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Multicriteria Analysis for Planning Renewable Energy (MapRE)

Ranjit Deshmukh, Grace Wu, & Amol Phadke April 2017

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An electronic version of this report is available at <http://mapre.lbl.gov/>

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Definitions and Abbreviations

Summary

India's targets of 175 GW of renewable energy capacity by 2022, and 40% generation capacity from non-fossil fuel sources by 2030 will require a rapid and dramatic increase in solar and wind capacity deployment and overcoming its associated economic, siting, and power system challenges. The objective of this study was to spatially identify the amount and quality of wind and utility-scale solar resource potential in India, and the possible siting-related constraints and opportunities for development of renewable resources.

Using the Multi-criteria Analysis for Planning Renewable Energy (MapRE) methodological framework, we estimated several criteria valuable for the selection of sites for development for each identified potential "zone", such as the levelized cost of electricity, distance to nearest substation, capacity value (or the temporal matching of renewable energy generation to demand), and the type of land cover. We find that high quality resources are spatially heterogeneous across India, with most wind and solar resources concentrated in the southern and western states, and the northern state of Rajasthan. Assuming India's Central Electricity Regulatory Commission's norms, we find that the range of levelized costs of generation of wind and solar PV resources overlap, but concentrated solar power (CSP) resources can be approximately twice as expensive. Further, the levelized costs of generation vary much more across wind zones than those across solar zones because of greater heterogeneity in the quality of wind resources compared to that of solar resources.

When considering transmission accessibility, we find that about half of all wind zones (47%) and two-thirds of all solar PV zones (66%) are more than 25 km from existing 220 kV and above substations, suggesting potential constraints in access to high voltage transmission infrastructure and opportunities for preemptive transmission planning to scale up RE development. Additionally and importantly, we find that about 84% of all wind zones are on agricultural land, which provide opportunities for multiple-uses of land but may also impose constraints on land availability. We find that only 29% of suitable solar PV sites and 15% of CSP sites are within 10 km of a surface water body suggesting water availability as a significant siting constraint for solar plants. Availability of groundwater resources was not analyzed as part of this study. Lastly, given the possible economic benefits of transmission extensions or upgrades that serve both wind and solar generators, we quantified the co-location opportunities between the two technologies and find that about a quarter (28%) of all solar PV zones overlap with wind zones. Using the planning tools made available as part of this study, these multiple siting constraints and opportunities can be systematically compared and weighted to prioritize development that achieves a particular technology target.

Our results are limited by the uncertainties associated with the input datasets, in particular the geospatial wind and solar resource, transmission, and land use land cover datasets. As input datasets get updated and improved, the methodology and tools developed through this study can be easily adapted and applied to these new datasets to improve upon the results presented in this study.

India is on a path to significantly decarbonize its electricity grid through wind and solar development. A stakeholder-driven, systematic, and integrated planning approach using data and tools such as those highlighted in this study is essential to not only meet the country's RE targets, but to meet them in a cost-effective, and socially and environmentally sustainable way.

Contents

Introduction

1

The Government of India has set ambitious targets for grid-connected renewable energy (RE) generation - 60,000 MW of wind and 100,000 MW of solar capacity by 2022 (GoI, 2016). Further, in its Intended Nationally Determined Contribution (INDC), India has committed to 40% of its installed generation capacity to come from non-fossil sources by 2030 (GoI, 2016). By the end of 2016, India had 27,000 MW of installed wind generation capacity and about 7,800 MW of solar (mostly PV) capacity. The 2022 targets will require more than doubling of this 2016 wind installed capacity and increasing the solar PV installed capacity by more than a factor of 10.

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.

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 subregion (He and Kammen, 2014; He and Kammen 2016; Lopez, 2012), and a few have even analyzed resource potentials at a global scale (Lu et al, 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; CTSEP, 2013), whereas others have covered the entire country (Hossain et al, 2011, Phadke et al, 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 are cost-effective and have low negative environmental and social impacts can enable preemptive transmission planning to evacuate energy to load centers and incentivize project developers to build plants in those prioritized 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 (ERCOT, 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 (DEA and CSIR, 2014).

Multi-criteria decision analysis (MCDA) or multi-criteria evaluation (MCE) are a set of methods that enable making decisions in the presence of multiple objectives. MCDA in conjunction with GIS allows for integration of environmental, economic, and social factors that affect land suitability for a certain use (Carrióna 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 et al., 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.

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.

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

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.](#page-15-0)

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](#page-15-0). 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 km2 to 1000 km2. The actual sizes of the zones 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](#page-14-2) Using 10 years of simulated hourly wind speed profiles from 3Tier for each of 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.

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

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 **multicriteria 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](#page-16-2)}

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](#page-58-0) for a list of datasets and their sources.

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](#page-58-0) in Appendix [E\)](#page-57-0). Specifications for thresholds and buffer distances for unsuitable areas follow international industry standards and previous studies (Black & Veatch Corp. and NREL, 2009; California Public Utilities Commission [CPUC], 2009; Lopez et al., 2012; Phadke et al., 2012). We imposed a minimum contiguous area of 2 km² for both wind and solar. The technology-specific land-use/land-cover (LULC) categories are listed in Table [2.1](#page-17-3). 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 NREL, 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 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/m2 power density for wind; 4.9 kWh/m2/day or 1800 kWh/m2/y for solar) (Black & Veatch Corp. and NREL, 2009; California Public Utilities Commission [CPUC], 2009).

Limitations

Results and data derived from meso-scale models such as Vaisala's can be inconsistent with groundbased 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 anal-

 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.

Code	Class Name	Solar PV and CSP	Wind (agricultural areas NOT included)	Wind (agricultural areas included)	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 (crop- land)	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 for- est	Ex	Ex	Ex	
11	Littoral swamp	Ex	Ex	Ex	
12	Grassland	In.	In.	In.	2
13	Other wasteland	In.	In.	In	
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	\overline{c}

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

Criteria scores were set by authors and are used in calculating the total renewable energy zone score for ranking. See section [2.8](#page-25-0)

ysis 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.

2.4. 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](#page-21-0)), these steps divide large resource areas into POAs that range from 2 km 2 - 25 km 2 (using a 5 x 5 km square grid) and have the potential to accommodate 15 - 187.5 MW solar power plants and 4.5 - 56.25 MW wind plants. These sizes were selected to represent utility-scale wind and solar power plants. See Wu et al., 2015 for a more detailed explanation of POA creation.

2.5. Estimation of project opportunity area attributes (stage 3)

For each POA, we estimated several attributes (Table [2.2](#page-18-0)) for direct use in multi-criteria scoring of zones or for calculations of capacity factors (section [2.5.1](#page-17-2)) and costs (section [2.5.2](#page-20-0)), which are described in greater detail in subsequent sections. For the remainder of the attributes in Table [2.2](#page-18-0), we provide a brief explanation in section [2.5.4,](#page-23-1) but for a more detailed explanation, please see Wu et al., 2015.

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

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. $^3\,$ $^3\,$ $^3\,$ 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 [2.6\)](#page-23-2). 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](#page-19-0) for assumptions).^{[4](#page-18-2)} 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 by proportionally adjusting the closest simulated capacity factor using the POA's average resource quality.

CSP. We used NREL's System Advisor Model (NREL, 2016) 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 numerical model developed at the State University

³Although 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, 2015).

⁴The solar radiation data in NSRDB were developed using the State University of New York (SUNY) semi-empirical model, and the meteorological data are from the National Aeronautics and Space Administration (NASA)'s Modern-Era Retrospective Analysis for Research and Applications (MERRA).

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

Parameter	Value
System DC capacity	1.1 MW $_{\text{dc}}$
DC-to-AC ratio	11
Tilt of fixed tilt system	Latitude of location
Azimuth	180°
Inverter efficiency	96%
Losses	14%
Ground cover ratio	04

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\)](#page-19-1). We used these fitted equations (Figure [2.2](#page-19-1)) 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 et al., 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-densityadjusted 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\)](#page-20-1).

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

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](#page-20-2)). 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

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](#page-21-0) 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\)](#page-21-0).

 $^{\rm a}$ Mean of U.S. empirical values (3 MW/km 2) (Ong et al., 2012) and theoretical land use factors (Black & Veatch Corp. and NREL, 2009)

^b (Ong et al., 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 (Collier et al., 2015) Costs are for two lane bituminous road, and inflation adjusted
- f (CERC, 2014)
- ^g Default value in the System Adviser Model (SAM) by NREL
- h (Tegen et al., 2013)</sup>

Cost Calculations

Using the size (km²) 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](#page-20-2) and [2.5,](#page-21-0) 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 Prayas Energy Group (2014) to estimate the LCOE for different capacity factors for each of the technologies (Figure [2.3\)](#page-22-0). For the second method, we used the simple LCOE calculation provided in Equation (6) in Wu et al. (2015).

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](#page-21-0) for definitions of cost notation that correspond to equations in Wu et al. (2015).

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

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 parameters other than capital costs 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 [2.7\)](#page-24-0).

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.

2.5.3. Human footprint score

The human footprint is an environmental impact metric for degree of human influence on a unit of land, and it is used in this study as a proxy for degree of human "disturbance" from natural, unaltered states (Sanderson et al., 2002). We estimated this metric following Sanderson et al.'s (2002) methods, using the following datasets that indicate the degree of human influence and access: population density, land use/land cover, road and railway access, and surface water (rivers and oceans). Datasets were coded into standardized scores ranging from 0 (least influenced) to 10 (most influenced) (Table 6). We summed the scores for each dataset to create a Human Influence Index. Lastly, these scores were normalized within global terrestrial biomes (Olson et al., 2001), since absolute scores in one ecoregion may have a different effect compared to scores in another ecoregion. Within each ecoregion, the lowest Human Influence Index was assigned a human footprint score of 0 and the largest Index value a human footprint score of 100. The resulting human footprint score represents the relative human influence within an ecoregion as a percentage. For example, a score of 1 for an area within a particular ecoregion suggests that that area is the top 1% least disturbed or most wild area within that ecoregion. We calculated the human footprint score for each 500 m grid cell and then averaged the scores across every grid cell in each POA.

2.5.4. Other project opportunity area attributes

In this section, we briefly explain the other project opportunity area attributes given in Table [2.2.](#page-18-0) For a more detailed explanation, please see Wu et al., 2015. We used locations of 220 kV and above substations for estimating distances to nearest transmission infrastructure. For estimating distances to road and transmission infrastructure, We applied a terrain factor of 1.3 to account for terrain and other development constraints that would dictate the actual path of the extended road or transmission line. We defined load centers as cities with a population of over 500,000. Using the lake, reservoir, and river categories in the Global Lakes and Wetlands Database and all rivers in the Natural Earth rivers dataset, we calculated the distance to the nearest surface water body. For each LULC category, we assigned a subjective score ranging from 1 (least impactful alteration of LULC) to 5 (most impactful alteration of LULC) based on social and environmental value (biomass) of particular LULC categories (Table [2.1\)](#page-17-3). To value co-location of renewable energy plants, we assigned a binary score of 1 if the POA for a RE technology overlaps with another RE technology. Finally, a water access score of 1 was assigned if a POA is within 10 km of a surface water body. For all data sources, see Appendix [E](#page-57-0).

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](#page-54-0) 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](#page-18-0) 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.

2.7. 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 et al., 2010). Since one of the main purposes of this study is to robustly compare zones within India, relative capacity values of zones are more useful than 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.

2.7.1. Selection of sites with hourly wind profiles

Estimation of capacity value required both time series data for demand and wind generation. Demand data were provided by the Power Systems Operations Corporation of India. For wind speeds, we used simulated hourly data for 100 sites across India provided by Vaisala. With the objective to achieve adequate spatial representation of these limited number of wind sites with time series data across all the suitable wind resource areas, we selected these 100 sites by considering the highest quality project opportunity areas within identified wind zones, their spatial representation across a state, the amount of resource within a state, and locations of existing project sites.

2.7.2. Capacity value

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 defined 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 assumed 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 defined three metrics for capacity value. For the first metric, we defined capacity value as the average capacity factor of a RE generator during the top 10% of peak demand hours in a year (Mills et al., 2010). For the second metric, we estimated 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](#page-25-1) 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\)](#page-25-1). 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 computed the capacity value ratios as the ratio of the capacity value to the capacity factor at the site for all three metrics. We then extrapolated the capacity value ratios of the 100 wind sites to all the wind zones based on proximity. Finally, we computed the capacity value for each zone as the product of the capacity value ratio (from the nearest wind site) and the annual average capacity factor for that zone.

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.

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

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 [2.7](#page-26-0)).

Table 2.7: Criteria value ranges and scores.

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. See Figure [2.5](#page-26-1) for an illustration of how to compute an RE zone score.

The illustration shows only three criteria along with their minimum and maximum values. The minimum and maximum values will either have a score of 1 or 0 depending on the preference for that value (e.g. minimum value of LCOE is preferred for lowest cost zones and hence, will have a score of 1; whereas the maximum value of 100 for human footprint score is assigned a score of 1

for its preference as an area with the most human disturbance). The RE zone score for each criteria is calculated based on a linear scale between the minimum and maximum scores. The user-defined weights for each criteria are required to fall between 0 and 100%, and the sum of all weights should equal 100%. Weights are multiplied by the criteria scores and summed up 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 identifiers and the interactive PDF map's analysis tools.

3

Results

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 [3.1,](#page-29-0) Table [3.2](#page-30-0), and Table [3.3](#page-31-0). 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.](#page-46-0) 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.](#page-48-0) A map of India and its state boundaries is provided in Appendix [F](#page-60-0)

Wind. Wind resources are concentrated mainly in the western states (Gujarat, Maharashtra, and Rajasthan) and southern states (Andhra Pradesh, Karnataka, Tamil Nadu, and Telangana) (Table [3.1,](#page-29-0) Figures [3.1a](#page-29-1) - [3.1b](#page-29-2)). 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 [3.2](#page-30-0), Figure [3.2a](#page-30-1) - [3.2b](#page-30-2)). 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 entirely by the project developer. See Appendix [C](#page-50-0) 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 [3.3](#page-31-0), Figure [3.3b\)](#page-31-1). While areas

Table 3.1: State-wise technical potential for electricity generation and capacity for wind

Figure 3.1: 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/km² with a 75% discount for uncertainty, equivalent to 2.25 MW/km².

Table 3.2: State-wise technical potential for electricity generation and capacity for solar PV.

Figure 3.2: 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/m²-day and land use factor of 30 MW/km² with a 75% discount for uncertainty, equivalent to 7.5 MW/km².

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.

Table 3.3: State-wise technical potential for electricity generation and capacity for solar CSP

Figure 3.3: 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/m²-day and land use factor of 30 MW/km² with a 75% discount for uncertainty, equivalent to 7.5 MW/km².

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 (INR 3.2-6.3 per kWh) for 80 m hub height turbines (See Figure [3.4](#page-32-1) and Table [3.4](#page-33-1)).

• Solar PV costs adjusted using 2017 Madhya Pradesh auction price

Wind State Electricity Regulatory Commission feed-in tariffs 2016-17

• Wind all-India auction price 2017

Figure 3.4: Electricity generation potential sorted by levelized cost of energy (LCOE) for generation (left) and distribution of LCOE's across suitable resource areas (right) for concentrated solar power (CSP), solar PV and wind. LCOE for generation is estimated using Central Electricity Regulatory Commission norms for 2016. Both, DNI resource threshold for CSP and GHI resource threshold for solar PV are 4.9 kWh/m²-day. Wind speed resource threshold is 5.5 m/s. Land use factor for CSP and solar PV is 30 MW/km² with a 75% discount for uncertainty, equivalent to 7.5 MW/km². Land use factor for wind is 9 MW/km² with a 75% discount for uncertainty, equivalent to 2.25 MW/km². Vertical lines show 10%, 20%, and 30% of expected electricity demand in 2030. The supply curve of solar PV LCOE's adjusted downward using the 2017 Madhya Pradesh auction clearing price at the Rewa solar park is shown for comparison with the CERC derived solar PV LCOE's. Wind State Electricity Regulatory Commission's feed-in tariffs for 2016-17 from 7 states and the wind all-India auction clearing price in 2017 are provided as benchmarks against the CERC derived wind LCOE's.

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/m2-day for GHI were estimated to cost USD 72-101 per MWh (INR 4.7-6.6 per kWh) for fixed tilt systems, whereas the cost of CSP resources above a threshold of 4.9 kWh/m2-day for DNI were estimated to be USD 148-191 per MWh (INR 9.7-12.4 per kWh) for parabolic trough systems. The LCOE estimates show that the distribution of solar PV LCOEs overlaps that of wind, but CSP resources may cost twice as much as solar PV or wind. Further, the distribution of LCOEs indicates a greater variability in wind quality across the country, whereas quality of solar PV resources varies less (See Figure [3.4](#page-32-1) and Table [3.4\)](#page-33-1).

Table 3.4: Levelized cost of energy (LCOE) for generation for wind, solar PV, and concentrated solar power (CSP).

Resource data for wind from Vaisala Inc. and for solar from NREL's NSRDB.

Cost assumptions based on CERC regulations (2014) with adjustments provided for 2016.

Solar PV prices are expected to continue their decline as technology advancement and economies of scale continue to reduce costs, and auction-based procurement continues to capture those reductions by inducing competition. As a result, solar PV prices determined through auctions are expected to be lower than those determined in this study using CERC norms for 2016. As a comparison, the auction clearing price for the Rewa solar park in Madhya Pradesh in 2017 was more than 40% lower than costs estimated using CERC norms for that location (See Figure [3.4\)](#page-32-1). Similarly, costs of wind generation are also expected to decline as developers increase hub heights and rotor diameters to capture faster and greater wind resources that increase energy generation without incurring a proportional increase in costs (Wiser and Bolinger, 2016). Appropriate procurement mechanisms will enable the capture of these cost decreases as illustrated by India's first wind auction held in 2017, which resulted in a clearing price that was lower than all State Electricity Regulatory Commissions' and CERC's 2016 feed-in tariffs. (See Figure [3.4\)](#page-32-1).

Costs and prices of solar PV and wind will continue to evolve with technology advancements, economies of scale, procurement mechanisms, and market dynamics. Further, actual costs at a site depend on project-specific factors including but not limited to on-the-ground measurements of resources, financing rates, and capital costs of equipment. Therefore, LCOE estimates in this study should be interpreted as only indicative, given the sensitivity of LCOEs to multiple factors. We provide LCOE estimates primarily to compare zones within a technology more than across technologies.

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 et al., 2015b). 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 many 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 [3.5](#page-34-1)). 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 [3.5,](#page-34-1) 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.

The Green Corridors plan of the Power Grid Corporation of India was a transmission plan to enable evacuation and transmission of renewable energy generation (PGCIL, 2012). The study used near-term siting plans of project developers as input to power flow models to plan transmission lines. Combining spatial data for prioritized renewable energy zones from our analysis with project developer siting plans will enable a more robust, stakeholder-driven transmission planning process.

Figure 3.5: 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.

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 [3.6b\)](#page-35-0). Wind sites in Rajasthan, which have relatively low annual-average capacity factors (< 25%), have relatively higher capacity values (25% - 30%), 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 [3.6b](#page-35-0)). 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.

Figure 3.6: Comparison of annual average capacity factor (a) and adjusted capacity factors (capacity value) for wind estimated using top 10% annual peak hours (b).

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 without considering the effect of renewable generation on the net load profile (demand minus renewable energy generation). 1 1 Increasing renewable energy generation will change the net load profile, and subsequently, the capacity value of the marginal generator. 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.

¹Capacity value estimated using net load assumes zero marginal cost for wind and solar. In India, wind and solar are not considered to have zero marginal cost by utilities, but are assumed to have a cost equivalent to their power purchase agreement tariffs. However, these renewable energy sources are considered "must-run" in the Indian Electricity Grid Code and therefore dispatched before other generators with positive variable costs. Considering these renewable energy sources as "must-run" is equivalent to assuming zero marginal cost for them (although there is a small variable cost associated with wind and solar generation).

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 [3.7\)](#page-36-1). 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](#page-17-3) 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. Policies such as land-leasing (even on a footprint basis) and revenue-sharing can further enable socially-equitable wind development.

Figure 3.7: Wind resources on agricultural and non-agricultural lands as identified using land-use/land-cover data from India's National Remote Sensing Center.

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., 2011). 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 only 29% of suitable solar PV sites and 15% of suitable CSP sites across India are within 10 km of a surface water body. Although Rajasthan contains almost half the country's identified solar PV potential (Figure [3.2a](#page-30-1) - [3.2b](#page-30-2)), 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 [3.8\)](#page-37-1). Ground water resources were not considered in this study, but may be an additional source of water in areas without surface water.

Figure 3.8: Solar PV (A) and solar CSP (B) resources that are within and beyond a distance of 10 km from surface water bodies.

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 [3.9a](#page-38-1) - [3.9b\)](#page-38-2). Regions where these two criteria align over larger land areas are in Western Gujarat, Eastern Tamil Nadu, and coastal Andhra Pradesh.

(b)

Figure 3.9: 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.

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 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 [3.10](#page-39-1)). 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 3.10: Co-location opportunities for wind and solar PV projects.

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, and the northern state of Rajasthan. 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 India's Central Electricity Regulatory Commission's cost assumptions, we find that the range of levelized costs of generation for wind and solar PV resources overlap, but concentrated solar power (CSP) resources can be approximately twice as expensive. Further, the levelized costs of generation vary much more across wind zones than those across solar zones because of greater heterogeneity in the quality of wind resources compared to that of solar resources.

LCOE estimates are sensitivity to multiple factors, and actual costs depend on project-specific parameters. Further, feed-in tariffs for procurement of renewable energy within a state are set by State Electricity Regulatory Commissions and can differ from those recommended by the CERC. Auction-based procurement of both solar PV and wind are capturing the decrease in costs of these technologies, and are lower than regulated tariffs. We provide LCOE estimates using CERC norms primarily for comparing zones within a technology across the country.

- 3. **Pre-emptive transmission planning.** Some areas with high quality resources are far from highvoltage 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 et al. 2015b).
- 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 minimize land availability constraints.
- 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 nonagricultural lands, can enable better land and transmission infrastructure utilization. Based on discounted land use factors of 2.25 MW/km² for wind and 7.5 MW/km² 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 (Figure [4.1](#page-42-0)). The interactive pdf [\(4.2\)](#page-42-1) 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.

Figure 4.1: RE Zones Supply Curve from MapRE Tool

Figure 4.2: Interactive PDF Map of RE Zones and Other Geospatial Layers

References

- Argonne National Laboratory, National Renewable Energy Laboratory, Oak Ridge National Laboratory, 2013. Energy Zones Study: A Comprehensive Web-Based Mapping Tool to Identify and Analyze Clean Energy Zones in the Eastern Interconnection.
- Black & Veatch Corp., NREL, 2009. Western Renewable Energy Zones, Phase 1: QRA Identification Technical Report (No. NREL/SR-6A2-46877). Western Governor's Association.
- Black & Veatch Corp., RETI Coordinating Committee, 2009. Renewable Energy Transmission Initiative (RETI) Phase 1B Final Report (No. RETI-1000-2008-003-F).
- Bolinger, M., and Seel, J., 2016. Utility-scale Solar 2015: An Empirical Analysis of Project Cost, Performance, and Pricing Trends in the United States. Lawrence Berkeley National Laboratory, LBNL-1006037.
- California Public Utilities Commission [CPUC], 2009. Renewable Energy Transmission Initiative (RETI) Phase 1B.
- Central Electricity Authority, 2012. 18th Electric Power Survey. Central Electricity Authority.
- CERC, 2014. Central Electricity Regulatory Commission (Terms and Conditions for Tariff Determination for Renewable Energy Sources) (Second Amendment) Regulations 2014. Central Electricity Regulatory Commission.
- Collier, P., Kirchberger, M., Soderbom, M., 2015. The cost of road infrastructure in developing countries. World Bank Policy Research Working Paper No. 7408.
- CPUC, 2009. Renewable Energy Transmission Initiative (RETI) Phase 1b. Technical Report, California Public Utilities Commission.
- CSTEP, 2013. Wind Power in Karnataka and Andhra Pradesh: Potential Assessment, Costs, and Grid Implications. Center for Study of Science, Technology and Policy, Bengaluru.
- CSTEP, WFMS, and SSEF, 2016. Reassessment of India's onshore wind potential. Center for Study of Science, Technology and Policy, WinDForce Management Services, and Shakti Sustainable Energy Foundation.
- DEA and CSIR, 2014. Renewable Energy Development Zones. Technical Report, Department of Environmental Affairs and Council for Scientific and Industrial Research.
- Denholm, P., Hand, M., Jackson, M., Ong, S., 2009. Land-use requirements of modern wind power plants in the United States. National Renewable Energy Laboratory Golden, CO.
- Dent, C.J., Keane, A., Bialek, J.W., 2010. Simplified methods for renewable generation capacity credit calculation: A critical review. IEEE.
- ERCOT, 2008. Competitive Renewable Energy Zones Transmission Optimization Study. Technical report, Electricity Reliability Council of Texas.
- Francis, D., 2012. Better Together: Co-Siting Wind and Solar Production in Texas. Tex. Environ. Law J. 42, 177–202.
- GoI, 2016. India's Intended Nationally Determined Contribution as submitted to the United Nations Framework Convention on Climate Change. Government of India (GoI).
- He, G. and Kammen, D.M., 2014. Where, when, and how much wind is available? A provincial-scale wind resource assessment for China. Energy Policy, Vol 24, 116-122.
- He, G. and Kammen, D.M., 2016. Where, when, and how much solar is available? A provincial-scale solar resource assessment for China. Renewable Energy, Vol 85, 74-82.
- Hossain, J., Sinha, V., Kishore, V.V.N., 2011. A GIS based assessment of potential for windfarms in India. Renewable Energy, Vol 36, Issue 12, 3257-3267.
- IEC, 1998. International Standard IEC 61400-12- Wind Turbine Generator Systems Part 12: Wind turbine power performance testing.
- International Monetary Fund, 2015. World Economic Outlook April 2015: Uneven Growth Short and Long Term Factors.
- IRENA, 2013. Concentrating Solar Power Technology Brief. International Renewable Energy Agency (IRENA).
- Janke, J.R., 2010. Multicriteria GIS modeling of wind and solar farms in Colorado. Renewable Energy, Vol 35, 2228-2234.
- Keane, A., Milligan, M., Dent, C.J., Hasche, B., D'Annunzio, C., Dragoon, K., Holttinen, H., Samaan, N., Soder, L., O'Malley, M., 2011. Capacity Value of Wind Power. IEEE Trans. Power Syst. 26, 564–572. doi:10.1109/TPWRS.2010.2062543
- Kiesecker, J.M., Evans, J.S., Fargione, J., Doherty, K., Foresman, K.R., Kunz, T.H., Naugle, D., Nibbelink, N.P., and Niemuth, N.D., 2011. Win-win for wind and wildlife: A vision to facilitate sustainable development. PLoS ONE, 6(4):e17566.
- King, J., Clifton, A., Hodge, B.-M., 2014. Validation of Power Output for the WIND Toolkit (No. NREL/TP-5D00-61714). National Renewable Energy Laboratory.
- Lopez, A., Roberts, B., Heimiller, D., Blair, N., Porro, G., 2012. U.S. Renewable Energy Technical Potentials: A GIS-Based Analysis (No. NREL/TP-6A20-51946). National Renewable Energy Laboratory, Golden, CO.
- Lu, X., McElroy, M.B., Kiviluoma, J., 2009. Global potential for wind-generated electricity. Prcoceedings of the National Academy of Sciences, Vol 106, no. 27.
- Macknick, J., Newmark, R., Heath, G., Hallet, K., 2011. A Review of Operational Water Consumption and Withdrawal Factors for Electricity Generating Technologies (No. NREL/TP-6A20-50900). National Renewable Energy Laboratory, Golden, CO.
- Milligan, M., Porter, K., 2008. Determining the capacity value of wind: An updated survey of methods and implementation (No. NREL/CP-500-43433). National Renewable Energy Laboratory.
- Mills, A., Phadke, A., Wiser, R., 2010. Exploration of Resource and Transmission Expansion Decisions in the Western Renewable Energy Zone Initiative (No. LBNL-3077E). Lawrence Berkeley National Laboratory.
- NREL, System Advisor Model (SAM). National Renewable Energy Laboratory, Golden, CO.
- Ong, S., Campbell, C., Denholm, P., Margolis, R., Heath, G., 2013. Land-Use Requirements for Solar Power Plants in the United States (No. NREL/TP-6A20-56290). National Renewable Energy Laboratory, Golden, CO.
- Ong, S., Campbell, C., Heath, G., 2012. Land Use for Wind, Solar, and Geothermal Electricity Generation Facilities in the United States (A report from the National Renewable Energy Laboratory to the Electric Power Research Institute). National Renewable Energy Laboratory.
- PGCIL, 2012. Report on Green Energy Corridors. Power Grid Corporation of India Ltd.
- Phadke, A., Bharvikar, R., Khangura, J., 2012. Reassing Wind Potential Estimates for India: Economic and Policy Implications. Lawrence Berkeley National Laboratory.
- PVTECH, 2016. Solar bids in India's Rajasthan near record low as 16 developers go below five rupees [WWW Document]. PV-Tech. URL http://www.pv-tech.org/news/solar-bids-in-indias-rajasthannear-record-low-as-16-developers-go-below-fi (accessed 9.12.16).
- Ramachandra, T.V. and Shruthi, B.V., 2005. Wind energy potential mapping in Karnataka, India, using GIS. Energy Conversion and Management, Vol 46, Issues 9-10.
- Stoms, D.M., Dashiell, S.L., and Davis, F.W., 2013. Siting solar energy development to minimize biological impacts. Renewable Energy, Vol 57, 289-298.
- Svenningsen, L., 2010. Power Curves Air Density Correction and Other Power Curve Options in WindPRO. EMD International A/S.
- Tegen, S., Lantz, E., Hand, M., Maples, B., Smith, A., Schwabe, P., 2013. 2011 Cost of Wind Energy Review (No. NREL/TP-5000-56266). National Renewable Energy Laboratory.
- TERI, 2012. Integrated Renewable Energy Resource Assessment for Gujarat. The Energy and Resources Institute, New Delhi.
- WISE, 2012. Action Plan for Comprehensive Renewable Energy Development in Tamil Nadu. World Institute of Sustainable Energy, Pune.
- Wiser, R., Lantz, E., Bolinger, M., Hand, M., 2012. Recent Developments in the Levelized Cost of Energy from U.S. Wind Power Projects. Lawrence Berkeley National Laboratory and National Renewable Energy Laboratory.
- Wiser, R. and Bolinger, M., 2016. 2015 Wind Technologies Market Report. Lawrence Berkeley National Laboratory.
- Wu, G.C., Deshmukh, R., Ndhlukula, K., Radojicic, T., Reilly, J., 2015. Renewable Energy Zones for the Africa Clean Energy Corridor (LBNL#187271). International Renewable Energy Agency and Lawrence Berkeley National Laboratory.
- Wu, G.C., Torn, M.S., Williams, J.H. 2015b. Incorporating Land-use Requirements and Environmental Constraints in Low-Carbon Electricity Planning for California. Environmental Science & Technology. 49 (4), pp 2013-2021.

Spatial distribution and electricity generation potential of renewable resources by resource quality

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

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

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

B

Spatial distribution and electricity generation potential of renewable resources by capacity factor

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

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

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

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Spatial distribution of renewable resources by levelized cost of energy for generation

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.

D

Variability of renewable 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,](#page-54-1) Figure [D.2,](#page-55-0) and Figure [D.3](#page-56-0) 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.

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)

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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)

E

Data sources and resource assessment thresholds

Table E.1: Data sources and resource assessment thresholds Table E.1: **Data sources and resource assessment thresholds**

F

Map of India and its state boundaries

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

Renewable Energy Zones for Balancing Siting Trade-offs in India Multicriteria Analysis for Planning Renewable Energy (MapRE) http://mapre.lbl.gov/