from studies on electricity systems in other regions.

3.1.3 Types of studies required for grid integration

Our study is one among a suite of different types of studies essential to analyze and plan for wind and solar integration. As such, there are limitations to our study. This study answers many but not all questions surrounding the impacts of variable RE. We do not optimize conventional generation or transmission capacity build-out using a capacity expansion model. We use the GoI's existing 2022 plans for generation and transmission capacity. We use a DC power flow model and a simplified transmission network, which allows us to simulate the system operation in 15-minute time steps for the whole year in reasonable amounts of time. However, an AC power flow model, typically used by transmission planners is essential to plan transmission lines, especially by simulating power flows during the stress periods identified through a production cost model. In addition, transient stability models help analyze the effect of potential disturbances that may be caused by wind and solar. Together, these studies can provide a holistic analysis to foresee and address issues that may arise with increased shares of wind and solar in electricity systems.

3.1.4 Relevant aspects of India's electricity system

Pandey (2007) and Gambhir, Sarode, and Dixit (2016) provide a detailed description of the institutional structures and electricity grid management practices of India's power system. India has one synchronized grid, with asynchronous interconnections with two of its neighboring countries - Bhutan and Bangladesh. Most of the 29 states are their own balancing areas managed by a system operator (state load dispatch center). All states fall in one of the five electricity regions operated by the Regional Load Dispatch Centers (RLDCs) that are responsible for inter-state transactions (see Appendix G for a map of the regions). The five RLDCs report to and are coordinated by the National Load Dispatch Center (NLDC) that monitors the entire grid. The NLDC and RLDCs are part of the Power System Operations Corporation Limited (POSOCO), a GoI entity. The Power Grid Corporation of India Limited, another GoI entity (which until 2016 was the parent company of POSOCO), builds and manages the inter-regional transmission infrastructure. Electricity regulations are issued by the Central Electricity Regulatory Commission (CERC) and the State Electricity Regulatory Commissions (SERCs). The Central Electricity Authority (CEA) formulates short and long-term plans for the development of India's electricity system, forecasts load growth, collates data, and prescribes grid codes and standards.

The structure of this chapter is as follows. In section 3.2, we describe the study scenarios, assumptions of the power system, and the overall methodology. We present the results in the following three sections - impacts of 160 GW of solar and wind in section 3.3, evaluation of strategies to increase system flexibility in section 3.4, and comparison of alternate VRE build-outs in section 3.5. We conclude in section 3.6.

3.2 Study Scenarios, Assumptions, and Methodology

In this section, we first describe the scenarios analyzed in this study, the base assumptions about the electricity system, and the overall methodology of this study.

3.2.1 Study Scenarios

A study scenario defines one possible future electric power system — projected electricity demand (load), generation, and transmission that will comprise a future power system. We chose four future scenarios to evaluate, as described in Table 3.1. The main scenario that we analyze in this study is the High-Solar scenario with 100 GW solar and 60 GW wind capacities, which reflect the official GoI policy targets. We use the No-New-RE scenario, which assumes the same VRE capacity as that in 2016, to compare the impacts of the High-Solar VRE targets on the overall electric system. In the High-Wind scenario, we switch the capacities of wind and solar relative to the High-Solar scenario in order to provide insights into an alternative VRE future. Finally, the Very-High-RE scenario with 150 GW solar and 100 GW wind provides insights into the impacts of a higher penetration of VRE generation.

Table 3.1: Description of scenarios

Scenario name	Solar (GW)	Wind (GW)	Description
No-New-RE	5	23	Wind and solar capacities in 2014
High-Solar (100Solar - 60Wind)	100	60	Current GoI target for 2022
High-Wind (60Solar - 100Wind)	60	100	Solar and wind targets reversed
Very-High-RE (150Solar - 100Wind)	150	100	Ambitious RE growth

3.2.2 Electricity system in 2022

This section reviews the study's assumptions regarding the major components of the 2022 electric system across the study scenarios: conventional generation, transmission, wind and solar, load, and operations.

3.2.2.1 Generation

The set of assumptions on 2022 conventional generation comprises both capacity expansion plans and generator properties.

For capacity expansion, we used the Central Electricity Authority's (CEA) transmission system planning model for 2022, which is a PSS/E AC network model.[1] This model includes locations and types of existing and any known planned capacity. We matched the conventional generators in this model against those expected to be installed by the end of India's 13$^{\text{th}}$ Plan, in addition to the knowledge of the existing system, to obtain the installed capacity that is expected for our study year.[2] Our study assumes no plant retirements, based on guidance from CEA.

This conventional generation build-out was used throughout our 2022 scenarios, and only wind and solar capacities varied between each scenario. Figure 3.1 summarizes installed capacity for each scenario.

Accurate generator properties are critical to ensuring that the production cost model realistically captures the flexibility of and constraints on the power system. We collected generator properties from multiple sources, and wherever possible used plant-specific information in our data sets. Table 3.2 summarizes the average characteristics for each thermal plant type.

[1]The Power System Simulator for Engineering (PSS/E) is a software tool developed by Siemens PTI to simulate optimal power flow. This tool is widely used by system operators and transmission planners in India.

[2]Data on installed generation capacity from India's 13th Plan provided by CEA.

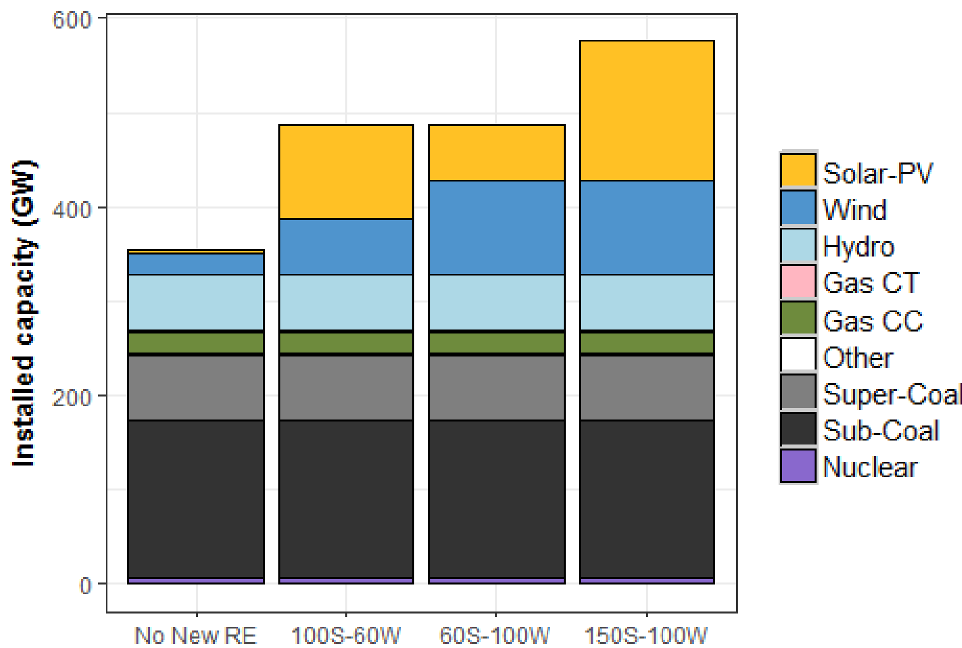


Figure 3.1: Installed generation capacity for four renewable energy build-out scenarios

We assumed the variable operations and maintenance costs for existing conventional generators in the future 2022 system to be the same as those in 2014 that we collected from the RLDCs and SLDCs. The majority component of these costs is the cost of fuel, which we assumed would remain the same in our study year. This assumption is not a projection of what the actual fuel costs would be in 2022. Because the relative costs of fuel are expected to remain the same, and with coal the dominant fuel source, assumptions on fuel costs do not significantly impact our conclusions, which are drawn from relative cost differences between sensitivities of how the system is operated.

Unless we had plant-specific information, new conventional generation capacity (plants built after 2015) is given the same physical parameters as existing capacity. For these new plants, we assumed their variable costs to be at the 10th percentile of existing plants of the same technology within a region, which is reflective of the higher efficiency expected of newly built plants.

Hydroelectric (hydro) plant characteristics are challenging to model due to hydro's multiple uses and diurnal and seasonal variations in resource availability. To recreate hydro availability, we used plant-specific generation data from 2014 (from POSOCO's SCADA data). Hydro with storage (reservoir or pondage) are constrained by maximum energy production (monthly) to capture the finite energy available, and daily minimum generation to capture the need to release water for agriculture or high discharge requirements during the monsoon season. Run-of-river plants are treated as must-take, with fixed flows based on a weekly average of generation, due to the inability of these plants to control the water

Table 3.2: Assumptions on Select Properties of Thermal Generators

Property and Source	Subcritical Coal	Supercritical Coal	Gas CC	Gas CT	Nuclear
Minimum generation level (% of maximum capacity)[1]	55	55	50	60	100
Ramp rate (% of maximum capacity per minute)[2]	1	1	3	3	-
Average variable operations and maintenance costs (INR/kWh)[3]	2.62	1.79	4.12	4.90	2.64
Average start-up cost (INR/MW)[4]	15038	15038	7030	6352	-
Average heat rate (GJ/MWh) [5]	10.46	10.15	7.07	10.96	-
Minimum up time (hours)	24	24	8	2	168
Minimum down time (hours)	24	24	8	2	168
Annual outage rates (sum of forced and maintenance outage rates) (% of year)[6]	25.14	24.94	47.7	31.1	40
Mean time to repair (hours)[7]	404	404	389	256	435

[1] Central Electricity Regulatory Commission's (CERC) regulations, 2016
[2] Provided by National Thermal Power Corporation (NTPC) as part of Technical Review Committee inputs.
[3] Collated by POSOCO from state and regional load dispatch centers, where available. Where not available, data were averaged by region and fuel type.
[4] NTPC and CEA Recommendations on Operation Norms for Thermal Power Stations Tariff Period 2014-19.
[5] CERC norms
[6] CEA Recommendations on Operation Norms for Thermal Power Stations Tariff Period 2014-19. Outage rates for gas generators include non-availability of fuel in addition to technical outages.
[7] Western Electricity Coordinating Council (WECC) 2024 common case

flow. Pumped storage plants are treated as a flexible resource, and are required to pump equivalent to energy production plus efficiency losses within their operable range.

3.2.2.2 Transmission

We adopted CEA's 2022 PSSE AC network model as the planned transmission buildout for 2022. This model reflects all finalized transmission plans by state transmission utilities and

PGCIL, including the Green Corridor plans. Refinements were made to this database in consultation with PGCIL to ensure that major transmission corridors are correctly represented in the production cost model. This refinement includes updates on the viability of future transmission projects, as well as estimated flow limits on major corridors. For this national study, we consider only interstate interconnections and ignore all intra-state transmission networks. The flow limits on inter-regional interconnections were based on projected available transfer capacities (ATCs), which are enforced in practice to ensure reliability. We also used knowledge of existing ATCs to inform the flow limits on inter-regional corridors that either do not have new capacity or are not expected to change dramatically before 2022. The flow limits on the rest of the interstate interconnections were based on the total surge impedance loading limits of all participating lines in a particular interconnection. Power flows between states are calculated using a linearized DC load flow model, which is a typical simplification made in large system production cost models.

3.2.2.3 Wind and Solar

In high RE futures, weather becomes a significant factor for not just electricity demand, but for supply as well. Because load and RE production are weather-correlated, we use the same weather year to generate model input data for wind, solar, and load. We chose 2014 as the base year for our study, meaning that we assume the weather in our study year of 2022 is identical to 2014.

RE Resource Data

Because we simulate both day-ahead unit commitment and real-time economic dispatch in our electricity system model, we created two sets of RE data: RE forecasts on which unit commitment decisions will be made; and RE actuals for the real-time dispatch. RE forecasts are intended to have an accuracy comparable to real-life day-ahead forecasting.

We simulated the wind actuals data using the Weather and Research Forecasting (WRF) model, a mesoscale numerical weather prediction model designed for atmospheric research and weather forecasting. We created an annual data set of physical parameters for the year 2014 that includes wind speed, relative humidity, and temperature at a spatial resolution of 3 kilometers (km), and a temporal resolution of 5 minutes. The Climate Forecast System Reanalysis data were used to define the boundary conditions (conditions that are specified at the edge of the India model domain). The wind actuals data set encompasses all states that are known to have a significant quality of wind resource. We then extracted the data at heights of 80 meters (m) and 100 m to correspond to the hub heights of wind turbines that are most likely to dominate the installed capacity in 2022.

For the wind forecasts, we used the WRF model with the Global Forecast Ensemble System (GEFS) data as boundary conditions at a spatial resolution of 9 km and a temporal resolution of 30 minutes. This method was adopted from the Wind Integration National Dataset (WIND) Toolkit, which was developed by NREL for the continental United States (Draxl et al. 2015). We chose GEFS data and a lower resolution of 9 km to produce day-ahead wind forecasts because higher resolution model runs, such as for the wind actuals, have shown to produce unrealistic forecast errors that were too low. The lower resolution of the forecast data enables us to simulate day-ahead forecast errors that are comparable to current state-of-the-art forecasts.

The solar actuals data, in the form of global horizontal irradiance (GHI), is from NREL's National Solar Radiation Database (NSRDB), simulated using the SUNY Semi-Empirical model (NREL 2016a). This model accounts for aerosols as well as cloud cover using observational data from 2014. These data have a temporal resolution of one hour, which we linearly interpolated to 15 minutes to match the resolution of our electricity model (see Section 3.2.2.5). The spatial resolution of the data is 10 km.

The solar forecasts were created from the same WRF model used to generate the wind forecasts data. The WRF model produced the GHI and meteorological data sets at half hourly and 9 km temporal and spatial resolutions. The data sets were interpolated to 15-minute interval, and translated to direct normal irradiance (DNI) and the diffuse horizontal irradiance (DHI), which were the required input parameters in the power generation software. Compared to the NSRDB used for solar actuals, the WRF model has a lower accuracy in predicting effects on radiation due to cloud cover. The WRF model also does not account for the effects of aerosols, thus over-predicting solar radiation. Therefore, the solar radiation forecasts provided, on average, a 5% bias toward higher solar resource availability compared to actuals. Because a 5% bias on 100 GW is potentially significant, we adjusted the power generation profiles as described in the section on RE Generation Data.

RE Site Selection

The RE site selection process determined the spatial distribution of wind and solar plants for each of our scenarios. We conducted a geospatial site suitability analysis for utility-scale RE by excluding protected areas, water bodies, high slope and elevation areas, certain land use land cover types, and thresholds for average wind speed and solar GHI (See Appendix F). We then split these suitable areas into spatial units of approximately 5 km^2, which we define as potential project sites. Typical land use factors for wind and utility-scale solar are 9 MW per km^2 and 30 MW per km^2, respectively (Denholm et al. 2009; Ong, Campbell, and Heath 2012. However, the entire area of a potential project site may not be available for RE development. By restricting the land availability to 25 percent, we assumed effective land use factors of 2.25 MW per km^2 for wind and 7.5 MW per km^2 for utility-scale solar plants. We then estimated the potential for installed capacity for each of these potential project sites.

In order to identify sites for each of our scenarios, we chose potential project sites that cumulatively totaled each RE capacity target.

- Existing locations (in 2015) (No-New-RE scenario: 5 GW solar; 23 GW wind): Because exact locations of all existing wind and solar plants are not publicly documented, we approximated these locations by selecting project sites with the highest resource quality that are within 25 km from a known RE pooling substation or an existing solar park. RLDCs and SLDCs provided existing wind and utility-scale solar PV capacity by substation, and PGCIL provided the locations and capacity of planned utility-scale solar parks.

- Wind capacity additions (High-Solar scenario: 37 GW new capacity to total 60 GW wind): To meet the additional 37 GW target of the High-Solar scenario, we chose the best potential project sites defined by resource quality from the among the states with MNRE capacity targets for 2022.
- Utility-scale solar capacity additions (High-Solar scenario: 55 GW new capacity to total 60 GW): Several utility-scale solar parks are being planned across the country. PGCIL provided the locations of planned solar parks with a cumulative capacity of 20 GW. To meet the solar capacity targets of the High-Solar scenario, we first selected potential project sites with the best resources within 25 km of these solar parks. We then selected the best potential project sites from across the country to meet the remainder of the utility-scale solar target. To ensure adequate geographic diversity, we restricted the installed utility-scale solar capacity within a state to no more than 15 percent of the total national target.
- Rooftop solar capacity additions (High-Solar scenario: 40 GW new rooftop capacity): We assigned all MNRE capacity targets to cities that were chosen to be part of the smart cities program, plus six additional large cities (e.g., Bangalore). For states with multiple smart cities, we assigned the state target in proportion to the built-up area of the chosen cities.

We used a similar approach for site selection for the other study scenarios (High-Wind and Very-High-RE). For wind in the High-Wind and Very-High-RE scenarios (both 100 GW wind), we began with all wind sites selected for High-Solar, and then added wind to states in proportion to the 60 GW state-wise wind targets. For solar in the Very-High-RE scenario (150 GW solar), we began with the sites in the 100 GW scenario, and added the new 50 GW as utility-scale solar PV from among the best resource sites, holding to the per state limit of 15% of total national utility-scale solar capacity.

RE Generation Data

The final step in preparing RE input data was to produce site-specific, time-series generation data, which we repeated for both actuals and forecast data. We first associated each selected RE project site with the nearest point with an RE resource time series. To create the 15-minute interval solar generation data, we used the solar data associated with each selected solar PV project site as inputs to the System Advisory Model (SAM). We assumed each solar PV project to be a fixed-tilt system, with the tilt set at the latitude of the site location. We estimated the power generation for 1 $MWac$ systems, and extrapolated those data to the potential installed capacity at each selected solar site. See Table 3.3 for assumptions used in the SAM simulation.

Table 3.3: Assumptions for solar PV capacity factor simulations in the System Advisor Model

Parameter	**Value**
System DC capacity	1.1 MW_{dc}
DC-to-AC ratio	1.1
Tilt of fixed tilt system	Latitude of location
Azimuth	180°
Inverter efficiency	96%
Losses	14%
Ground cover ratio	0.4

We simulated the 15-minute interval wind generation data for the selected sites using the wind speed resource data and wind power curves. Apart from wind speeds, wind power generation depends on the class of wind turbine, its hub height, and the air density of the location. We assumed an 80 m hub height for all existing wind turbines, and a 100 m hub height for all new installations. We classified each selected wind project site into the three prevalent wind turbine classes based on the average wind speed for that site. We used normalized wind power curves for each of the classes, and adjusted them for 10 different air densities (Svenningsen 2010). We estimated air densities for all sites using temperature and relative humidity data from the WRF model, and elevation from the digital elevation model. Associating each wind project site to the appropriate wind power curve based on the wind turbine class, hub height, and average air density of the location, we then converted the wind speeds into wind power generation for all selected sites.

For creating the wind and solar generation inputs for the production cost model, we had to associate each selected RE site to the nearest geospatially located substation. We then aggregated the generation profiles of all RE sites associated with a particular substation to create a normalized RE generation profile and an aggregated installed RE capacity for that substation.

3.2.2.4 Load

The CEA published their last annual state-wise energy and peak load forecasts to 2031-32 in their 18th Electric Power Survey (EPS) (CEA 2012). However, these forecast figures are expected to be significantly scaled down in the not-yet-released 19th EPS. In the meantime, the CEA has provided interim load forecasts, which we have used in this study.

To create the time series profiles of load for the 2022 study year, we used a combination of algorithms to extrapolate the historical 15-minute interval data for 2014 for each state, which were provided by POSOCO. The historical 2014 load data had some extreme sub-hourly variations, primarily due to two reasons - 1) missing data because of loss of link in the SCADA system, or a temporary lapse in the communication system, and 2) sudden load curtailment events, both planned or unplanned. Because we did not want to extrapolate and exaggerate these data anomalies to the study year, we created load trends by smoothing the sub-hourly variations using a moving average filter with a window spanning 75 minutes (two data points before and after the actual point). We then linearly extrapolated the load duration curves of the 2014 load trend to 2022. Using a combination of linear and exponential functions, we adjusted the load duration curves to match both the annual energy and peak load forecasts of CEA. Figure 3.2 shows the national average daily load profiles for each month in 2014 and 2022.

Load shapes in 2022 may also change with changing appliance ownership (e.g., air conditioners) and usage patterns. However, we did not modify the load shapes, assuming that the changes may not be significant by 2022.

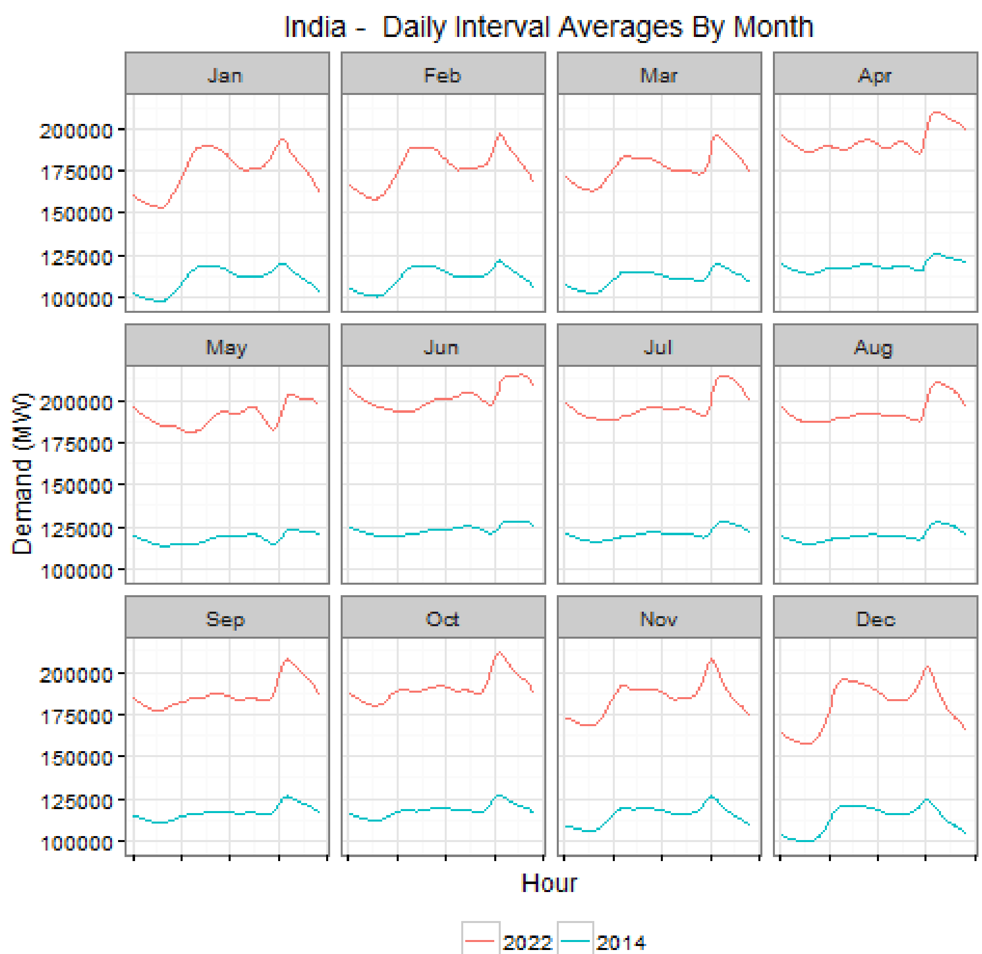


Figure 3.2: Average daily load curves by month for India for 2014 (actuals) and 2022 (forecast).

3.2.2.5 System Operations

The operation of the power system is simulated using an economic unit commitment and dispatch model that incorporates constraints such as transmission, scheduling sequences, and physical parameters of generation plants. The model commits generating units on an hourly basis 24-hours ahead using forecasts for load and RE; and then runs an economic dispatch using real-time load and RE data for each 15-minute block of the year. Within each 15-minute time-block, the model finds a least cost solution for meeting the electricity demand of the whole system. The model assumes that all plants, within their physical constraints, are available for scheduling if they are not on an outage and that all electricity demand is met with 24/7 reliability. Constraints that we have not modeled include bilateral contracts, allocations of centrally owned plants, and must-run status of conventional plants needed for reliability.

The modeled process of scheduling is relatively close to actual operational procedures, although there are a number of inefficiencies within the actual scheduling that we capture. The most prominent of these is the existence of small balancing authorities (typically SLDCs) that serve their own demand with a smaller subset of resources with limited knowledge of schedules of neighboring balancing authorities (BA). This knowledge gap is essentially a barrier to more efficient trade, which we represent in the model through an import cost (this cost is excluded from production cost calculations). By assigning import costs, a state is incentivized to use its own resources to balance generation and load before importing, similar to present practices. We validated this method by comparing 2014 modeled and actual data, such as inter-regional power flows and state-wise generation.

RE Operations

In India's present system, central generators of coal and gas recover capital costs through fixed tariffs (capacity charges), which are paid based on availability, independent of actual production. Separately operating costs are recovered through production-based tariffs (energy charges). In contrast, fixed costs for utility-scale RE, which have no fuel costs, are recovered through a production-based feed-in tariff. The feed-in tariff, which is a levelized cost of renewable energy, is either set by state tariff regulations or discovered via an auction mechanism. Our model does not use this feed-in tariff as the variable cost for RE because production costs are zero. Nevertheless, because in practice, wind and solar are considered must run, modeling RE with zero variable costs achieves a similar dispatch outcome to India's treatment of RE as having variable costs but with must-run status.

Our model treats utility-scale wind and solar plants the same as conventional plants in that they are dispatched according to least cost principles. This means that wind and solar can be curtailed if it is economical from a total system optimization perspective, for example, to avoid an uneconomical (from a system perspective) shutdown and restart of a conventional generator. Rooftop-PV, on the other hand, is must-take because SLDCs are not likely to have control of those resources and must balance rooftop PV along with load and generation.

Reserves
We modeled operating reserves for ancillary services by optimally provisioning for them alongside energy based on least cost principles. Reserves are held according to the CERC roadmap of secondary reserves, equivalent to the largest unit in the region, held by central plants, and tertiary reserves equal to 50% of the largest unit in the state. For tertiary reserves, all generators within a state are eligible to provide them. We assumed that utility-scale RE plants are equipped with automatic generation control and are eligible to provide down reserves. The model will choose eligible generating plants to meet these reserve requirements; this capacity is therefore not available for scheduling and dispatch for energy production. The model holds but does not dispatch these reserves because dispatch under 15 minutes is outside the scope of the study.

3.3 Operational Impacts of 160 GW Variable Renewable Energy

Using a variety of metrics, we analyzed the results of the High-Solar scenario to better understand how 100 GW of solar and 60 GW of wind could impact India's power system. In particular, we address the following questions:

1. How does wind and solar contribute to total generation?
2. How do operations of the conventional fleet change?
3. How does the RE affect inter-regional power flows?

Where relevant, we compared these results to the No-New-RE scenario. For both the High-Solar and No-New-RE scenarios, we assume a state managed scheduling and dispatch, as described in Section 3.2.

3.3.1 Solar and wind generation's contribution to the electricity system in 2022

Solar and wind generation can be measured in a variety of ways to inform planning and operations: total generation, annual and instantaneous penetration levels, capacity factors and values, and curtailment (the energy that could have been generated but was not used), among others.

The 160 GW of solar and wind in the High-Solar scenario generates 370 TWh annually, resulting in annual averages of 10.9% of solar and 11.6% of wind penetration levels in 2022.

The total annual generation from solar and wind in the High-Solar scenario is 4.7 times greater than that from the 28 GW of variable RE capacity in the No-New-RE scenario.[3] These 160 GW of variable RE contribute towards meeting 22.5% of India's demand in 2022.[4]

Figure 3.3 shows solar and wind generation and their penetration levels (percentage of demand) by month. Solar generation output remains fairly constant month-to-month, with the greatest being in the summer months of March, April, and May. Wind generation is seasonal and is greatest during the monsoon months, peaking in June and July. The highest monthly RE penetration levels occur during June (31.7%) and July (31.9%), with an instantaneous peak of 65%. The lowest monthly average RE penetration level is 15.3% in November, when wind generation is at its lowest level.

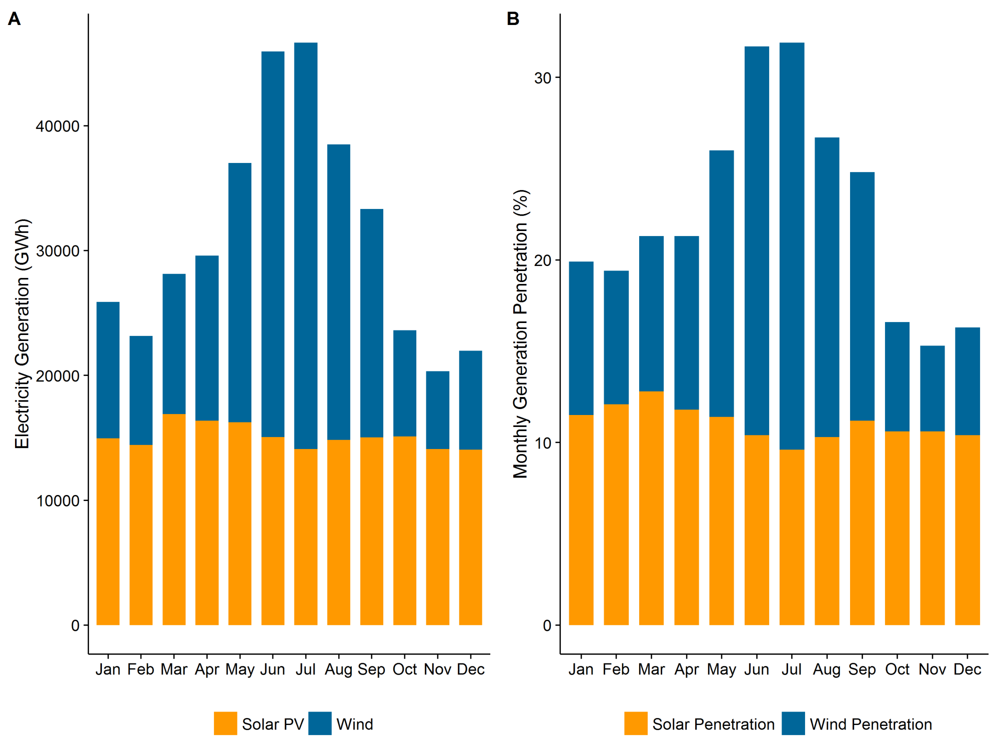


Figure 3.3: Monthly electricity generation (A) and share of demand (B) of 100 GW solar and 60 GW wind in 2022.

Significant spatial variation in RE generation exists across India (See Figure 3.4). South-

[3]Although the No-New-RE scenario has the same installed variable RE capacity as 2014, the simulated RE generation is significantly greater than actual RE generation in 2014 because of our assumption that the entire fleet of existing wind turbines have an 80m hub height, which is likely higher than the average hub height of the existing fleet. Actual 2014 RE generation is also lower because of curtailment.

[4]Actual contribution of wind and solar generation will depend on realized demand in 2022, and multiple factors including but not limited to hub heights of wind turbine fleets, weather in 2022, fleet-wide efficiency, locations of new RE capacity, and curtailment due to congestion and other factors.

ern and western states are expected to install and generate RE significantly more than the rest of the country. The eight states shown in Figure 3.5 generate 90% of the total RE generation in 2022. Six of these states exceed annual averages of 50% penetration levels relative to the states' load.

The spatial and temporal variation of RE generation and how it interacts with variations in conventional generation and load will have different impacts in different regions and at different times of the day or year.

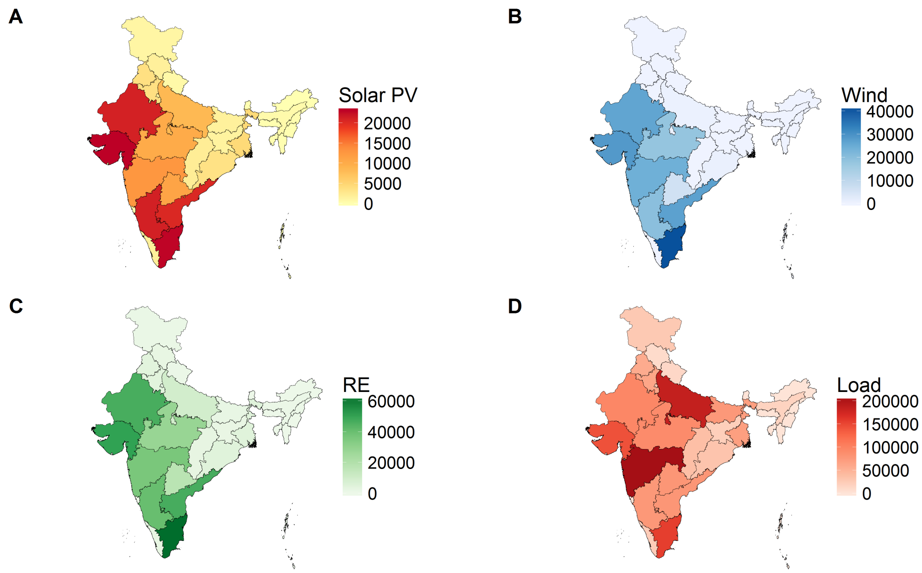


Figure 3.4: Spatial distribution of RE generation and load by state for 100 GW solar and 60 GW wind in 2022.

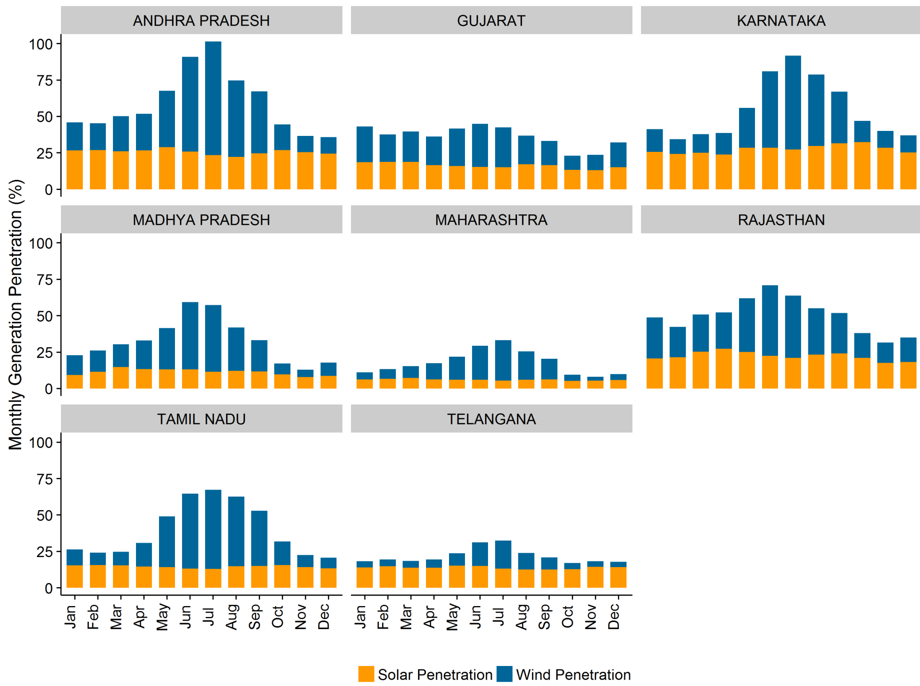


Figure 3.5: Monthly penetration or share of demand of 100 GW solar and 60 GW wind in 2022 in eight states of India that account for 90% of wind and solar generation in the High-Solar scenario.

Average annual capacity factor is 21% for solar PV plants and 37% for wind plants.

Capacity factor is a measure of how much energy is produced by a generator compared with its maximum rated output. The average annual capacity factors for solar and wind derived from our model are indicated in Table 3.4.

The capacity factors of wind in our modeling outputs are greater than the existing fleet due to higher assumed hub heights (80m and 100 m in 2022, versus a mix of 50 m and 80 m today), better site selection (best wind resource areas, without consideration of all factors determining availability of those sites), and no curtailment due to local transmission constraints and line outages, Simulated capacity factors of the solar PV fleet could differ from those realized in the future depending on how the mix of solar PV technologies (fixed tilt or tracking) evolves and how the aerosol layer changes across India. Note that wind and solar generation in 2022 assumes that the weather in 2022 is identical to 2014.

The solar capacity factors are similar across all states, except for Jammu & Kashmir where high insolation levels in the Ladakh region result in high capacity factors. Tamil Nadu has the highest capacity factors for wind, whereas Rajasthan, Madhya Pradesh, and Uttar Pradesh have the lowest.

Table 3.4: Average annual capacity factors for utility-scale solar PV, rooftop solar PV, and wind

	Solar Utility-scale	**Solar Rooftop PV**	**Wind**
Capacity Factor	29.9%	20.4%	36.4%

At 160 GW, wind and solar may lose 1% of their generation potential to curtailment annually.

Curtailment is the reduction in output of a plant from what it would otherwise be able to generate given available resources. Although RE curtailment discards generation that is free to produce, there are times when curtailing RE helps produce the least-cost electricity production. Curtailment can occur for a number of reasons, including insufficient transmission capacity or an event where ramping requirements exceed the capabilities of available conventional plants.

Figure 3.6 shows the average day of RE curtailment in different periods of the year. The monsoon months experience much higher levels of curtailment as wind, solar and hydro availability is higher and flexibility in hydro is lower. Curtailment in our model primarily occurs during the day due to economics i.e. curtailing RE produces the least-cost production. For example, when solar output is high during the day, coal, which should otherwise be reduced due to higher fuel costs, may need to be dispatched because its generation is needed during evening peak net load periods. RE is curtailed because the value of this curtailed RE generation is less than the cost of shutting down and restarting the coal plant to meet evening peak. In most cases, it is difficult to isolate the cause of curtailment, as changing different factors (transmission capacity and locations, minimum thermal generation set points, operating costs) all affect the timing and locations of curtailment. As a hypothetical example, curtailment that occurs because local generating plants are not able to ramp quickly to match net load could be eliminated by any number of different strategies: improving ramp rates, increasing transmission capacity to neighboring regions, increasing the balancing area to include other RE generation that smooths net load, changing contract terms that free up available physical capacity, and so forth. These interrelationships - RE curtailment and the physical and operational aspects of the power system - are explored further in Section 3.4.

Figure 3.7 shows RE curtailment by energy (total GWh energy curtailed) and as a percentage reduction compared to output that would have been generated given available wind and solar resources. The figures are provided by region and by month. The Southern Region dominates the curtailment, accounting for 97% of the country's total curtailment, with 86% of that happening in the monsoon months of June through September. Almost one-third of the total happens in July alone leading to 4% of curtailment in that month. The Eastern Region, while having a small portion of the overall installed RE, still faces potentially high curtailment during certain times of the year reaching 1.4% in September.

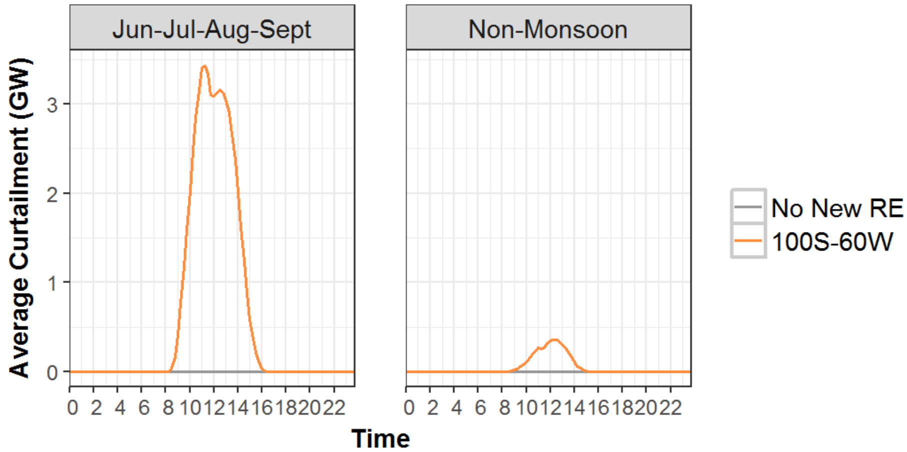


Figure 3.6: Average day of curtailment for the whole country for different periods of the year. Monsoon months include June, July, August, and September when wind generation is high in the western and southern states.

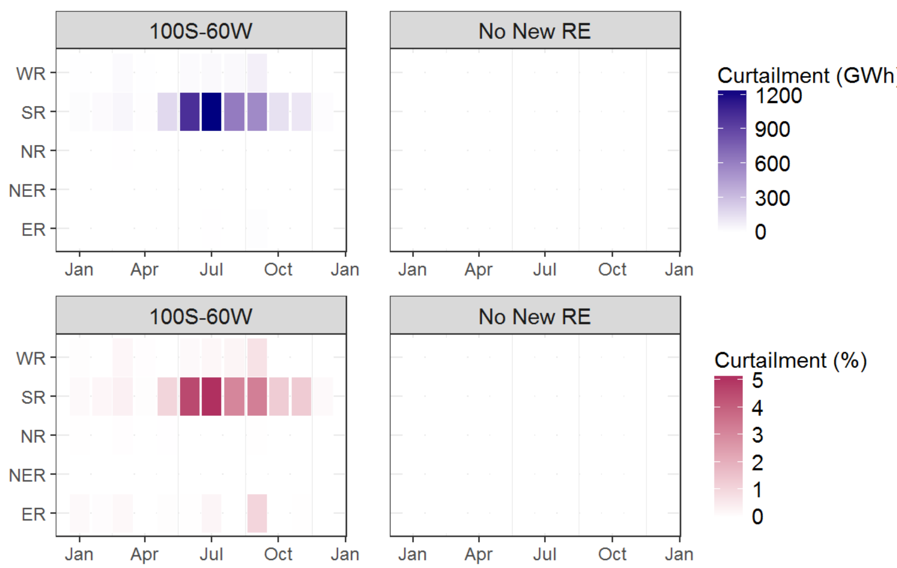


Figure 3.7: RE curtailment in energy (GWh) and as a percentage reduction against available, by region and month

3.3.2 Impacts of RE on operations of thermal plants

Wind and solar not only displace conventional, especially thermal generation and their associated fuels, but also impact their operations in terms of reduced plant load factors and greater cycling.

Generation from the additional 132 GW of solar and wind in the High-Solar scenario avoids 272 TWh (21%) of coal and 18 TWh (36%) of gas compared with the No-New-RE scenario.

Figure 3.8 illustrates annual generation by type, comparing the High-Solar (100S-60W) scenario with No-New-RE. The increase in RE generation displaces generation that has more expensive operating costs. Compared to the No-New-RE scenario, subcritical coal is most affected by the installation of solar and wind. Depending upon their variable costs, overall generation at subcritical coal plants fell by 24%, whereas generation at supercritical coal plants dropped by 15%.

Gas generation reduces by 36% in the High-Solar scenario because it is displaced by both zero marginal cost RE and cheaper coal generation from overbuilt coal capacity in that scenario. However, gas-based generation only accounts for a small fraction of the overall generation (3% in the No-New-RE scenario).

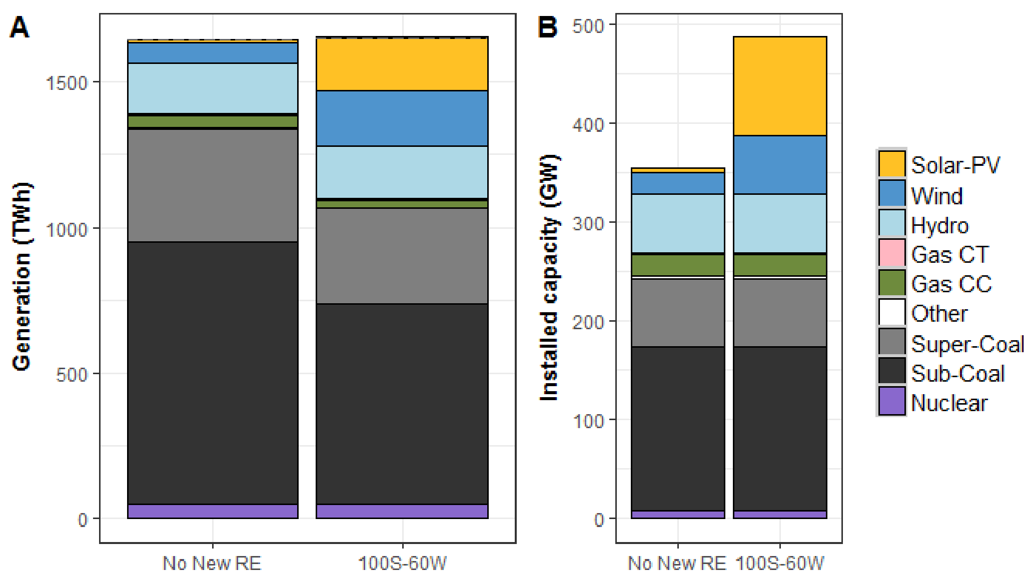


Figure 3.8: Annual generation (A) and installed capacity (B) by generation type for No-New-RE and High-Solar (100Solar - 60Wind) scenarios

Figure 3.9 shows the difference in annual generation of the High-Solar and No-New-RE scenarios, by region. Based on the RE capacity expansion discussed in Section 3.2, the majority of new RE generation occurs in the southern and western regions, and the state of Rajasthan in the northern region. Wind and solar displace mainly coal generation, but this displacement is not uniform across regions. In the High-Solar scenario, much more coal generation is displaced in the western and eastern regions relative to the RE generation within those regions, mainly because of increased exports from the southern region, as we illustrate later.

Because of the reduction in thermal generation, coal consumption drops from 680 million metric tonnes to 540 million metric tonnes, a reduction of 21%, whereas gas consumption drops by 37%.

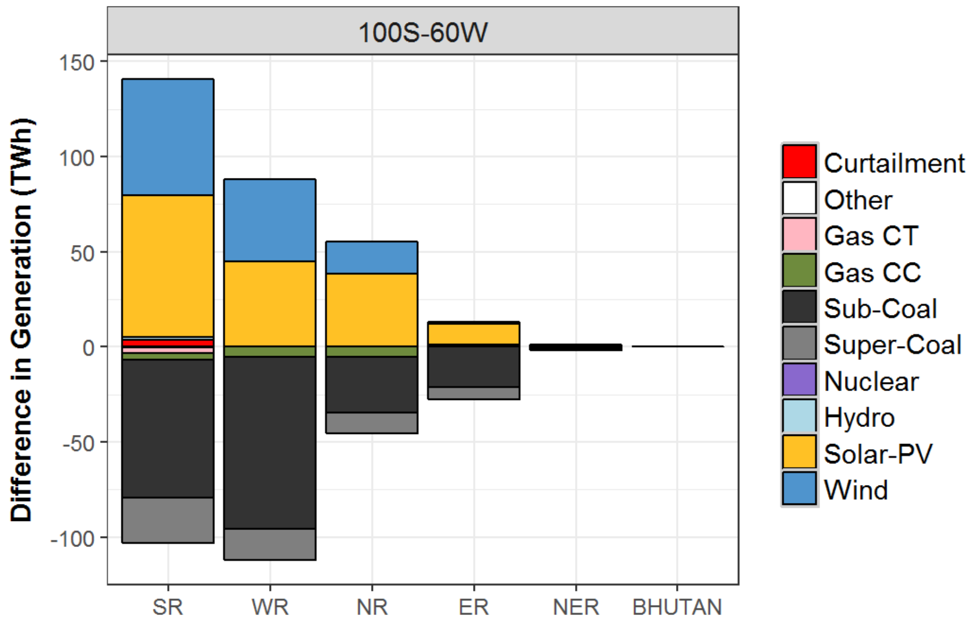


Figure 3.9: Difference in generation of High-Solar (100Solar - 60Wind) scenario from No-New-RE scenario

Plant load factors of coal plants fall to an average of approximately 50%, with 19 GW capacity that never starts

Table 3.5 summarizes the plant load factors (PLF) of gas, super-critical coal, and sub-critical coal plants. In each case, the thermal load factors drop, with sub-critical coal plants affected the most. The amount of coal capacity that never starts rises from 21.5 GW in the No-New-RE scenario to 33 GW in the High-Solar scenario (see Table 3.6). These plants are uneconomical to run at any point in the year, reflecting excess generation capacity even in the absence of new wind and solar installations.

Cycling of coal and gas plants increases in the High-Solar scenario. Ramping is discussed in section 3.5.2. The cycling of thermal plants, while an instrumental source of flexibility for the power system, does cause damage and affect plant life expectancy. The primary type of damage is thermal fatigue, created by large temperature swings, for example as a plant starts up and materials heat up at different rates, which causes cracking and part failures (Cochran, Lew, and Kumar 2013). Other types of damage include wear and tear on cycling-specific auxiliary equipment and corrosion from oxygen entering the system and from condensation from cooling steam.

Several studies have evaluated the costs of cycling, including Kumar et al. (2012), which calculated operating, maintenance, and repair costs associated with start ups, operations at minimum generation, and other cycling operations. Lew and Brinkman (2013) incorporated these cycling costs into a unit commitment and dispatch optimization of a high RE future in the western interconnection of the United States as part of phase 2 of WWSIS. The cycling costs affect dispatch through reduced cycling compared to WWSIS phase 1 (NREL 2010) that did not include these costs. Nevertheless, from a system perspective the costs of cycling were relatively small. These costs ranged from USD 0.92-2.36/MWh, a small fraction of fuel costs that range from USD 20-40/MWh, which is the major driver of dispatch decisions and production costs.

Table 3.5: Comparison of plant load factors of thermal plants by generation type for No-New-RE and High-Solar scenarios

Type of Generator	No-New-RE	High-Solar
Gas CC	22%	14%
Gas CT	59%	34%
Sub-critical coal	62%	47%
Super-critical coal	64%	55%

Table 3.6: Comparison of capacity of thermal plants that never turns on, by generation type for No-New-RE and High-Solar scenarios

Type of Generator	No-New-RE	High-Solar
Gas	2 GW	2 GW
Sub-critical coal	9 GW	16 GW
Super-critical coal	3 GW	4 GW

3.3.3 Effect of RE on hydro generation

Hydro generation includes generation from storage hydro, run-of-river hydro, and pondage hydro plants. Some part of the hydro generation is must-run based on historical SCADA data from 2014, and the rest was allowed to be dispatched to meet net load and minimize overall costs. Because hydro generation is assumed to have zero marginal cost, the dispatchable energy from hydro plants is generated during the net peak load intervals subject to monthly energy constraints.

Hydro generation develops a distinct diurnal pattern with high generation during morning and evening peak net load hours.

Figure 3.10 shows the hydro generation for an average day for the five electricity regions in the monsoon and non-monsoon months. In the High-Solar scenario, hydro is dispatched more in net peak load hours during the mornings and evenings, and less during the middle of the day when solar generation is high. The higher generation from hydro plants during the monsoon months, especially in the Northern Region, is mainly due to must-run run-of-river plants and greater flows required from storage plants due to high storage levels. Hence, this higher energy generation during the monsoons does not translate into greater dispatchable energy available for balancing the higher wind and overall VRE generation during those months.

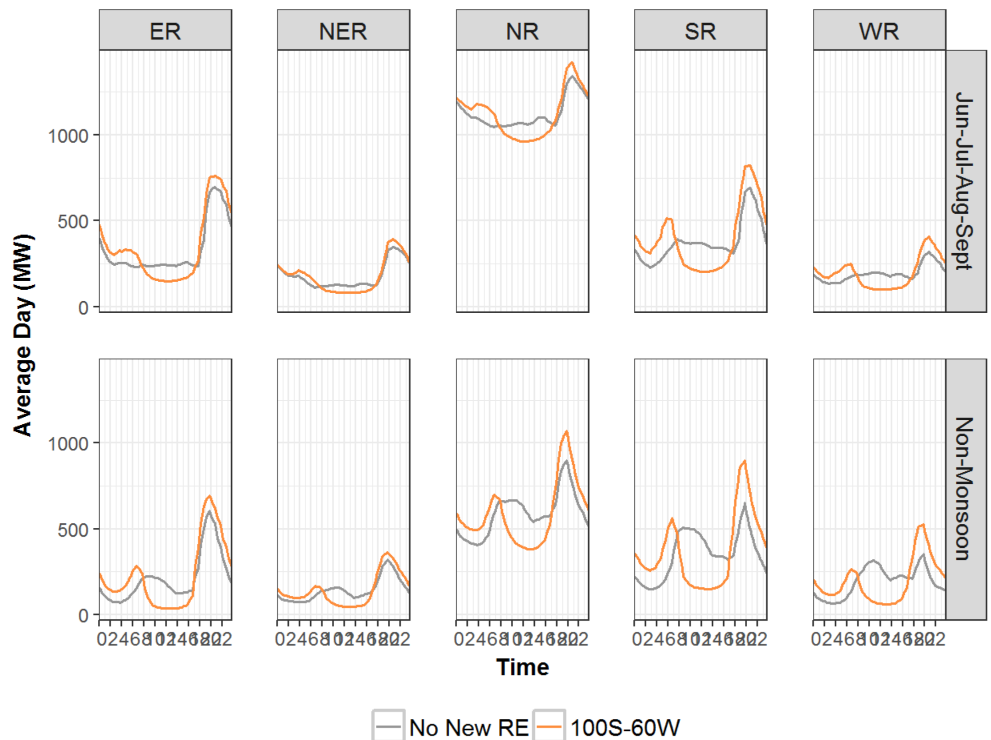


Figure 3.10: Hydro generation for an average day in the monsoon and non-monsoon months for No-New-RE and High-Solar (100Solar - 60Wind) scenarios

3.3.4 Changes in transmission flows due to spatial effects of RE generation

The spatial diversity of wind and solar resources and the resulting generation from those plants affect transmission flows. Quantifying transmission flows and congestion on interfaces can identify bottlenecks and inform transmission planning studies.

Total transmission flows across all interfaces decrease by 8%.

Absolute total transmission flows (sum of all flows on all transmission interfaces) within regions (on intra-regional transmission interfaces) fell by 7% from 410 TWh for the No-New-RE scenario to 380 TWh for the High-Solar scenario. Total flows between regions (on inter-regional transmission interfaces) also decreased by 11% in the High-Solar scenario, falling from 180 TWh to 160 TWh. The largest reduction in inter-regional transmission flows is on the ER-SR interface because of higher VRE generation in the Southern Region and the resulting lower imports (Figure 3.11). Flows on the WR-SR interface changed from flowing predominantly from the Western Region to the Southern Region in the No-New-RE scenario to flowing in both directions in the High-Solar scenario. Exports from the Southern Region increased 12 times because of the high VRE generation in the southern states.

In the High-Solar scenario, congestion decreased on some inter-regional interfaces (WR-NR, WR-ER, and ER-SR) but increased on others (NR-ER and SR-WR) as compared with the No-New-RE scenario.[5] Results of congestion can be used to inform transmission planning studies.

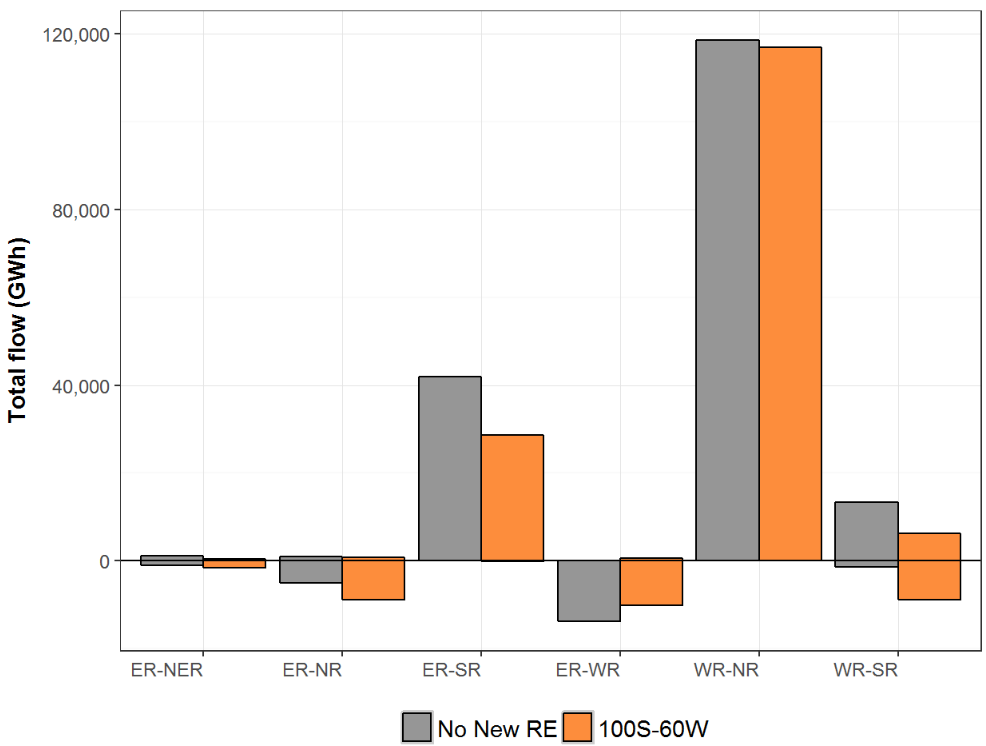


Figure 3.11: Transmission flows on inter-regional interfaces for No-New-RE and High-Solar (100Solar - 60Wind) scenarios. Flows are shown in both directions.

[5]Direction of flow is from the first region to the second region.

Summary: The 160 GW of solar and wind capacity has significant impacts on operations of conventional generation plants including greater cycling and lower plant load factors. Higher VRE generation also effects transmission flows including direction of flows and congestion. Constraints on both conventional generators and transmission interfaces affect the overall production costs and curtailment of VRE. In the next section, we analyze different strategies to mitigate the impacts of the 160 GW VRE target on the 2022 power system.

3.4 Evaluating Strategies to Mitigate Impacts of RE Generation

The objective of this section is to evaluate strategies to improve variable RE integration. To evaluate the effectiveness of VRE integration, we focus primarily on electricity production costs and VRE curtailment. This means that we can address the cost-effectiveness of mitigation measures by comparing production costs between a reference or base case and a sensitivity case. By introducing only a single change in the modeling, this makes it possible to evaluate the monetary benefit of specific mitigation measures, either one at a time or in combination, so that we can provide some insights for decision-makers. By comparing the level of curtailment of VRE, we gain indirect insights to overall costs (high levels of curtailment make VRE more expensive) but can also see which measures may allow for the unconstrained use of all potential VRE that has been installed. We also analyze transmission flows and congestion on inter-regional transmission interfaces to gain insights into potential reasons for change in productions costs and VRE curtailment.

Based on this background, we are now in a position to answer some key questions about the effective integration of VRE:

1. How can VRE curtailment be reduced?
2. How can the system be operated more cost-efficiently?
3. How sensitive are the results to assumptions on coal flexibility and transmission development?

We evaluated several strategies, also termed as sensitivities, by changing the appropriate inputs and specifications in the electricity production cost model used in this study. The sensitivities that we evaluated are listed in the following tables and address four aspects of flexible operations:

1. Coordination of scheduling and dispatch
2. Operation of coal plants
3. Availability of transmission

Table 3.7: Coordination of scheduling and dispatch (market/transactional flexibility)

Sensitivity	Base	More Flexible	Most Flexible
Size of balancing area for scheduling and dispatch	State dispatch (current practices)	Regionally coordinated dispatch	Nationally coordinated dispatch

Table 3.8: Operation of coal plants (supply-side flexibility)

Sensitivity	Base	Less Flexible	More Flexible
Minimum plant generation levels (% rated capacity)	55%	70%	40%
Ramp rates (% rated capacity per minute	1%	0,5%	
Minimum up/down times (hours)	24/24		12/12
Start-up costs (INR)	15,038	Double	

Table 3.9: Transmission capacity (supply-side flexibility)

Sensitivity	Base	Less Flexible	More Flexible
Inter-regional transmission	CEA projections	-25% interface capacity	+25% interface capacity

3.4.1 Improved coordination across state balancing areas

When power system coordination is done on a larger geographic and electrical footprint, this improves the cost-effectiveness of operations. A larger balancing region combines diverse loads and therefore leverages the diversity in demand. At the same time, aggregating VRE over larger regions performs a similar function and reduces per-unit ramping and variability. A larger pool of conventional generation is also more cost-effective to operate because economical units sometimes become available to more remote regions under pooling. The first sensitivity evaluates two alternative levels of coordination: regional and national. Both of these approaches are compared to the reference case (Business-as-usual or Base case) in which state balancing areas are responsible for maintaining system balance.

To represent alternative levels of operational coordination, we used hurdle rates (export and transmission charges) to capture existing preferences among states to conduct their own scheduling and dispatch, without coordination with other states. Because coordination between balancing areas has been demonstrated in other areas to be a significant strategy to integrate RE, we analyzed three levels of coordination: state (business-as-usual, our reference case), regional coordination (e.g., through Regional Load Dispatch Centers), and national coordination (e.g., through the National Load Dispatch Center or wholesale power market).

1. State scheduling and dispatch reflects business-as-usual operations.
2. Regionally coordinated scheduling and dispatch implies that system operators in each of the five electricity regions have access to all generation within their region in order to schedule and dispatch generation at least cost.
3. Nationally coordinated scheduling and dispatch assumes a national system or market operator can create schedules (or adjust state-supplied schedules) to operate plants at least cost.

Hurdle rates on state balancing area exports capture constraints on the ability of states to import freely from other states, whereas hurdle rates on inter-regional transmission interfaces are used to calibrate modeled flows against observed data. Table 3.10 summarizes the hurdle rates used in our sensitivities.

Table 3.10: Hurdle rates used to capture existing barriers to trade and to evaluate the value of alternative operating practices

Hurdle rates	**State scheduling/ dispatch**	**Regionally coordinated scheduling/ dispatch**	**Nationally coordinated scheduling/ dispatch**
Inter-regional interfaces[1]	175-1200 INR	175-1200 INR	None
Balancing area exports	1000 INR (except 400 INR in NER)	None	None

[1]Hurdle rate on each inter-regional interface was tuned based on a 2014 production cost model of India's electricity system.

Greater coordination amongst states results in lower overall production costs because system operators have access to both cheaper and more flexible conventional generation sources across their regions. Coordinating scheduling and dispatch over a broad area also smooths per-unit load and VRE variability, reduces net ramp requirements, and reduces curtailment by enabling more export of VRE.

The results of these sensitivities are illustrated below. Figure 3.12 compares the production costs across these three modes of scheduling and dispatch. Production costs drop INR 6,600 crore (approximately USD 960 million), equivalent to 3.0%, when schedules are optimized at the region rather than by state. Nationally coordinated scheduling and dispatch further reduces production costs by INR 1,500 crore, totaling INR 8,100 crore (USD 1,200 million) or 3.7% less as compared to state-based schedules.

Removing the hurdle rates on the balancing area exports in the regionally coordinated dispatch scenario affects merit order dispatch, with cheaper conventional generation from some states being more available for exports and thus displacing more expensive generation from other states. Further, removing hurdle rates on the inter-regional interfaces in the

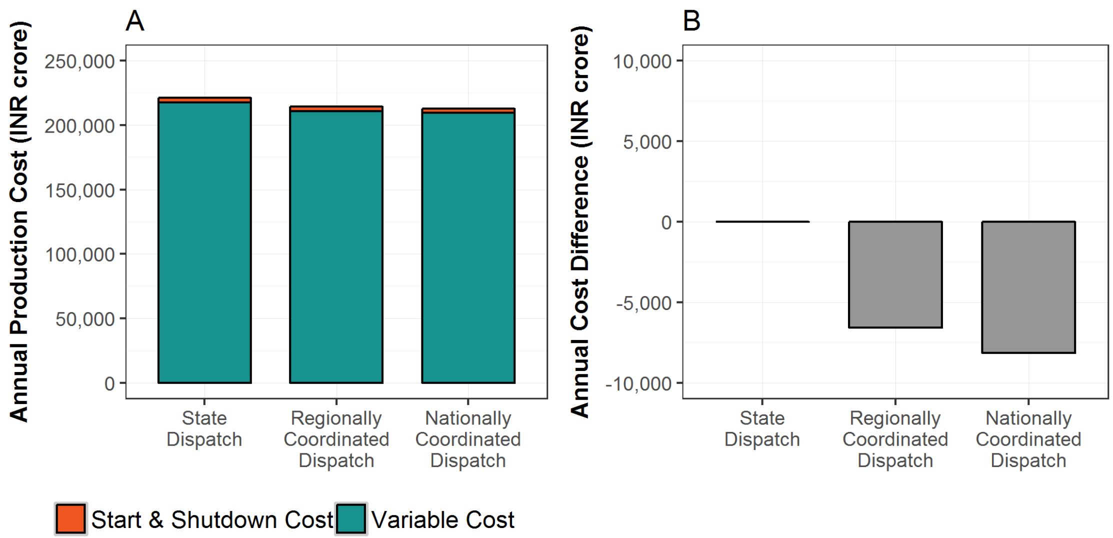


Figure 3.12: Impact of coordinated dispatch on annual production costs - total (A) and differences from state dispatch (B)

nationally coordinated dispatch scenario allows greater trade between regions and lowering overall costs.

As illustrated in Figure 3.13 and Figure 3.14, the impact by region depends on the level of coordination. Overall, with increased coordination, generation increases in the Western and Eastern Regions, and decreases in the Southern and Northern Regions. Generation and generation costs increase in the Eastern Region in shifting from state to regionally coordinated dispatch, but fall when further increasing coordination to the national level, when generation in the Western Region increases. Generation in the Western Region increases with both regionally and nationally coordinated dispatch, but generation costs decrease with regional coordination and increase with national coordination.

Figure 3.15 further illustrates the impact to each region by showing changes in annual generation for each generator based on its variable cost when shifting from state dispatch to regionally coordinated dispatch. Each dot represents the difference in annual generation of a generator plotted against its variable cost (which is assumed constant throughout the year). The figure highlights the reshuffling of generation when shifting from state to regionally coordinated dispatch. The significant change in merit order dispatch occurs in the western region. The plot, on the far right, shows lower cost sub-critical coal offsetting more expensive sub- and super-critical coal, which (not illustrated) are located in different states of the Western Region. The most significant increase in coal generation occurs in Chhattisgarh, Madhya Pradesh, Odisha, and Andhra Pradesh, whereas the largest decrease in generation occurs in Maharashtra.

Figure 3.16 illustrates a relatively smaller impact on RE curtailment, compared to impact

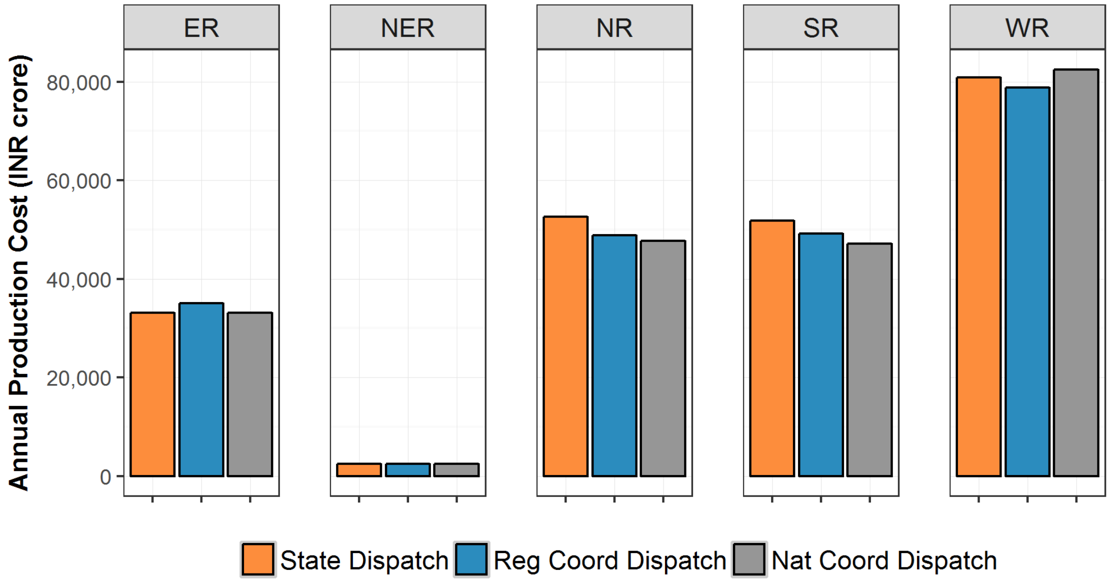


Figure 3.13: Impact of coordinated dispatch on annual production costs - total (A) and differences from state dispatch (B)

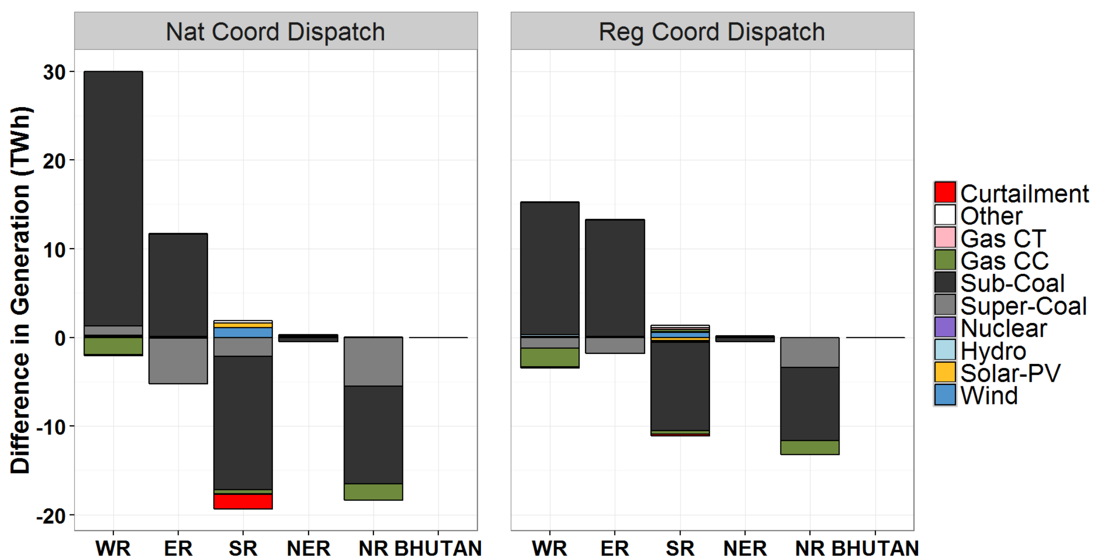


Figure 3.14: Impact of coordinated dispatch on annual generation, by fuel type and region; differences are in comparison with state dispatch

on production costs. In shifting from state to regional to nationally coordinated scheduling and dispatch, RE curtailment decreases from 4,100 to 3,800 to 2,400 GWh, respectively, translating to 1.1%, 1%, and 0.7% levels of VRE curtailment. Greater coordination allows

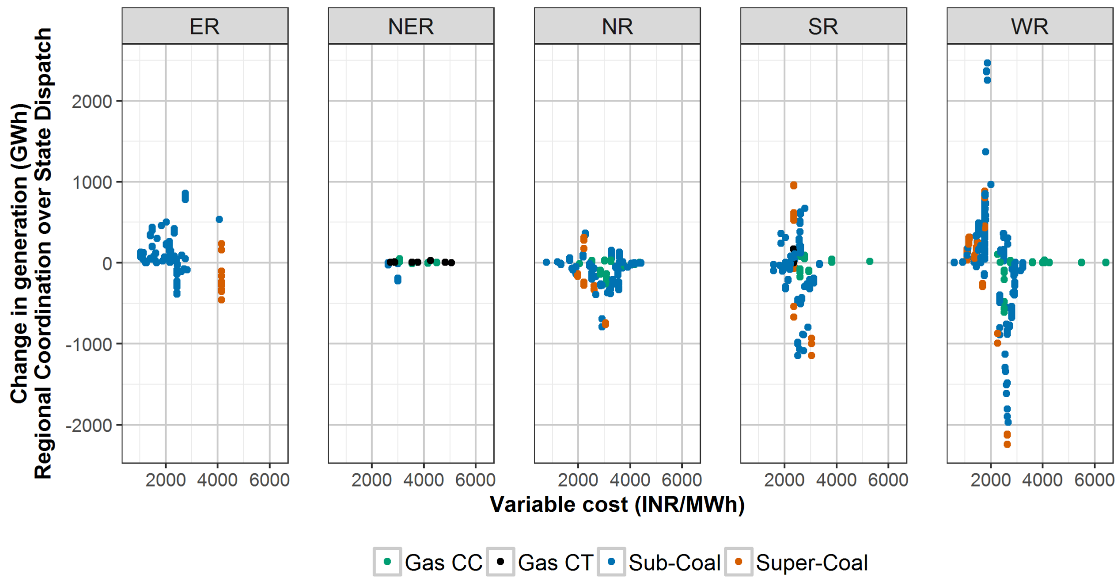


Figure 3.15: Change in generation between regionally coordinated and state dispatch, by region, fuel type, and variable cost

sharing of generation resources, requiring fewer conventional generation units to be committed in the day-ahead schedule. As a result, overall minimum generation levels of the thermal fleet are lower in scenarios with better coordination, leading to greater flexibility in the committed coal units to reduce output, and therefore less curtailment of RE during low net load periods.

Figure 3.17 disaggregates curtailment by region, with the greatest drop seen in the Southern region, which is where curtailment is most pronounced. With increasing coordination, the southern states share their thermal resources and rely more heavily on imports, resulting in an average decrease in committed coal capacity of 6%, with regionally coordinated dispatch, and 12%, with nationally coordinated dispatch. With fewer thermal units committed but run at higher plant loading, the ability of the Southern Region to turn down its thermal fleet increases, and with it, the ability to absorb more RE also increases.

Figure 3.18 shows the impact of coordination on transmission flows (A) and congestion (B) on inter-regional interfaces. With more coordinated dispatch, total flows across all inter-regional interfaces increases. Annual absolute flows on inter-regional interfaces increase from 160 TWh for state dispatch to 180 TWh (11% rise) in the regionally coordinated dispatch scenario and to 250 TWh (52% rise) in the nationally coordinated dispatch scenario. At the same time, the percentage of time that these interfaces are congested also increases. Some interfaces such as ER-NR (in the direction of NR to ER) are congested for more than 40% of the year in all scenarios. When congestion occurs it prevents access to the lowest cost generation thus increases overall system costs.

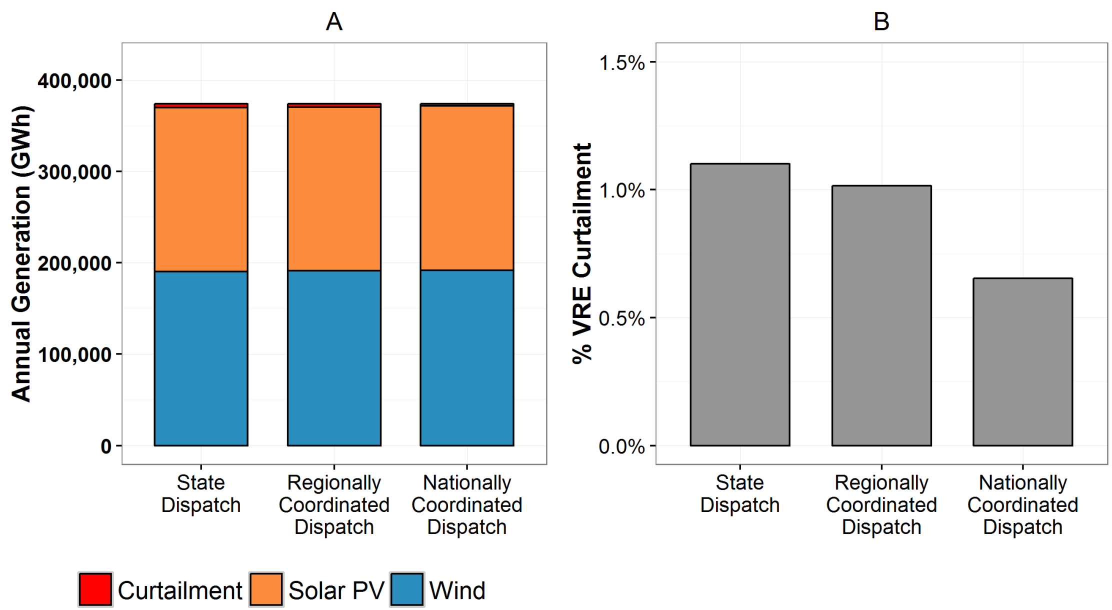


Figure 3.16: Change in generation between regionally coordinated and state dispatch, by region, fuel type, and variable cost

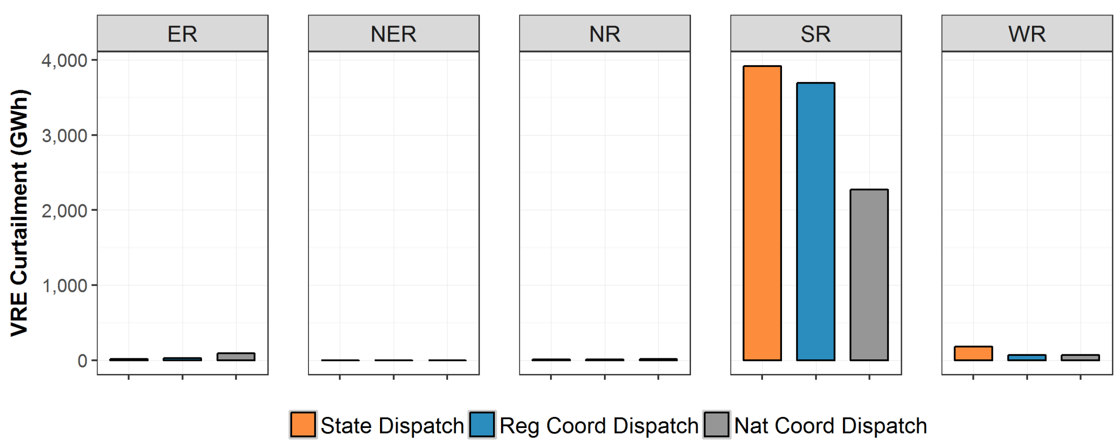


Figure 3.17: Change in generation between regionally coordinated and state dispatch, by region, fuel type, and variable cost

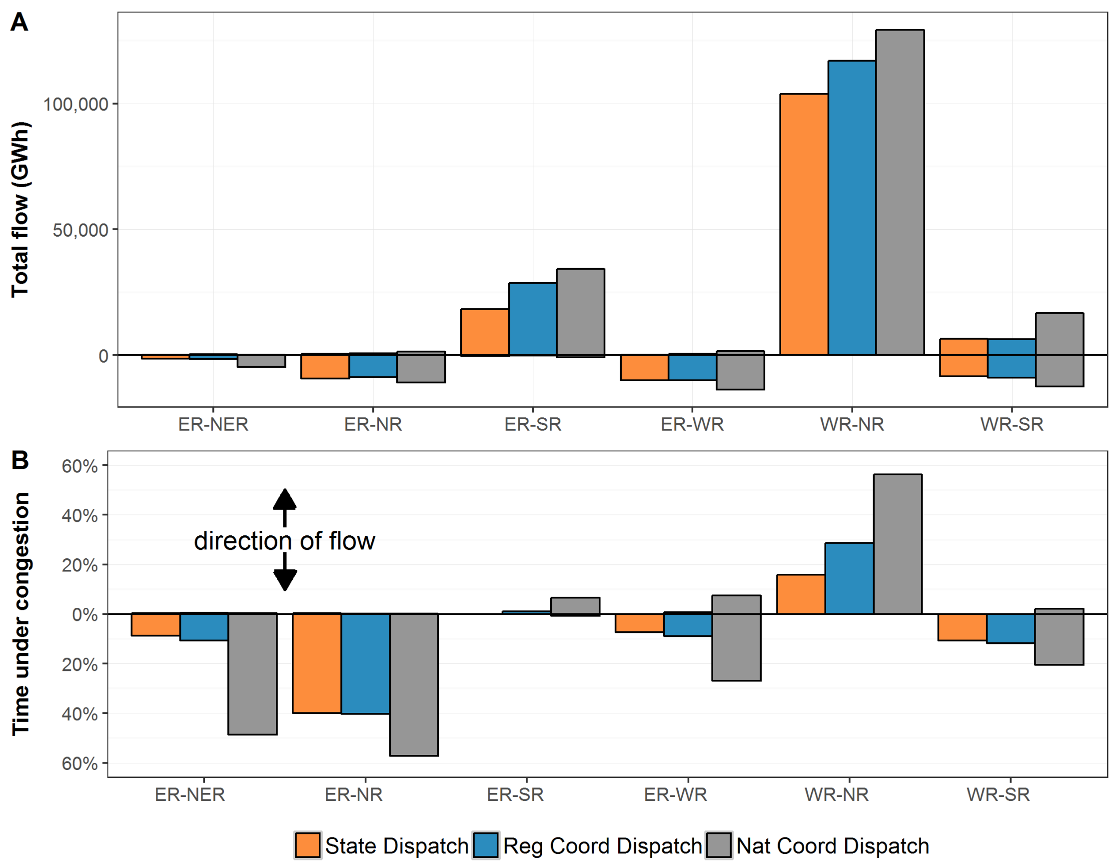


Figure 3.18: Change in generation between regionally coordinated and state dispatch, by region, fuel type, and variable cost

Summary: This section has explored the value of alternative levels of operational coordination to efficiently integration VRE. Based on our modeling results we find that moving from State to Regional coordination would result in savings of INR 6,600 crore for India as a whole, with varying benefits accruing by region as shown in Table 3.11. Moving to a higher level of coordination (National) results in additional savings. Changes in the production costs of individual regions are due to both, savings and reshuffling of generation based on least-cost dispatch. For example, overall production costs in the Eastern Region increase, but the cost of generation per MWh sees a slight decrease when scheduling and coordination shifts from state to regional level, mainly because the overall generation in that region increases. Although VRE curtailment even in the State reference case was not significant as shown in Table 3.12, we find that there is some reduction in curtailment moving from state to region, and to nationally coordinated dispatch.

Table 3.11: Summary of production cost changes for coordinated scheduling and dispatch sensitivities. Percentages in parentheses are changes from the base scenario of state dispatch.

‘	**Production Cost Changes (INR crore)**			
Region	**Regionally Coordinated Dispatch**		**Nationally Coordinated Dispatch**	
NR	3,800	(7.2%)	4,900	(9.4%)
WR	2,000	(2.5%)	-1,600	(-1.9%)
SR	2,700	(5.1%)	4,700	(9.1%)
ER	-2,000	(-5.9%)	20	(0.1%)
NER	60	(2.5%)	40	(1.4%)
India	6,600	(3.0%)	8,100	(3.7%)

Changes in India's production costs are overall savings. Changes in each region's production costs include savings and reshuffling of generation.

Table 3.12: Summary of renewable energy curtailment for coordinated scheduling and dispatch sensitivities. Percentages in parentheses are changes from the base scenario of state dispatch.

‘	**VRE curtailment (GWh)**					
Region	**State Dispatch**		**Regionally Coordinated Dispatch**		**Nationally Coordinated Dispatch**	
NR	10	(0.0%)	10	(0.0%)	20	(0.0%)
WR	180	(0.1%)	70	(0.1%)	70	(0.1%)
SR	3,900	(2.3%)	3,700	(2.2%)	2,300	(1.3%)
ER	20	(0.1%)	30	(0.2%)	90	(0.7%)
NER	0	(0.0%)	0	(0.0%)	0	(0.0%)
India	4,100	(1.1%)	3,800	(1.0%)	2,400	(0.7%)

3.4.2 Value of increased flexibility of thermal generators

Conventional generation, in particular, coal, which dominates the Indian power system, has an instrumental role in contributing to a flexible power system. The ability to run at low minimum loads and cycle allows coal to generate when it is of most value to the system, such as when RE generation is low. This study analyzes the flexibility of coal and the value of this flexibility in reducing RE curtailment and production costs from several aspects:

1. Minimum plant generation levels - Low minimum generation levels allow the plants to turn down when the value of its generation to the system is low, such as during the day when solar generation is high, and yet still be available to ramp up for the evening net load peaks.

2. Ramp rates - Fast ramp rates increase the coal plants' ability to follow changes in net load that result from either high levels of variability or forecast errors.

3. Start-up costs - Lower start-up costs increases the ability of coal plants to shut down and start-up more frequently because of better economics, whereas higher start-up costs reduce the flexibility of coal plants.

4. Minimum up/down times - Shorter up and down times allow coal plants to cycle off/on more frequently, e.g., to be turned off during periods of high RE generation

The results of these sensitivities are illustrated in the following figures. We provide results in the context of two modes of operation - state dispatch and regionally coordinated dispatch.

Figure 3.19 and Figure 3.20 show impacts of coal flexibility on production costs. Changing minimum plant generation levels has the largest impact on cost savings - INR 3,500 crore savings from reducing 70% to 55%, and INR 2,000 crore savings reducing from 55% to

40% minimum generation level, in operations with state-based dispatch. Operations with regionally coordinated dispatch experience even larger savings, mainly because less number of units are committed due to intra-regional cooperation and more gains are to be had with lower minimum generation levels for those units.

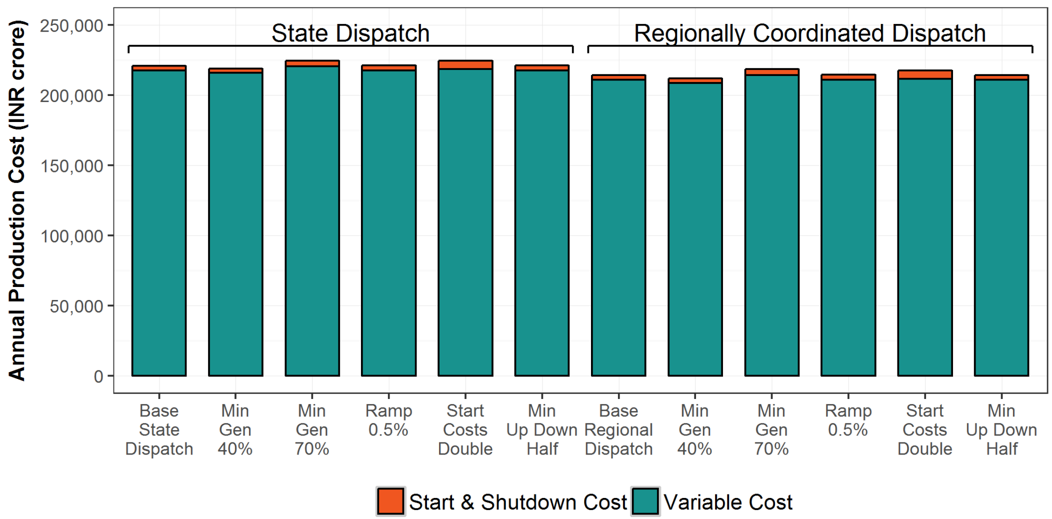


Figure 3.19: Change in generation between regionally coordinated and state dispatch, by region, fuel type, and variable cost

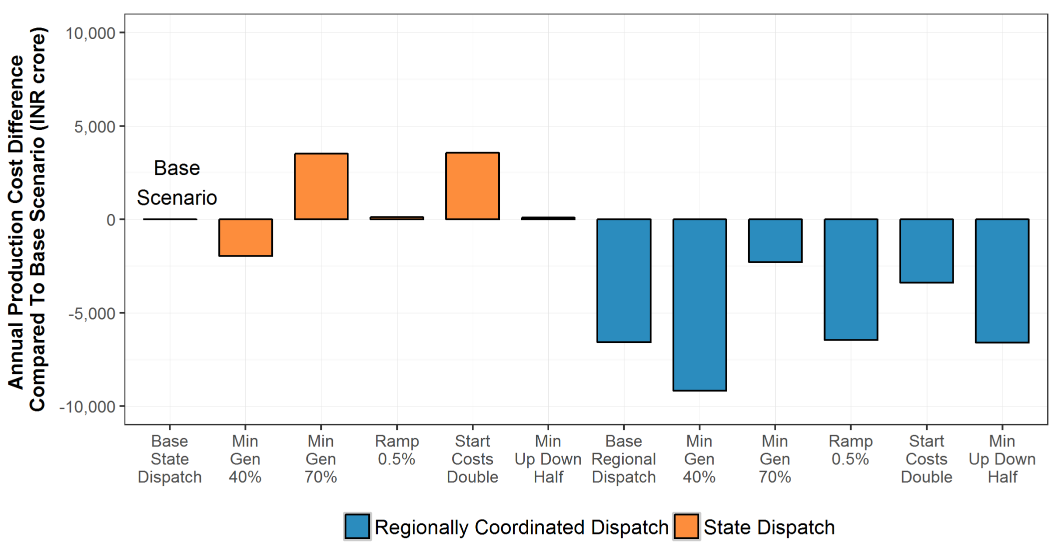


Figure 3.20: Change in generation between regionally coordinated and state dispatch, by region, fuel type, and variable cost

Combining two (or more) mitigation approaches from these sensitivities increases cost savings compared to a single measure. Moving from state-level coordination to a regional dispatch simultaneously with a reduction in coal minimum generation constraints (70% to 55%) offers a production cost savings of INR 10,000 crore (approximately USD 1.5 billion). This compares to INR 6,600 crore benefit from wider regional coordination and INR 3,500 crore benefit from reducing coal min-gen separately.

Improving the flexibility of coal plants, reduces RE curtailment, although the key contributor to this curtailment reduction appears to be the reduction in minimum generation constraints of the coal plants. Figure 3.21, Figure 3.22, and Figure 3.23 illustrate the impact of coal flexibility on RE curtailment. VRE curtailment reduces from 3.4% to 1.1% when minimum generation levels are dropped from 70% to 55%, in a system operated with state-based dispatch. Further reducing minimum generation levels to 40% reduces curtailment to 0.5%. In contrast, coal ramp rates, startup costs, and minimum up/down time does not significantly affect RE curtailment. Doubling start-up costs does increase the overall costs by approximately 1.5% for both state and regional coordinated dispatch, but the higher start-up cost itself, not resulting changes to merit order or RE curtailment, is the primary driver behind the change in production costs. VRE curtailment is most affected in the southern region where most of the overall curtailment is seen (see Figure 3.23).

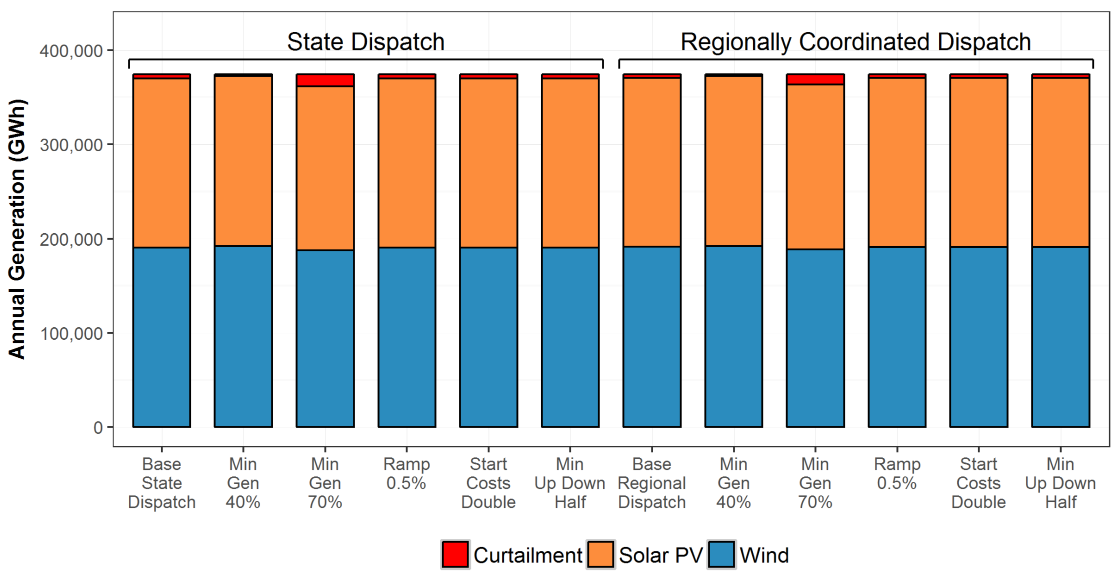


Figure 3.21: Impact of coal flexibility on annual generation, state dispatch (left) and regionally coordinated dispatch (right)

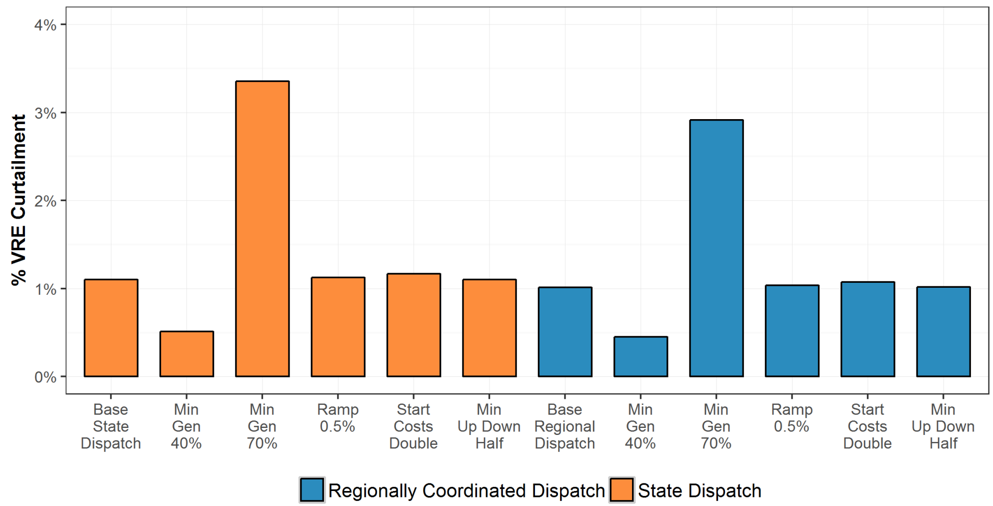


Figure 3.22: Impact of coal flexibility on RE curtailment, state dispatch (left) and regionally coordinated dispatch (right)

Figure 3.23: Impact of coal flexibility on RE curtailment, by region for state dispatch

Summary: Increasing the flexibility of coal plants can help improve the ability of the system to efficiently integrate VRE. The results are summarized in Table 3.13 We found that relaxing the constraint on coal plant minimum generation levels plays a larger role in curtailment reduction than increasing coal ramp capability. However, coal ramping capability may become important when only a part of the coal-based fleet is available for ramping because of contractual constraints on other plants. We also found that these improvements on coal plants reduced operating cost whether operational coordination was at the state or the regional level.

Table 3.13: Summary of production cost savings and renewable energy curtailment for coal flexibility sensitivities. Percentages in parentheses are changes from the base scenario for state dispatch.

‘	State Dispatch				Regional Coordination			
Sensitivity	**Production Cost Savings (INR crore)**		**VRE curtailment (GWh)**		**Production Cost Savings (INR crore)**		**VRE curtailment (GWh)**	
Base	0	-	4,100	(1.1%)	6,600	(3.0%)	3,800	(1.0%)
Coal min gen 40%	2,000	(0.9%)	1,900	(0.5%)	9,200	(4.1%)	1,700	(0.5%)
Coal min gen 70%	-3,500	(-1.6%)	13,000	(3.4%)	2,300	(1.0%)	11,000	(2.9%)
Coal ramp 0.5%	-130	(-0.1%)	4,200	(1.1%)	6,500	(2.9%)	3,900	(1.0%)
Double start costs	-3,600	(-1.6%)	4,400	(1.2%)	3,400	(1.5%)	4,000	(1.1%)
Halve min up down	-90	(0.0%)	4,100	(1.1%)	6,600	(3.0%)	3,800	(1.0%)

3.4.3 Value of increased inter-regional transmission capacity

India's wind and solar resources are concentrated in the west and south, and maximizing these lower-cost resources to achieve national RE targets requires sufficient transmission capacity to meet load across a broader area. In addition to transmitting RE generation, improved connections between regions is fundamental to enabling regionally and nationally coordinated scheduling and dispatch. Coordinated system operations has the effect of smoothing RE and load variability, accessing more efficient merit order, and increasing system flexibility.

To explore the significance of interregional transmission capacity to RE integration, we evaluated two sensitivities: +/- 25% inter-regional transmission interface capacity compared to CEA projections. Reducing the interface capacity by up to 25% (we do not decrease capacity below what is currently available) can indicate the sensitivity of RE curtailment and production costs to delays in transmission expansion. Increasing the interface capacity by 25% provides a comparison to alternative sources of flexibility, such as from coal plants.

The results of these sensitivities are illustrated in the following figures. We provide results in the context of two modes of operation - state dispatch and regionally coordinated dispatch.

Figure 3.24 and Figure 3.25 illustrate the impacts of changes to inter-regional transmission capacity on production costs, for both state and regionally coordinated dispatch. The changes in both directions are small compared to the earlier sensitivities - extent of coordination and coal flexibility. In a system with state dispatch, lower interface transmission capacity raises costs INR 2,000 crore (approximately 1% of total production costs), whereas higher capacity reduces costs by INR 1,100 crore (approximately 0.5% of total production costs). In the regionally coordinated dispatch scenarios, because savings have already been realized through greater intra-region coordination, the effect of lower or higher inter-regional transmission capacity is slightly less than that seen in the state dispatch scenarios.

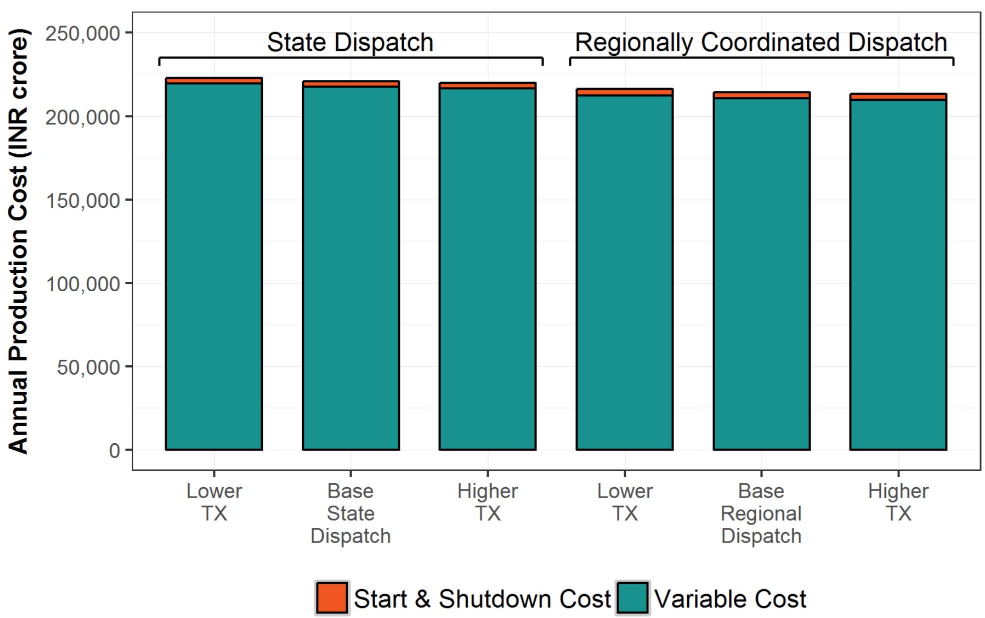


Figure 3.24: Impact of inter-regional transmission capacity on annual generation, state dispatch (left) and regionally coordinated dispatch (right)

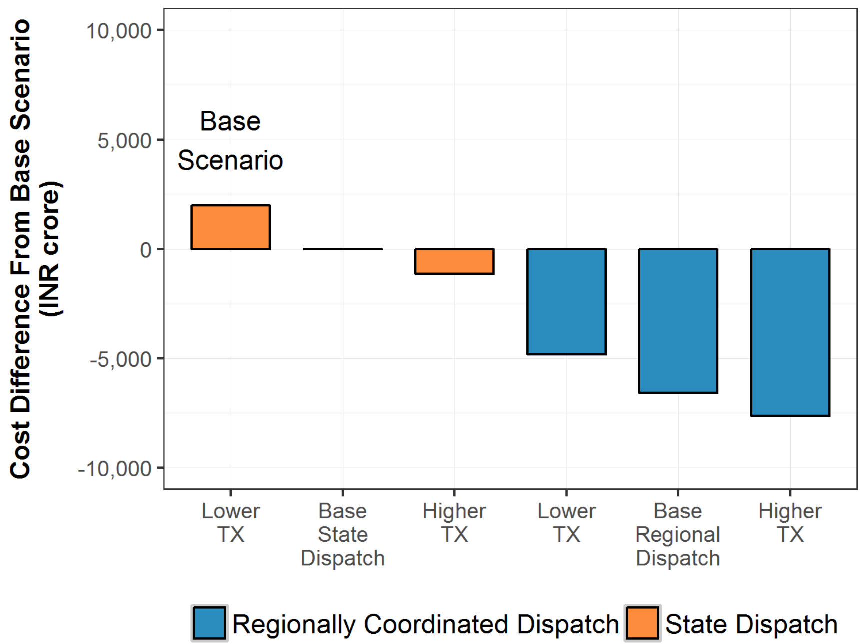


Figure 3.25: Impact of inter-regional transmission capacity on annual production costs compared to base scenario of state dispatch

Figure 3.26 and Figure 3.27 illustrate the impact of changes to inter-regional transmission capacity on RE curtailment. Curtailment decreases from 1.3%, to 1.1%, to 0.9% for state dispatch and 1.2%, to 1.0%, to 0.8% for regionally coordinated dispatch, respectively, with increasing available transmission interface capacity (-25%, base, +25%). Most of the gains in terms of reduction in RE curtailment are seen in the Southern Region where higher inter-regional transmission capacity increases exports by approximately 12% (see Figure 3.27).

Figure 3.28 compares the flows on inter-regional interfaces for the base, -25%, and +25% transfer limit scenarios with a regionally coordinated dispatch. Increased transfer limits increase energy flows across many but not all inter-regional interfaces. The ER-WR interface experiences a small drop in flows with higher interface limits. One would expect that increased transfer limits will reduce congestion. However, as shown in Figure 3.28 (B), lower transfer limits eliminate congestion on the ER-NR and WR-SR interfaces. Energy flows across interfaces are a function of the DC power flow algorithms. Change in flows on one interface can significantly affect flows on other interfaces.

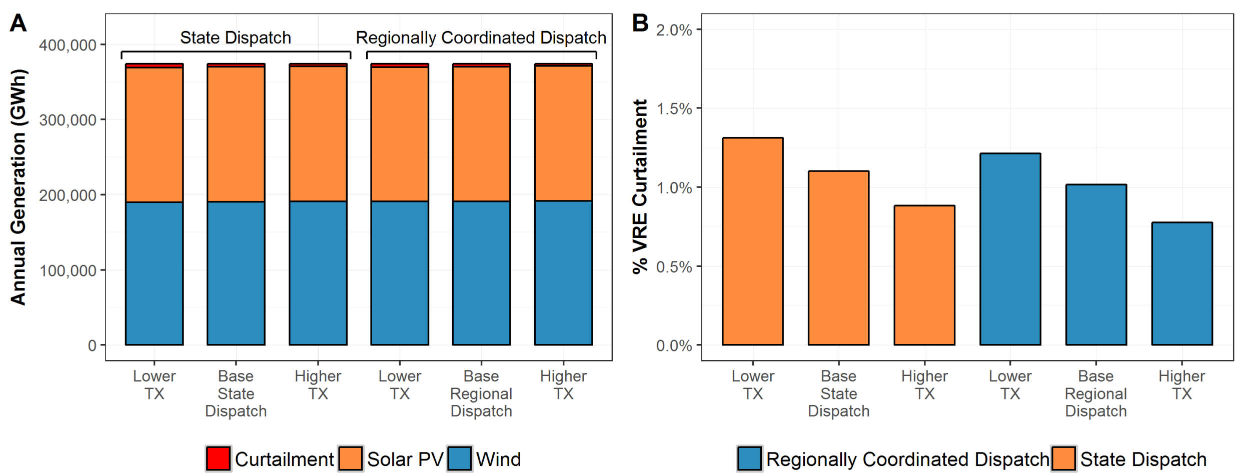


Figure 3.26: Impact of inter-regional transmission capacity on annual RE generation (A) and RE curtailment (B)

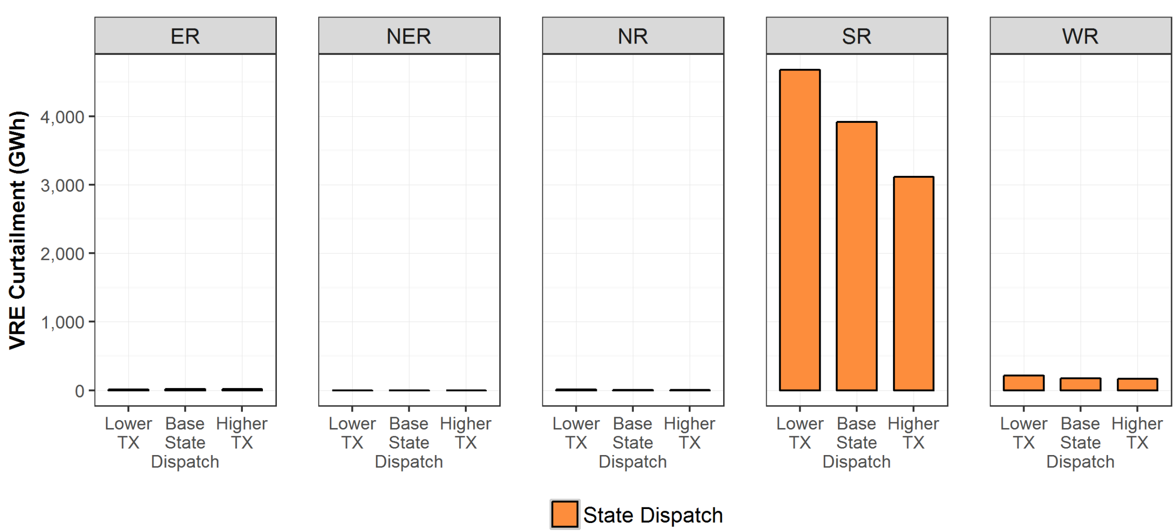


Figure 3.27: Impact of inter-regional transmission capacity on RE curtailment, by region for state dispatch

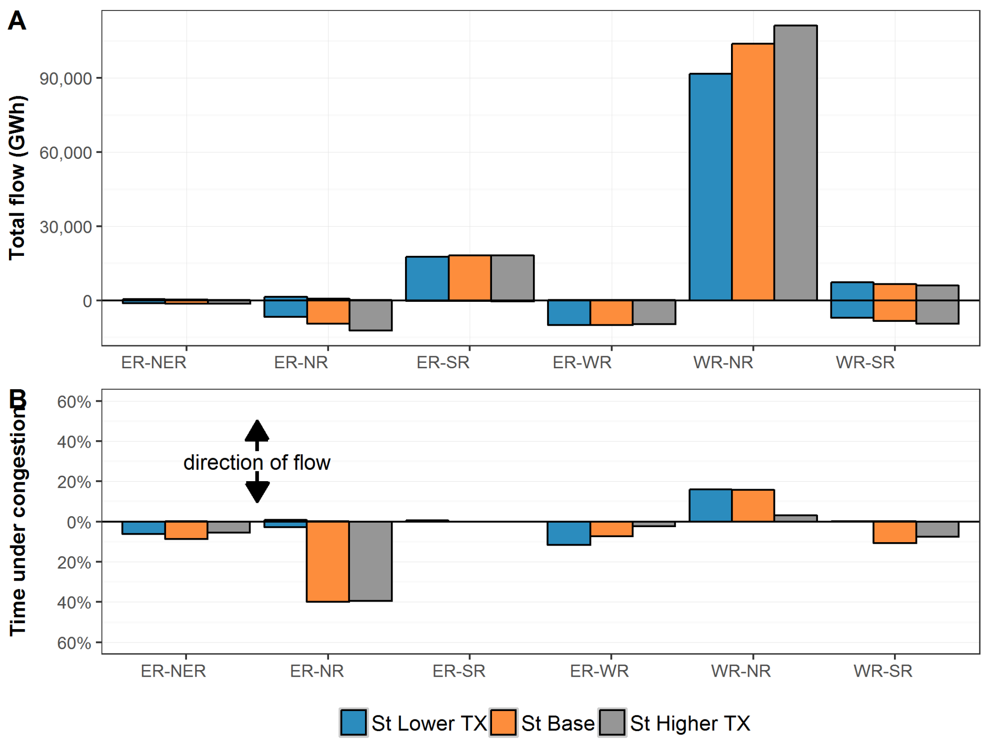


Figure 3.28: Impact of inter-regional transmission capacity on inter-regional transmission flows (A) and interface congestion (B) for state dispatch

Summary: Increasing transmission capacity enables greater trade between balancing areas and access to lowest cost resources across larger geographical footprints, thus lowering overall production costs. VRE curtailment also reduces with increasing inter-regional transmission capacity irrespective of whether scheduling and dispatch is at the state or regional levels. The results for the transmission sensitivities are summarized in Table 3.14.

Table 3.14: Summary of production cost savings and renewable energy curtailment for transmission capacity sensitivities. Percentages in parentheses are changes from the base scenario of state dispatch.

‘	**State Dispatch**				**Regional Coordination**			
Sensitivity	**Production Cost Savings (INR crore)**		**VRE curtailment (GWh)**		**Production Cost Savings (INR crore)**		**VRE curtailment (GWh)**	
Lower TX	-2,000	(-0.9%)	4,900	(1.3%)	4,800	(2.2%)	4,500	(1.2%)
Base	-	-	4,100	(1.1%)	6,600	(3.0%)	3,800	(1.0%)
Higher TX	1,100	(-0.5%)	3,300	(0.9%)	7,600	(3.5%)	2,900	(0.8%)

3.5 Comparison between alternate VRE build-outs

The objective of this section is to understand the effect of different shares of wind and solar, and a higher penetration of VRE generation on system operations. We measure these effects mainly on VRE curtailment, ramp rates, and generation duration curves. We also estimate the potential carbon emissions for each scenario.

We do not compare costs across the VRE build-out scenarios because we assume the same conventional generation build-out for all these scenarios. Not accounting for the potential savings due to avoided investments in conventional generation capacity provides an incomplete comparison of costs between different VRE build-out scenarios. Such savings can only be estimated through a capacity expansion model, which is beyond the scope of this study.

3.5.1 VRE generation and curtailment

Table 3.15 provides the summary of VRE generation and curtailment, and Figure 3.29 shows the generation by fuel type. Switching the wind and solar targets of the High-Solar scenario, the High-Wind scenario results in an increase in overall share of VRE generation from 22% to 26%. This increase is due to the higher capacity factors of wind compared with solar. The 250 GW VRE installed capacity in the Very-High-RE scenario generates 33% of overall energy in 2022. VRE curtailment in the High-Wind scenario is slightly lower than that in the High-Solar scenario, and they are both very low in absolute terms. However, VRE curtailment in the Very-High-RE scenario increases significantly to 8.4%, with most curtailment experienced in the Southern Region followed by the Western Region. Further, curtailment is highest in the monsoon months of June to September.

Table 3.15: Summary of solar and wind generation and curtailment for variable renewable energy build-out scenarios

Scenario	Solar PV (TWh)	Wind (TWh)	Total VRE (TWh)	VRE share	Curtailment (TWh)	Curtailment Share
No New RE	10	69	79	4.8%	0	0%
High-Solar (100S-60W)	180	190	370	22%	4.1	1.1%
High-Wind (60S-100W)	110	320	430	26%	3.1	0.7%
Very-High-RE (150S-100W)	250	300	550	33%	46	8.4%

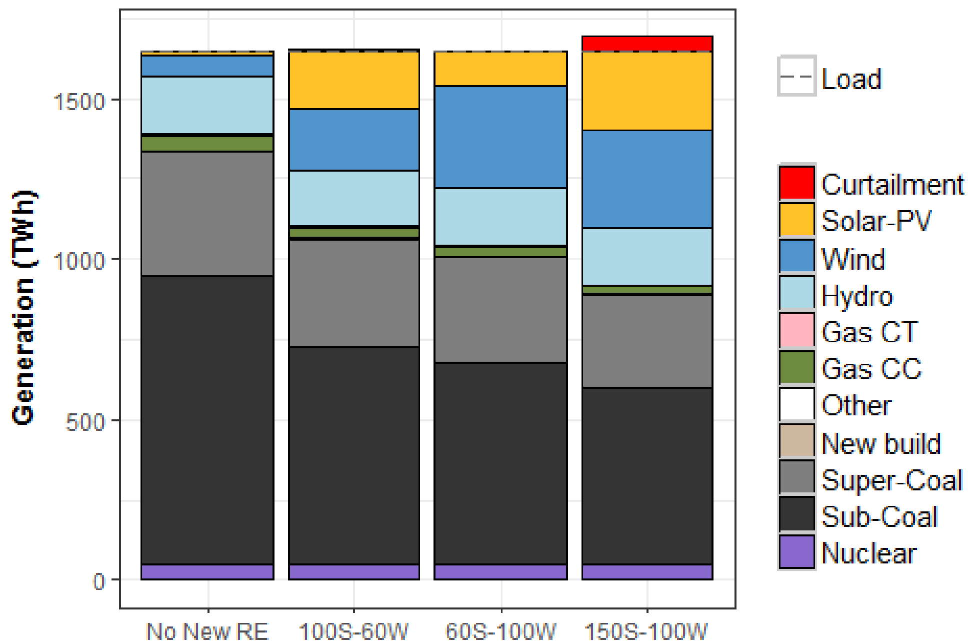


Figure 3.29: Annual generation by generator type including VRE curtailment for VRE build-out scenarios

3.5.2 Impacts on ramp rates and conventional generation

Conventional generators like coal, gas, and hydro need to balance the net load (load minus solar and wind generation) to ensure supply equals demand at all times. Ramp rates of net load are a metric for understanding the effect of variability of VRE generation on the overall system.

Figure 3.30 and Table 3.16 show the hourly net load ramp rates for the VRE build-out scenarios. On the one hand, both the max up and down ramp rates in the High-Solar scenario resulted in a significant increase (50%) as compared with the No-New-RE scenario. On the other hand, the High-Wind scenario, which has the same total VRE installed capacity as the High-Solar scenario, introduced only a modest increase in the max up and down net load ramp rates over those of the No-New-RE scenario. The highly correlated generation profiles of solar plants, especially in the evenings when solar generation drops off and evening load increases, leads to the higher net load up ramp rates in the High-Solar scenario. Similarly, the coincident rise in generation from solar plants in the mornings result in high net load down ramp rates. The Very-High-RE scenario more than doubled the max ramp rates compared with No-New-RE scenario.

Total ramps are the sum of all positive (up) and all negative (down) ramps over the whole year. This metric indicates the extent of cycling that conventional generators are subjected to in order to balance net load. As shown in Table 3.16, and indicated by the spread in the boxplot of Figure 3.30, total ramps increase from the No-New-RE scenario to High-Wind, then High-Solar, and finally the Very-High-RE scenario.

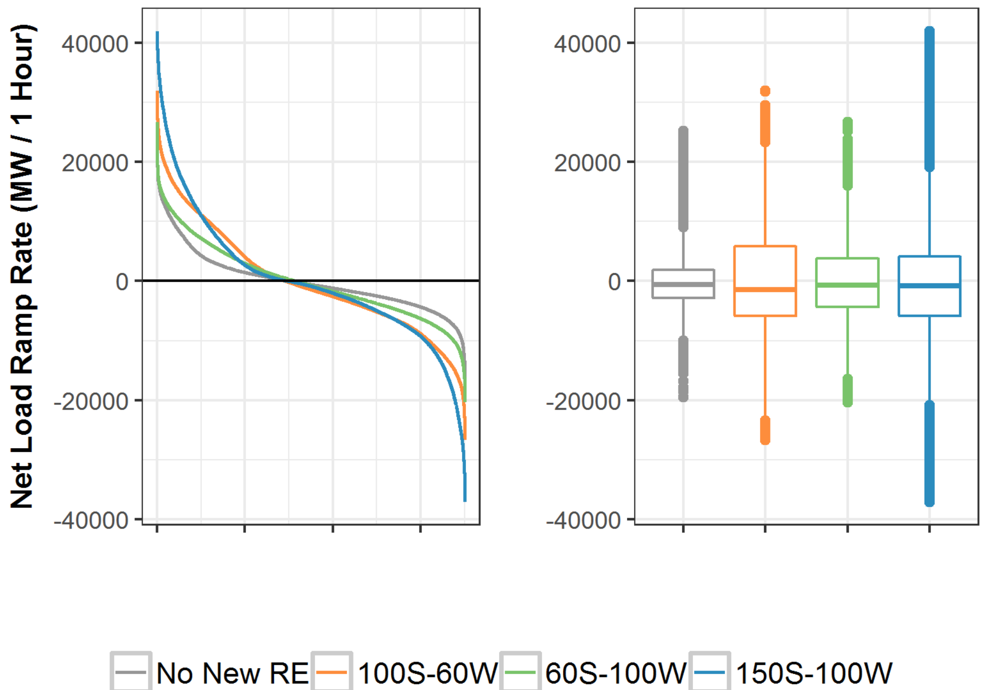


Figure 3.30: Hourly ramp rates for VRE build-out scenarios. Ramp rates estimated for each 15-minute interval.

Table 3.16: Summary of hourly net load ramp rates for VRE build-out scenarios

Scenario	Ramp Rate Up (GW/hour) (99.9 percentile)	Ramp Rate Down (GW/hour) (0.1 percentile)	Total Ramps Up (GWh)	Total Ramps Down (GWh)
No New RE	19	-14	15,000	-15,000
High-Solar (100S-60W)	27	-23	31,000	-31,000
High-Wind (60S-100W)	19	-17	22,000	-22,000
Very-High-RE (150S-100W)	39	-33	34,000	-34,000

As discussed in Section 3.3, VRE generation results in lower plant load factors for coal and gas generators. Generation load duration curves (generation interval data sorted from highest generation level to lowest) indicate how generation from different sources is affected over a whole year. The difference between the top of the duration curve (first data point) of the No-New-RE scenario and a VRE build-out scenario approximately indicates the additional capacity that is never used because of the higher VRE penetration. Further, the steeper the load duration curve is, the lower are the plant load factors for the fleet of that fuel type.

As shown in Figure 3.31, the additional coal generation capacity that is never used in the High-Solar, High-Wind, and Very-High-RE scenarios does not increase significantly with higher penetration of VRE, indicating that the capacity value of the wind and solar fleets is small. In other words, wind and solar generation is unlikely to avoid significant investments in conventional generators such as coal unless strategies such as demand response and storage are pursued to reduce the peak net load profile over the year. At the same time, the generation duration curves get increasingly steeper with higher penetration of VRE generation, and result in lower plant load factors, especially for coal.

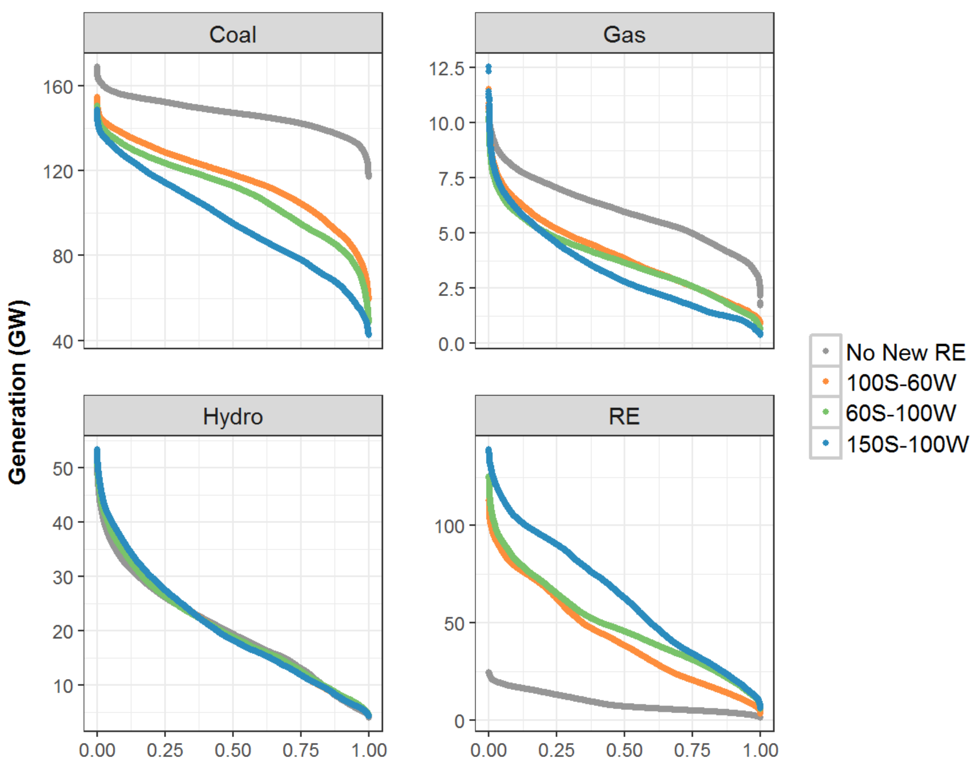


Figure 3.31: Annual generator duration curves by fuel type. X axis shows fraction of year.

3.5.3 Carbon emissions

Figure 3.32 shows the annual emissions for the VRE build-out scenarios. We estimated the carbon emissions for the No-New-RE scenario to be approximately 1,350 million tonnes-CO_2 in 2022. The carbon emissions-free energy generation from the 160 GW of solar and wind in the High-Solar scenario reduced carbon emissions by 21% over the No-New-RE scenario. The High-Wind scenario had even lower emissions than the High-Solar scenario because of higher capacity factors of wind. The 250 GW of solar and wind reduced carbon emissions by 35% over the No-New-RE scenario. The majority of the emissions were from coal-fired plants, and only a small fraction - less than 2% in all scenarios - were from gas, diesel, and oil-based generation.

Figure 3.33 shows the estimated grid emissions factor for different VRE build-out scenarios. We estimated the grid emissions factor for the High-Solar scenario - the GoI target of 160 GW of VRE installed capacity - to be 0.64 tonnes-CO_2/MWh, 21% lower than the No-New-RE scenario.

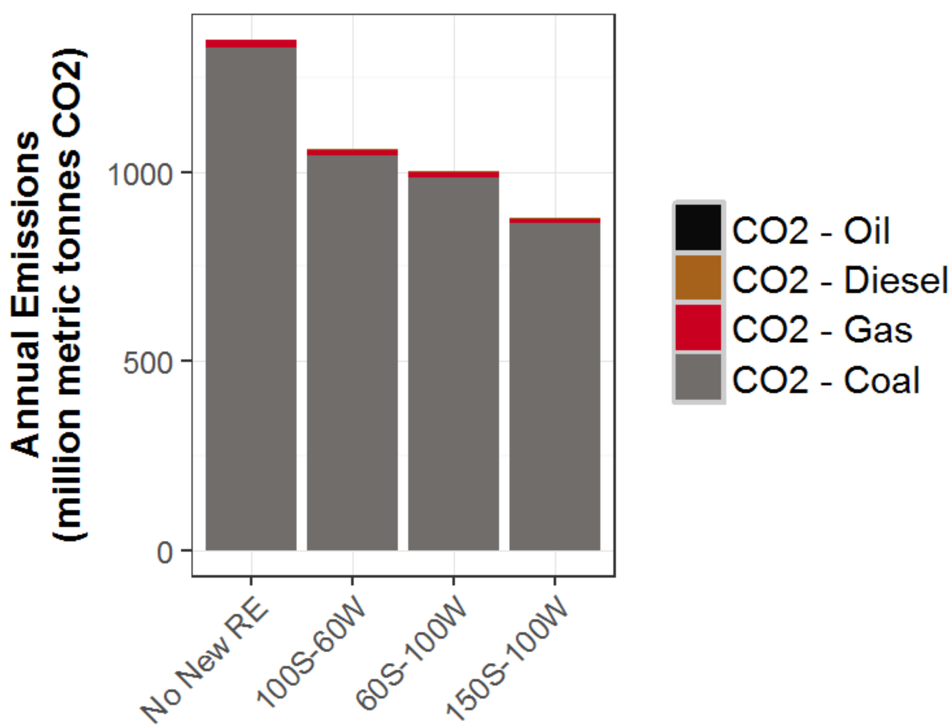


Figure 3.32: Annual carbon dioxide emissions by fuel type

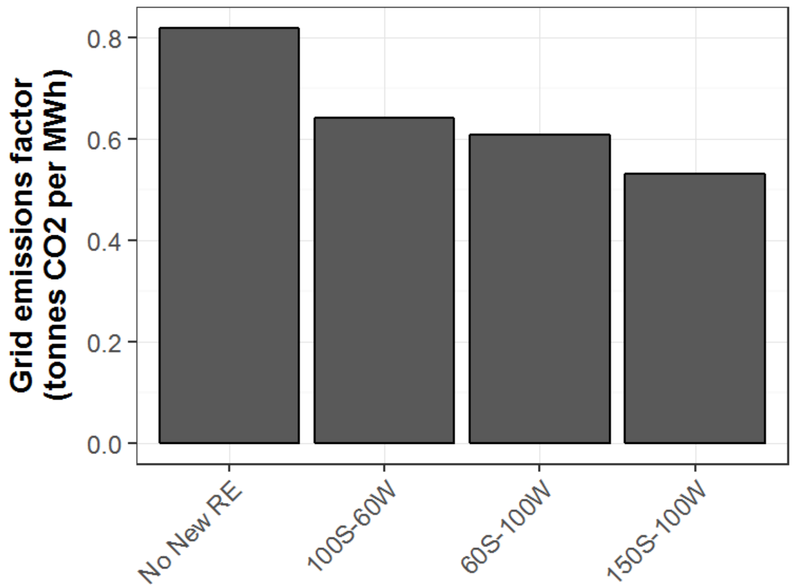


Figure 3.33: Grid emissions factors for different VRE build-out scenarios

Summary: Switching the wind and solar GoI targets in the high-Wind scenario results in a higher VRE penetration of 26% and lower curtailment compared with the High-Solar scenario. Whereas curtailment in the High-Solar and High-Wind scenarios is small (1%), it increases significantly in the Very-High-RE scenario - 8.4%. Without curtailment, VRE penetration in the Very-High-RE scenario would be 36%. Compared with No-New-RE scenario, carbon emissions reduce by 21% in the High-Solar scenario, 26% in the High-Wind scenario, and 35% in the Very-High-RE scenario.

3.6 Conclusions

To analyze the impacts of the GoI targets of 100 GW solar and 60 GW wind on system operations in 2022, we developed a suite of models with high spatial and temporal resolution - RE site selection and generation profile model, load forecast model, and production cost model – to simulate different electricity system futures for India. Based on our modeling results, the 100 GW solar and 60 GW wind in the High-Solar scenario generates 370 TWh annually, resulting in annual averages of 10.9% of solar and 11.6% of wind penetration levels in 2022. Generation from the additional 132 GW of solar and wind in the High-Solar scenario avoids 272 TWh (21%) of coal and 18 TWh (36%) of gas compared with the No-New-RE scenario, reducing carbon emissions by 21%. Curtailment of VRE is only approximately 1%.

As zero marginal cost VRE generation displaces thermal generation, coal plants experience lower plant load factors (annual average of 50%), which means that investments in coal plants will be under-utilized. In other words, fixed costs of coal plants will be spread across a lesser amount of generation, which has financial implications for both, plant owners and consumers.

Total transmission flows across interfaces reduce in the High-Solar scenario by 8% compared to the No-New-RE scenario, mainly because of decreased imports into the RE-rich Southern Region.

We looked at three different types of sensitivities to evaluate strategies to mitigate impacts of the 160 GW VRE on the 2022 Indian electricity system. These include coordinated dispatch, flexibility in coal operations, and transmission transfer capacities on inter-regional interfaces. Although max up and down hourly ramp rates increase by 50% in the High-Solar scenario and total hourly ramps double as compared with the No-New-RE scenario, we found that relaxing the constraint on coal minimum generation levels plays a larger role in reducing VRE curtailment than increasing coal ramp capability. Reducing the minimum generation level of coal plants from 70% (current practices) to 55% (introduced in 2016 CERC regulations) reduced the most amount of VRE curtailment (from 3.4% to 1.1%) among all system flexibility strategies. The lower minimum generation levels allow more solar generation to be absorbed during the day but keep coal plants online to meet the evening peak net load. Other sensitivities on coal plant flexibility such as halving the ramp rates and doubling start costs (both decreasing flexibility), and halving the minimum up and down times (increasing flexibility) did not significantly affect the share of VRE curtailment, although doubling start costs did increase production costs by 1.6% relative to the base High-Solar case. However, coal ramping capability may become important when only a part of the coal-based fleet is available for ramping because of contractual constraints on other plants. Ramping capability may also become a constraint at higher VRE penetration levels.

Moving from state balancing area to regionally coordinated scheduling and dispatch result in savings of INR 6,600 crore (approximately USD 960 million or 3% of total production costs), with varying benefits accruing by region. These savings are almost twice those in the No-New-RE scenario showing the increased value of coordination across balancing areas with higher shares of renewable energy. These gains are also higher when the coal fleet is less flexible - 70% minimum generation level as opposed to 55% minimum generation level. Increase in transmission capacity also reduces production costs as well as curtailment.

The data sets, models, and tools developed through this analysis can be used to evaluate many other development paths, scenarios, and mitigation of greenhouse gas emissions in India's electricity sector. The products of this analysis can support India's efforts in decarbonizing its electricity sector and play its critical role in mitigating future climate change.

Chapter 4

Cost and Value of Wind and Solar

4.1 Introduction

Electricity generation from solar and wind has emerged as one of the foremost strategies to mitigate climate change with many countries setting explicit targets and incentives. Although the costs of solar photovoltaic (PV) and wind have declined over the last several years, these variable renewable energy (VRE) sources are still more expensive than some conventional generation sources such as coal and gas in many jurisdictions. Further, the variability and relative unpredictability of solar and wind pose additional challenges and costs to the overall electricity system. What is the cost of mitigation of carbon emissions using the strategy of implementing VRE? To answer this question, we examined a subset of VRE costs and its value to the overall electricity system for different penetrations and mixes of solar and wind.

We define costs as those required for installing and operating VRE generators.[1] Value represents the avoided costs from conventional generators that include avoided capital investments in new plants (capacity value) and displaced variable fuel and operations and maintenance costs (energy value). We developed a unique set of models to first create different build-outs of solar and wind, and estimate their costs, then build new conventional generation capacity using a screening curves-based model, and finally assess system operations cost using a dispatch model.

In this analysis, we estimated the costs and value of VRE in India's electricity system in 2030. In its quest to reduce carbon intensity of its economy, the Government of India (GoI) has set targets of 100 GW for solar and 60 GW of wind capacities by 2022, and a goal of 40% non-fossil generation capacity share by 2030 in its Nationally Determined Contribution submitted to the United Nations (GoI 2016b). In 2016, seventy percent of India's electricity generation was from coal making the Indian grid not only one of the highest

[1] Although variability and uncertainty of VRE generation may impose additional costs to maintain the same level of reliability as conventional generation, we do not consider those costs in this analysis. We do discuss about these costs in later sections.

carbon emitting large electricity systems in the world, but also one of the least flexible, which makes integrating large shares of VRE challenging. India's system is also one of the fastest growing large electricity systems in the world, and will be making investments in both VRE and conventional generators in the medium term as opposed to western electricity systems that may find it difficult to rearrange their already built-up conventional generation fleets to make room for more VRE. This allowed us to explore realistic conventional generation build-outs in conjunction with VRE build-outs in the medium term (2030).

We find that the economic value of VRE decreases with increasing penetration across all mixes of wind and solar.[2] Value of solar PV decreased at a higher rate than wind because generation profiles of solar sites are highly correlated at the hourly timescale, even across larger geographical regions. The highly correlated solar profiles also increase the likelihood of solar being curtailed at high penetration levels because of minimum generation constraints of thermal generators, thus increasing costs. The value of VRE derived from the displacement of conventional generation, what we define as energy value, is approximately half that of the direct cost of VRE. However, the limited correlation of VRE generation profiles with load during the net peak hours of the year leads to a relatively small conventional generation capacity being avoided by VRE, thus resulting in a small capacity value across all VRE build-outs. We estimated the average additional costs to the entire electricity system for the initial 200 GW VRE (12% VRE share by energy generation) to be 6-9% more than a system without any VRE. These costs rise further with higher VRE penetration (18-23% for 400 GW and 30-40% for 600 GW), not only because of the additional direct costs of VRE, but also due to the lower economic value and curtailment of VRE.

Attributing the entire additional cost of implementing a VRE target to mitigating the negative externality of carbon emissions, we find that the optimal mix of 25% solar and 75% wind would cost USD 31/tonne-CO_2 for the 200 GW VRE target (VRE generation share of 12 %). However, the cost of mitigation increases by approximately 50% to implement the next 200 GW, and by about 100% for another additional 200 GW, mirroring the effects on the additional costs of implementing VRE targets.

Although the results presented in this analysis are specific to a particular electricity system and to the present costs of renewable and conventional generation technologies, the methodology will enable policymakers to evaluate their policies and VRE targets on a continual basis.

4.1.1 Previous studies

Our study focuses on both, estimating the costs and economic value of VRE, and finding the mix of wind and solar that provides the best value (or lowest cost). As such, we reviewed literature that covered either or both these areas of study.

[2]Note that the value does not account for costs due to negative externalities such as GHG and other emissions.

Previous studies have shown the inadequacy of levelized cost of energy as a metric to assess VRE costs and highlighted the need to better understand the economic value of VRE based on the time of its generation and other conditions in the power system (Joskow 2011; Borenstein 2012). Several studies have examined the economic value of VRE, mainly focused on US or European wholesale energy markets. Some of these have evaluated the market value of VRE using current wholesale prices, in what is termed as a short-run analysis (Borenstein 2008; Boccard 2010; Hirth 2013. Other studies have simulated future systems to examine the effect of higher penetration of VRE on its value in the long run (Denholm and Hand 2011; Mills and Wiser 2012; Gowrisankaran, Reynolds, and Samano 2015).

Milligan et al. (2011) note that estimating the additional cost of VRE to an electricity system in the long run is a difficult question, mainly because it is hard to attribute any additional costs to VRE alone. Comparing future versions of an electricity system with and without VRE can enable us to estimate these additional costs, although the assumptions that go into building the future system do dictate results. Notwithstanding these limitations, understanding the costs and economic value of VRE is important for long term policy decisions.

Mills and Wiser (2012) focus on how the economic value of VRE changes with increasing penetration levels in the long run. They define economic value as the avoided costs from other non-renewable power plants in the power system including capital investment cost, variable fuel, and variable operations and maintenance costs, an assumption that we borrow in our study. In addition, they also include the costs incurred due to day-ahead forecast error and increased ancillary service requirements due to increased short-term variability and uncertainty of VRE. They use a long-run model to simulate power system operations and dispatch with hourly load and VRE, unpredictability of VRE, ancillary service requirements, and technical and economic constraints on conventional thermal generators. Evaluating four different types of VRE technologies (wind, solar PV with single axis tracking, and concentrated solar power without and with 6 hour storage), they find a decline in the marginal economic value with increasing penetration levels for all four VRE technologies, with value of solar PV falling at a higher rate than wind. However, this study does not include the cost of investments in wind and solar, nor do they examine the spectrum of wind and solar shares in the VRE mix.

Ueckerdt et al. (2013) analyze both the short and long run costs of VRE integration and note that low market value of wind and solar in the German electricity system are because of a reduced utilization of thermal plants, a phenomenon we observe in our analysis. Gowrisankaran, Reynolds, and Samano 2015 (2015) use an economics model to quantify social costs and reductions in carbon emissions from VRE generation, and apply their model to a 20% solar penetration in the US state of Arizona. They find that the high installation cost of solar is the biggest component of VRE costs. They conclude that an installation cost of USD 1.52 per W will be welfare neutral if the benefits of CO_2 mitigation (at the US Environmental Protection Agency-adopted rate of US 39/tonne-CO_2) are taken into account.

Denholm and Hand (2011) use a reduced form dispatch model to analyze different penetrations and mixes of VRE in the Electric Reliability Council of Texas (ERCOT) system.

They identify minimum generation level of thermal generators as a key constraint to flexibility, a constraint that we include in our analysis. They use only the present conventional generation build-out in their future ERCOT system, and restrict new investments to VRE build-outs and storage.

A few studies have quantified the optimal mix of wind and solar, especially in 100% renewable future electricity systems. Becker et al. (2014) optimized the mix between wind and solar PV for a 100% renewable US electricity system using three different ways - minimizing storage energy capacity, minimizing system imbalance energy, and minimizing levelized cost of renewable electricity generation. They found the mixes that minimized storage energy capacity needs to have a high share of solar (75% solar and 25% wind as the weighted average across balancing regions) because of the lower seasonal variation of solar, but the mixes that minimized the balancing energy required to smooth hourly variations had high shares of wind (20% solar and 80% wind as the weighted average across balancing regions). Heide et al. (2010 found the seasonal optimal mix to be 55% wind and 45% solar power generation for a pan-European 100% wind and solar hypothetical future electricity system. These studies mainly use time series analysis and optimization techniques to minimize the mismatch between load and VRE.

Finally, there are studies that have applied a combination of long-term capacity expansion and economic dispatch models to optimize future investments in generation, transmission, and storage, but only using a small sample of hours (Nelson et al. 2012; Hand et al. 2012). While these studies optimize the future investment mix to meet a particular VRE or carbon emissions target, they do not explicitly estimate the economic value of these resources. However, these studies provide a strong methodology for long-term capacity expansion with high VRE penetrations. Although we use a simplified screening curves approach for capacity expansion in this study, a more comprehensive methodology developed in these studies will improve the overall methodology of this analysis.

In this analysis, we estimate the long run costs and value of VRE for different targets and mixes of solar and wind, and evaluate the strategy of VRE implementation . We first describe the models, assumptions, and data in the Methods section. We then discuss the results of the base suite of scenarios, and the scenarios that test the sensitivity of our results to lower solar PV costs and higher coal capital costs. Finally, we conclude.

4.2 Methods

The objective of our study is to estimate the direct costs of installing large shares of solar PV and wind, as well as the savings or economic value from avoiding to build new conventional generation plants and displacing the energy generation from new and existing conventional generation plants. The direct costs and economic value together provide the cost (or value) of VRE to the overall system.

Unlike some previous studies, we do not value VRE based on the prices in a wholesale electricity market, which depend on either the variable cost of the marginal generator in each time period or a scarcity price set by a peaker plant. We consider the variable and fixed costs of all generators as costs incurred by the overall electricity system.

To assess and compare costs of different VRE penetration scenarios, most studies assume VRE targets on an energy basis. However, given that the GoI policies specify targets based on installed capacity and not generation, in this study, we chose to examine different combinations of installed capacity targets for wind and solar PV. Because different combinations of wind and solar PV shares for the same total VRE capacity can result in different VRE energy generation, we present our cost and value metrics based on per unit of VRE generation absorbed by the electricity system.

There are three main steps in our overall methodology, which are outlined in Figure 4.1. The first step includes site suitability and site selection of VRE for different build-out scenarios, estimating the costs of those build-outs, and creating generation profiles for use in the subsequent steps. In the second step, we use the VRE generation profiles for the year of analysis (in this case, 2030), the load forecast profile for the same year, existing generators, and costs of future conventional generators to build the new conventional generation fleet to meet future load. In the third and final step, we simulate the electricity system operations for all 8760 hours of the future year, and estimate energy generation from different sources, total system costs, and emissions. We break down these steps and describe them in detail in the subsequent sections.

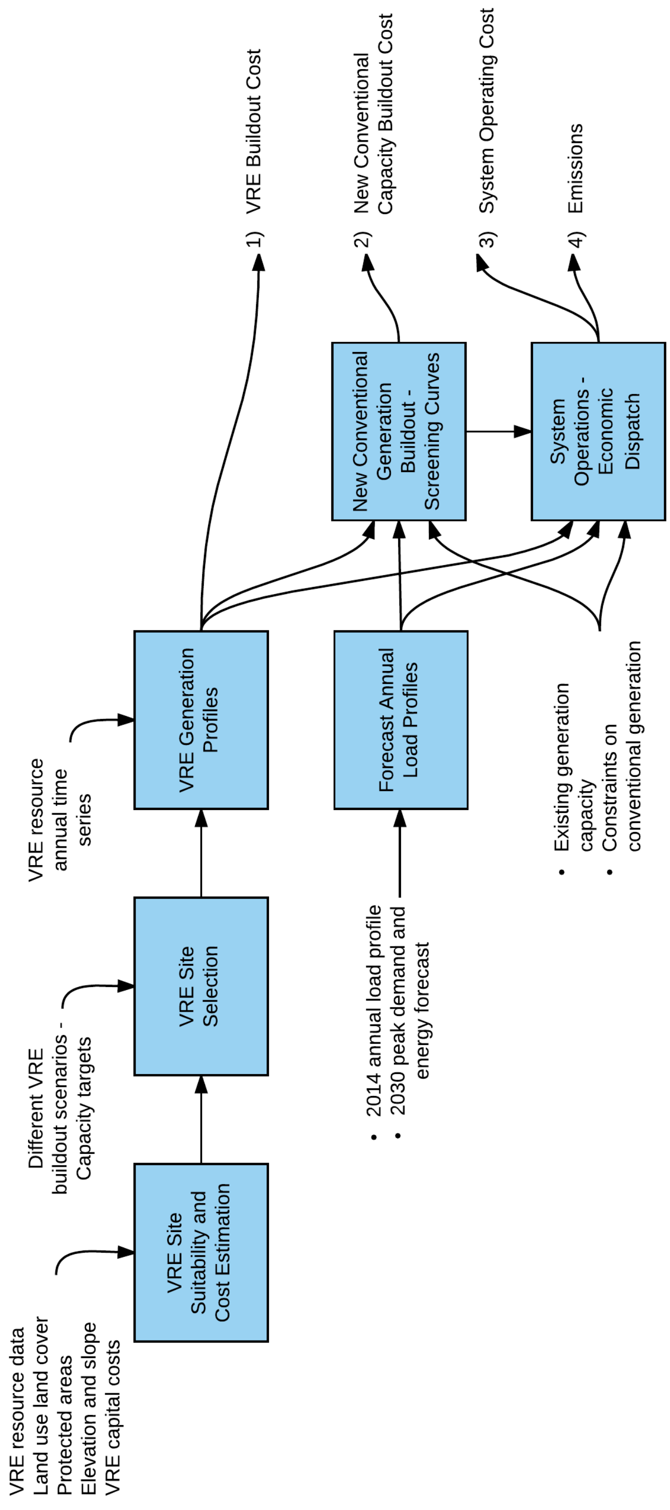


Figure 4.1: Methodology for evaluating cost and value of variable renewable energy.

4.2.1 Site suitability and cost estimation

The site suitability analysis and levelized cost of energy generation for wind and solar PV follows the methodology outlined in chapter 2. Using Python and Arcpy package for spatial analysis, we first conducted the site suitability analysis (or renewable energy resource assessment) using thresholds for wind speed and global horizontal irradiance (GHI) for wind and solar PV respectively, as well as for elevation and slope. We also excluded protected areas, water bodies, and certain land use land cover types (e.g. agricultural land in the case of solar, forested land in case of both technologies) from areas considered suitable for wind and solar development. Please refer to chapter 2 for the threshold values and land use land cover categories that were excluded from the assessment. For wind, we used 10-year averages of wind speeds at a hub height of 80 m and a spatial resolution of 3.6 km^2 from Vaisala's mesoscale modeled wind data set (Vaisala 2015). For solar PV, we used the 2014 annual average GHI data from the National Renewable Energy Laboratory's (NREL) National Solar Radiation Database (NSRDB) (NREL 2016a). All analyses were performed at 500 m resolution using South Asia Albers Equal Area Conic projection.

We aggregated the suitable areas into larger units of analysis - project opportunity areas (POAs) - with a maximum size of 5km. Applying a land use factor of 30 MW/km^2 for solar PV and 9 MW/km^2 for wind (Ong et al. 2013; Wu et al. 2015), and an additional land use discount factor of 75% for both technologies to account for on-the-ground uncertainties (e.g. land ownership, conflict areas), the POAs can accommodate 15 - 187.5 MW size solar PV plants and 4.5 - 56.25 MW size wind plants. These plant sizes are roughly in the range of utility-scale solar and wind plants being built today.

For each POA, we then estimated the annual average capacity factor, which is the ratio of the estimated annual output of a power plant to the potential output of that plant if it were to generate continuously at its rated capacity. For solar PV, we assumed that all systems are south-facing fixed tilt systems, with their tilt equal to the latitude of the location. Only annual average GHI data are insufficient to estimate capacity factors for fixed tilt systems. Because the latitude varies significantly along the length of the country, the relationship between GHI (the solar resource per unit area measured on the horizontal surface) and capacity factor of a fixed tilt system (which is dependent on the solar resource per unit area measured along the plane of the solar panels) is not linear across the country. To address this data limitation, we chose 617 locations spread across the suitable solar sites and estimated their energy generation and annual capacity factors using simulated hourly solar radiation, temperature, and wind speed data from NREL's NSRDB.[3] We used the "PVWatts" module in NREL's System Advisor Model (SAM) for estimating the hourly and annual average capacity factors.[4] See Table 4.1 for assumptions. We then spatially associated each POA to the nearest location with a simulated annual average capacity factor, and estimated each POAs capacity factor by proportionally adjusting the closest site's simulated capacity factor

[3] Access to hourly solar radiation data from NSRDB is limited.

[4] System Advisor Model is an NREL model that simulates energy generation from renewable energy plants.

using the POA's annual average GHI.

Table 4.1: Assumptions for solar PV capacity factor simulations in the System Advisor Model

Parameter	**Value**
System DC capacity	1.1 MW_{dc}
DC-to-AC ratio	1.1
Tilt of fixed tilt system	Latitude of location
Azimuth	180^o
Inverter efficiency	96%
Losses	14%
Ground cover ratio	0.4

source: NREL 2016b

The capacity factor of a wind turbine installation depends on the wind speed distribution at the wind turbine hub height, the air density at the location, and the power curve of the turbine. We first used a Weibull distribution to generate a wind speed probability distribution per 3.6 km grid cell (spatial resolution of Vaisala data). To account for the effect of air density on power generation, we first estimated the air density using elevation and average annual temperature for each grid cell, and then applied power curves modified for different air densities to the wind speed distributions. See Wu et al. (2015) for details.

On-shore wind turbines are generally classified into three International Electrotechnical Commission (IEC) classes depending on the wind speed regimes. We used normalized wind curves for the three IEC classes developed by the National Renewable Energy Laboratory (King, Clifton, and Hodge 2014) and assigned IEC classes based on each grid cell's annual average wind speed (Wiser et al. 2012). For each of the three turbine classes, we adjusted the power curves for a range of air densities by scaling the wind speeds of the standard curves according to the International Standard IEC 61400-12 (IEC 1998; Svenningsen 2010).

To compute the capacity factor for each 3.6 km grid cell, we selected the appropriate air-density-adjusted power curve given the average wind speed, which determines the IEC class, and the air density, which determines the air-density adjustment within the IEC class. For each grid cell, we then discretely computed the power output at each wind speed given its probability (using a Weibull distribution with a shape factor of 2) and summed the power output across all wind speeds within the turbine's operational range to calculate the mean wind power output in W ($\overline{P}$). The capacity factor (cf_{wind}) is simply the ratio of the mean wind power output to the rated power output of the turbine (P_r), accounting for any collection losses (η_a) and outages (η_o) (Eq. 4.1).

$$cf_{wind} = \frac{(1-\eta_a)\cdot(1-\eta_o)\cdot\overline{P}}{P_r} \tag{4.1}$$

Finally, we estimated the levelized cost of energy for each solar PV and wind POA using equation 4.2. The capital recovery factor (CRF) is estimated using Equation 4.3. The assumptions for capital cost of the generator (C_g), fixed annual operations and maintenance costs ($OM_{f,g}$), discount rate (i), and plant life (N) are given in Table 4.2. The discount rate and plant life are from India's Central Electricity Regulatory Commission's (CERC) regulations (CERC 2014). Discount rates are different for different economies based on inflation rates. Although the results in this analysis are presented in USD, the discount rate specified by CERC is for INR (Indian Rupee). The capital costs are adjusted so the LCOE estimates match the CERC tariffs. The operations and maintenance costs are adjusted to be the same as those set by CERC regulations, but without annual escalation.

$$LCOE_{generation} = \frac{C_g \cdot CRF + OM_{f,g}}{cf \cdot 8760} \tag{4.2}$$

$$CRF = \frac{i(1+i)^N}{(1+i)^N - 1} \tag{4.3}$$

Table 4.2: Parameters for wind and solar PV generation cost estimates

	Wind	**Solar PV**
Capital cost C_g [USD/kW]	1,230	1,030
Fixed annual O&M costs $OM_{f,g}$ [USD/kW]	35	25
Discount Rate i	10.8%	10.8%
Plant life N [years]	25	25

source: CERC 2016

4.2.2 Site selection and build-out scenarios

We analyzed three VRE installed capacity targets - 200 GW, 400 GW, and 600 GW - each with five combinations of solar and wind capacity shares - 100%-0%, 75%-25%, 50%-50%, 25%-75%, and 0%-100%. These combinations result in 15 build-out scenarios plus one scenario with no VRE.

For each of the build-out scenarios, we selected project opportunity areas (POAs) that had the highest capacity factors across the country to meet the specific installed capacity targets for solar and wind (Figure 4.2). We imposed two other conditions on the selection of sites. First, for those scenarios that had non-zero targets for wind or solar, we selected sites to meet the existing installed capacities in 2016 in each state before meeting the rest of the target for that scenario. Second, we limited the capacity built in each state to 15% of the country's overall target for a scenario. This ensures geographical diversity in the build-out and prevents our algorithm from selecting a large share of sites in just one state (e.g. solar in the northwestern desert state of Rajasthan). We chose limit of 15% because most of the wind resources lie in six states. A higher limit will result in lower geograhical diversity, and as a result lower capacity value for VRE. A smaller limit for each state prevents the algorithm from selecting enough sites to meet the overall VRE capacity target.

Choosing sites with the highest capacity factors approximate the actual and potential development of VRE sites as project developers seek areas with the highest yield. However, other factors such as proximity to transmission infrastructure, and land availability are likely to influence the overall build-out as well. At the same time, the operational impacts of our selected wind and solar sites on the overall system are indicative of what the future build-out will be. The objective of the analysis is to understand the broad issues resulting from VRE generation, which transcend the particular sites selected by the site-selection algorithm.

4.2.3 Renewable energy generation profiles

We created hourly generation profiles for each of the selected sites or POAs using simulated wind and solar resource data for 2014. Both wind and solar energy generation is based on the underlying weather. By using a numerical weather prediction model (NWP) with 2014 data, we capture any implicit correlation between wind and solar.

Applying the methodology described in section 4.2.1, for solar PV, we converted hourly GHI and temperature data for 617 sites from NREL's NSRDB into hourly capacity factor profiles using the System Advisor Model (SAM). We then spatially associated each POA to the nearest of the 617 sites. For wind POAs, we first converted the wind speed hourly time series for 100 sites from Vaisala into capacity factor time series, using the methodology described in 4.2.1. We then associated each wind POA to the nearest of the 100 wind sites.

To derive the capacity factor time series for each solar and wind POA, we adjusted the hourly capacity factor profile of the associated site by the ratio of the annual average GHI (for solar PV) or annual Weibull distribution-based capacity factor (for wind) for that POA and that for the associated site. The power generation time series is simply the product of the installed capacity potential of the POA and its hourly capacity factors.

4.2.4 Load forecast

For creating the hourly load time series for 2030, we extrapolated the hourly load profile for the base year of 2014 using the peak load and energy generation forecast projected by India's Central Electricity Authority (CEA 2012). India's peak load and energy generation in 2014 was 134 GW and 1020 TWh respectively, and according to the CEA, are expected to grow to 470 GW and 3480 TWh respectively. This more than three-fold growth over 15

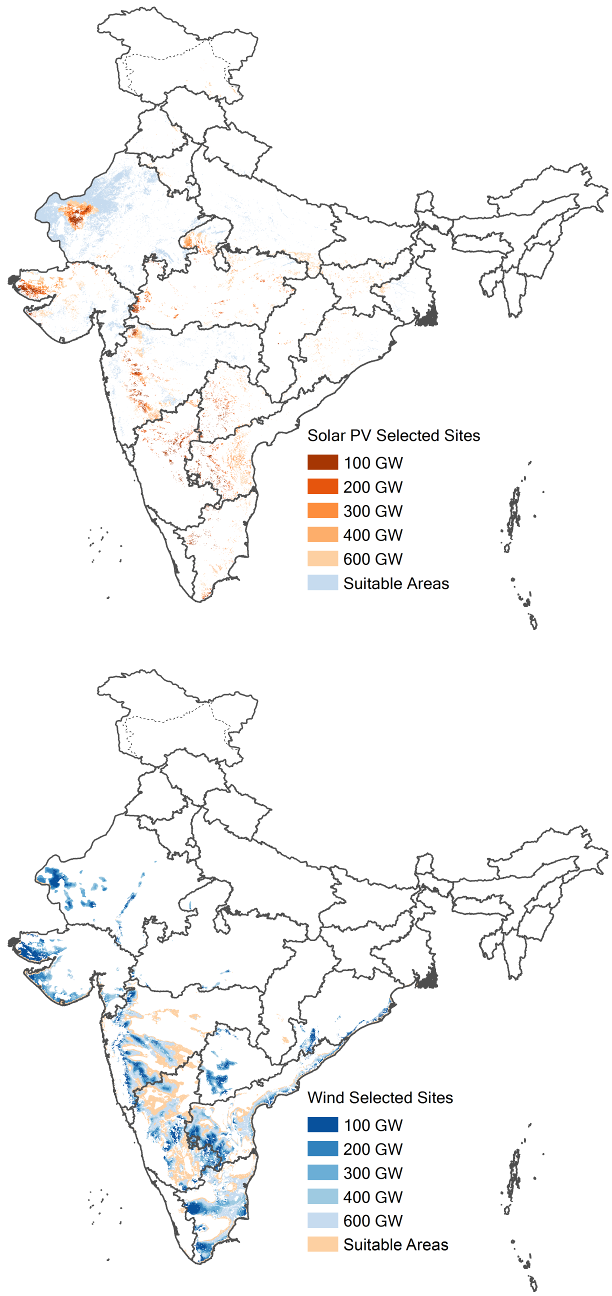


Figure 4.2: Sites selected for different solar PV and wind build-out scenarios. Higher capacity build-outs include areas under the lower capacity build-outs. Suitable areas are the remaining areas that were not selected for any scenarios. Capacity selected in each state was restricted to 15% of total country-wide target for a technology. Co-location of plants was allowed.

years may change, given the significant progress on energy efficiency initiatives in India, but for the purpose of this study, we did not modify the CEA forecasts.

To create the forecast time series, we developed an algorithm using linear and exponential functions. We first linearly extrapolated the 2014 load duration curve (load values sorted from highest to lowest) for each state in proportion to the forecasted increase in energy generation in 2030. If the resulting peak load is lower than the CEA forecast, we uniformly reduced the load duration curve in all intervals by a small amount using a heuristic. We then distributed this reduced "energy" in the peak hours using an exponential function by pegging the start of the function at the CEA peak load forecast value. If the resulting peak load from the linear extrapolation is higher than the CEA forecast, we used a similar logic, and adjusted the load duration curve to have more energy in the base hours. Finally, we re-sorted the load values on hour of the year to create the hourly time series for the 2030. Because the simulated VRE data are also based on 2014 weather, we capture the implicit correlation between VRE and load.

Daily and seasonal load shapes are likely to change in the future because of changing consumption patterns such as increasing air-conditioning load. Such load shape changes can affect the value of VRE e.g. higher demand during the day can increase the value of solar PV. However, for this study, we have assumed a similar load shape for 2030 as that in 2014.

4.2.5 New conventional generation build-out

India has limited options for new conventional generation resources. Remaining untapped hydro resources, a majority that lie in four north and northeastern states with a fragile Himalayan ecosystem, are mainly suitable for run-of-river plants, and may not provide much additional flexibility to the system (Kumar and Katoch 2014). India has 5,780 MW of existing nuclear capacity (NPCIL 2016) and few new plants under construction (GoI 2016a), but this capacity will be a small fraction of the overall demand in 2030. With reserves of 300 billion tonnes, coal is the single largest domestic resource that India is pushing to develop (GoI 2014). Domestic natural gas resources are limited, and LNG imports constituted 32% of total natural gas consumption in 2014 (GoI 2016a). In the last 7 years, India doubled its LNG imports, and has plans to more than double its import capacity to 55 million tonnes in the next 5 years (Bloomberg 2016).

In creating India's future electricity system, we allowed only three technologies to be built - coal, combined cycle gas turbine (CCGT), and combustion turbine (CT) (See Table 4.3). We assumed all new coal units to be super-critical running on domestic coal. Both new CCGT and CT generators are assumed to use imported LNG, with a price of USD 10.7 per MMBtu based on the "Indonesian LNG in Japan" benchmark (IMF 2016). This price is the average of medium term commodity baseline that includes past baseline data from 2009 to 2016, and future projections till 2021. CT generators and existing diesel plants are considered peaker units i.e. they have fast ramps and can start and stop in less than an hour.

Table 4.3: Parameters for conventional generation cost estimates

	Coal	**CCGT**	**CT**
Capital cost [USD/kW]	1,000	1,230	650
Fixed annual O&M costs [USD/kW]	23	6.3	5.3
Variable annual O&M costs [USD/MWh]	3.7	3.7	30
Discount Rate	10.8%	10.8%	10.8%
Plant life [years]	25	25	25
Auxiliary consumption	10%	3%	1%
Minimum stable level [% of rated capacity]	55%	50%	0%
Fuel cost [USD/GJ]	2.6	10.14	10.14
Heat rate [GJ/kWh]	9,890	8,370	12,550
Annualized fixed cost [USD/kW-y]	140	150	81
Variable cost [USD/MWh]	33	91	160
Emissions factor [tonnes CO_2/MWh]	0.92	0.42	0.63

Because of their limited potential, we did not consider other technologies such as nuclear, hydro, or biomass as part of the new conventional generation build-out. However, inclusion of these technologies could affect the ability of the future electricity system to absorb VRE e.g. greater share of nuclear capacity would make the system less flexible due to constraints on minimum stable levels and lower ramp rates; more storage and pumped hydro plants would increase the ability of the system to absorb variability in net load; new storage technologies would enable the smoothing of short-term (diurnal) and long-term (seasonal) variability introduced by higher shares of VRE. We leave the analysis of these scenarios to future research.

To create a new conventional generation build-out that reliably meets demand in 2030 for each of our scenarios, we used a simple screening curves approach (Stoft 2002, Masters 2004). This approach is typically used by regulated utilities where both price of generation and the load duration curve are fixed, i.e. there is no competition and demand is inelastic. Further, fixed and variable costs are assumed to adequately describe all generators. Fixed costs are annualized capital costs and fixed operations and maintenance (O&M) costs. Variable costs include fuel and variable O&M costs. To generate the resource screening curves, these costs for different technologies are plotted as lines with the fixed cost as the y intercept and variable cost as the slope. The capacity factor (defined by the number of hours that a plant operates during the year) dictates the annual overall cost or revenue required by the plant to break even. The screening curves for coal, CCGT, and CT are shown in Figure 4.3, which represent the "base", "mid" and "peaker" types of generation plants. In the base scenarios, our assumptions for fixed and variable costs of coal, CCGT, and CT (Table 4.3) make CCGT plants too expensive to build leaving only coal and CT generators as options for new capacity build-outs.

For each of the VRE build-out scenarios, we first estimated the hourly net load profile for India by subtracting 2014 generation from must-run generators (nuclear, run-of-river hydro, and minimum generation from storage hydro) and expected generation from future

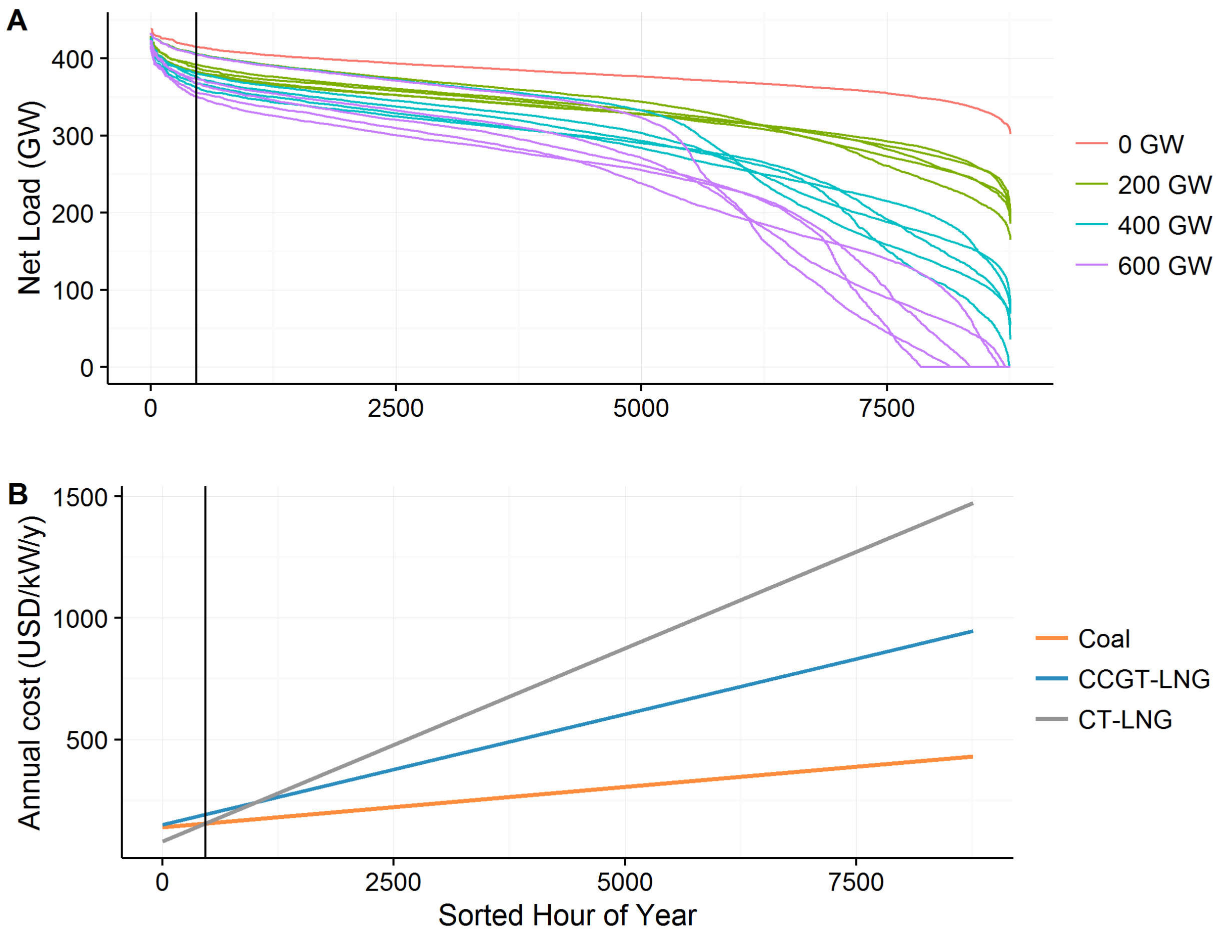


Figure 4.3: Net load duration curves for all VRE build-out scenarios and screening curves with three technologies - coal, combined cycle gas turbines (CCGT), and combustion turbines (CT), the latter two powered by liquefied natural gas (LNG). In this set of scenarios, CCGT capital and variable costs are higher than coal. Only new CTs and coal plants are built with shares dependent on the intersection of the vertical line and the net load duration curve for a scenario. Each group of VRE target scenarios includes five combinations of shares of solar PV and wind.

wind and solar build-outs from the load forecast for 2030. We then distributed the daily available dispatchable energy from the storage hydro fleet over the peak demand hours of each day to minimize daily net peak load without violating the constraint of maximum available generation capacity. Dispatchable energy from storage hydro is the energy left after accounting for minimum generation required for environmental flows, irrigation needs, or releases due to high water levels in the monsoon season. We assumed this dispatchable energy to be all used for "peak-shaving", and not for other grid services such as balancing short-term, sub-hourly variation. Hydro energy could be shifted across days to optimize the balancing of variability in net load. So on the one hand, our assumption to limit storage hydro dispatch to daily energy limits decreases the flexibility of the overall system. But on the other hand, this assumption may be realistic given the greater uncertainty of VRE forecasts beyond 24 hours and the unwillingness of system operators to reschedule and readjust hydro dispatch across multiple days based on uncertain forecasts. We sorted the remaining hourly net load across the whole year to create the final net load duration curves.

The crossover points from the resource screening curves when extended to the net load duration curves give the optimal mix of conventional generation capacity as determined by the y coordinates of the intersection points on the net load duration curves (Figure 4.3). We then subtracted the existing CT and diesel peaker plants from the total required CT (or peaker) capacity to derive the new CT capacity for each scenario. Similarly, we subtracted the existing coal, CCGT, biomass, and waste heat recovery capacity from the overall coal capacity requirement to estimate the new required coal capacity. In the sensitivity scenarios with high capital costs for coal, we identified new capacity requirements for CCGT in addition to coal and CT generators.

To ensure reliability of the electricity system, utilities or balancing areas need to ensure resource adequacy within their jurisdiction, i.e. maintain adequate generation capacity to meet demand. The resource adequacy is usually dictated by a reserve margin target. Ideally, the reserve margin is decided based on reliability metrics such as Loss of Load Expectation (LOLE), which is the number of hours in year that supply cannot meet demand. Depending on the uncertainty in resource availability, forced and maintenance outages, system planners decide upon a reserve margin that will meet a certain reliability standard. In high VRE systems, wind and solar also contribute towards reliability. The contribution of these resources is determined by estimating the Effective Load Carrying Capability (ELCC), which is the amount of capacity that can be counted towards meeting load.

In this analysis, we did not use a reliability model for capacity expansion, Instead, we used a simpler approach to ensure resource adequacy. By subtracting wind and solar profiles from load to estimate the net load to be met by conventional generation, we assumed no uncertainty in the 2014 VRE generation. In future analysis, we intend to use multiple years of VRE data. Next, we assumed a reserve margin of 15% of annual peak load (not net peak load), a reference level used in the US for thermal-dominant generation systems (NERC 2016). This reserve margin will be met only by conventional generators.

We assigned this reserve margin to the CT, CCGT, and coal generators in proportion to their share determined by the screening curves method. In our model, this assumption about reserve margin leads to additional build-out of low variable cost or infra-marginal coal capacity. Because we do not use a stochastic process to simulate outages, but only a deterministic derating of generator capacity to account for outages (as explained in the following section), the additional build-out of conventional generation results in higher plant load factors for coal and lower for peaker plants than those estimated in the screening curves method. This is a limitation of our methodology.

In its investment decisions, the screening curves methodology does not value generator capabilities such as higher ramp rates, minimum stable levels, quick and low cost start up and shut down that may prove crucial for balancing the increased variability and uncertainty in net load due to VRE. However, it provides a simple first cut analysis to determine the optimal mix of conventional generation given different build-outs of VRE.

4.2.6 System operations and economic dispatch

A unit commitment and economic dispatch model can simulate electricity system operations. The unit commitment part of the model commits generation units one day ahead based on load and VRE forecasts, maintenance outages, reserve requirements among other considerations. The economic dispatch part of the model simulates the least-cost operation of the electricity system subject to technical constraints and dispatches each generator to meet demand in every time period of the simulation.

To estimate the overall system operating costs in 2030 for each scenario, we developed a mixed-integer economic dispatch model to simulate India's future electricity system. Our model (Equation 4.4) dispatches generators based on their marginal cost in order to meet demand in every hour while minimizing total system cost over a period of 24 hours. In other words, the model runs in steps of 24 hours for the whole year (8760 hours), but ensures that the supply and demand are balanced in every hour of the day. We used the Python-based open-source optimization modeling language (Pyomo) to develop the economic dispatch model (Hart et al. 2012).

We did not simulate an explicit unit commitment process. Instead, for coal and CCGT plants, which are base and mid-merit order plants, we constrained the plants to be online throughout the day if they are dispatched during that day. In other words, if a plant needs to be dispatched during any time period in a particular day, we do not allow the plant to be shut down during the low net load hours of the day. This assumption constrains the plants to operate at their minimum generation levels, and may force VRE generation to be curtailed. However, the plant can be shutdown or another plant can be started on the subsequent day as we explain later.

We assumed a "copperplate" electricity system, which implies no transmission constraints. Although transmission capacities in an electricity system can significantly affect flows and overall cost of the system, we chose to ignore existing and new transmission build-outs in our model. Because we are simulating a system in 2030, there are uncertainties in how the transmission build-out will evolve. Further, the objective of this study is to understand the broader impacts on cost and value of VRE generation.

The objective function of the model (Equation 4.4) minimizes the overall cost of generation and the cost of unserved energy. The first constraint ensures conservation of energy where generation needs to equal demand minus unserved energy. The second constraint requires the generation of a plant in any time period to be less than its available capacity. The available capacity of a generator is its rated capacity derated by its expected outage rate. The third constraint forces generation of certain types to generate at a minimum generation level if they are committed during the day. Coal, CCGT, and generator types such as oil and biomass have a certain minimum stable level below which they cannot operate due to technical limitations. This constraint ensures that if the generator is committed in the day-ahead schedule, then the generator needs to stay online throughout the day. In reality, generators can shut down during times of low net demand and start back up during the day, and have costs associated with the start-ups and shut-downs. However, the generators included in this constraint typically have high start-up costs and have technical requirements for minimum down and up times. So it is realistic to constrain these generator types to operate based on their day-ahead schedule. Peaker plants that include CTs and diesel plants are excluded from this constraint, which allows them to start and stop during the day without incurring any additional costs. For storage hydro, as explained earlier, the minimum generation level ensures the mandated environmental flows, usage for irrigation, or discharges due to overflowing reservoirs. Storage hydro minimum generation levels, which vary throughout the year, are based on historic data. For must-run generators (run-of-river hydro and nuclear), the generation capacity factors are also based on historic data and are fixed through constraint four.

Constraint five limits the generation from variable RE to their maximum capacity factors in all time periods. However, variable RE generators are allowed to be curtailed for technical or economic reasons. For example, because several conventional generator types cannot reduce their outputs below their minimum generation levels if they are committed for a particular day, VRE generators may be curtailed in the event of excess generation and low demand. Finally, constraint six ensures that generation from storage hydro fleet does not exceed its daily energy limit.

The economic dispatch model estimates the hourly dispatch for all generator types and the total annual dispatch cost for each scenario. We do not include any ramp constraints in the model because even coal generators, the most inflexible technology among the dispatchable conventional generators included in this analysis, can ramp up to 1% of their rated capacity per minute, which allows them to ramp from 55% (minimum stable level) to 100% rated capacity within one hour. Intra-hour ramping capabilities will become more important with higher penetrations of VRE, but our hourly time resolution model will be unable to capture those constraints. We ignore costs due to uncertainty (forecast errors) and do not include transmission constraints.

$$\min \quad \sum_{t=1}^{T} \sum_{i=1}^{G} q_{it} * c_i + UE_t * VOLL \tag{4.4}$$

$$\begin{aligned}
\text{s.t.} \quad \sum_{i=1}^{G} q_{it} &= D_t - UE_t && \forall t \in T \\
q_{it} &\leq Q_i * u_i && \forall i \in G; \forall t \in T \\
q_{it} &\geq minCF_i * Q_i * u_i && \forall i \in G_c, G_{ccgt}, G_{hs}, G_o; \forall t \in T \\
q_{it} &= CF_i * Q_i && \forall i \in G_{hror}, G_{nu}; \forall t \in T \\
q_{it} &\leq maxCF_i * Q_i && \forall i \in G_{vre}; \forall t \in T \\
\sum_{t=1}^{T} q_{it} &= H_i && \forall i \in G_{hs}
\end{aligned}$$

Decision variables

q_{it}	Power generated by generator i in time period t
UE_t	Unserved energy in time period t
u_i	Binary variable indicating whether generator i is committed

Parameters

c_i	Variable cost of generator i, includes fuel and variable O&M costs
$VOLL$	Value of lost load or cost of unserved energy
D_t	Demand in time period t
Q_i	Available capacity of generator i
$minCF_i$	Minimum capacity factor of generator i across all time periods
$maxCF_it$	Maximum capacity factor of variable RE generator i in time period t
H_i	Total energy available for hydro generator i across all time periods

Sets

G	Set of all generators
G_c	Set of coal generators, subset of G
G_{ccgt}	Set of CCGT generators, subset of G
G_{ct}	Set of CT generators, subset of G
G_d	Set of diesel generators, subset of G
G_o	Set of 'other' generators that include oil and biomass generators, subset of G
G_{hs}	Set of storage hydro generators, subset of G
G_{hror}	Set of must-run run-of-river hydro generators, subset of G
G_{nu}	Set of must-run nuclear generators, subset of G
G_{vre}	Set of wind and solar generators, subset of G
T	Set of time periods

4.2.7 Cost and Value

We estimated the cost and value of implementing a VRE target in terms of per unit of renewable energy absorbed by the system. We estimated the cost of VRE by the product of installed wind and solar PV capacities and their respective annual fixed costs from Table 4.2 divided by the total VRE generation after curtailment.

We define the capacity value of VRE as the investment in new conventional generation capacity that is avoided by VRE, and depends on the correlation between load and the combined VRE generation profile in the peak load hours of the year. A higher correlation lowers the annual net peak load, thus necessitating a lower amount of new conventional generation capacity to reliably meet load.

We define the energy value of VRE as the annual variable costs of conventional generation including fuel and O&M costs that the VRE generation displaces. These costs are determined by the economic dispatch model. Both capacity value and energy value for a particular VRE build-out scenario are estimated as the difference in costs between the No RE scenario and the VRE scenario.

4.2.8 Emissions and cost of mitigation

We consider CO_2 emissions as the only negative externality in this analysis. Other negative externalities such as NO_x and SO_x emissions emitted by fossil fuel generators, damage to local environment through the improper disposal of effluents, environmental degradation due to mining, displacement of communities, and others are important to consider, but beyond the scope of this analysis. As such, costs of these externalities are ignored. Avoiding these negative externalities can be considered as co-benefits of mitigation of carbon emissions.

We define the average cost of mitigation of carbon emissions as the additional cost incurred for implementing a VRE target per tonne of CO_2 emissions avoided by VRE generation as compared with the No RE scenario. We also define and estimate the marginal cost of

CO2 emissions mitigation as the annual additional cost of implementing an additional 200 GW VRE capacity per tonne of additional CO_2 avoided as compared with the next lower VRE build-out scenario. We define the average cost of mitigation of carbon emissions as the additional cost incurred for implementing a VRE target per tonne of CO_2 emissions avoided by VRE generation as compared with the No RE scenario. We also define and estimate the marginal cost of CO emissions mitigation as the annual additional cost of implementing an additional 200 GW VRE capacity per tonne of additional CO_2 emissions avoided as compared with the next lower VRE target scenario.

4.3 Results

4.3.1 Potential and cost of wind and solar PV resources

We estimated the potential for wind generation as 850 GW using a threshold of 5.5 m/s annual average wind speed at a hub height of 80 m and a land use factor of 2.25 MW/km^2 (see Table 2.6 in Chapter 2). Similarly, we estimated the potential for solar PV generation as 1300 GW using a threshold of 4.9 kWh/m^2-day for GHI and a land use factor of 7.5 MW/km^2 (see Table 2.7 in Chapter 2). Whereas the potential for solar PV resources will not change much due to its resource threshold, the potential estimate for wind will increase with a lower resource threshold or considering wind resources at higher hub heights. For this study, both estimates for wind and solar PV are adequate to analyze VRE targets up to 600 GW.

We also estimated the levelized cost of energy (LCOE) for the two VRE technologies to understand their spread across the suitable areas identified for VRE development. As shown in Figure 4.4, the cost of solar PV generation varies much less across its suitable areas, but there is significant variation in the costs of wind. Figure 4.4 shows the supply curve for all wind and solar PV resources along with estimates for energy generation targets of 10%, 20%, and 30% of 2030 demand. Based on CERC cost assumptions, the LCOE estimates overlap significantly between the two technologies. Further, there is much more variation in the cost of wind generation across its suitable areas than that of solar PV generation. In other words, wind resources vary widely across the country, whereas solar resources are very similar in terms of quality. If we assume that the best resources get utilized first, wind resources will get increasingly more expensive to develop with higher VRE targets, all else being equal, as the results presented in the subsequent sections suggest.

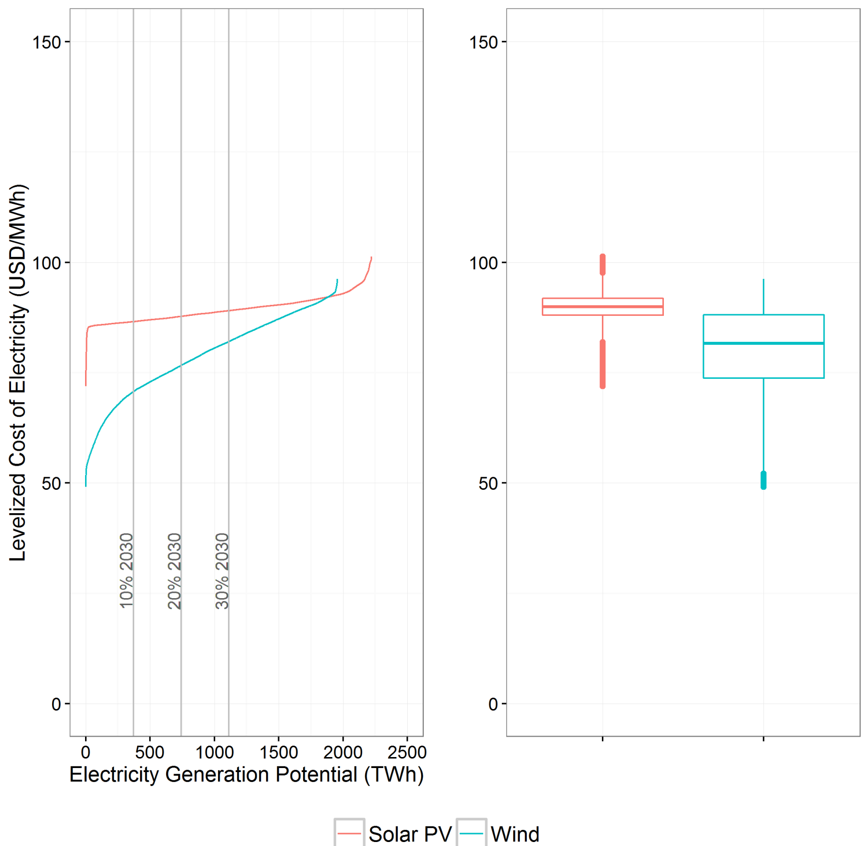


Figure 4.4: Levelized cost of energy for wind and solar PV

4.3.2 Cost and value of VRE generation

To evaluate the cost and value of VRE build-outs with different installed capacity targets and solar-wind mixes, we first selected the VRE sites for each scenario (Figure 4.2), created conventional generation build-outs, and then estimated the cost of installing VRE and its value through avoiding conventional generation investments and energy generation.

4.3.2.1 New conventional and VRE generation build-out

The conventional generation build-outs for all VRE build-out scenarios are shown in Figure 4.5. Only new coal and CT gas generators are built in these scenarios. More CT generators are built in the 25%-75% and 50%-50% solar-wind mixes because of their "peakier" net load profiles. Avoided conventional generation capacity per MW of VRE installed capacity is 0.03-0.09 for 200 GW, 0.02-0.07 for 400 GW, and 0.01-0.05 for 600 GW VRE targets. These low values are a function of India's weather patterns and the VRE sites chosen for these scenarios. As VRE energy generation increases with higher installed capacities, the plant load factors of conventional generators drop. But the high installed capacities for conventional generation are required to reliably meet demand in all hours. Additional storage, ability to shift demand to non-peak hours through demand response, and energy efficiency measures can reduce the need for new conventional generation capacity.

Because the capacity factors of solar PV are lower than wind, the energy generation potential of VRE build-outs with higher solar shares is lower than those with higher wind shares. As shown in Figure 4.6, for the same overall VRE installed capacity target, the share of potential VRE generation in the total energy generation mix reduces as the share of solar PV capacity in the VRE mix increases.

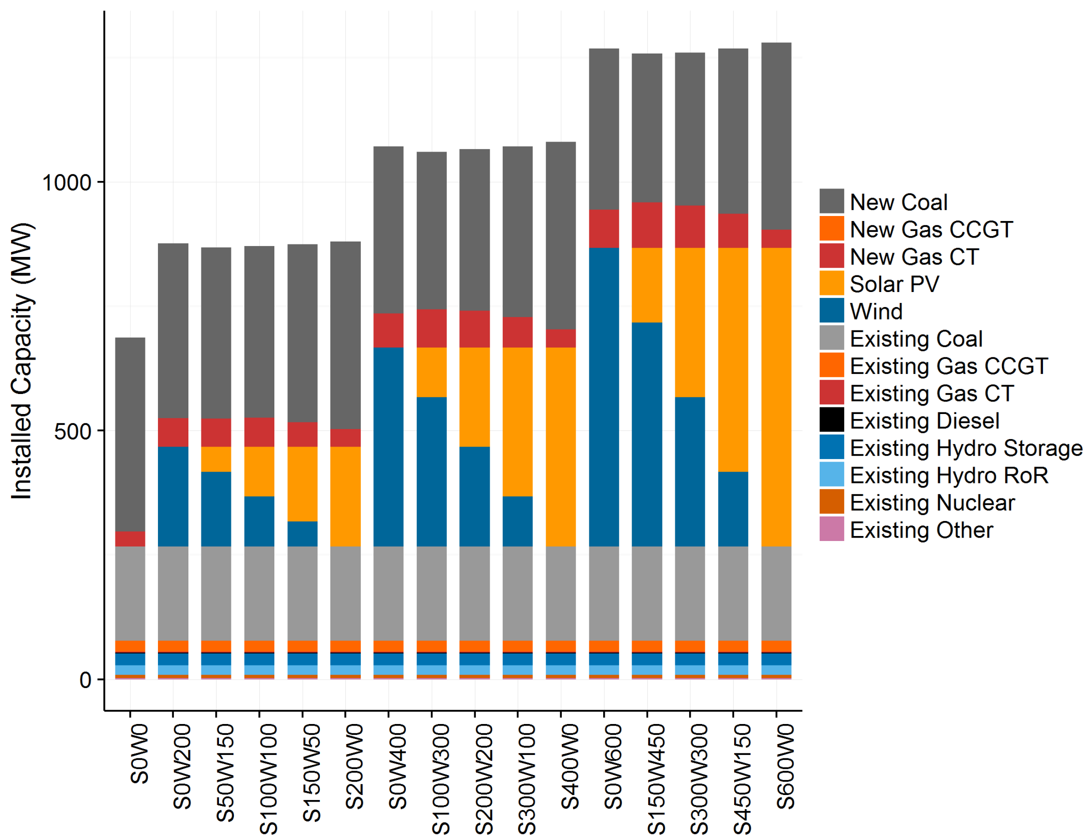


Figure 4.5: Existing and new conventional and VRE generation build-outs. VRE installed capacity targets include 200 GW, 400 GW, and 600 GW, each with five combinations of shares of solar PV and wind - 0%-100%, 25%-75%, 50%-50%, 75%-25%, and 100%-0%.

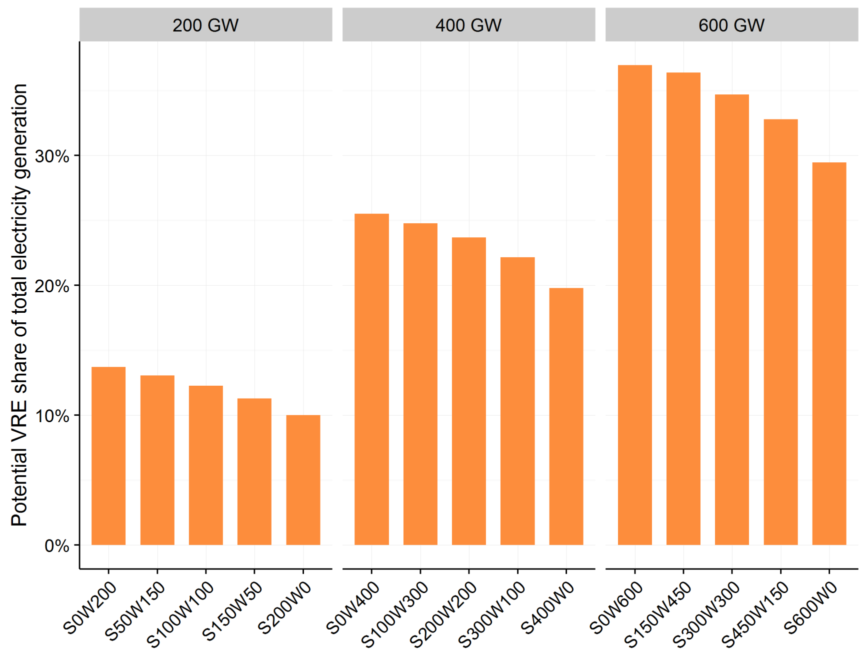


Figure 4.6: Potential VRE generation as share of total demand. VRE installed capacity targets include 200 GW, 400 GW, and 600 GW, each with five combinations of shares of solar PV and wind - 0%-100%, 25%-75%, 50%-50%, 75%-25%, and 100%-0%.

4.3.2.2 Cost of VRE generation

The cost of VRE generation depends on the capital costs of wind and solar PV, and their annual capacity factors. Greater number of installations lead to higher average costs as better resource quality sites are exhausted and developers seek lower resource quality sites. As seen in Figure 4.4, resource quality of wind has much more diversity than that of solar PV. So the effect of changing resource quality on levelized cost of VRE generation is much more pronounced for wind. This is illustrated in Figure 4.7 where the average LCOE of uncrutailed VRE generation rises by 11% between the 200 GW and 600 GW all-wind scenarios, whereas the same increase for the all-solar scenarios is less than 2%.

However, curtailment of VRE increases its levelized cost of generation that is absorbed by the system. As curtailment increases, the cost of installing and operating VRE is spread across a smaller amount of clean energy that avoids environmental externalities.

Curtailment increases with greater penetration of VRE and with more shares of solar PV (Figure 4.8). The high correlation of generation profiles among solar PV sites leads to days with low net load when it is more economical to dispatch coal to meet peak neat load and curtail VRE during low net load periods of the day than to dispatch more flexible but significantly more expensive gas CT or diesel generators that could meet peak load but shut down during high solar periods. This phenomenon is famously demonstrated by the

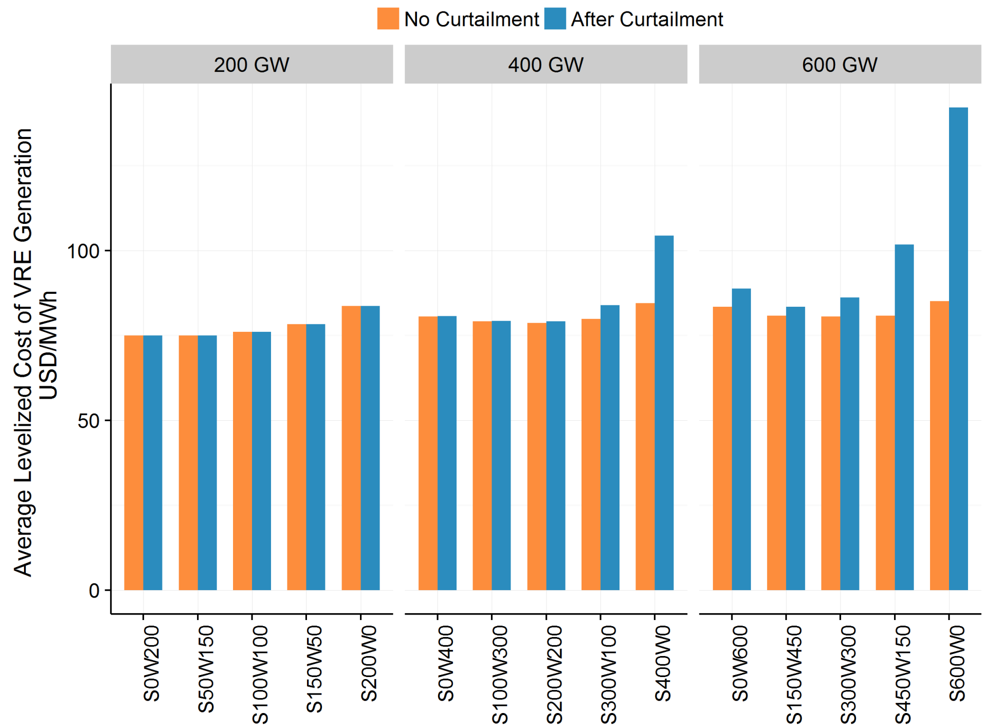


Figure 4.7: Average levelized cost of VRE potential generation (no curtailment) and generation after curtailment during system operations shown for conventional generation build-outs with high (A) and low (B) capital costs for coal. VRE installed capacity targets include 200 GW, 400 GW, and 600 GW, each with five combinations of shares of solar PV and wind - 0%-100%, 25%-75%, 50%-50%, 75%-25%, and 100%-0%.

California "Duck" chart (CAISO 2016).

VRE is not curtailed in the 200 GW VRE build-out scenarios because of the relatively low shares of VRE generation in the overall mix. For the 400 GW and 600 GW scenarios, VRE curtailment is lowest for the 25%-75% solar-wind mixes, which is reflected in their average LCOEs (Figure 4.7).

4.3.2.3 Energy and capacity value of VRE generation

The energy value of VRE is the difference between the system operations costs of a VRE scenario and those of the No-RE scenario. Energy value of the 25%-75% and 50%-50% solar-wind mix scenarios is slightly greater than the other mixes because their generation profiles avoid more expensive gas generation. However, the energy value is overall similar across all VRE mixes and build-out targets. The main reason for this similarity is the dominance of low (and similar) cost coal generation in all build-outs. The energy value of the 25%-75% solar-wind mix for 600 GW of VRE drops by only 5% over that for the same mix for the

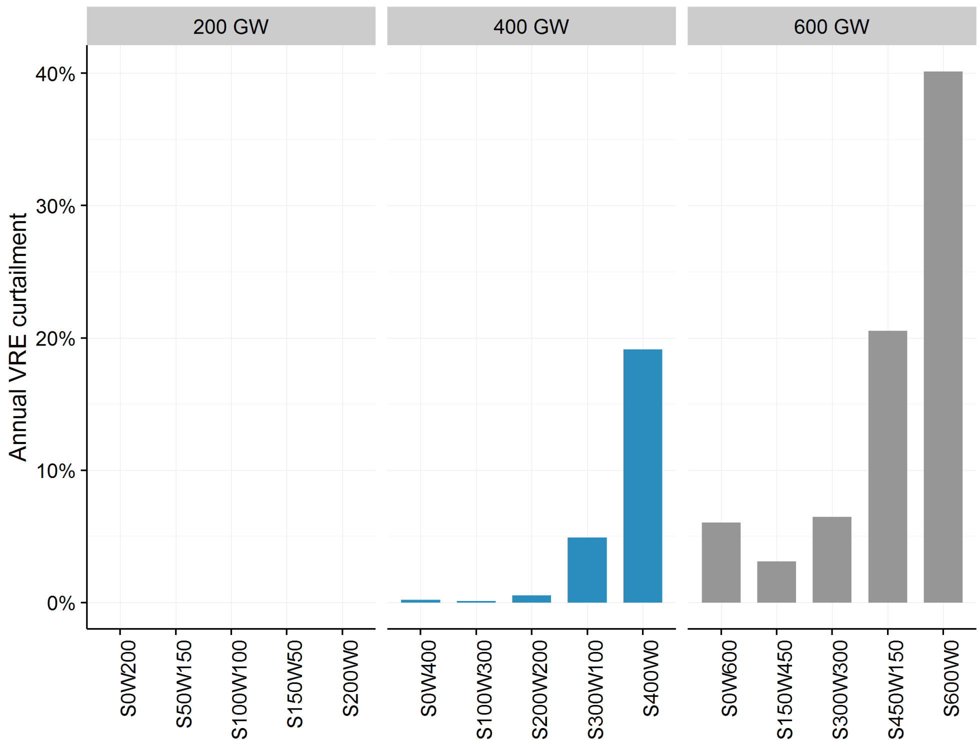


Figure 4.8: Curtailment of variable renewable energy shown for conventional generation build-outs with high (A) and low (B) capital costs for coal. VRE installed capacity targets include 200 GW, 400 GW, and 600 GW, each with five combinations of shares of solar PV and wind - 0%-100%, 25%-75%, 50%-50%, 75%-25%, and 100%-0%.

200 GW capacity. Because of adequate capacity to meet load in all time intervals of the simulation, there was no unserved energy across all scenarios, and hence, no cost associated with unserved load.

The capacity value of VRE is the savings from avoided investments in conventional generation capacity, and depends on the capital costs of the new conventional generators and the amount of avoided capacity. The capacity value across all scenarios is relatively low because of both, low capital costs of coal plants (USD 1000/kW) and low amounts of conventional generation capacity avoided by VRE generation. The latter is due to two reasons. First, daily net peak load on most days occurs in the evenings when there is no solar generation. Second, hourly capacity factors of the entire wind fleet are very low for several hours during the year - wind fleet capacity factors were below 5% during 7-10% of hours for all VRE build-out scenarios.

Capacity value further varies across scenarios. It reduces with increased overall VRE targets, especially of solar. As more VRE with similar generation profiles is added to the system, VRE generation can get more concentrated during low net load, and not contribute towards avoiding conventional generation capacity. As a result, conventional generators experience reduced plant load factors, as observed in other studies (Hirth, Ueckerdt, and Edenhofer 2015).

Comparison between scenarios with different shares of VRE show that that the 25%-75% and 50%-50% solar PV - wind mixes have the most favorable combined VRE generation profiles during the peak hours of net load, and therefore, are able to avoid the most conventional generation capacity.

The higher total value for the 25%-75% and 50%-50% solar PV - wind mixes agrees with other studies focused on other regions (Heide et al. 2010; Denholm and Hand 2011; Becker et al. 2014). Although capacity value estimates using reliability models and effective load carry capacities can provide more accurate estimates, our methodology enables us to evaluate multiple scenarios and provide reasonable estimates within reasonable computing times. Our estimates can be improved by using multiple years of data. Capacity value of solar is likely to increase if the shapes of daily load change by 2030, especially when peak load hours occur during the middle of the day due to higher air conditioning demand. Choosing VRE sites (especially wind) based on their generation profiles in order to minimize the overall net peak load as opposed to choosing sites with the highest capacity factors would increase the capacity value of the VRE fleets. Our wind data is limited to 100 modeled wind sites. Higher spatial resolution and ground-validated wind data sets will improve the accuracy of these results.

4.3.2.4 Additional cost of VRE generation

An important question is how much additional cost per MWh of load served would be required to implement a particular VRE target. On one hand, if the energy and capacity value of VRE is greater than its cost, then it is cost-effective to implement a particular VRE target. On the other hand, if the economic value is lower than the cost of VRE, then the additional cost has to be borne by the electricity consumers and potentially taxpayers depending on the type of incentives available for VRE. Figure 4.10 shows the average additional cost for different VRE targets and mixes per MWh of load served. With the assumptions for the base set of scenarios, the 50%-50% solar-wind mix for each of the three VRE targets incurs the lowest cost per MWh load served. For the 200 GW VRE target, the additional average cost ranges from USD 3.6 - 4.4 per MWh of load served - 6-9% of the average system cost of USD 48 per MWh for the No RE scenario. This additional cost increases to USD 8.4 - 10.9 per MWh (18-23% of No RE) for 400 GW scenarios, and USD 14.4 - 18.8 per MWh (30-40% of No RE) for the 600 GW scenarios.

Note that we did not include the costs of VRE integration such as those for ancillary services including regulation, load following, and ramping reserves, and for handling potentially larger day-ahead forecast errors of net load. These costs will increase the additional costs incurred to implement VRE targets. Results from Mills and Wiser (2012 show that these costs together reduce the overall economic value by less than 10% for up to 30% VRE penetration levels. We also ignored costs for any additional transmission infrastructure that

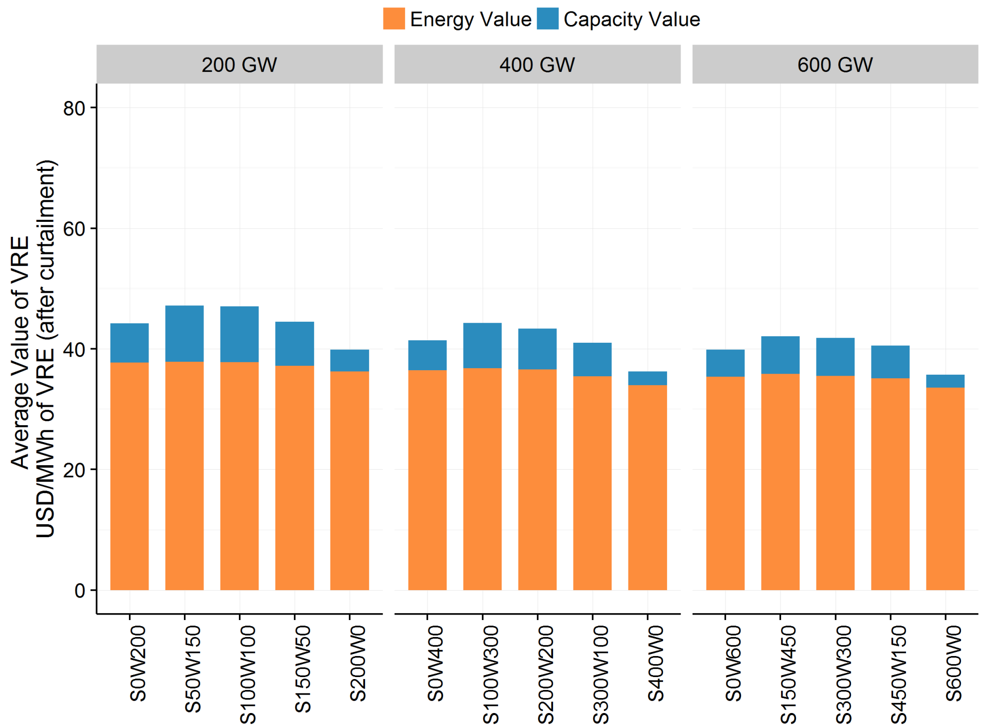


Figure 4.9: Energy and capacity value of VRE generation absorbed by the system (after curtailment) shown for conventional generation build-outs with high (A) and low (B) capital costs for coal. VRE installed capacity targets include 200 GW, 400 GW, and 600 GW, each with five combinations of shares of solar PV and wind - 0%-100%, 25%-75%, 50%-50%, 75%-25%, and 100%-0%.

may be required for evacuating VRE generation to load centers. These costs will increase the overall additional costs of achieving high VRE targets.

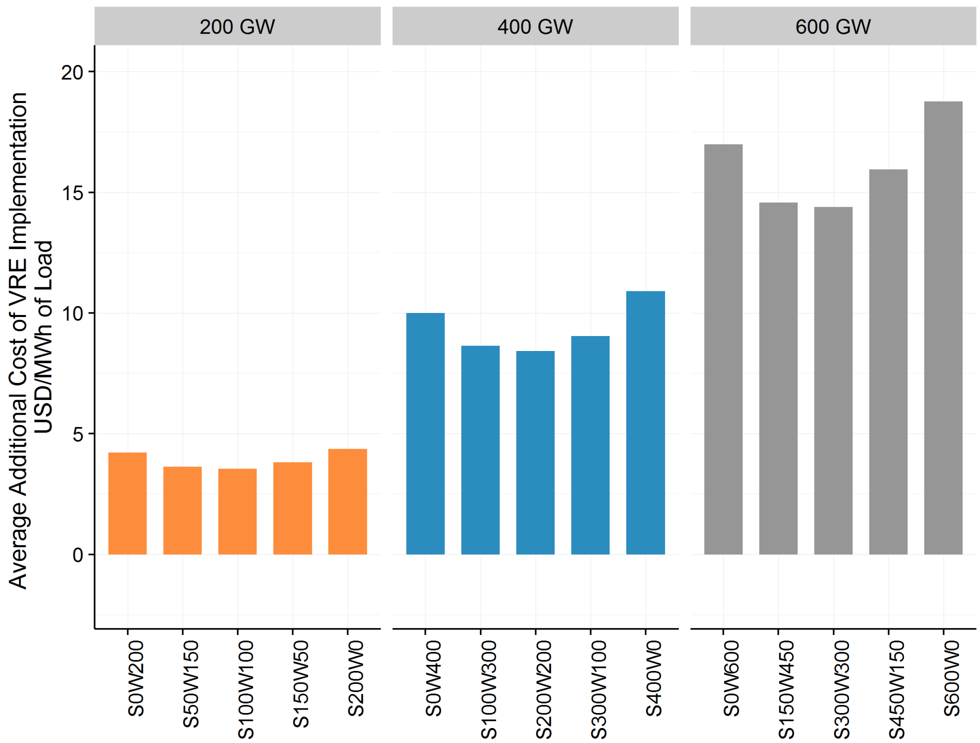


Figure 4.10: Average additional cost of VRE generation per load served. VRE generation is generation after curtailment. VRE installed capacity targets include 200 GW, 400 GW, and 600 GW, each with five combinations of shares of solar PV and wind - 0%-100%, 25%-75%, 50%-50%, 75%-25%, and 100%-0%.

4.3.2.5 Mitigation cost of carbon emissions

The additional costs of VRE are justified by their role in avoiding negative externalities associated with conventional energy generation. In this analysis, we assumed that global climate change through CO_2 emissions is the only negative externality due to conventional fossil fuel-based generation. By assigning the entire additional costs of VRE to this externality, we estimated the cost of avoided or mitigated carbon emissions for each scenario.

Figure 4.11 (A) and (B) show the average and marginal cost of carbon emissions mitigation. The scenarios with the 25%-75% solar - wind mix have the lowest mitigation costs

Average carbon emissions mitigation costs for this VRE mix were estimated as USD 31/tonne-CO_2 for 200 GW, USD 38/tonne-CO_2 for 400 GW, and USD 45/tonne-CO_2 for 600 GW. The marginal cost of carbon emissions mitigation, which is the cost of mitigation for an additional 200 GW VRE, were USD 47/tonne-CO_2 to meet the 400 GW target, and USD 61/tonne-CO_2 to meet the 600 MW target. Other scenarios have higher costs of carbon emissions mitigation. Scenarios with 100% solar especially have significantly high costs, mainly because of curtailment.

Conventional generation, both fossil fuel-based and hydro, have several other negative externalities as highlighted earlier. Including the benefits of avoiding these negative externalities, although outside the scope of this analysis, will improve the economics of carbon emissions mitigation.

Next, we examine the effects of lower solar PV and higher coal capital costs on the costs of VRE implementation and carbon emissions mitigation.

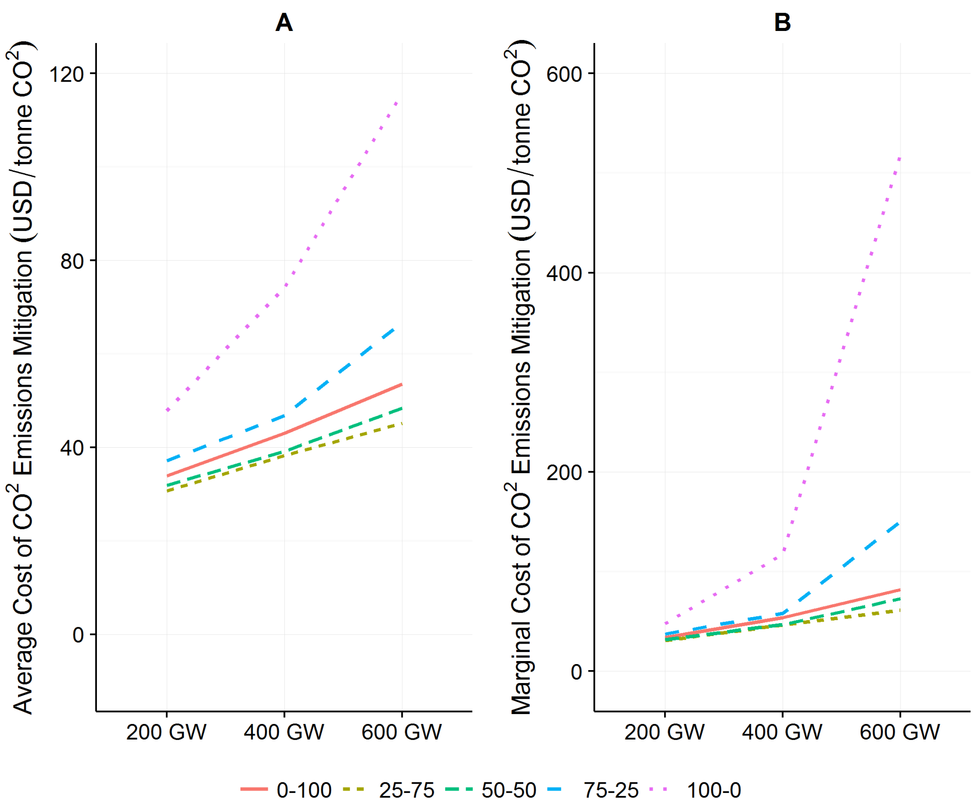


Figure 4.11: Average and marginal cost of mitigation of carbon dioxide emissions through VRE deployments. Each line represents different combinations of shares of solar PV - wind installed capacities - 0%-100%, 25%-75%, 50%-50%, 75%-25%, and 100%-0%.

4.3.2.6 Sensitivity to solar PV costs

Costs of solar PV have declined dramatically in recent years due to technological advancements, economies of scale, and a glut in the photovoltaics market. Further, auction-based procurement programs in India continue to capture these cost reductions by driving down the prices of utility-scale solar PV through competition. For wind, India is yet to conduct its first auction-based procurement, and most of its previous procurement has been through feed-in tariffs. So while solar PV shows a high potential of both cost and price reduction in

India, wind procurement policies may not show as much promise of price reduction in the near future. We tested the effect of a 20% reduction in solar capital costs on the cost and value of implementing VRE targets and the cost of carbon mitigation.

The 20% reduction in solar PV capital costs resulted in an average levelized cost of solar PV generation of approximately USD 70/MWh across all VRE build-out scenarios, an 18% reduction over the base scenarios (see the cost of VRE generation with no curtailment for the all-solar scenarios in Figure 4.12 (B)). The Indian utility-scale solar PV market has already seen this level of cost reduction. Auctions conducted in three states of India in 2015 and 2016 received winning bids of USD 67-79 per MWh with a weighted average of 71 per MWh for a total procured capacity of 1770 MW.[5]. The cost reduction is uniform across the three VRE targets because of the relatively uniform solar resource quality across the country.

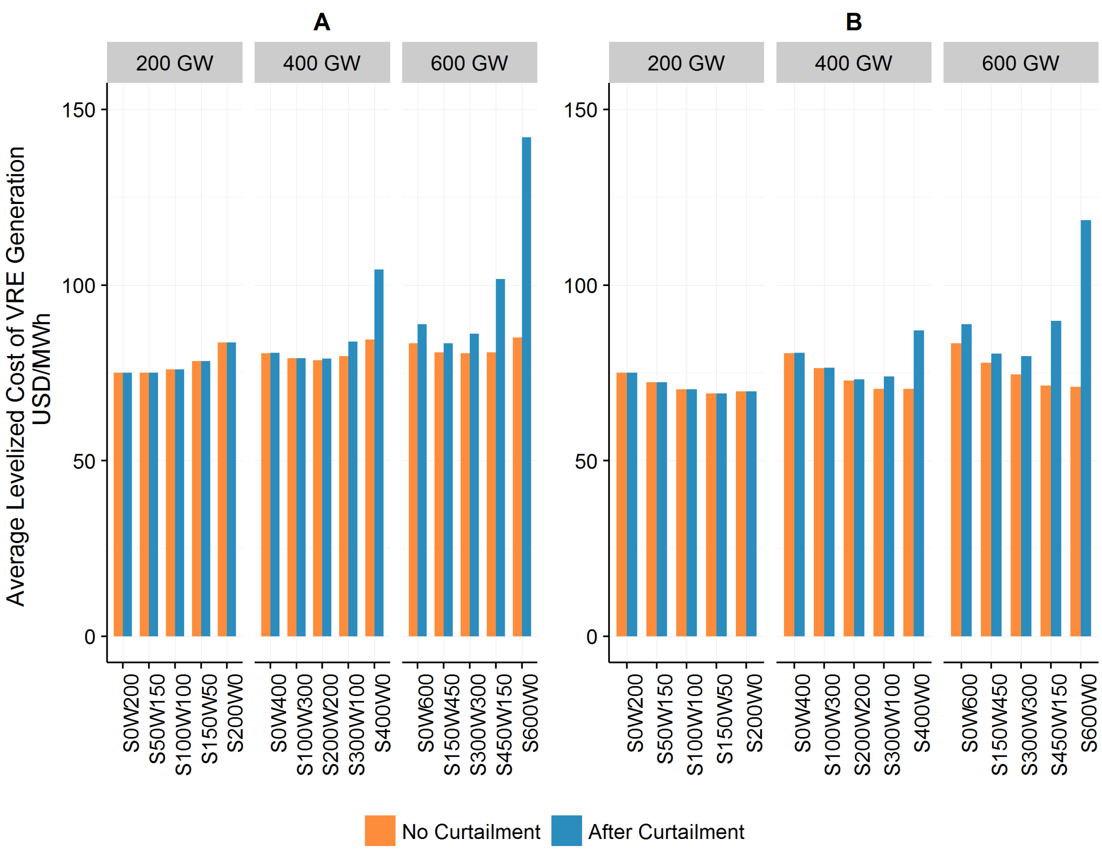


Figure 4.12: Average levelized cost of VRE generation for base scenario (A) and scenario with 20% lower capital costs for solar PV (B). VRE installed capacity targets include 200 GW, 400 GW, and 600 GW, each with five combinations of shares of solar PV and wind - 0%-100%, 25%-75%, 50%-50%, 75%-25%, and 100%-0%.

[5]Benefits of accelerated depreciation if availed are approximately USD 10 per MWh

With a 20% solar cost reduction, the 100% solar - 0% wind scenario has the lowest levelized cost for uncurtailed VRE generation. However, the higher solar mix scenarios for the higher VRE targets of 400 GW and 600 GW still remain more expensive in terms of VRE generation absorbed in the system due to curtailment of excess solar generation.

The energy and capacity values of the low solar cost scenarios are the same as the base scenarios as the generation profile of the VRE build-outs do not change. The 25% solar PV - 75% wind VRE build-out remains the mix with the highest value. However, the combination of lower solar PV costs and limited curtailment as compared to scenarios with higher shares of solar PV makes the 50% solar - 50% wind scenarios have the lowest average costs of carbon emissions mitigation (see Figure 4.16). The costs for this VRE mix range from USD 25/tonne-CO_2 for 200 GW to USD 42/tonne-CO_2 for 600 GW. These costs are lower or within the range of the social cost of carbon adopted by the EPA.

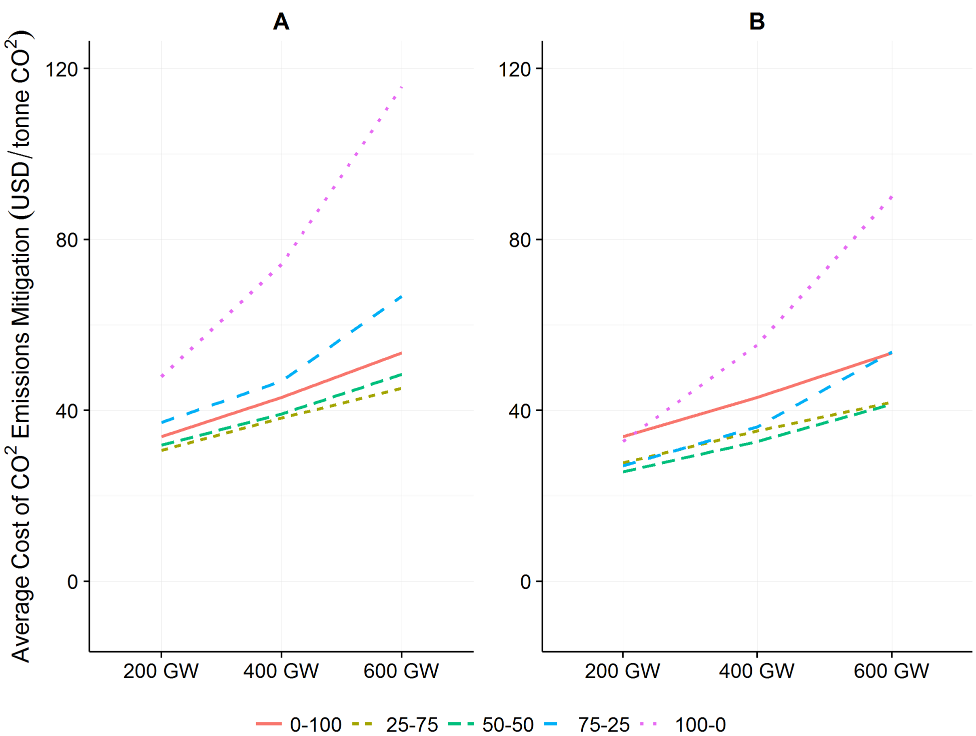


Figure 4.13: Average cost of mitigation of carbon dioxide emissions through VRE deployments for the base scenarios (A) and scenarios with 20% lower capital costs for solar PV (B). Each line represents different combinations of shares of solar PV - wind installed capacities - 0%-100%, 25%-75%, 50%-50%, 75%-25%, and 100%-0%.

4.3.2.7 Sensitivity to coal capital costs

Capital cost of coal plants in the US are significantly higher than those in India - almost three times greater by some estimates (EIA 2015). We tested the sensitivity of our results to higher capital costs of coal by assuming a cost of USD 2900/kW of installed coal capacity (Veatch 2012).

With the higher capital costs of coal, new capacity for all three conventional generation technologies - coal, CCGT, and CT - gets built through the screening curves method (see Figure 4.14. We used the new conventional generation build-outs to simulate the system operations for all the VRE build-outs scenarios.

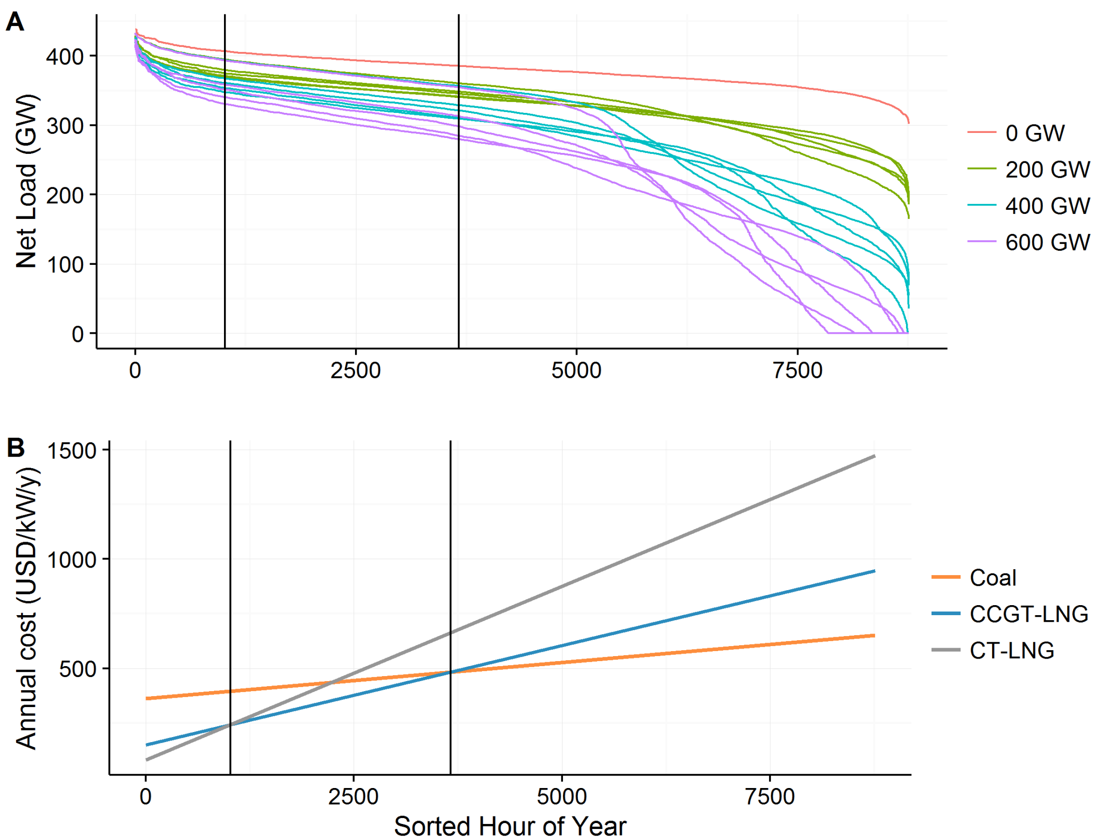


Figure 4.14: Net load duration curves for all VRE build-out scenarios and screening curves with three technologies - coal, combined cycle gas turbines (CCGT), and combustion turbines (CT), the latter two powered by liquefied natural gas (LNG). Capacities are determined by the intersection of the vertical lines and the net load curve for a scenario. Each group of VRE target scenarios includes five combinations of shares of solar PV and wind.

We found VRE curtailment to be the same between corresponding VRE build-out scenarios within the High-Cost-Coal and Low-Cost-Coal scenarios. Curtailment took place during low demand and high VRE periods when the commitment of units is similar between the High-Cost-Coal and Low-Cost-Coal scenarios, both of which are dominated by low variable cost and inflexible coal units. The inability of coal units to turn down below the 55% minimum generation level led to curtailment of zero marginal cost VRE.

The capacity value of VRE is significantly greater in the High-Cost-Coal scenarios as compared with the Low-Cost-Coal scenarios mainly because the higher costs of conventional capacity that is avoided (See Figure 4.15).

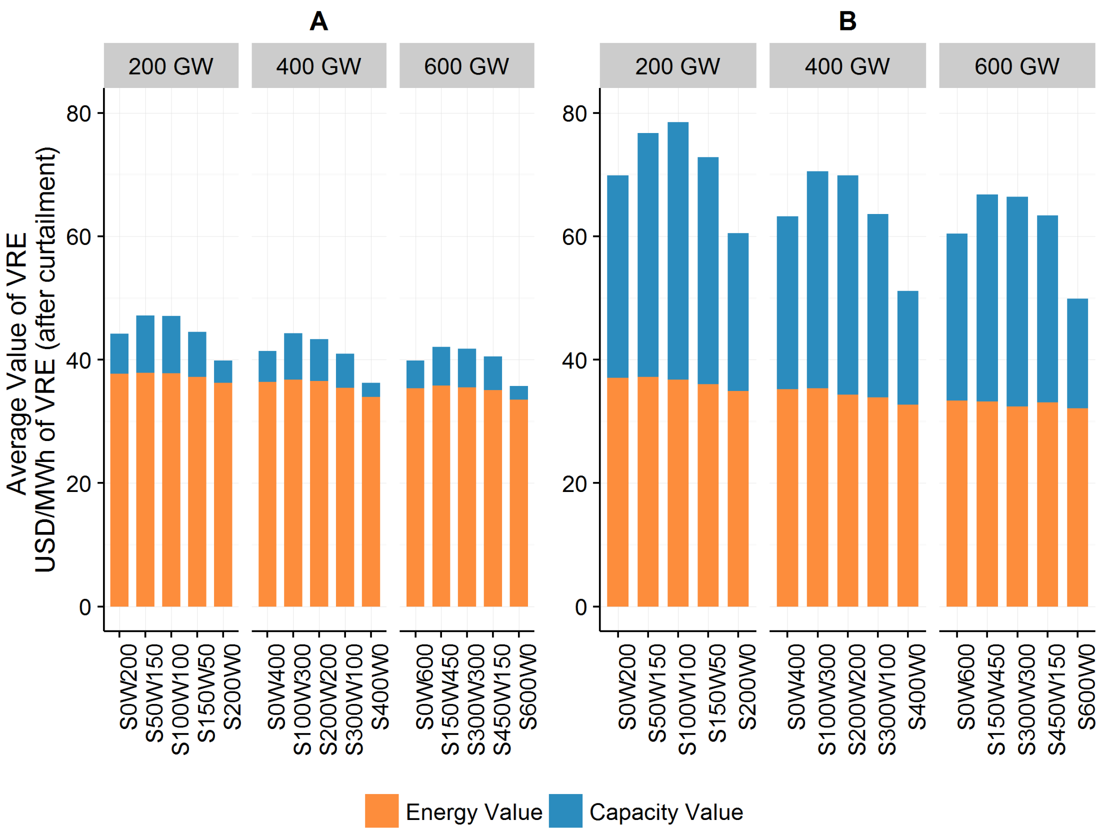


Figure 4.15: Average additional cost of VRE shown for conventional generation build-outs with low (A) and high (B) capital costs for coal. VRE installed capacity targets include 200 GW, 400 GW, and 600 GW, each with five combinations of shares of solar PV and wind - 0%-100%, 25%-75%, 50%-50%, 75%-25%, and 100%-0%.

Energy value of Low-Cost-Coal scenarios is greater than that for High-Cost-Coal , which may be counter-intuitive if one assumes that in Low-Cost-Coal scenarios, VRE will displace mainly low variable cost coal as opposed to displacing a combination of low variable cost coal and high variable cost gas generation in the High-Cost-Coal scenarios. The explanation lies in the changes in CT and CCGT generation. On one hand, for High-Cost-Coal scenarios, annual gas and diesel generation increased with higher VRE penetration, especially in hours when coal capacity was generating at its maximum. These increased gas and diesel costs decrease the overall energy value of VRE in the High-Cost-Coal scenarios. However, the differences in energy value are relatively small.

The average costs of carbon emissions mitigation for High-Cost-Coal scenarios are much lower than those for Low-Cost-Coal scenarios because investments in more expensive coal plants are avoided. For the 25%-75% and 50%-50% solar - wind mix scenarios for the 200 GW VRE build-out, costs of mitigation are negative, which means it is cost-effective to implement that VRE target without even internalizing the negative externalities of carbon emissions.

The reasons for lower capital costs of coal power plants in India compared to those in the US are several. Some of these include lower labor and steel costs, as well as permitting costs. Other reasons may include lower standards for emissions such as SOx and NOx as well as effluents, which impose significantly greater externality costs on the local environment and communities. So lower capital costs for coal plants may seem to increase the cost of mitigation of carbon emissions because less capital investment is avoided by VRE, but these low cost plants are likely to increase other externality costs, which we do not estimate in this study.

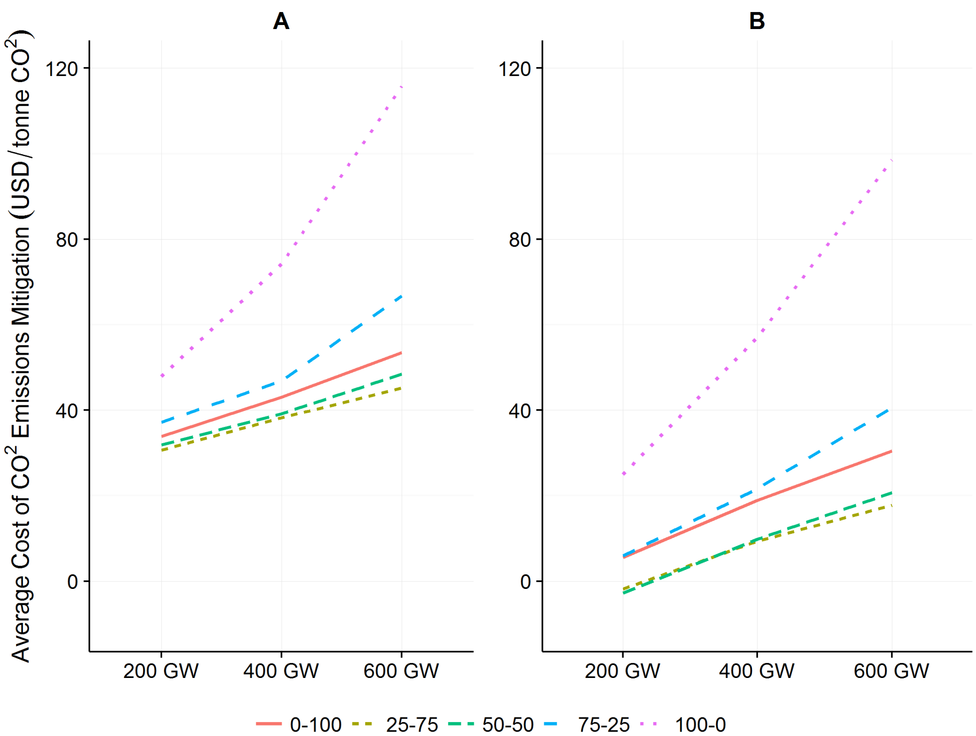


Figure 4.16: Average cost of mitigation of carbon dioxide emissions through VRE deployments shown for conventional generation build-outs with low (A) and high (B) capital costs for coal. Each line represents different combinations of shares of solar PV - wind installed capacities - 0%-100%, 25%-75%, 50%-50%, 75%-25%, and 100%-0%.

4.4 Conclusions

We examined the effects of different wind and solar installed capacity mixes and total targets on overall system cost and avoided emissions. In agreement with previous studies, we find that value of VRE decreases with increasing penetration across all mixes of wind and solar. Value of solar PV decreases at a higher rate than wind mainly because of the higher correlation between solar profiles across larger geographical regions. The highly correlated solar profiles increase the likelihood of solar being curtailed because of minimum generation constraints on thermal generators, thus increasing costs. The energy value of VRE derived from the displacement of conventional generation, is approximately half that of the direct cost of VRE (without considering curtailment). The limited correlation of VRE generation profiles with load across the year leads to a relatively small conventional generation capacity being avoided by VRE, thus resulting in a small capacity value across all VRE build-outs. We estimated the average overall additional costs to the entire electricity system as only USD 3.6 - 4.4 per MWh, 6-9% higher for the initial 200 GW VRE (approximately 12% VRE share by energy generation) as compared with a system without any VRE. However, these costs rise significantly with higher VRE penetration (USD 8.4 - 10.9 per MWh or 18-23% greater for 400 GW and 14.4 - 18.8 per MWh or 30-40% greater for 600 GW), not only because of the additional direct costs of VRE, but also due to the lower economic value and curtailment of VRE.

Attributing the entire additional cost of implementing a VRE target to mitigating the negative externality of carbon emissions, using present costs for VRE and conventional generators, we find that the optimal mix of 25% solar and 75% wind would cost USD 31/tonne-CO_2 for the 200 GW VRE target (approximately 12 % total VRE generation share), which is lower than the USD 39/tonne CO_2 adopted by the US EPA. However, the cost of mitigation increases to USD 47/tonne CO_2 to implement the next 200 GW (25% total VRE generation share), and further rises to USD 61/tonne CO_2 for another additional 200 GW (35% total VRE generation share). As costs of solar PV and potentially wind drop in the future, and stricter environmental norms make coal-based generation more expensive, carbon emissions mitigation through the implementation of high shares of VRE will become more economically attractive. Although the specific results in this analysis are likely to change as VRE costs and electricity systems evolve, the methodology outlined in this paper can be used to evaluate policies and VRE targets on an ongoing basis. Including other integration costs of VRE such as those due to forecast errors and additional requirements for ancillary services will improve this analysis. Similarly, location constraints and transmission investments are crucial to evaluate the spatial effects of VRE investments. Further, including strategies to mitigate VRE curtailment such as demand response and storage will increase the utility of our models. Finally, incorporating the benefits of mitigating negative externalities like SO_x, NO_x and particulate emissions, as well as environmental degradation and social costs due to mining, water inundation, or displacement, some of which are hard to quantify, will only enhance the analysis, of not only evaluating VRE investments, but all long-term investments in future electricity systems.

Chapter 5

Overall Conclusions

The ambitious targets for solar and wind set by the Government of India (GoI) - 160 GW of wind and solar, and 40% installed generation capacity from non-fossil fuel-based sources - will have significant economic, social, and environmental implications. In this thesis, I address three broad questions.

1. How can the economic, social, and environmental impacts of large-scale deployment of wind and solar resources be mitigated by incorporating multiple criteria in planning?

2. What are the impacts of VRE generation on system operations in the medium-term, and what strategies can mitigate these impacts?

3. How do the cost and value of wind and solar resources evolve in the long-term?

In Chapter 2, we apply the Multi-criteria Analysis for Planning Renewable Energy (MapRE) approach to identify and comprehensively value high-quality wind, solar photovoltaic (PV), and concentrated solar power (CSP) resources across India in order to support multi-criteria prioritization of development areas through planning processes.

India has abundant wind and solar resources but these are unevenly distributed, with the best resources available in the western and southern states. The spatial unevenness of RE resources across the country underscores the importance of inter-regional transmission lines and sharing of balancing resources across the entire grid to ensure cost-effective and reliable integration of high shares of variable renewable energy generation. Identifying such RE zones for pre-planning of high-voltage transmission infrastructure will encourage development in these areas and avoid long-distance low-voltage transmission interconnections that often result in congestion and land fragmentation. Given the importance of incorporating multiple attributes in renewable energy infrastructure planning including levelized cost of generation, proximity to transmission infrastructure, road, and load centers, capacity value, co-location opportunities, and access to water resources, the multi-criteria analysis for planning renewable energy (MapRE) tools enable stakeholders to prioritize RE zones within a multi-criteria decision analysis framework. The MapRE tools and maps will enable a more informed, stakeholder-driven process for prioritizing and selecting RE zones for cost-effective, and environmentally and socially sustainable development.

In Chapter 3, we analyzed the impacts of the GoI targets of 100 GW solar and 60 GW wind on system operations in 2022. We developed a suite of models with high spatial and temporal resolution - RE site selection and generation profile model, load forecast model, and production cost model – to simulate different electricity system futures for India. In spite of a generation fleet dominated by relatively inflexible coal power plants (230 GW or 70% of total conventional installed capacity), the 160 GW of VRE, which generates 22% of total electricity, can be integrated into India's 2022 power system with only 1.1% of curtailment in the base scenario. As zero marginal cost VRE generation displaces thermal generation, coal plants will experience lower plant load factors (annual average of 50%), which has economic impacts on power plant operators and consumers.

We also looked at three different types of sensitivities to evaluate strategies to mitigate impacts of VRE on the 2022 Indian electricity system. These include coordinated dispatch, flexibility in coal operations, and transmission transfer capacities on inter-regional interfaces. Although max up and down hourly ramp rates increase by 50% in the scenario with 100 GW solar and 60 GW wind and total ramps double as compared with the no new renewables scenario, we found that relaxing the constraint on coal minimum generation levels plays a larger role in reducing VRE curtailment than increasing coal ramp capability. Other sensitivities on coal plant flexibility such as halving the ramp rates and doubling start costs (both decreasing flexibility), and halving the minimum up and down times (increasing flexibility) did not significantly affect the share of VRE curtailment, although doubling start costs did increase production costs. However, coal ramping capability may become important when only a part of the coal-based fleet is available for ramping because of contractual constraints on other plants. Ramping capability may also become a constraint at higher VRE penetration levels.

Moving from state balancing area to regionally coordinated scheduling and dispatch result in savings of 3% of total production costs, with varying benefits accruing by region. These savings are almost twice those in the no new renewables scenario showing the increased value of coordination across balancing areas with higher shares of renewable energy. These gains are also higher when the coal fleet is less flexible - 70% minimum generation level as opposed to 55% minimum generation level. Increase in transmission capacity also reduces production costs as well as curtailment.

The data sets, models, and tools developed through this analysis can be used to evaluate many other development paths and scenarios for mitigating greenhouse gas emissions in India's electricity sector. The products of this analysis can help support India's goal of decarbonizing its electricity sector and play a critical role in mitigating future climate change.

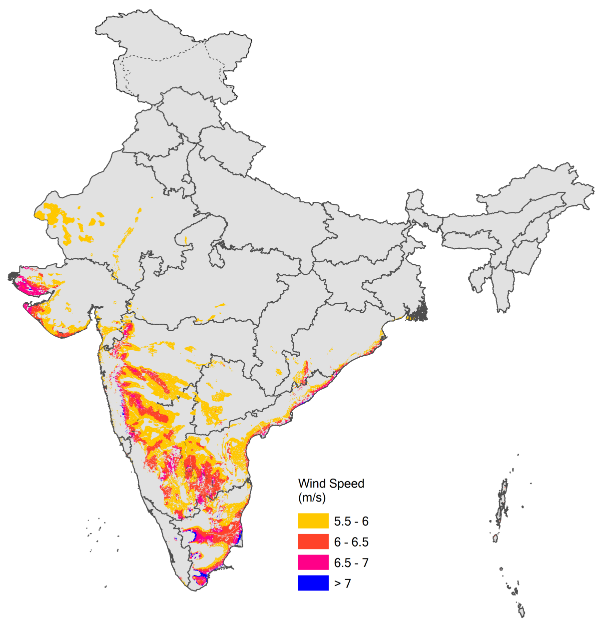
In Chapter 4, using an economic dispatch model, we examined the effects of different wind and solar installed capacity mixes and total targets on overall system cost and avoided emissions. In agreement with previous studies, we find a decreasing trend in the value of VRE with increasing penetration across all mixes of wind and solar. Value of solar PV decreases at a higher rate than wind with greater penetration mainly because of the relatively higher correlation between solar profiles across larger geographical regions as compared with wind, which increases the likelihood of solar being curtailed when minimum generation constraints on thermal generators are hit. The energy value of VRE derived from the displacement of conventional generation, is approximately half that of the direct cost of VRE (without considering curtailment). In India, the limited correlation of VRE generation profiles with load across the year leads to a relatively small conventional generation capacity being avoided by VRE. We estimated the average additional costs to the entire electricity system for the initial 200 GW VRE (12% VRE share by energy generation) to be 6-9% more than a system without any VRE. These costs rise further with higher VRE penetration (18-23% for 400 GW and 30-40% for 600 GW), not only because of the additional direct costs of VRE, but also due to the lower economic value and curtailment of VRE.

Attributing the entire additional cost of implementing a VRE target to mitigating the negative externality of carbon emissions, using present costs for VRE and conventional generators, we find that the optimal mix of 25% solar and 75% wind would cost USD 31/tonne-CO_2 for the 200 GW VRE target. However, the cost of mitigation increases to USD 47/tonne CO_2 to implement the next 200 GW (25% total VRE generation share), and further rises to USD 61/tonne CO_2 for another additional 200 GW (35% total VRE generation share). As costs of solar PV and potentially wind drop in the future, and stricter environmental norms make coal-based generation more expensive, carbon emissions mitigation through the implementation of high shares of VRE will likely become more economically attractive. Although the specific results in this analysis are likely to change as VRE costs and electricity systems evolve, the methodology outlined in this paper can be used to evaluate policies and VRE targets on an ongoing basis.

High spatio-temporal resolution data and models are essential to evaluate the impacts of VRE generation because of the significant spatio-temporal variability in their generation and availability. The key contribution of this thesis is the development of tools and models to analyze future low carbon electricity systems and develop strategies and policies to ensure that the integration of wind and solar is cost-effective and socially and environmentally sustainable.

Appendix A

Renewable resources by resource quality



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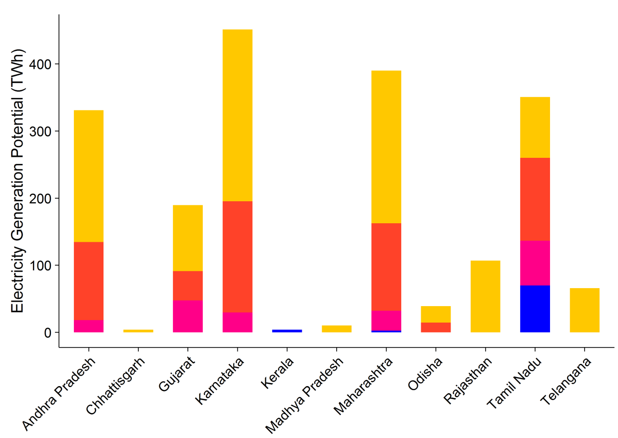

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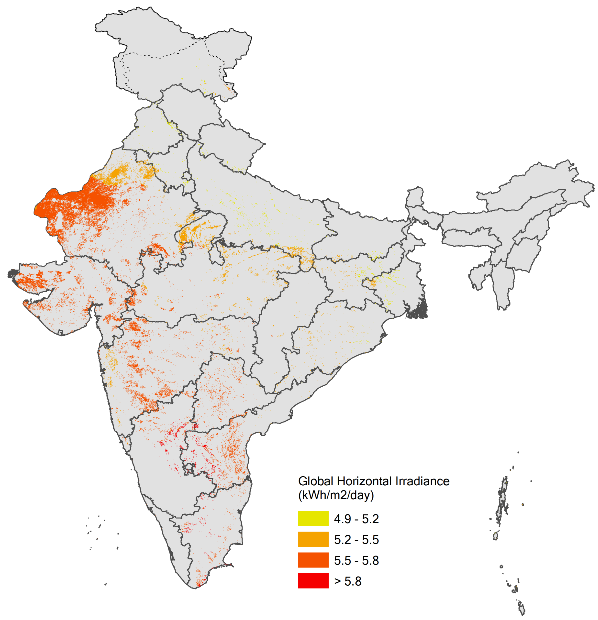
Figure A.1: Spatial distribution (a) and state-wise state-wise electricity generation potential (b) for wind by resource quality.



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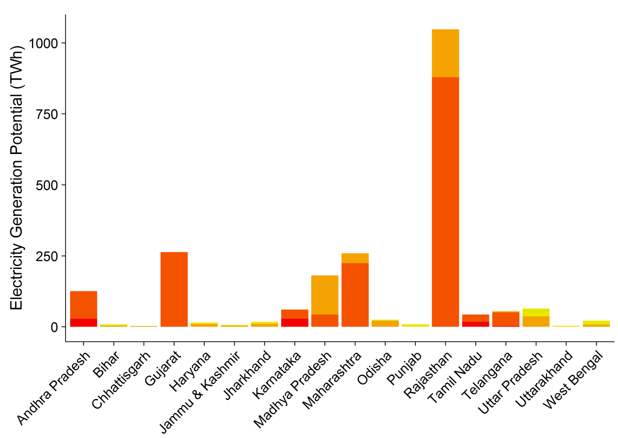

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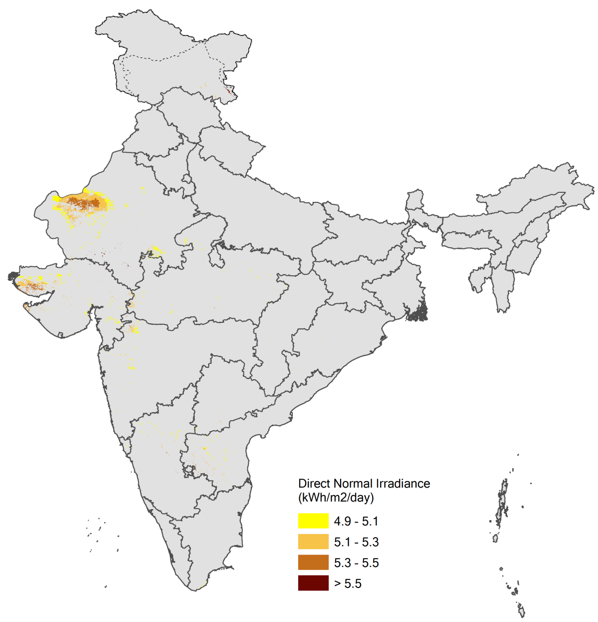
Figure A.2: Spatial distribution (a) and state-wise state-wise electricity generation potential (b) for solar PV by resource quality.



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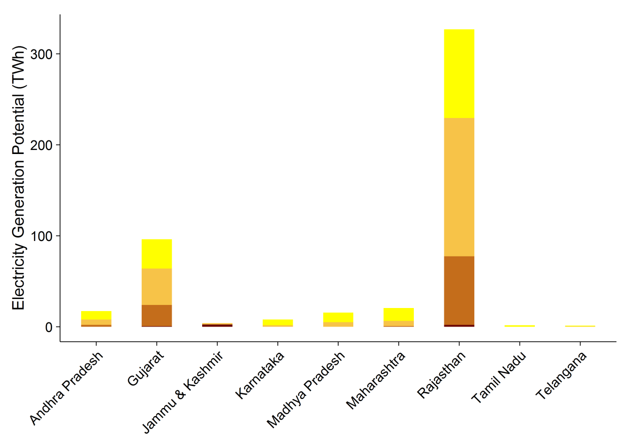

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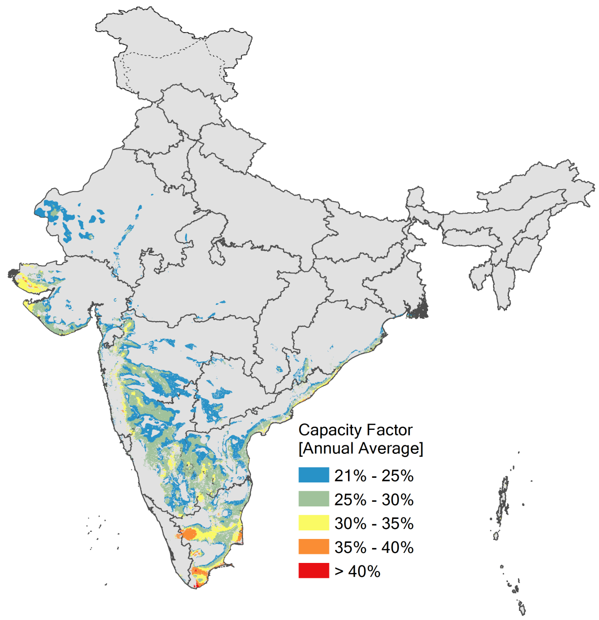
Figure A.3: Spatial distribution (a) and state-wise state-wise electricity generation potential (b) for CSP by resource quality.

Appendix B

Renewable resources by capacity factor



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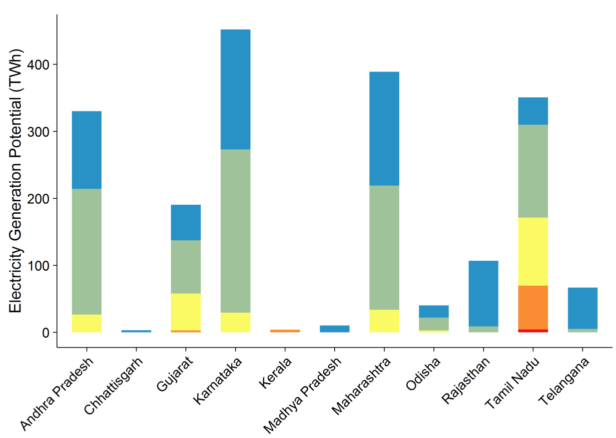

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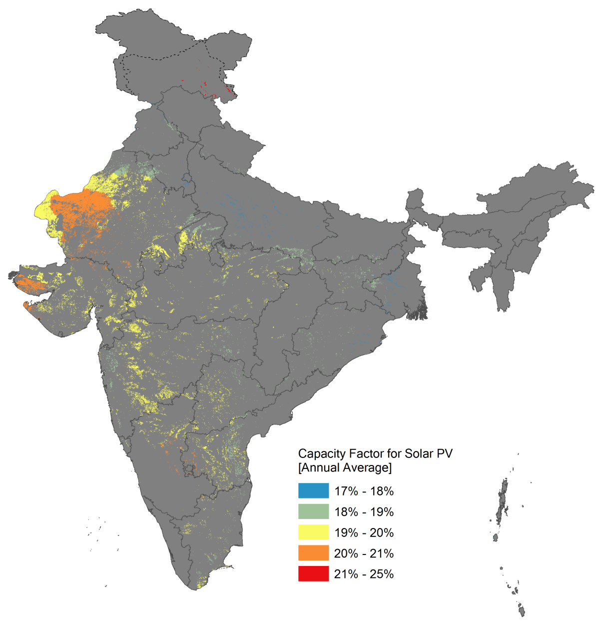
Figure B.1: Spatial distribution (a) and state-wise state-wise electricity generation potential (b) for wind by capacity factor.



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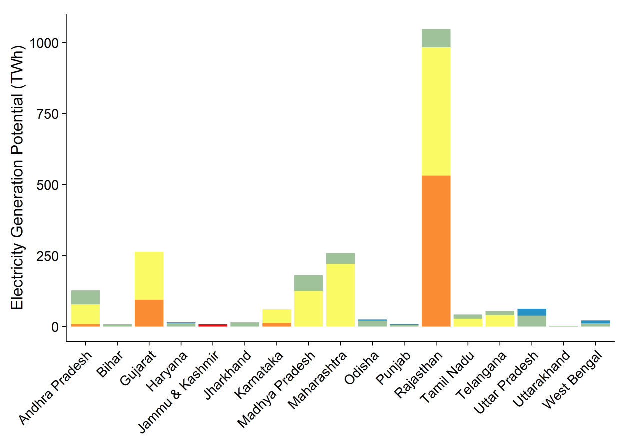

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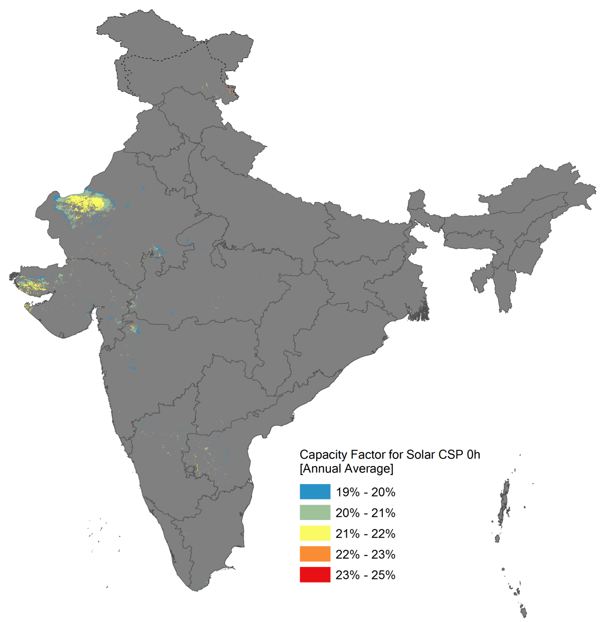
Figure B.2: Spatial distribution (a) and state-wise state-wise electricity generation potential (b) for solar PV by capacity factor.



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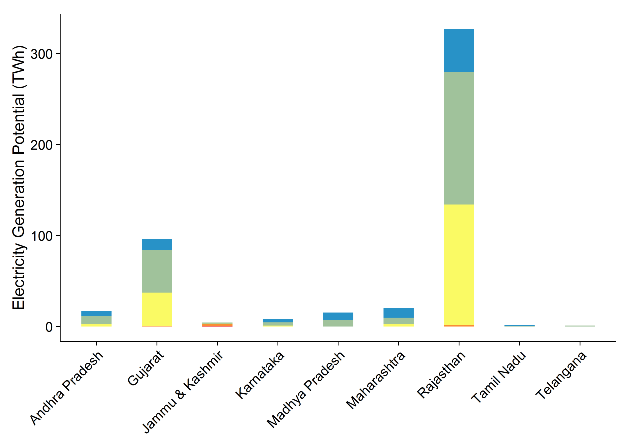

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Figure B.3: Spatial distribution (a) and state-wise state-wise electricity generation potential (b) for CSP by capacity factor.

Appendix C

Renewable resources by levelized cost

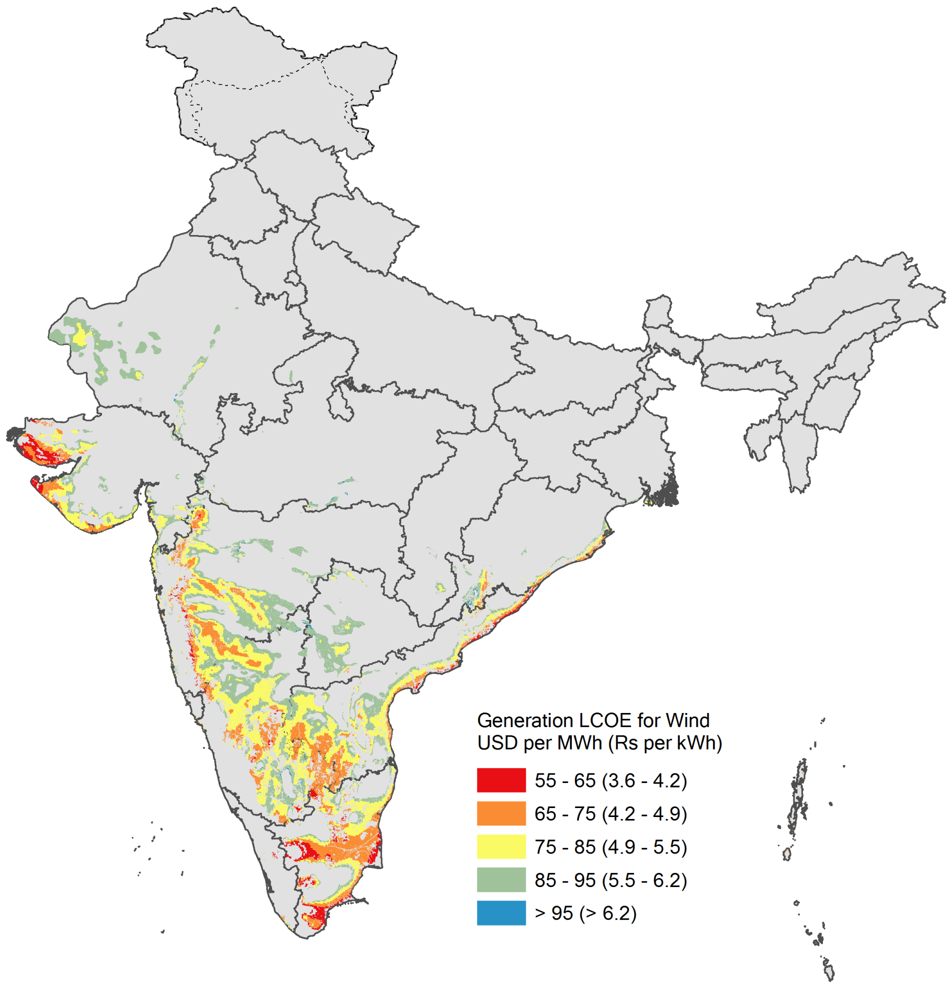

Figure C.1: Spatial distribution of wind resources by generation LCOE.

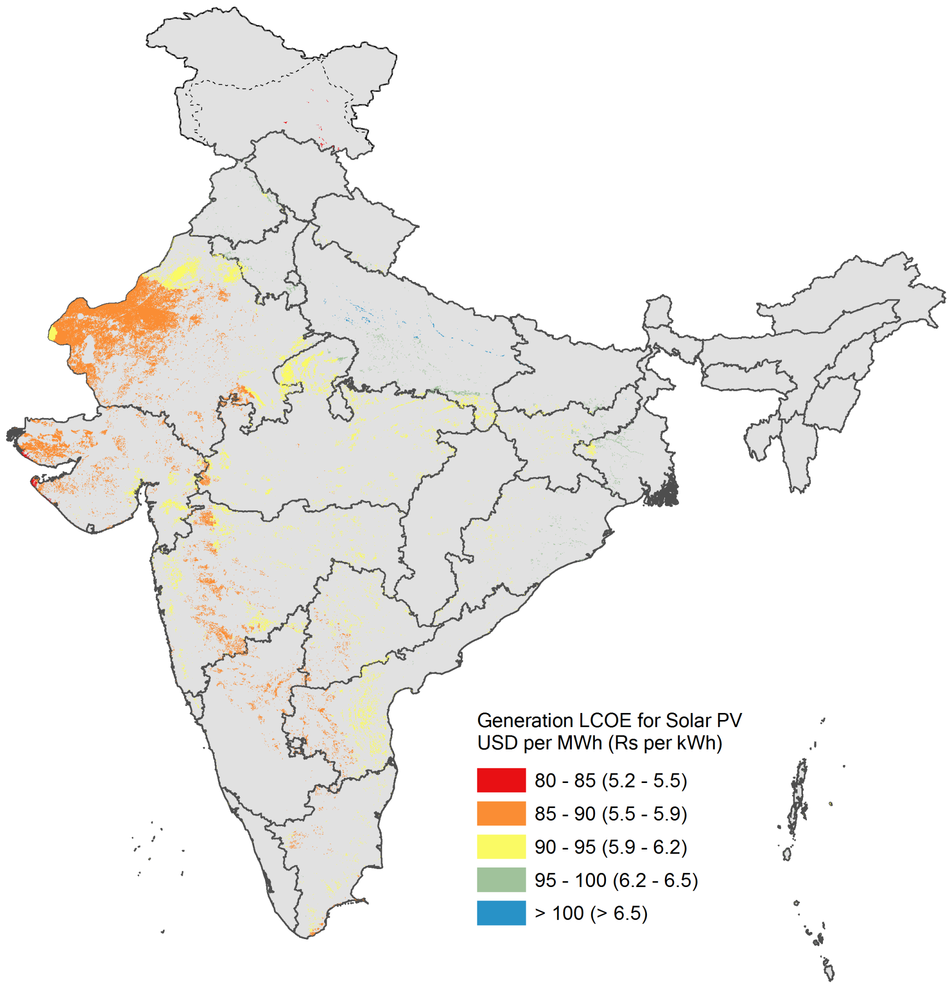

Figure C.2: Spatial distribution of solar PV resources by generation LCOE.

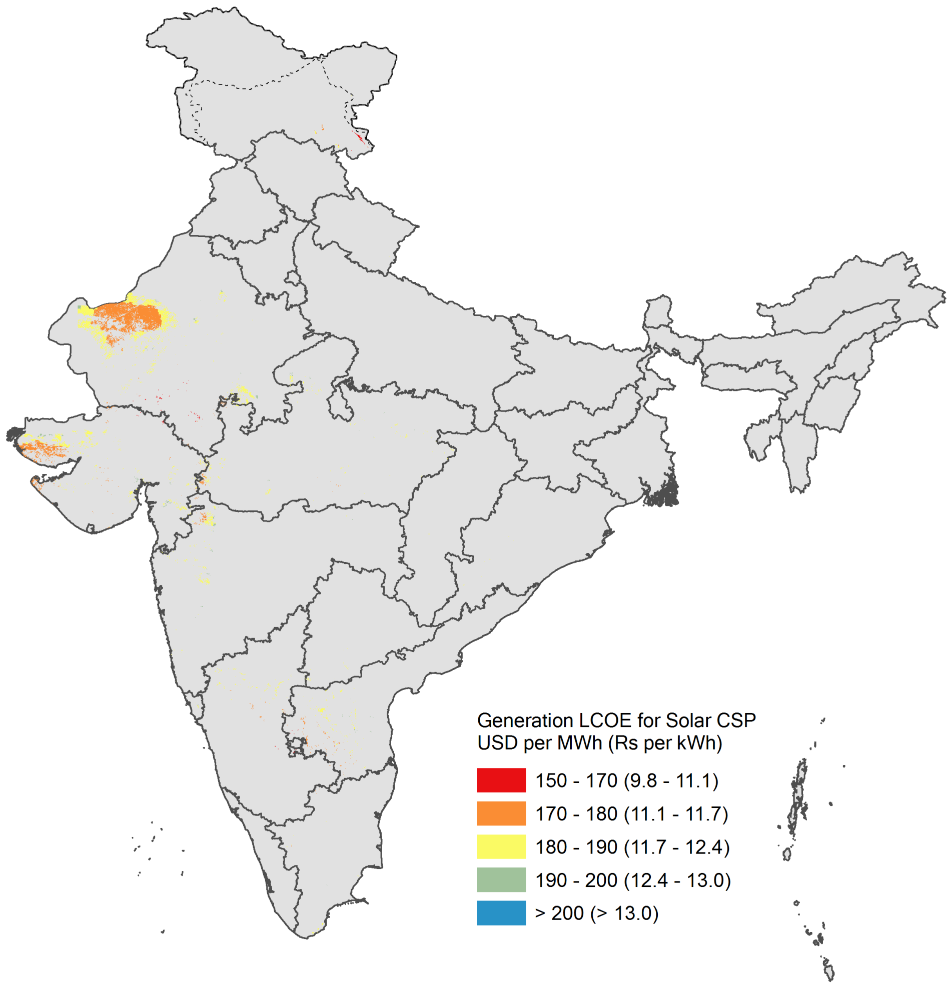

Figure C.3: Spatial distribution of CSP resources by generation LCOE.

Appendix D

Variability of resource quality across zones

We spatially aggregated the project opportunity areas into RE zones by proximity and minimizing the standard deviation of resource quality. Figure D.1, Figure D.2, and Figure D.3 show the standard deviation of resource quality in relation to the area of the zone, and the mean resource quality for the zone. Wind speeds tend to vary much more across regions compared to solar radiation. The standard deviation of resource quality does not tend to increase with the area of the zones for any of the technologies.

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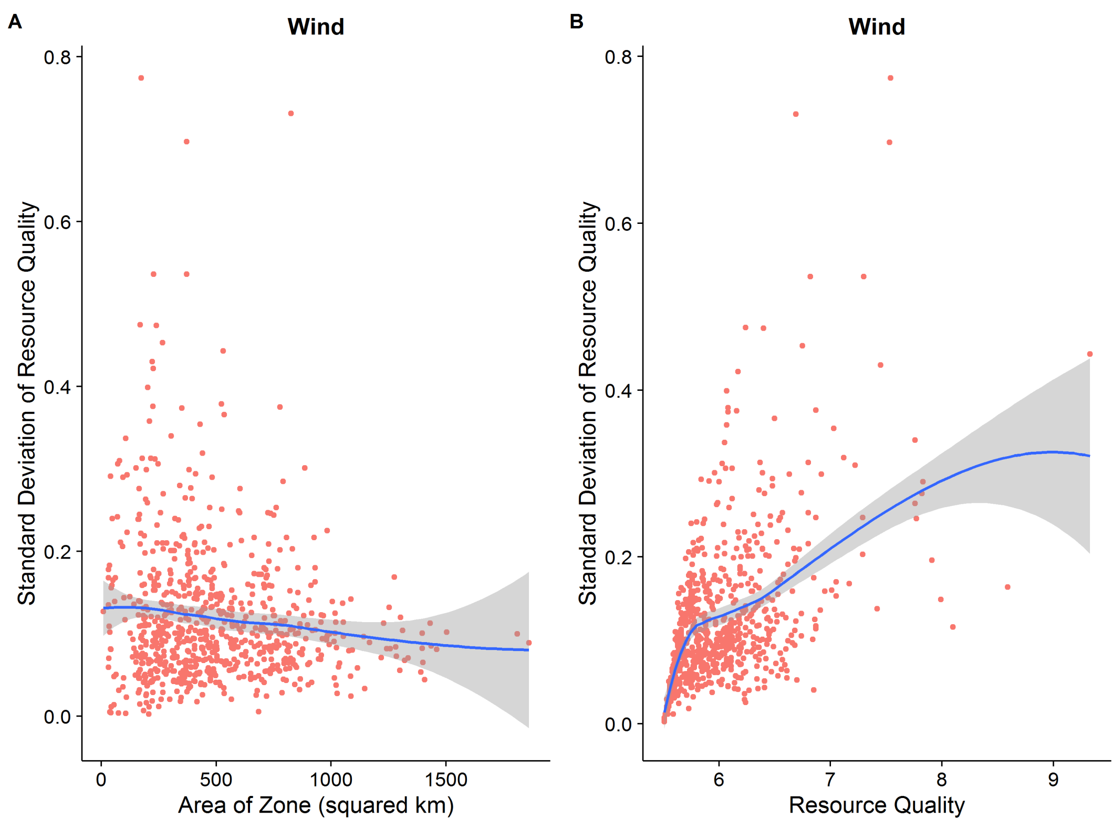

Figure D.1: Standard deviation of resource quality across wind zones in relation to the area (A) and the mean resource quality (B) of the zone - wind speed (m/s)

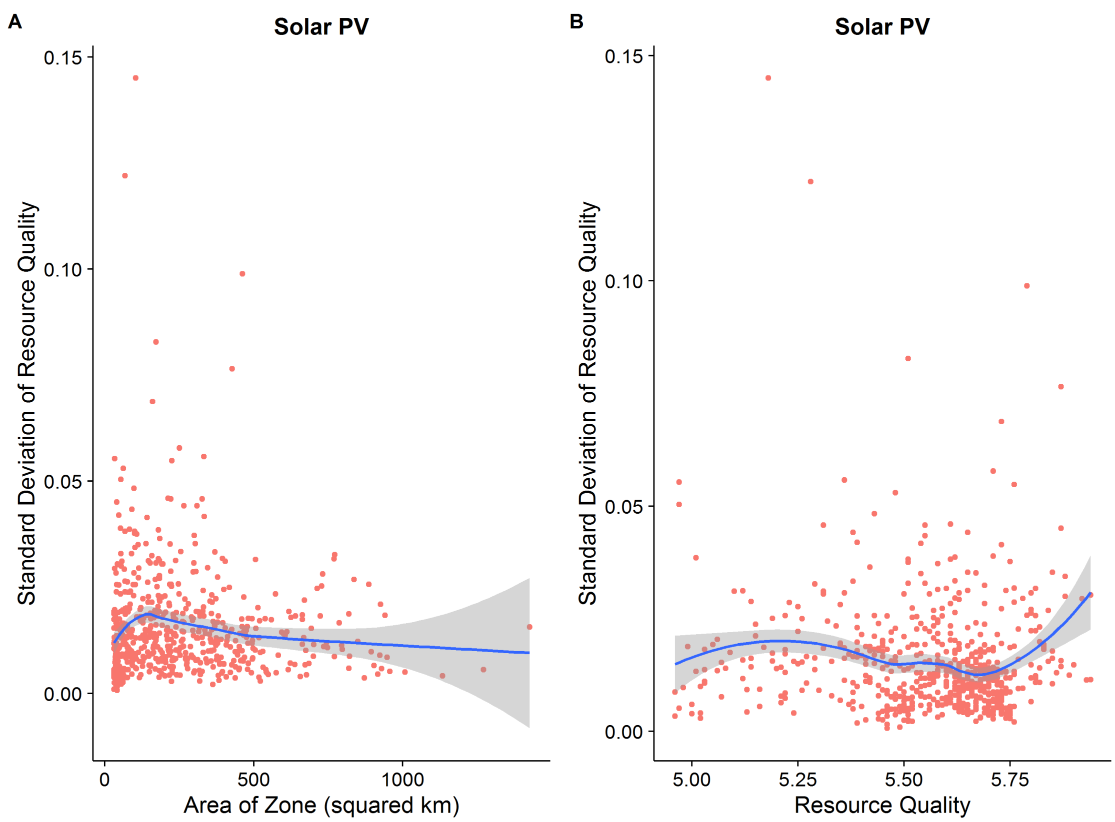

Figure D.2: Standard deviation of resource quality across solar PV zones in relation to the area (A) and the mean resource quality (B) of the zone - GHI (kWh/m2-day)

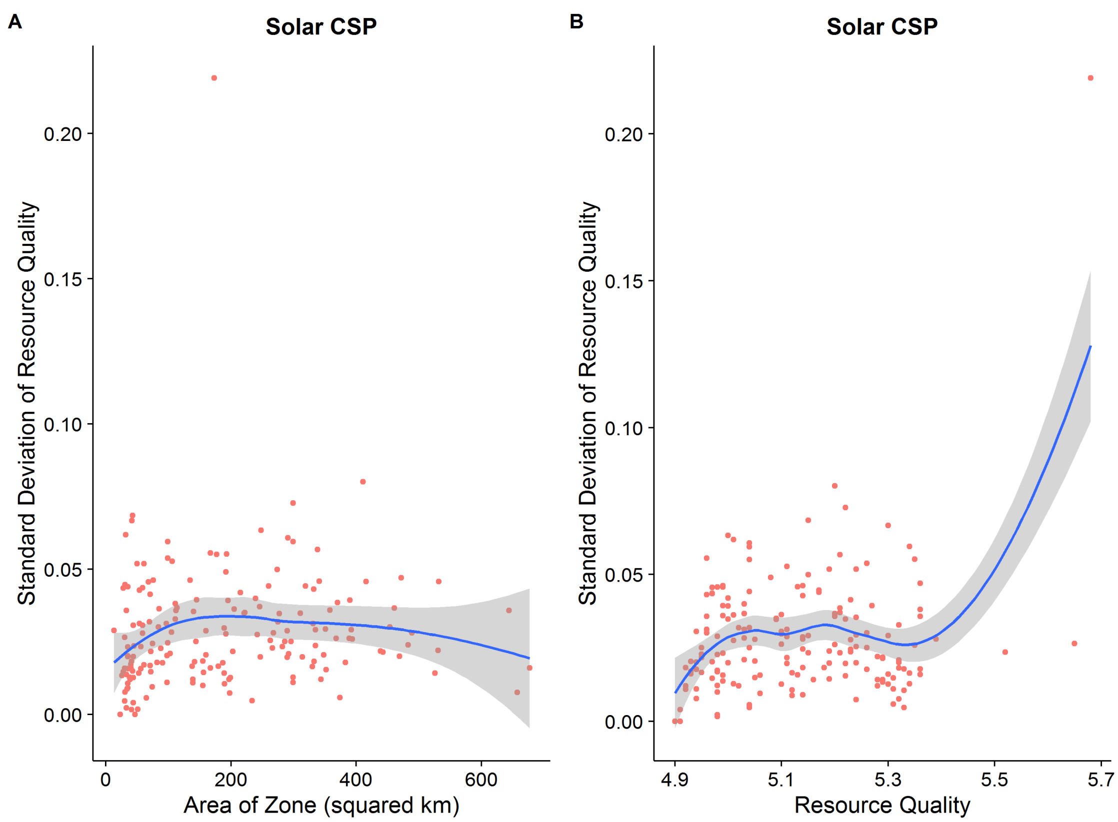

Figure D.3: Standard deviation of resource quality across CSP zones in relation to the area (A) and the mean resource quality (B) of the zone - DNI (kWh/m2-day)

Appendix E

Data sources and resource assessment thresholds

Table E.1: **D**ata sources and resource assessment thresholds

Stage of analysis	**C**ategory	**F**ile type	**S**ource	**D**escription	**Y**ear	**D**efault exclusion thresholds
Resource assessment	Boundaries	vector	Global Administrative Database (GADM) v2	GADM is a spatial database of the location of the world's administrative areas (or administrative boundaries) for use in GIS and similar software. Administrative areas in this database are countries and lower level subdivisions.	2012	
Resource assessment	Boundaries	vector	Ministry of New and Renewable Energy	The Ministry of New and Renewable Energy of India published a map of the state and district boundaries of India as part of its solar resource assessment.	Unknown	
Resource assessment	Elevation	raster	Shuttle Radar Topographic Mission (SRTM) – CGIAR-CGI Digital Elevation dataset v4.1	Produced by NASA originally, the SRTM is a major breakthrough in digital mapping of the world and provides a major advance in the accessibility of high quality elevation data for large portions of the tropics and other areas of the developing world. 3 arc seconds (approx. 90 m) resolution.	2000	>5000 m (all technologies)
Resource assessment	Slope	raster	SRTM - CGIAR	Created from elevation dataset using ArcGIS 10.2 Spatial Analyst.	2000	>5% (solar); >20% (wind)
Estimation of Project opportunity area attributes	Temperature	raster	WorldClim	WorldClim is a set of global climate layers (climate grids) with a spatial resolution of about 1 square kilometer. Hijmans, R.J., S.E. Cameron, J.L. Parra, P.G. Jones and A. Jarvis, 2005. Very high resolution interpolated climate surfaces for global land areas. International Journal of Climatology 25: 1965-1978. http://www.worldclim.org/formats	1950 - 2000	
Resource assessment	Land use/land cover (LULC)	raster	National Remote Sensing Center (NRSC) of India	Developed by the National Remote Sensing Centre of the Indian Space Research Organisation, this land use-land cover dataset is provided at a scale of 1:50,000. Overall accuracy of different LULC classes can vary from 79% (agro-horticulture) to 97% (waterbodies).	2010-11	See Table 2.1

Stage of analysis	**C**ategory	**F**ile type	**S**ource	**D**escription	**Y**ear	**D**efault exclusion thresholds
Resource assessment and Project opportunity area attributes	Water bodies	vector	World Wildlife Federation Global lakes and wetlands database	Comprises lakes, reservoirs, rivers and different wetland types in the form of a global raster map at 30-second resolution. We excluded the following categories: lake, reservoir, river, freshwater marsh, floodplain, swamp forest, flooded forest, coastal wetland, brackish/saline wetland, and intermittent wetland/lake from. http://www.worldwildlife.org/pages/global-lakes-and-wetlands-database	2004	<¡500 m buffer
Project opportunity area attributes	Rivers	vector	Natural Earth	Natural Earth is a public domain map dataset featuring both cultural and physical vector data themes. The rivers datasets are originally from the World Data Bank 2. All rivers received manual smoothing and position adjustments to fit shaded relief generated from SRTM Plus elevation data, which is more recent and (presumably) more accurate. http://www.naturalearthdata.com/downloads/	Unknown (version 3.0.0)	
Project opportunity area attributes	Population density	raster	LandScan (Oak Ridge National Laboratory)	ORNL's LandScanTM is the community standard for global population distribution. At approximately 1 km resolution (30" X 30"), it is the finest resolution global population distribution data available and represents an ambient population (average over 24 hours).	2012	
Resource assessment	Wind	raster	Vaisala (formerly 3Tier)	Data were created from computer simulations using a meso-scale numerical weather prediction model and validated using publicly available wind speed observations from 194 meteorological stations within Africa from the National Centers for Environmental Prediction (NCEP). Annual wind speed, wind power density, and wind power output were provided at 80 m hub height and 5 km resolution for a typical meteorological year.	10-year model run	<¡5.5 m/sec

Stage of analysis	**C**ategory	**F**ile type	**S**ource	**D**escription	**Y**ear	**D**efault exclusion thresholds
Resource assessment	Solar DNI	raster	NREL	Annual average global horizontal irradiance and direct normal irradiance data were provided by the National Renewable Energy Laboratory, and have a resolution of 10km.	2013	<¡ 4.9 kWh/m2-day
Resource assessment	Solar GHI	raster	NREL	Same as Solar DNI dataset	2013	<¡ 4.9 kWh/m2-day
Resource assessment	Protected Areas	vector	World Database of Protected Areas (WDPA)	The World Database on Protected Areas (WDPA) is the most comprehensive global spatial dataset on marine and terrestrial protected areas available. The WDPA is a joint project of UNEP and IUCN, produced by UNEP-WCMC and the IUCN World Commission on Protected Areas working with governments and collaborating NGOs.	2014	<¡500 m buffer
Resource assessment	Protected Areas	vector	Protected Planet	Open source database that includes most WDPA locations, but also include polygon representations of the WDPA point locations (those with unknown extents/boundaries)	2014	<500 m buffer
Project opportunity area attributes	Roads	vector	gROADSv1 -Columbia University	Global Roads Open Access Data Set, Version 1 was developed under the auspices of the CODATA Global Roads Data Development Task Group at Columbia University. The data set combines the best available roads data by country into a global roads coverage, using the UN Spatial Data Infrastructure Transport (UNSDI-T) version 2 as a common data model.	Variable; compiled 2010 (1980-2010)	
Project opportunity area attributes	Transmission substations	vector	POSOCO	Transmission substation location data was provided by the Power Systems Operation Corporation of India, and various internet sources.	2016	
Project opportunity area attributes	Renewable energy locations	vector	PGCIL, various state load dispatch centers	Locations of wind plants were compiled from the Green Corridors Report of the Power Grid Corporation of India Ltd. and various internet sources.	2012	

Stage of analysis	**C**ategory	**F**ile type	**S**ource	**D**escription	**Y**ear	**D**efault exclusion thresholds
Project opportunity area attributes	Load centers	Lat-long coordinates	Geonames	The GeoNames geographical database is available for download free of charge under a creative commons attribution license. It contains over 10 million geographical names and consists of over 9 million unique features including 2.8 million populated places and 5.5 million alternate names (www.geonames.org)	2014	
Project opportunity area attributes	Wind speed time series	.csv	Vaisala (formerly 3Tier)	Hourly wind speed data for 10 years (same simulated data that was used to create the typical meteorological year (TMY) average values); approximately 3.6 km resolution	10-year model run	
Project opportunity area attributes	Solar GHI time series	.csv	NREL-NSRDB	Hourly GHI and temperature data from the National Solar Radiation Datab; 10 km resolution	2014	

Appendix F

Map of India and its state boundaries

Figure F.1: Map of India and its state boundaries.

Appendix G

Electricity regions

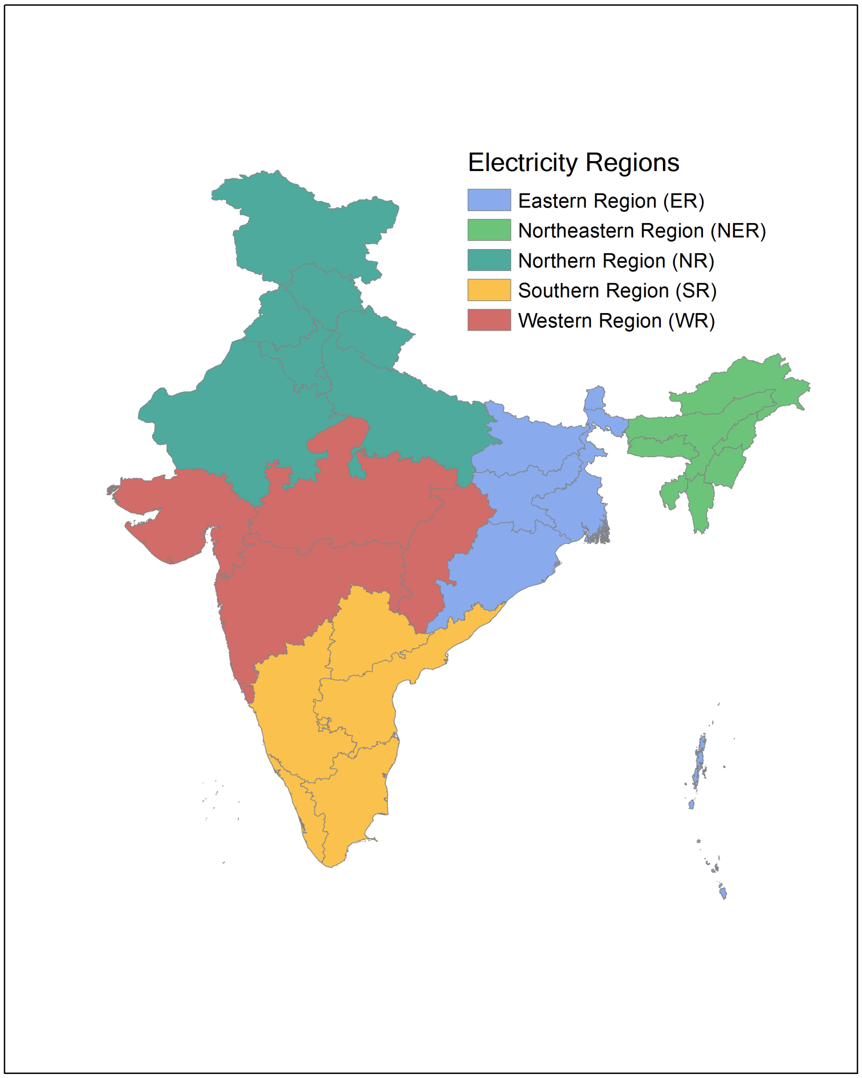

Figure G.1: Electricity Regions of the Indian Electricity Grid. Each state belongs to one of the five electricity regions. Each region's scheduling and dispatch is coordinated by the Regional Load Dispatch Center.

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