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Least-cost targets and avoided fossil fuel capacity in India's pursuit of renewable energy

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India has set aggressive targets to install more than 400 GW of wind and solar electricity generation by 2030, with more than two-thirds of that capacity coming from solar. This paper examines the electricity and carbon mitigation costs to reliably operate India's grid in 2030 for a variety of wind and solar targets (200 GW to 600 GW) and the most promising options for reducing these costs. We find that systems where solar photovoltaic comprises only 25 to 50% of the total renewable target have the lowest carbon mitigation costs in most scenarios. This result invites a reexamination of India's proposed solar-majority targets. We also find that, compared to other regions and contrary to prevailing assumptions, meeting high renewable targets will avoid building very few new fossil fuel (coal and natural gas) power plants because of India's specific weather patterns and need to meet peak electricity demand. However, building 600 GW of renewable capacity, with the majority being wind plants, reduces how often fossil fuel power plants run, and this amount of capacity can hold India's 2030 emissions below 2018 levels for less than the social cost of carbon. With likely wind and solar cost declines and increases in coal energy costs, balanced or wind-majority high renewable energy systems (600 GW or ≈ 45% share by energy) could result in electricity costs similar to a fossil fuel-dominated system. As an alternative strategy for meeting peak electricity demand, battery storage can avert the need for new fossil fuel capacity but is cost effective only at low capital costs (≈ USD 150 per kWh).

renewable energy | emissions | India | wind | solar

India emitted 3.2 billion metric tons of CO_2e in 2016, or 6% of annual global greenhouse gas emissions, placing it third only to China and the United States (1). One-third of these emissions were from coal-based electricity. At the same time, both per capita emissions and energy use remain well below global averages, suggesting a massive potential for growth of electricity generation and emissions (1). India's primary energy demand is expected to double by 2040 compared to 2017 (2). Whether this energy comes from fossil or low-carbon sources will significantly affect the ability to limit average global temperature rise to below 2 °C.

India is already pursuing significant technology-specific renewable energy targets—100 GW of solar and 60 GW of wind by 2022—and, in its Nationally Determined Contributions (NDC), committed to a 40% target for installed generation capacity from nonfossil fuel sources by 2030 (3). In 2019, in part to fulfill its NDC commitment, the Indian government proposed to install 440 GW of renewable energy capacity by 2030, with 300 GW of solar and 140 GW of wind capacity (4). Although costs of solar photovoltaic (PV) and wind technologies have declined significantly in recent years (5–7), the low cost of coal and integration costs associated with variable renewable energy (VRE) technologies like wind and solar may hinder India's cost-effective transition to a decarbonized electricity system. This paper seeks to answer a number of questions that arise in the Indian context. What targets for wind and solar capacity have the lowest associated integration costs? Will these targets significantly offset the need to build fossil fuel generation capacity? What additional measures can we take to mitigate VRE integration costs?

Merely comparing the levelized costs of VRE with the costs of conventional generation ignores additional cost drivers, which depend on the timing of VRE production and other conditions in the power system (8, 9). Quantifying these drivers requires models that choose lowest-cost generation capacity portfolios and simulate optimal system operation with detailed spatiotemporal data. Several prior studies address these system-level integration costs in a capacity expansion planning framework (10–16), often making decisions based on a limited sample of representative hours. Other studies explicitly estimate the relationship between long-run economic value (including integration costs) of VRE penetration levels (17, 18) but do not include VRE investment costs in their analysis. Few prior studies explore the impacts of high VRE penetration on India's electricity system, and those that do either use the capacity expansion framework and do not evaluate the economic value of multiple VRE targets (4, 19, 20) or do not optimize capacity build around proposed VRE targets (21).

Here we address this gap by estimating how different VRE targets affect the cost to reliably operate the Indian electricity system. To do so, we work with three interrelated models. First, using a spatially explicit model for VRE site selection, we identify the lowest levelized cost wind and solar sites to meet different VRE capacity targets, and study how the resource quality—and corresponding levelized cost—of selected sites changes with increasing VRE targets.

Significance

This study examines electricity and carbon mitigation costs associated with achieving aggressive renewable energy targets in India's electricity grid in 2030. We find that wind-majority or balanced wind–solar targets have the lowest carbon mitigation costs, which invites revisiting India's proposed solar-majority targets. Contrary to prevailing assumptions, achieving high renewable energy targets will not avert the need to build new fossil fuel power plants. However, building significant numbers of wind and solar plants (600 GW) will reduce how often fossil fuel power plants must run, holding India's 2030 electricity emissions at its 2018 level at costs comparable to a fossil fuel-dominated grid. As costs decrease, battery storage can cost-effectively avert the need for new fossil fuel power plants.

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Second, using a capacity investment model that accounts for VRE production patterns and optimal dispatch of hydropower and battery storage, we determine the capacity requirements and investment costs for coal, combined cycle gas turbines (CCGT), and combustion turbine (CT) peaker plants. Due to uncertainties in their future deployment (22), and because their current targets are relatively low (4), we did not consider new nuclear or hydro capacity in the main scenarios but include those in the sensitivity scenarios presented in *SI Appendix*, section 2. Third, we use a unit commitment and economic dispatch model to simulate hourly operation of the electricity system and estimate annual system operational costs. This model captures important technical constraints, including minimum operating levels, daily unit commitment for coal and natural gas plants, and energy limits on hydropower and battery storage. Rather than cooptimize VRE capacity, we compute the system-level economic value of a range of VRE targets by comparing the sum of the avoided new conventional capacity and energy generation costs to a no-VRE scenario. The net cost for a scenario is then the difference between the levelized cost of the VRE and the system-level economic value. *Materials and Methods* provides more detail on this process.

Our results show that, despite greater levelized cost reduction forecasts for solar PV compared to wind technologies, VRE targets with greater amounts of wind have the lowest projected net carbon mitigation costs. This finding is robust to a range of scenarios, including low-cost solar and storage, and lower minimum generation levels for coal generators.

We find that, although VRE production displaces energy production from conventional generators, it does very little to defer the need for capacity from those generators due to low correlation between VRE production and peak demand. Our findings suggest that VRE in India avoids far less conventional capacity than VRE in other regions in the world. These capacity requirements are slightly mitigated if India's demand patterns evolve to more closely resemble demand in its major cities. Overall, we conclude that the importance of choosing the right VRE mix is significant when measured in terms of carbon mitigation costs: Whereas most solar-majority scenarios we examined lead to costs greater than or equal to estimates of the social cost of carbon (SCC), wind-majority mixes all cost far less than the SCC.

Results and Discussion

Levelized Costs of Wind and Solar. Capturing the spatial variability in renewable resources is critical in estimating levelized costs of high VRE targets. Using 2017–2018 winning auction bids for wind and solar to compute costs per megawatt of capacity, we calculated the levelized costs of wind and solar PV (cost per megawatt-hour) from modeled resource qualities across suitable areas for the two technologies.

Fig. 1 *A* and *B* depicts the location of the lowest levelized cost wind and solar resources; these are broadly distributed over the southern and western regions of the country. Fig. 1*C* shows that, although we find that levelized costs of wind and solar PV resources have overlapping distributions, wind costs have a wider distribution compared to solar PV, reflecting greater variability in wind capacity factor across the country. Therefore, assuming

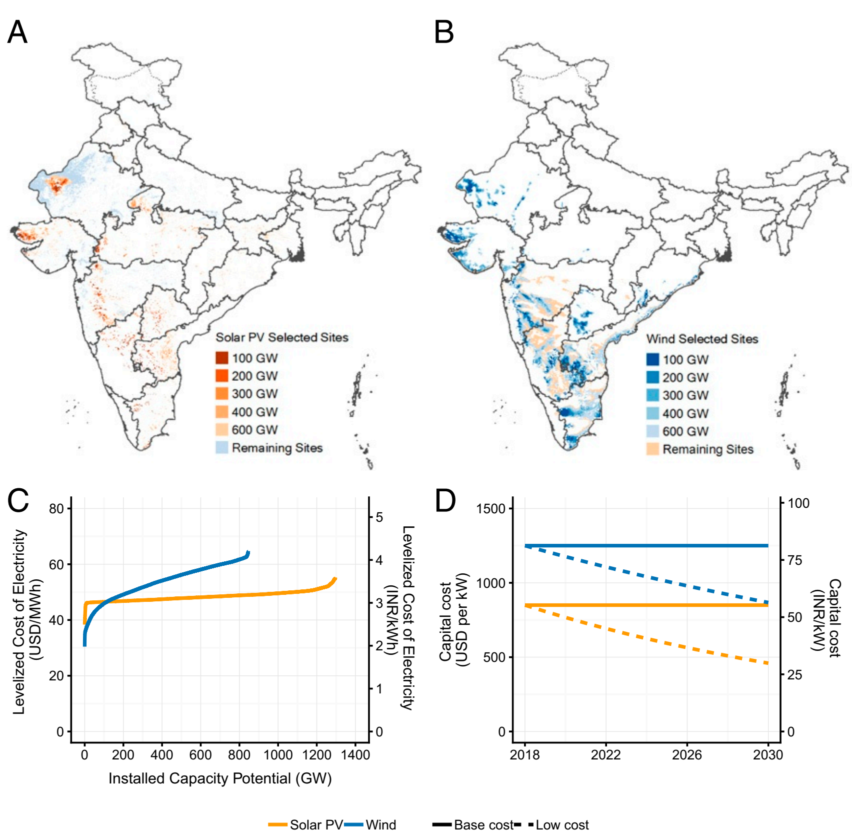

Fig. 1. (*A* and *B*) Selected sites for solar PV and wind to meet installed capacity targets of 100 GW to 600 GW for each technology. VRE sites were selected based on highest annual capacity factors, limiting the selected capacity in each state to 15% of target to ensure spatial diversity. (*C*) Installed capacity potential for solar PV and wind sorted by levelized cost of energy assuming capital costs in 2018. (*D*) Capital cost trajectories for renewable energy technologies for base scenario (no cost decline) and low-cost scenario (annual cost decline of 5% for solar PV and 3% for wind). INR, Indian Rupee. Northern India boundaries are disputed and indicated by dotted lines in *A* and *B*.

no technology advancement or cost reduction, as more VRE sites are developed to meet higher capacity targets, levelized costs for additional wind facilities are likely to increase much more than levelized costs for additional solar PV.

To generate VRE portfolios to feed into a capacity expansion model, we chose the lowest levelized cost portfolios for 200-, 400-, and 600-GW total VRE targets, with different shares of solar and wind capacity varying by 25% increments within each target ("all-solar," "more-solar," "balanced," "more-wind," and "all-wind"). Selecting VRE sites based on levelized costs before optimally choosing conventional generation capacities reflects on-the-ground project development practices in India, which respond to fixed-price long-term contract incentives.

Fig. 2*A* shows how average levelized costs vary across these portfolios. Average levelized costs of VRE for the base case, derived directly from 2017–2018 auctions as discussed above, grow with increasing VRE targets across mixes (USD 47 to 51 per MWh for 200 GW, USD 48 to 55 per MWh for 400 GW, and USD 48 to 57 per MWh for 600 GW). Because the cost distribution for wind is larger than it is for solar, average levelized costs for the "all-wind" portfolios are more sensitive to the VRE target. Fig. 1*D* shows the impact of capital cost declines for wind and solar technologies. Assuming annual cost declines of 5% for solar PV and 3% for wind (23), the size of the VRE target ceases to be an important cost driver, and average levelized costs of VRE across all targets and mixes fall by 18 to 35%.

Economic Value of Renewable Energy. We define the economic value of VRE as the savings in grid capacity investments and operating costs that accrue from integrating VRE into a system, as compared to a baseline without VRE. There are two key sources of this value: avoided investment in conventional generation capacity and avoided expenditures on fuel. We address these sources, in sequence, below.

To compute avoided investments in capacity, we ran our capacity expansion model for each VRE capacity scenario above. The results, summarized in Fig. 3, indicate that new VRE capacity will displace the need to build only a small fraction of conventional coal and natural gas to meet growing demand. Compared to the zero VRE scenario, new conventional capacity avoided by each megawatt of VRE capacity—alias the capacity credit—is only 0.04 MW to 0.1 MW for 200 GW, 0.02 MW to 0.06 MW for 400 GW, and 0.02 MW to 0.05 MW for 600 GW of VRE target.

Our results indicate that capacity credits for VRE are significantly lower in India than in North America and Europe. For example, with the exception of one study in Germany, the 15 global locations reported in Holttinen (24) have wind power capacity credits 2 to 5 times greater—after controlling for VRE penetration—than those we identify in India. Similarly, all locations reported in Mills and Wiser (25), which are concentrated in North America, have solar capacity credits well in excess of those we observe in India, after controlling for penetration. India's poor capacity credits result from low seasonal wind generation during after-sunset peak-demand hours from the postmonsoon months of September to November (*SI Appendix*, Fig. S6).

Fig. 2*B* shows the capacity value of VRE, defined as avoided investment in conventional generation capacity per megawatt-hour of potential VRE production. Because capacity credit is small, the capacity value is small as well, ranging from USD 1 to 7 per MWh of potential VRE generation in the base scenario. Capacity value is greatest for "more-wind" mixes across all VRE targets.

We compute the second component of VRE economic value, avoided energy costs, by running a unit commitment and economic dispatch model for the capacity identified in our capacity investment model. The resulting energy value of VRE generation is significantly greater than capacity value across all scenarios. For the base scenario, energy value is USD 25 to 35 per MWh for 200 GW, USD 15 to 32 per MWh for 400 GW, and USD 10 to 28 per MWh for 600 GW of VRE, mainly dictated by the marginal cost of coal generation that VRE displaces in each hour (Fig. 2*D*). Energy value of VRE generation decreases with higher penetration levels due to thermal plant inflexibility—including minimum generation levels and cycling constraints—and VRE production in excess of available demand, both of which lead to curtailment. Curtailment effects are particularly pronounced for solar-majority mixes, which show as much as 67% curtailment at

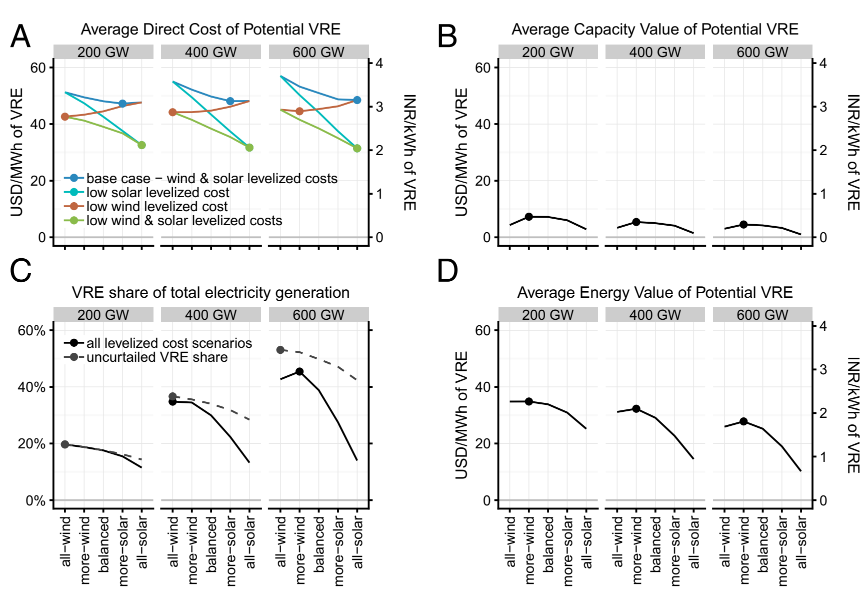

Fig. 2. (*A*) Average direct levelized cost of potential (uncurtailed) VRE, (*B*) average capacity value of potential VRE, (*C*) VRE share of total electricity generation, and (*D*) average energy value of potential VRE for base and low capital cost trajectories for solar PV and wind in 2030. Results are shown for VRE installed capacity targets of 200, 400, and 600 GW, each with five combinations of shares of solar PV and wind. Results for average capacity and energy value and VRE share of total electricity generation are the same across base and low VRE cost scenarios. Highlighted points show the most desirable (either lowest or highest, depending on the variable) values among the five mixes of solar PV and wind capacities for each scenario. INR, Indian Rupee.

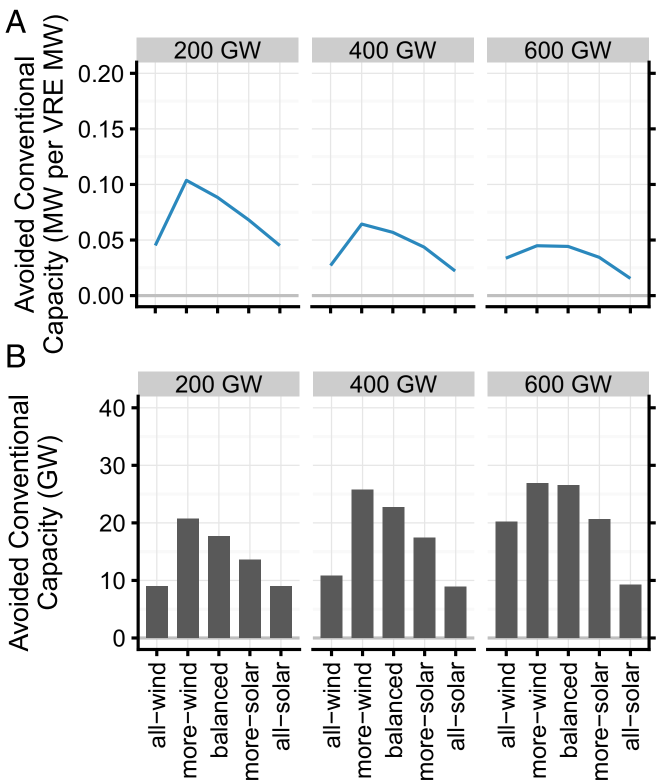

Fig. 3. Avoided conventional (coal and natural gas) capacity expressed as both (*A*) per MW of VRE installed capacity and (*B*) total avoided capacity for base capital cost trajectories for solar PV and wind in 2030. Results are shown for VRE installed capacity targets of 200, 400, and 600 GW, each with five combinations of shares of solar PV and wind.

high penetration levels and the lowest energy values (Fig. 2 *C* and *D*). We note that adding storage to the system, which we discuss later, reduces curtailment.

Net System Costs. In all cases, both capacity value and energy value for VRE are highest for the "more-wind" scenario, suggesting that VRE targets weighted toward higher shares of solar may not be cost optimal. However, levelized costs and economic value of VRE must be taken together to understand the total system cost impacts due to additional VRE capacity.

Fig. 4*A* depicts the net system cost impacts in terms of avoided CO_2 emissions. Note that we do not report total system costs but instead cost differences relative to a no-VRE case. This focuses our results on the additional cost of different VRE scenarios. Focusing first on the base-case cost scenario, we see that net system costs are well below the US SCC of USD 40 per tCO_2, except in the solar-majority scenarios with high VRE penetration. Indeed, the lowest carbon mitigation costs occur for the "balanced" or "more-wind" scenarios, ranging from USD 8 per tCO_2 for 200 GW of VRE to USD 26 per tCO_2 for 600 GW of VRE. The "more-wind" scenarios also have the highest share of VRE generation and avoid the most carbon emissions (*SI Appendix*, Fig. S12).

We note that total carbon emissions for the 600 GW "more-wind" mixes are 1,060 million tonnes of CO_2, an amount similar to direct emissions from India's electricity sector in 2018 (see *SI Appendix*, Table S1). In other words, pursuing a VRE target of 600 GW with a "more-wind" mix could freeze carbon emissions from India's electricity sector at the 2018 level.

Fig. 4*B* depicts net system cost impacts per megawatt-hour of load served. This provides insight into the incremental growth in customer tariffs that would be required to recover the added costs of VRE. Focusing again on the base-case cost scenario, we see that solar-majority mixes cost more than "balanced" or "more-wind" scenarios, per megawatt-hour of load served. Concentrating on the "more-wind," "balanced," and "more-solar" mixes, we see that these costs lie in range of USD 1 to 2 per MWh of load for 200 GW, USD 5 to 7 per MWh of load for 400 GW, and USD 11 to 13 per MWh of load for 600 GW (Fig. 3), which is 1 to 2%, 7 to 9%, and 14 to 16% of the average cost of supply in India during 2015–2016 (26).

We view these base-case costs as upper limits on the system costs of added VRE capacity. Costs of both solar PV and wind are likely to decline with technology improvements and economies of scale (23). These cost trends would make pursuing higher VRE targets increasingly cost effective. For example, in the "low-cost wind and solar" scenario, optimal additional system costs and carbon mitigation costs are negative for the 200 GW target, and 2 to 3 times lower than the base-case cost scenario for the 400 and 600 GW VRE scenario (Fig. 4 *A* and *B*). We note that, if wind costs remain flat and solar costs decline, the "more-solar" case would be slightly less expensive than

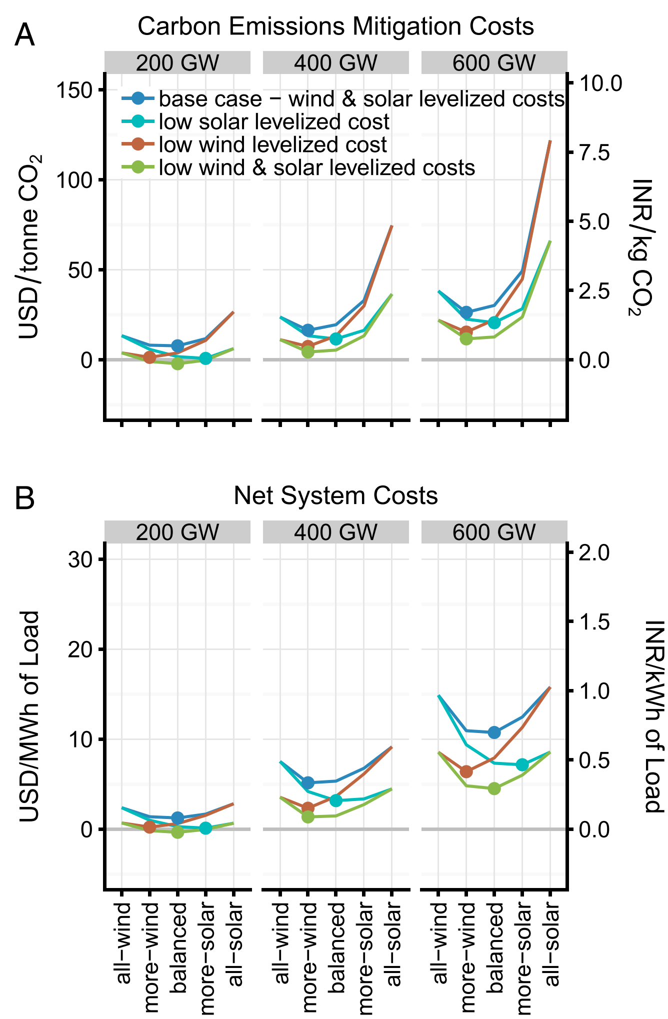

Fig. 4. (*A*) Carbon emissions mitigation costs and (*B*) net system costs for base and low capital cost trajectories for solar PV and wind in 2030. Results are shown for VRE installed capacity targets of 200, 400, and 600 GW, each with five combinations of shares of solar PV and wind. Highlighted points show the most desirable (lowest) values among the five mixes of solar PV and wind capacities for each scenario. INR, Indian Rupee.

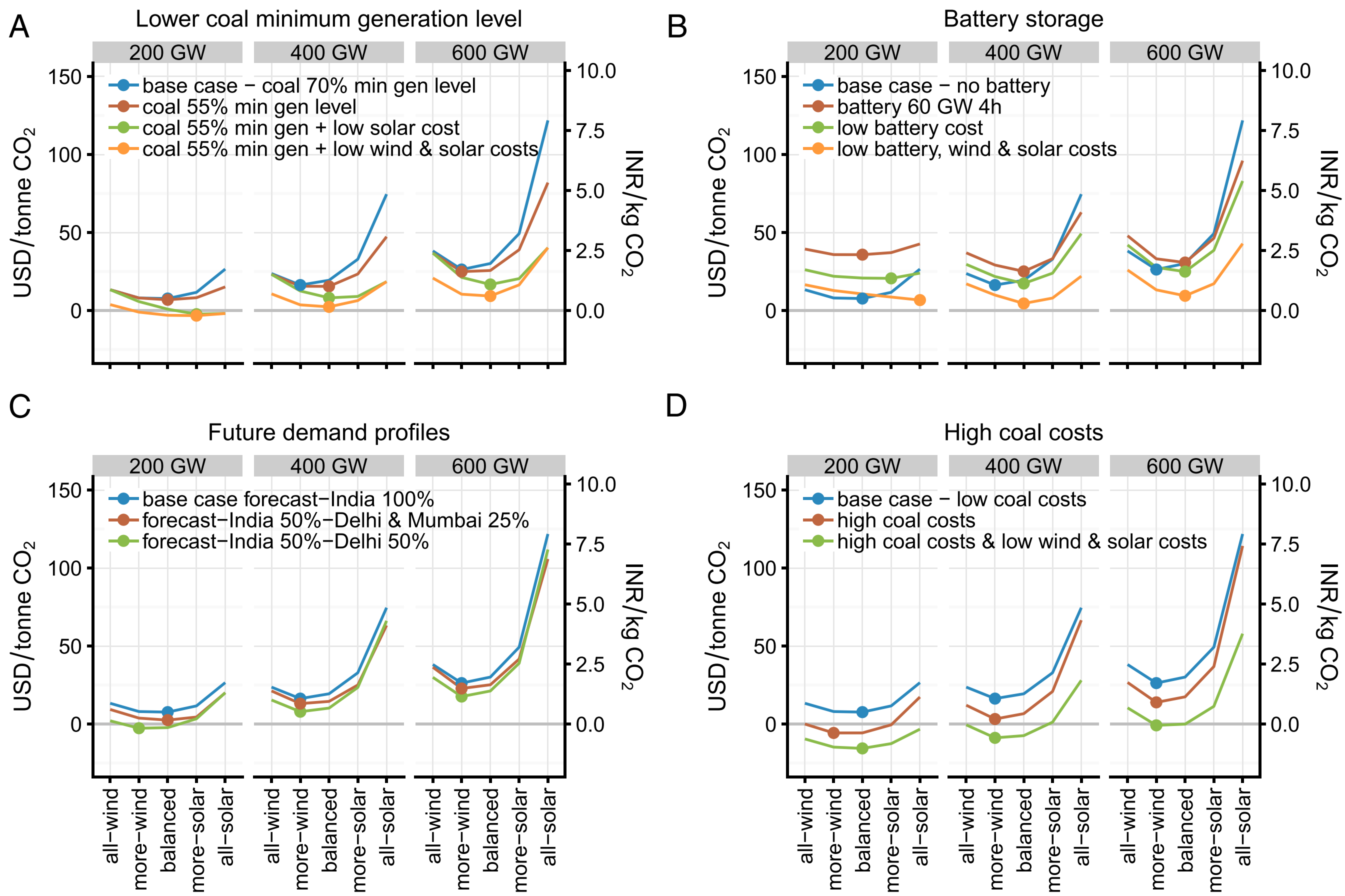

Fig. 5. Carbon emissions mitigation costs for (*A*) base case (70%) and lower (55%) minimum generation level constraints on coal plants, (*B*) no battery storage and 60 GW with 4-h battery storage installed capacity, (*C*) same national hourly demand profile as 2014 and urbanized national demand profiles reflecting different weights for national, Delhi, and Mumbai's 2014 demand profiles, and (*D*) low and high capital and fuel costs for new coal plants. Results are shown for VRE installed capacity targets of 200, 400, and 600 GW, each with five combinations of shares of solar PV and wind. Highlighted points show the most desirable (lowest) values among the five mixes of solar PV and wind capacities for each scenario. INR, Indian Rupee.

"balanced" in terms of net system costs, but only in the 600-GW VRE case.

Although we assume all solar capacity is utility scale, we note that distributed solar plants including rooftop PV and urban minigrids have additional benefits such as avoiding land constraints and reduced transmission losses and will likely be part of the solar fleet. However, distributed solar plants have lower capacity factors compared to utility-scale solar and will make solar-majority mixes cost more than "balanced" or "more-wind" scenarios.

System Cost Reduction Factors. Our results indicate that system costs and, in particular, the suboptimality of high solar penetration scenarios are strongly influenced by solar curtailment. Curtailment, in turn, stems from low correlation between solar production and demand as well as inflexibility of coal plants. We now consider four factors that could plausibly change in the future and would directly impact these drivers of curtailment: coal plant minimum generation levels, energy storage, more urbanized load shapes, and higher coal costs.

Lower minimum coal generation levels. We find that reducing minimum coal generation levels does not substantially lower system and emissions mitigation costs (Fig. 5*A* and *SI Appendix*, Fig. S11*A*). Lowering minimum operating levels for coal plants from 70 to 55% (27) increases VRE energy value by reducing curtailment, and, because solar production is curtailed more in the base-case scenarios, this strategy benefits solar-majority mixes more than wind-majority mixes. However, because the impact on total system costs is small, wind-majority or balanced mixes remain the most cost effective for all but the 200-GW VRE scenarios with low-cost solar.

Battery storage. Batteries can reduce system costs by reducing VRE curtailment, avoiding expensive energy generation, and avoiding conventional generation capacity but can increase overall costs because of their capital investments and efficiency losses incurred in their charge–discharge cycles. The greatest gains due to battery storage in terms of avoided conventional capacity and reduced curtailment accrue to solar-majority mixes (Fig. 5*B* and *SI Appendix*, Fig. S11*B*), which is consistent with other studies (17). However, the mix with the lowest carbon mitigation costs changes from "more-wind" or "balanced" to "more-solar" only for the lowest of the VRE targets (200 GW) and when battery costs are low (USD 150 per kWh). For the higher VRE targets of 400 GW to 600 GW, even with low-cost battery storage, the "more-solar" mixes are not the preferred VRE configurations.

At a cost of USD 330 per kWh of battery storage, net system costs of all battery storage scenarios are greater than the base scenario without battery storage, because of both battery investment costs and efficiency losses (28, 29). Battery storage becomes increasingly cost effective with greater VRE targets as it captures more value by smoothing the greater variability in VRE generation. But, even at an average low cost of USD 150 per kWh for battery storage, we find that the lowest carbon mitigation cost among all VRE mixes for the 60-GW battery storage is lower than that of the no-storage base scenario only for the highest VRE target of 600 GW.

Urbanized future demand. If India were to undergo rapid urbanization and its national demand profile becomes increasingly similar to that of Delhi's and Mumbai's, costs of mitigating carbon emissions are likely to be lower than the base scenario (Fig. 5*C* and *SI Appendix*, Fig. S11*C*). This is because Delhi's and Mumbai's demand profiles are better correlated with VRE generation across all mixes and targets, resulting in more new conventional capacity avoided by VRE, and less curtailment, compared to the base-case demand profile. We note, however, that, while these alternate demand futures have the same energy demand as the base scenario, they have higher peak demand, which requires a greater amount of new conventional capacity in all scenarios, including the zero VRE case. If India experiences a lower growth rate of demand ($\sim$15% lower than the base case), total carbon emissions are lower but costs of mitigating carbon emissions are higher than the base scenario, because of greater VRE curtailment (*SI Appendix*, section 2 and Fig. S16). Even at this lower demand, new coal and gas capacity is required to meet peak demand, because of the low capacity value of wind and solar (*SI Appendix*, Fig. S15).

Higher coal costs. Higher costs for new coal plants (*SI Appendix*, Table S3) reflecting higher capital costs for environmental compliance equipment to meet India's stricter environmental norms and higher fuel cost due to rising mining and transportation costs result in small increases in capacity value ($\approx$ USD 1 per MWh of VRE) but significant increases in energy value of VRE (25 to 33%) compared to the base scenario (*SI Appendix*, Fig. S10). As a result, although wind-dominated mixes remain best, net system and emissions mitigation costs decrease across all VRE targets and mixes (Fig. 5*D* and *SI Appendix*, Fig. S11*D*).

Conclusions

Across most scenarios, including those with different cost and demand trajectories, operational strategies, and battery storage investments, we find that a "balanced" or "more-wind" capacity mix for VRE targets will be the cheapest, both for consumers and for mitigating carbon emissions. This result invites revisiting India's present policies of pursuing a greater share of solar capacity in its VRE targets (100 GW solar in 160 GW of VRE by 2022 and 350 GW solar in 440 GW VRE by 2030).

Even in high-VRE scenarios, our model indicates that significant amounts of coal capacity will be required to support demand growth. Although studies in other regions of the world have found that VRE cannot avoid conventional generation capacity on a one-to-one basis, we find that VRE in India has particularly low capacity values and is thus particularly ineffective at displacing dispatchable generation capacity requirements. However, these conventional plants will be operated at low plant load factors, which reduces their carbon emissions, but will likely also reduce the cost effectiveness of their operations.

A number of factors have the potential to reduce the cost to integrate VRE for the levels we studied. Battery storage holds promise, but only if storage capacity costs fall to the low end of cost forecasts [weighted average cost of $\approx$ USD 150 per kWh (23)] and if VRE penetration is high (600 GW). VRE cost declines and coal energy cost growth, both of which are likely (23, 30), could, together, result in costs similar to a fossil fuel-dominated system, even with 600 GW of VRE.

In sum, our results indicate that a wind-majority portfolio of 600 GW of VRE has the potential to hold India's 2030 electricity system carbon emissions at 2018 levels, at costs well below the SCC, even in the midst of significant growth in demand. A number of options hold promise for further reducing emissions. Some of these are likely to be low in cost, for example, coupling demand response strategies like shifting India's large agricultural demand to high VRE generation times. Other options such as expanding nuclear and hydropower capacity may hold large potential but may also cost more and have lower public acceptance. All merit further investigation to identify least-cost pathways for India to continue reducing its carbon emissions.

Materials and Methods

To estimate the levelized costs and economic value of VRE, we developed three models—a spatially explicit VRE site selection and cost model, a capacity investment model, and an economic dispatch model (*SI Appendix*, Fig. S1). Although our modeling approach is customized to address the specifics of capacity expansion planning in India, it builds on well-established work. The model has three main decision steps: VRE site selection, conventional generator capacity expansion, and operating cost evaluation. For capacity expansion, we used the screening curve approach (31, 32) because its computational efficiency enables evaluation of conventional generator economics over an entire year of demand and renewables production. Using screening curves enables us to easily explore different annual demand patterns. Our use of screening curves is a key point of comparison to other recent capacity expansion planning efforts, which limit cost evaluation to a small sample of time points for computational reasons (10, 11, 13, 16). Because screening curves cannot capture the time series aspects of VRE production, we used an investment step that precedes conventional capacity expansion. In this approach, based on refs. 33 and 34, VRE site selection is made on the basis of lowest levelized cost. This is consistent with an environment in which VRE project developers are not compensated for temporal value of VRE production and instead maximize capacity factor.

VRE Site Selection and Levelized Costs. Following the methodology from refs. 33 and 34, we used modeled wind speeds at 80-m hub heights (35) and global horizontal irradiation data (36) to identify suitable areas for VRE development with thresholds for wind and solar resource quality and exclusions for protected areas, water bodies, and certain land use land cover types (agricultural land for solar, and forested land for both technologies). From these suitable areas, we created discrete potential project sites with a maximum area of 25 km^2, and applied land use factors of 7.5 MW/km^2 for solar PV and 2.25 MW/km^2 for wind to estimate potential generation capacity and annual capacity factors. We then created 15 VRE build-out scenarios with three VRE installed capacity targets—200, 400, and 600 GW—each with five combinations of shares of solar PV and wind—0%–100% (all-wind), 25%–75% (more-wind), 50%–50% (balanced), 75%–25% (more-solar), and 100%–0% (all-solar). To meet individual wind and solar capacity targets for each VRE scenario, we selected sites with the highest annual capacity factors, limiting the selected capacity in each state to 15% to ensure spatial diversity. We estimated the levelized cost of VRE for each scenario assuming capital costs derived from India's solar auctions (see *SI Appendix*, Table S2).

For low levelized cost VRE scenarios, we assumed wind and solar PV capital costs to decline at 3% and 5% per year, respectively (23). We then created hourly generation profiles for each of the selected project sites from modeled wind (35) and solar (36) resource data for 2014, which captured the diurnal and seasonal weather patterns of wind and solar generation and formed the inputs to the capacity investment and system operation models (37); see *SI Appendix*, section 1.

Future Demand Profiles. To create the 2030 hourly demand profile, we linearly increased the 2014 hourly demand for India (38) to meet the energy demand forecast for 2030 (39). We then applied an adjustment across all time periods, linearly proportional to the demand in that period so that the 2030 time series matched both the 2030 annual peak demand and energy forecast (37). Employing renewable resource data and base electricity demand data from the same year maintained temporal correlation between weather and demand. We assume that the government of India forecast for energy demand includes growth in electricity access and agricultural and industrial demand. For urbanized demand profiles, we weighted and summed national, Delhi, and Mumbai hourly demands; see *SI Appendix*, section 1 and Fig. S2. We also present a low electricity demand growth scenario in *SI Appendix*, section 2 (40).

Conventional Capacity Investments. We considered three technologies for new conventional capacity—coal, CCGT, and CT. We assumed all new coal units to be supercritical running on domestic coal. We assumed CCGT and CT generators use imported liquefied natural gas (LNG) [which is already increasing in India (41)] at USD 10 per MMBtu (42). We did not include nuclear or hydropower in new build-outs considered in the main scenarios, but we include proposed new build-outs in sensitivity scenarios presented in *SI Appendix*, section 2. We modeled pumped hydro capacity as hydro capacity with storage in our scenarios because existing capacity is less than 1% (2.6 GW) of total installed generation capacity (4). Operating this capacity as rechargeable storage would have effects on system operations similar to but less pronounced than the battery storage capacities considered in this paper.

For battery storage scenarios, we exogenously added 15, 30, and 60 GW of 4-h battery storage, which is approximately 5%, 10%, and 20% of India's expected peak demand in 2030. Further, we assumed a round-trip charge–discharge efficiency of 85%. Because results for all three capacities are qualitatively similar, we show results for only 60-GW storage capacity.

Our capacity investment model proceeds in two steps: 1) net demand curve construction and 2) capacity investment decisions. To construct net demand curves, we used a simplified dispatch model to generate sequences of hydropower (storage) and battery operations. This model is similar to the linear economic dispatch model we used to compute generator economic dispatch described in the next section. The simplified dispatch model dispatches storage, hydro, and a simplified conventional generator with a convex cost curve and no constraints on maximum capacity or minimum operating level. Subtracting the resulting hydro and battery storage dispatch and must-run (run-of-river hydropower and nuclear) and VRE generation from demand in each hour gives the net demand profile.

To make conventional generator capacity investment decisions, we used a screening curve model (31, 32) with the net demand profiles. This approach assumes that generators are dispatched by marginal cost, and demand is inelastic. Generator costs, shown in detail in *SI Appendix*, Table S3, are described by fixed costs (annualized capital costs and fixed operations and maintenance [O&M] costs) and variable costs (fuel and variable O&M). Applying screening curves to the final net demand profiles, we determined new capacities for coal, CCGT, and peaker CTs in 660-, 250-, and 200-MW increments, respectively. We assumed a reserve margin of 15% of annual peak load to ensure resource adequacy (43), and assigned this reserve margin to the CT, CCGT, and coal generators in proportion to their overall share.

System Operation Costs. To compute total operating costs in each scenario, we developed a mixed-integer unit commitment and economic dispatch model in the Python-based open-source optimization modeling language (Pyomo) (44). The model optimally dispatches existing and new generators and storage over 24 h to meet demand for each day of the year and determines realized VRE share in total generation, VRE curtailment, conventional generator plant load factors, emissions, and system operational costs.

The objective functions of both net demand curve dispatch used in the capacity investment model and the full system economic dispatch models minimize the overall cost of generation and the cost of unserved energy. Formulations of both models are given in *SI Appendix*, section 1.

We obtained variable costs and capacity for all existing generators from 2016 data (*SI Appendix*, Fig. S3) and derived daily energy budgets and minimum generation levels for hydropower storage plants, and operating capacity factors of run-of-river hydropower and nuclear power plants from historical 2014 data (38, 45). We note that other papers also use similarly granular data on power plant costs, for example, refs. 46 and 47. Variability in variable costs of coal, gas, and diesel power plants reflects the heterogeneity in heat rates across plants. We assume constant heat rates across different loading levels for thermal power plants. Although hydropower storage plants may be able to reassign available energy potential across days and seasons depending upon the accuracy of forecasts for energy demand and other uses, we restrict the daily energy generation potential to historical generation levels. We assume an outage rate of 10% for all coal and gas generators. We did not include ramping constraints in our simplified model because even the most inflexible coal plants can ramp from a 55% minimum generation level to 100% of their rated capacity in 1 h (ramp rate of 1 MW per min), which is the temporal resolution of the model. We note that ramping capabilities of power plants may be a constraint at subhourly timescales and in transmission-constrained areas. Our model assumes a well-functioning, national electricity market with no transmission, political, or institutional constraints. We derive CO_2 emissions factors of 0.63, 0.42, 0.92, and 0.82 tonnes-CO_2 per MWh for CT, CCGT, coal, and diesel generators from average heat rates from the Central Electricity Authority (48) and fuel emissions intensities provided by the Energy Information Administration (49) (*SI Appendix*, Table S4). We note that these assumptions about emissions factors do not impact our core results on capacity expansion and dispatch, since these depend only on cost assumptions. However, any difference between our estimates of emissions factors and reality will pass through to estimates of fleet-wide CO_2 emissions.

Data Availability. Wind resource data from Vaisala and demand, hydropower energy generation, and generator cost data from the Power Systems Operation Corporation of India are proprietary and can be accessed through those entities. Solar resource dataset is available from the National Renewable Energy Laboratory's National Solar Radiation Database. Processed and aggregated wind, solar, and demand data, modified hydropower energy generation and generator cost data, and processed results data are available on Zenodo (https://doi.org/10.5281/zenodo.4558674). Python and R scripts of the renewable energy value model are available on GitHub (https://github.com/cetlab-ucsb/renewable_energy_value).

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