

Strategic siting and regional grid interconnections key to low-carbon futures in African countries

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Edited by M. Granger Morgan, Carnegie Mellon University, Pittsburgh, PA, and approved February 23, 2017 (received for review July 18, 2016)

Recent forecasts suggest that African countries must triple their current electricity generation by 2030. Our multicriteria assessment of wind and solar potential for large regions of Africa shows how economically competitive and low-environmental-impact renewable resources can significantly contribute to meeting this demand. We created the Multicriteria Analysis for Planning Renewable Energy (MapRE) framework to map and characterize solar and wind energy zones in 21 countries in the Southern African Power Pool (SAPP) and the Eastern Africa Power Pool (EAPP) and find that potential is several times greater than demand in many countries. Significant fractions of demand can be quickly served with “no-regrets” options—or zones that are low-cost, low-environmental impact, and highly accessible. Because no-regrets options are spatially heterogeneous, international interconnections are necessary to help achieve low-carbon development for the region as a whole, and interconnections that support the best renewable options may differ from those planned for hydropower expansion. Additionally, interconnections and selecting wind sites to match demand reduce the need for SAPP-wide conventional generation capacity by 9.5% in a high-wind scenario, resulting in a 6–20% cost savings, depending on the avoided conventional technology. Strategic selection of low-impact and accessible zones is more cost effective with interconnections compared with solutions without interconnections. Overall results are robust to multiple load growth scenarios. Together, results show that multicriteria site selection and deliberate planning of interconnections may significantly increase the economic and environmental competitiveness of renewable alternatives relative to conventional generation.

Africa | energy policy | interconnections | renewable energy | siting

As a region, Africa has the lowest per capita electricity consumption in the world, due in large part to lack of generation and transmission infrastructure development at both the national and regional levels (1). However, the average cost of electricity in most African countries is at least twice that of other developing countries (1). For the region to successfully meet goals to increase affordable electricity access and reduce demand curtailment, electricity generation will need to grow exponentially. By some estimates, demand in the Eastern Africa Power Pool (EAPP) and Southern African Power Pool (SAPP), which encompass more than 50% of the continent’s population, may collectively exceed 1,000 TWh by 2030, nearly triple their electricity consumption in 2010 (2, 3).

To meet energy goals, decision makers are looking to fossil fuel and hydropower as familiar and untapped resources (1–3). With the insecurity and high costs of fossil fuels, the planning paradigm has become increasingly hydropower centric (1–3). Yet climate vulnerability (4), international cooperation barriers and transboundary water rights issues, large cost overruns (5), and high socio-environmental impacts (6) plague this paradigm and perpetuate risks of hydro-dependence. Among the alternatives, geothermal is considered underdeveloped but geo-

graphically limited with long lead times, and wind and solar have historically been dismissed as too expensive and temporally variable (1, 7).

However, costs of utility-scale wind and solar generation are rapidly declining (8). Levelized cost of wind energy is competitive with that of hydropower in Kenya and Ghana (9). Wind and solar photovoltaics (PV) are now South Africa’s cheapest and third-cheapest form of generation, respectively (10). As a result of these competitive costs, renewable energy deployment is growing in a handful of African countries (11–13). However, the contribution of wind and solar in each power pool remains below 1%, likely due to multiple perceived risks of uncertain resource quality, interconnection unavailability, and high investment costs.

Multicriteria resource mapping can minimize risk by enabling strategic site selection. To identify “no-regrets” siting options—or those that are low cost, low impact, and highly accessible and thus can be justified from multiple-stakeholder perspectives of risk—large amounts of data across large spatial scales must be synthesized (14) and incorporated in a multicriteria framework. Comprehensive wind and solar energy assessments and integration analyses have highlighted their potential to contribute to energy transitions in many countries (15, 16), yet roughly half of the EAPP and SAPP countries lack even the most basic

Significance

This study identifies, characterizes, and values wind and solar electricity resources for 21 countries in the Eastern and Southern Africa Power Pools. We find that many countries possess potential many times their projected demand. However, because the most competitive wind and solar resources are spatially uneven, international transmission could allow the region as a whole to benefit from “no-regrets” or low-cost, low-impact, and highly accessible resources. International energy trade also lowers system costs by reducing the need for conventional power plants and allows lower impact, more accessible renewable energy sites to be cost competitive. Regional interconnections planned around strategic siting opportunities are crucial for realizing no-regrets wind and solar energy development that can be competitive with conventional generation in African countries.

Author contributions: G.C.W., R.D., and D.S.C. designed research; G.C.W., R.D., and J.R.-M. performed research; G.C.W., R.D., and D.S.C. contributed analytic tools; G.C.W. and R.D. analyzed data; G.C.W., R.D., K.N., T.R., J.R.-M., A.P., D.M.K., and D.S.C. wrote the paper; and K.N., T.R., and J.R.-M. collected data.

The authors declare no conflict of interest.

Freely available online through the PNAS open access option.

This article is a PNAS Direct Submission.

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This article contains supporting information online at www.pnas.org/lookup/suppl/doi:10.1073/pnas.1611845114/-DCSupplemental.

spatially explicit wind and solar assessments. Existing studies typically omit critical cost, interconnection, and socio-environmental impact information (17).

To address this gap, we developed a large-scale multicriteria resource assessment of grid-connected wind, solar PV, and concentrating solar power (CSP) and integrated it into a suite of tools—Multicriteria Analysis for Planning Renewable Energy (MapRE). The resource mapping approach is based on techno-economic criteria, generation profiles (for wind), and socio-environmental constraints. The suite of MapRE spatial models and tools (mapre.lbl.gov) gives any stakeholder the ability to weigh multiple siting criteria—e.g., generation cost, distance to transmission lines and load centers, and possible conservation impact—and examine their trade-offs. Considering these criteria in site selection could avoid difficult-to-monetize barriers, such as ecological impacts or challenging transmission extensions and upgrades, which often stall projects (18).

In addition to these factors, strategic siting of wind and solar power plants can help manage the temporal variability of generation, which can be a major challenge for grid integration, particularly in countries without strong institutional capacity and infrastructure. Technological solutions for balancing variability—such as excess reserve generation capacity, fast generators, and battery storage—are expensive (19) and are significant barriers to economies with limited access to capital. Strategic spatial diversification of sites is an alternative, potentially more cost-effective strategy for managing variability (20–24); however, no study has examined the grid value of geographic diversification in large regions of Africa.

Studies in other parts of the world suggest that extensive interconnections can strengthen the value of renewable energy spatial diversification (25), and other studies have found that it is significantly cost effective to support energy trade in Africa (26–30). However, those studies that examined renewable energy trade in Africa (29, 30) lacked the spatial and temporal resolutions necessary for modeling integration of highly temporally and spatially variable renewable energy. The EAPP and SAPP are considering new interconnections, but to exchange future conventional and hydroelectric generation (2, 3). Those required to support renewables may be substantially different.

We provide a comprehensive multicriteria assessment of wind and solar resources in EAPP and SAPP and identify no-regrets options. We also examine the importance of strategic siting for managing temporal variability of generation by increasing hourly correlation between aggregate wind production and electricity demand, specifically whether international interconnections enable cost-effective deployment of wind capacity in the SAPP. The power pools include the following 21 countries: Angola, Botswana, Burundi, Djibouti, Democratic Republic of Congo, Egypt, Ethiopia, Kenya, Lesotho, Libya, Malawi, Mozambique, Namibia, Rwanda, South Africa, Sudan, Swaziland, Tanzania, Uganda, Zambia, and Zimbabwe.

We apply the MapRE approach to examine trade-offs between wind and solar resource quality and multiple-siting criteria, including transmission connectivity, distance to the nearest load center, and ecological intactness of potential project areas. Using a unique dataset of hourly demand profiles for nine SAPP countries and hourly wind profiles, we optimally select wind sites to minimize conventional capacity, with and without interconnections and with and without consideration of multiple-siting criteria. We examine wind specifically because it is currently more cost competitive than solar in Africa and exhibits more spatiotemporal variability. We compare this approach with the prevailing practice of selecting sites to minimize the levelized cost of wind electricity.

Results and Discussion

Wind and Solar Resources Are Heterogeneous in Quality and Quantity, but Sufficient No-Regrets Potential Exists in Each Power Pool. After excluding areas on the basis of physical, technical, and socio-economic suitability for large-scale renewable energy development (*SI Appendix, Table S2*), the resulting quantities (TWh) of wind, solar PV, and CSP resources that exist within the EAPP and SAPP collectively exceed the projected 2030 demand two- to fivefold (Fig. 1 and *SI Appendix, Fig. S1* for power pool supply curves). However, these resources, particularly high-quality resources (e.g., high insolation or wind speed) that meet multiple-siting criteria, are unevenly distributed between and within countries.

Examining just resource quality and quantity alone, results show that high-quality resources in a majority of countries are one or two orders of magnitude greater than their projected 2030 demand (Fig. 1*B*). Although about one-fifth of all countries in the study region (Angola, Democratic Republic of Congo, Rwanda, and Burundi) lack sufficient high-quality wind resources, their neighboring countries have wind resources that exceed their projected demand (Tanzania, Zambia, and Namibia). Nearly all countries have large and high-quality solar PV potential (Fig. 1*B*). CSP is the most spatially limited of the three technologies, with potential significantly less than the projected 2030 demand in at least six countries. The distribution of resource availability and quality supports the need for resource sharing to cost-effectively achieve low-impact electricity development regionally.

To examine trade-offs between economic costs and other siting barriers, we selected resource areas across the entirety of each power pool that are in the top 20% and 50% of areas closest to transmission infrastructure, closest to load centers, and that have the highest human footprint score. The multiple dimensions to consider in prioritizing energy projects—resource sufficiency, cost, and other siting barriers—are represented in the shape of each supply curve (Fig. 2 and *SI Appendix, Fig. S1*).

Distances to load centers and transmission infrastructure account for the institutional, financing, and time barriers associated with connecting multiple distributed generation projects, barriers that are often not fully captured in the transmission component of the levelized cost of electricity (LCOE). Transmission availability is often cited as the greatest challenge to scaling-up wind energy (18), with some studies showing that it is often more cost and time effective to develop lower wind-speed projects closer to transmission than attempt to interconnect high-quality sites far from existing lines and load centers (31). The distance to load center is a proxy for investments in transmission infrastructure required to deliver electricity from generators to load centers. Finally, we used the human footprint score as a proxy for the degree of human “disturbance” from natural, unaltered states (32).

For solar PV, numerous countries have sufficient potential for no-regrets—low-cost, low-impact, easily accessible—development, but a subset of these countries would require additional domestic or international transmission infrastructure to achieve 2030 targets. Specifically, Tanzania, Zimbabwe, Botswana, and Lesotho can meet 30% of their projected 2030 demand with low-impact solar PV (thick lines in Fig. 2 represent the top 20% of all sites), with Tanzania able to export up to 20 TWh of inexpensive and low-impact solar electricity to neighboring countries (Fig. 2*A*). In the EAPP, Ethiopia, Sudan, Uganda, and Tanzania can most favorably achieve 30% solar PV generation targets domestically (Fig. 2*B*). For these countries, high resource quality sites have the lowest impact and are closest to load centers and existing infrastructure. This is not the case for all countries. Democratic Republic of Congo, Zambia,

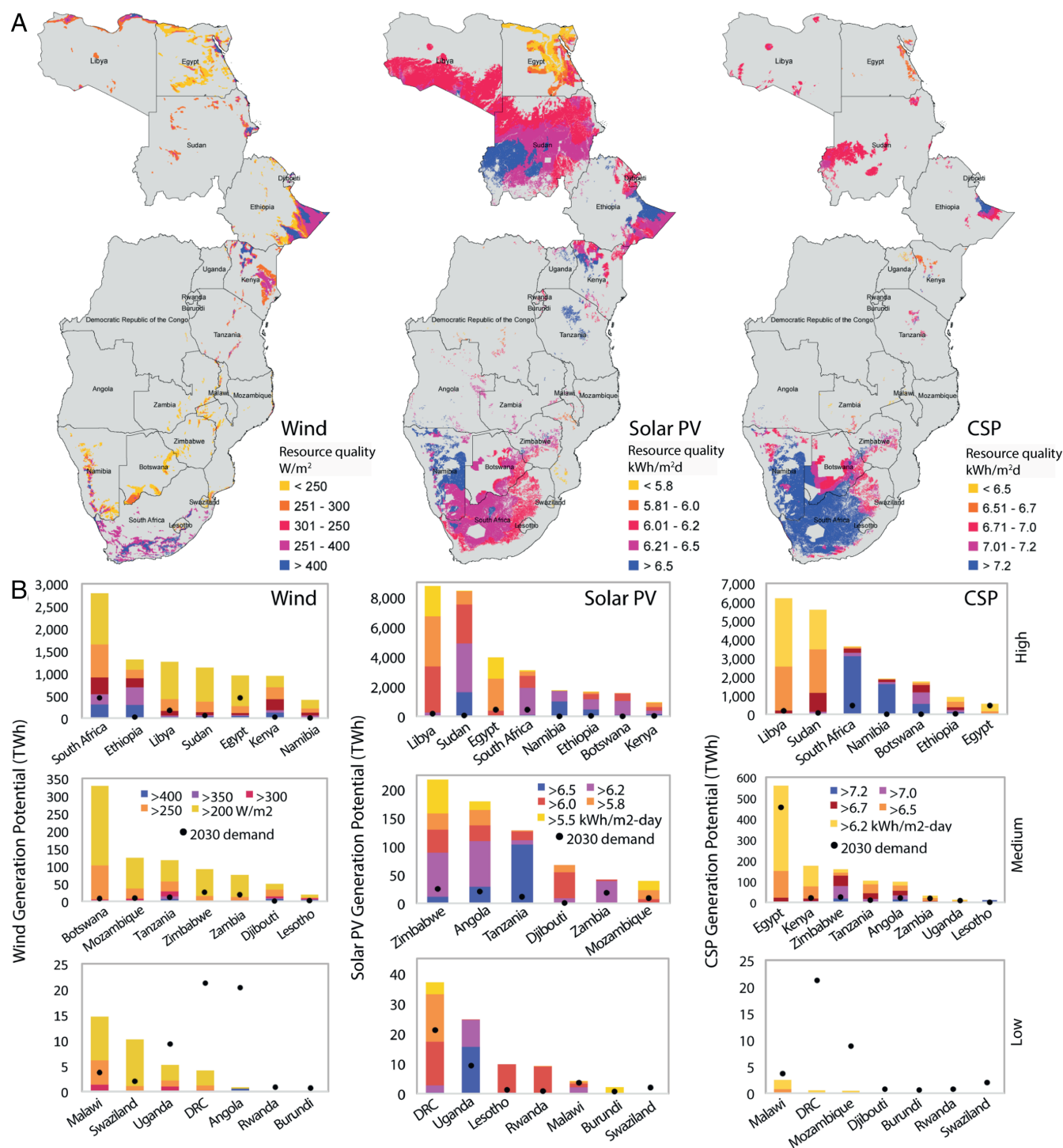


Fig. 1. Location and potential (TWh) of each country's renewable resources within the SAPP and EAPP. (A) Maps show the location and quality of renewable energy potential. (B) Corresponding bar charts for each technology show the generation potential (TWh) of each resource quality range (in $\text{kWh}\cdot\text{m}^{-2}\cdot\text{d}^{-1}$ for insolation and m/s for wind speed) for each country. Countries are sorted by generation potential (high, medium, low). The 2030 demand for each country, as projected by the EAPP and SAPP Master Plans, is provided as a reference point (2, 3).

Angola, South Africa, Egypt, Kenya, and Libya possess some cost-effective sites that should receive high prioritization, but are not in the top 20% primarily due to limited transmission access. For these countries, meeting an ambitious 2030 target would require investing in transmission extensions to access lower-cost PV resources or importing from neighbors. For CSP, the pattern of project prioritization is very similar to that of solar PV, but

with fewer countries meeting all sufficiency, low-cost, and other siting criteria dimensions.

Wind resource supply curves are generally steeper and more divergent than those for solar technologies, indicating more variation in cost and quality of sites within a country (Fig. 2). The least-cost wind resource areas are distributed across several countries, including Malawi, Lesotho, Zambia,

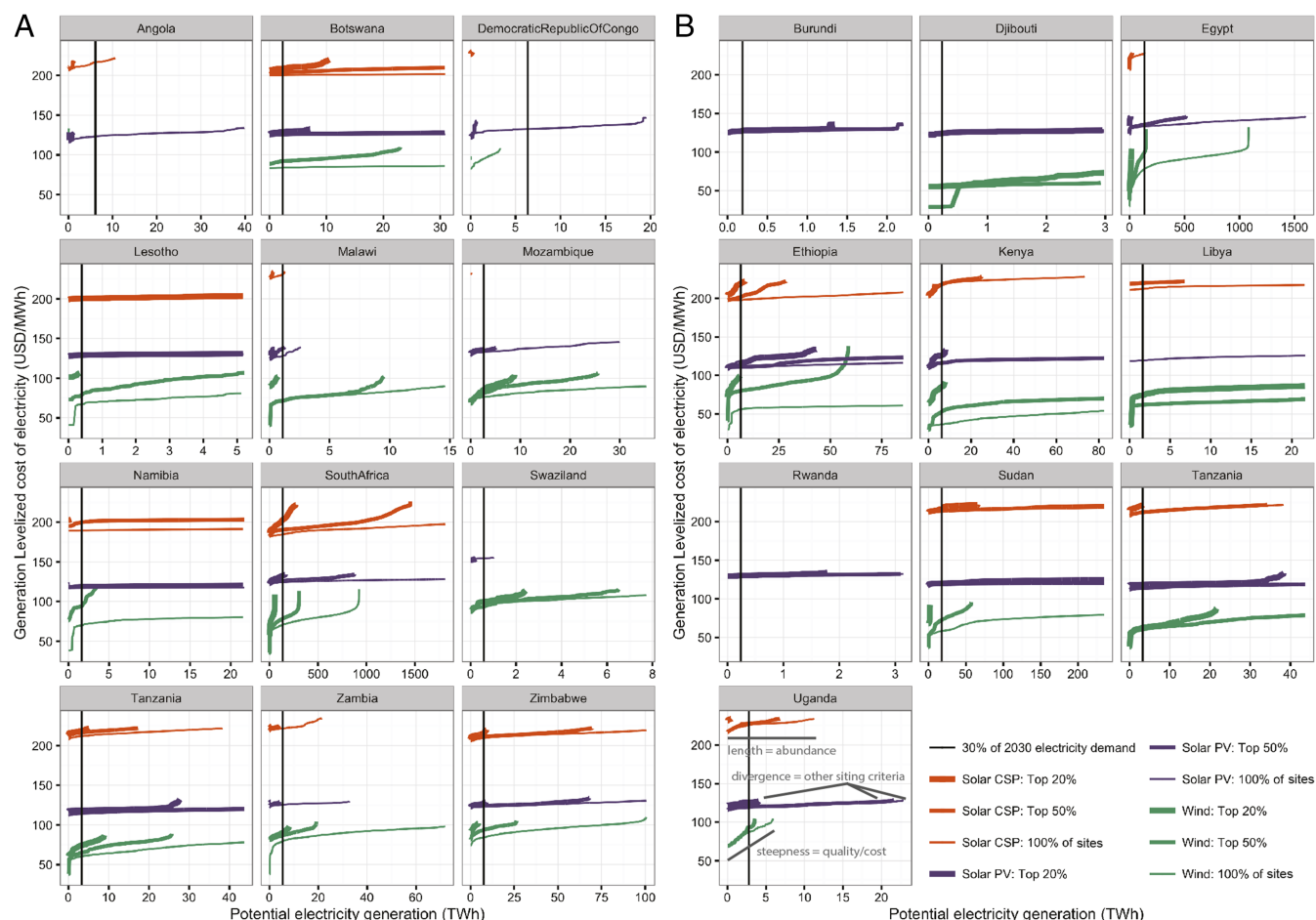


Fig. 2. Multicriteria project opportunity area supply curves for countries in the SAPP and EAPP. Supply curves show the cumulative potential of all wind, solar PV, and CSP sites and those that meet the top 20% and 50% of criteria values within the SAPP (A) and EAPP (B). Project opportunity areas are sorted by generation LCOE. Vertical lines show 30% of each country's projected electricity demand in 2030. Criteria values include transmission distance, distance to nearest load center, and human footprint score. For example, the quantities of CSP potential in the top 50% and all sites in Uganda meet 2030 targets, and the difference between solar PV supply curves shows that although the top 20% of sites are limited in Uganda, they are sufficient to meet 2030 targets. Note that the x axis varies between countries whereas the y axis is fixed. For countries with large potential, the maximum value of the x axis is six times the anticipated 2030 demand. Tanzania is a member of both power pools. The top 20% or 50% of sites are selected relative to other sites within the power pool. Assumptions for LCOE, including discount rate, are consistent across countries.

Djibouti, Ethiopia, Kenya, Libya, South Africa, Egypt, and Tanzania. However, these low-cost, high-quality wind sites generally score low in other siting criteria, as is seen in the large divergence between the supply curves within these countries. Tanzania, Swaziland, Djibouti, and Libya are exceptions in being able to meet 30% of their demand with accessible, low-impact, and cost-effective wind sites. Although trade-offs between cost and other siting factors appear to be greater for wind power, leaving fewer no-regrets areas, generation cost is not the only important determinant of wind resource quality. Selecting sites with wind-speed regimes that generate most during the highest demand hours will increase their value (20), a consideration we address in the following section.

International Transmission Interconnections Enable Least-Cost Wind Deployment and Greater Displacement of Conventional Generation by Wind. With hourly electricity demand data for nine countries in the SAPP (*SI Appendix, section S1.3.1*), we selected wind zones using four approaches: (i) “Min-Net-Demand,” minimizing the maximum hourly net electricity demand (i.e., demand remaining after accounting for wind generation) across an entire year using all zones (*SI Appendix, section S1.3.2*); (ii) “Min-LCOE,” minimizing the annual average generation LCOE of wind using

all zones; and (iii and iv) “Top-50%,” performing approaches *i* and *ii* using a subset of zones that meet the top 50% of other siting criteria within a power pool, as described in the previous section. For a given investment or installed capacity target, the Min-LCOE approach maximizes wind generation, which reduces the need for conventional energy, whereas the Min-Net-Demand approach reduces integration costs by minimizing need for nonwind, typically conventional generation capacity. We selected wind zones with and without international interconnections, referred to as “Interconnected” and “Isolated” scenarios, respectively. Each scenario installs a total of 61 GW of wind capacity, the amount needed to meet a 30–33% wind energy target by 2030 across the SAPP (*SI Appendix, Table S7*).

We compared the distribution of selected wind zones and found that the Min-Net-Demand, Interconnected, Top-50% scenario results in the most even distribution of capacity across countries (Fig. 3A). Instead of meeting South Africa's large demand domestically, a fully interconnected SAPP allows for a large portion of its demand to be met internationally, in areas where wind generation profiles are better matched to SAPP's demand profile. In the Top-50%, Interconnected scenario, many countries—Swaziland, South Africa, Malawi, Zambia, and Zimbabwe—see an increase in their share of wind

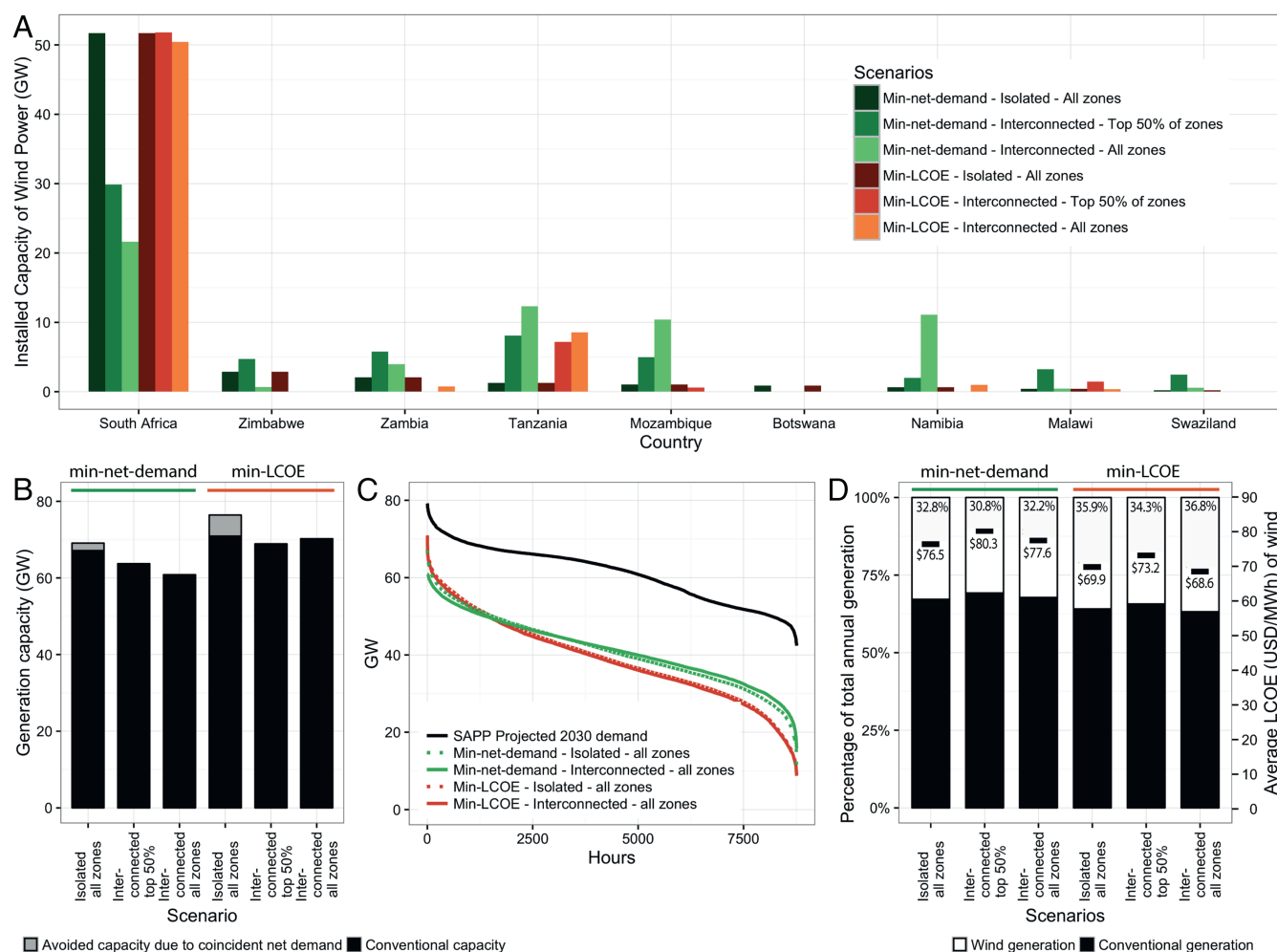


Fig. 3. Impacts of wind build-out scenarios for the SAPP in 2030. (A) Distribution of installed wind capacity among countries in the SAPP. (B) Conventional installed capacity needed to meet the highest hourly net demand within 2030. (C) The hourly net electricity demand in gigawatts (GW) sorted from highest to lowest compared with the projected 2030 electricity demand. (D) The percentage of annual electricity from wind and nonwind generation (primary x axis and bar plot) compared with the average LCOE of wind generation (secondary y axis and horizontal lines).

capacity because of their more favorable sites, whereas others—Namibia, Mozambique, and Tanzania—reduce their share relative to the “All-Zones” approach (Fig. 3A). With interconnections, both Min-Net-Demand and Min-LCOE approaches significantly increase capacity in Tanzania at the expense of capacity in other countries with lower capacity factors (Fig. 3A).

Results show a trade-off between selecting sites to maximize wind generation (Min-LCOE) and minimize additional conventional capacity (Min-Net-Demand; Fig. 3B), although system costs are on the whole lower for the Min-Net-Demand approach (Fig. 4A). With interconnections, the Min-LCOE, All-Zones approach generates 12% (24.5 TWh) more wind energy than the Min-Net-Demand, All-Zones approach, resulting in 11% reduction in average wind LCOE (Fig. 3D), yet it requires 15% more, or 9.4 GW, conventional capacity (Fig. 3B). We estimated system costs assuming the extra conventional capacity needed would be met by natural gas combustion turbine (CT), scrubbed coal, or hydropower, as these are the technologies that have high-priority status in the SAPP (*SI Appendix, section S1.3.3*). Costs show that the Min-Net-Demand, Interconnected, All-Zones scenario leads to 0.4–2.5 billion USD/y in cost savings over the Min-LCOE, Interconnected, All-Zones approach, depending on the technology assumption (Figs. 4A and 5). These cost savings account for 3.5–19% of the total annual costs of wind capac-

ity. Assuming hydropower or coal capacity would be avoided, selecting sites to minimize peak net demand is more cost effective from the systems perspective than selecting sites to minimize wind LCOE.

Other, nonmonetized system benefits of the Min-Net-Demand approach include reduction in the temporal variability of hourly wind capacity factors and net demand (20–30% reduction in the coefficients of variation; Table 1). In contrast, there are few or no differences in the coefficient of variation between Interconnected and Isolated scenarios when selecting sites to minimize LCOE (Table 1). That is, the main factor determining temporal variability of wind generation is the site selection approach, not the presence or absence of interconnections. For example, two countries with existing wind farms sited based on minimizing LCOE that later interconnect may not see reductions in the variability of generation or net demand. Interconnections, however, do increase the diversity of available sites, allowing a Min-Net-Demand siting approach to further reduce variability. This finding that increasing the geographic diversity of wind sites decreases the coefficient of variation is consistent with empirical studies examining interconnection scenarios of wind plants (33).

Lower aggregate net demand variability reduces the need to ramp up or down conventional generators to balance the variability (see *SI Appendix, Fig. S2* for hourly ramp rate distributions),

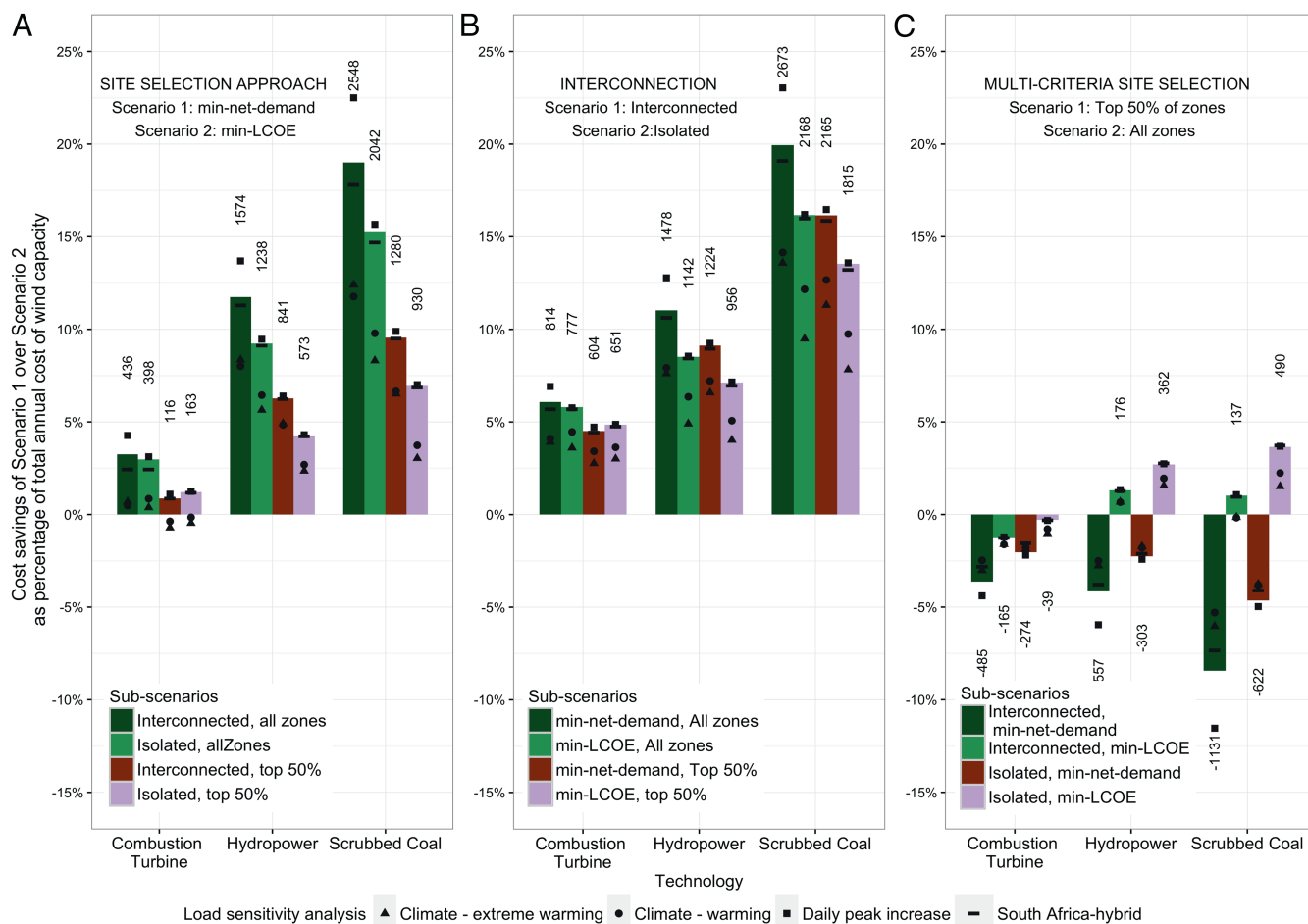


Fig. 4. Cost differences between wind build-out scenarios. Cost differences are expressed as percentage of total annual wind capacity cost, which is constant across scenarios. Actual cost differences in millions of USD/y are labeled above each bar for the base-load sensitivity case. Positive percentage and cost values indicate cost savings of scenario 1 compared with scenario 2, and negative values indicate additional costs of scenario 1 compared with scenario 2 in each panel. Costs were estimated assuming three different possible conventional capacity technologies—natural gas combustion turbine (CT), hydropower, and scrubbed coal (x axis). (A) The cost savings of the Min-Net-Demand over the Min-LCOE site selection approach. Positive values indicate that Min-Net-Demand is more cost effective. (B) The cost savings of the Interconnected over the Isolated scenario. Positive values indicate that the Interconnected scenario is more cost effective. (C) The cost savings of the Top-50% over the All-Zones site selection approach. Positive values indicate that the Top-50% scenario is more cost effective. The set of points for each bar (defined at bottom) shows results from load sensitivity analyses of four plausible future load growth scenarios: “Climate - extreme warming,” “Climate - warming,” “Daily peak increase,” and “South Africa - hybrid.” See *SI Appendix, section S1.3.4 and Figs. S10 and S11* for descriptions of the load growth scenarios.

and a flatter load curve allows for more efficient use of base-load generators (Fig. 3C). Therefore, a site selection process based only on minimizing wind LCOE may not minimize system-wide costs and may not maximize the cost savings of interconnections compared with a site selection approach that best matches wind generation with electricity demand.

Comparisons between Interconnected and Isolated scenarios show that interconnections reduce system costs regardless of site selection approach or assumptions about the conventional generation technology wind may displace (Fig. 4B). Compared to the Isolated scenario, the Interconnected scenario using the Min-Net-Demand, All-Zones approach results in avoiding close to 10% or 6.3 GW of conventional generation capacity in the SAPP (Fig. 3B and C). The annual cost savings of interconnections combined with the Min-Net-Demand approach are particularly large when assuming additional coal (2.2–2.7 billion USD or 14–20% of annual wind capacity costs) or hydropower capacity (1.2–1.5 billion USD or 9–12%; ranges represent Top-50% and All-Zones approaches, respectively; Fig. 4B).

Using SAPP’s recent wheeling charges as a proxy for transmission capital costs per MWh traded (*SI Appendix, section*

S1.3.3), we find that transmission costs in the Interconnected scenario are 1.6–1.8% of the amortized annual cost of wind capacity for the Min-Net-Demand, All-Zones site selection approach and 0.40–0.44% for the Min-LCOE, All-Zones approach (*SI Appendix, Table S1*). These percentage cost ranges are less than the range of potential savings from avoided conventional capacity resulting from the availability of interconnections under these same scenarios (6–20% for Min-Net-Demand and 4–16% for Min-LCOE; Fig. 4B). When international interconnection costs are included, interconnections would save 4.3% at worst (assuming CT capacity) and 18% at best (assuming scrubbed coal capacity) in avoided conventional capacity, represented as percentage of amortized annual wind capacity costs (Fig. 4B).

Multicriteria site selection is not significantly more costly and, for the Min-LCOE scenarios assuming hydropower or scrubbed coal capacity displacement, yield cost savings (Fig. 4C). This is because sites selected using multiple-siting criteria (Top-50%) and the Min-LCOE approach result in lower net peak demand compared with the All-Zones approach, reducing conventional capacity costs. Nearly all cost differences between the

Top-50% and All-Zones site selection scenarios are $<5\%$ of the annual cost of wind capacity (Fig. 4C). When examining ranked cost differences across all scenarios, results show that the Min-Net-Demand, Interconnected, Top-50% scenario is the second-most cost-effective option by a large margin when the avoided conventional technology is hydropower or coal (~ 1 billion/y USD; Fig. 5). Regardless of the conventional technology, interconnections reduce the system costs of multicriteria selection relative to all scenarios without interconnections (Fig. 5).

Load Sensitivity Analysis and Limitations. Because only one year of load data was available and load profiles in 2030 are highly uncertain, we performed a sensitivity analysis using four future load growth trajectories that represent load responsiveness to climate change, economic structural changes, and grid-connected electrification and reduced load curtailment (see *SI Appendix*, Figs. S10 and S11 and section S1.3.4 for detailed scenario descriptions). Results show that the cost effectiveness of Interconnected scenarios and the Min-Net-Demand site selection approaches is sensitive to different load growth trajectories, but the range of results suggests that the baseline load scenario is in the middle (Figs. 4 and 5). Despite the trajectories being fairly extreme scenarios of load shifting and growth, on the whole, they do not change the conclusion that interconnections are very likely to reduce system costs from avoided conventional capacity (Figs. 4B and 5).

The South Africa - hybrid scenario, which represents economic structural changes, is very similar to that of the baseline (unmodified) load growth profile. The two climate-warming scenarios increase the conventional generation capacity requirements for the Interconnected scenario, but decrease it for the Isolated scenario, with a smaller yet still positive avoided capacity difference between Interconnected and Isolated scenarios compared with baseline (*SI Appendix*, Fig. S4). For the “daily peak increase” load growth scenario, both the Interconnected and Isolated conventional capacity requirements increase, but the avoided capacity of the Interconnected scenario is larger relative to baseline

Table 1. Coefficient of variation of hourly time series of net demand and site-averaged wind capacity factor for all site selection approaches (Min-Net-Demand and Min-LCOE) and interconnection scenarios

Interconnection scenario	Min-Net-Demand		Min-LCOE	
	Net demand	Wind capacity factor	Net demand	Wind capacity factor
Interconnected, All-Zones	0.197	0.320	0.283	0.426
Interconnected, Top-50%	0.199	0.334	0.258	0.426
Isolated, All-Zones	0.224	0.354	0.280	0.440
Isolated, Top-50%	0.223	0.357	0.256	0.442

(*SI Appendix*, Fig. S4). These results suggest that the cost effectiveness of the Interconnected scenario is highly dependent on the annual peak demand. We posit that the two climate load growth scenarios represent fairly extreme load responses to climate change such that the entire seasonal pattern disappears or inverts (*SI Appendix*, Fig. S10 C and D), without the counterbalancing likelihood of increased electrification or reduced curtailment, which has the effect of elevating demand during the daily peak hours. On the whole, the Interconnected scenario remains the more cost-effective choice, with load growth uncertainty reducing the confidence of this result only if natural gas CT were the avoided conventional technology under the climate-warming load growth scenario (Fig. 5). Otherwise, for hydropower and coal, the differences in additional costs of the Isolated scenario remain large even under climate-warming scenarios (1–3 billion USD/y; Fig. 5) and the differences would be very significant under the daily peak increase scenario (1.9–5.6 billion USD/y; Fig. 5). These costs would be adjusted downward by 0.04–0.24 billion USD/y (depending on site selection approach) due to transmission costs (*SI Appendix*, Table S1).

Currently, hydropower and coal appear to be the marginal generation technologies in the SAPP, although recent discoveries of natural gas in Mozambique may change this trend. However, transport of natural gas through a pipeline network would add significant capital costs that have not been considered in the cost estimates for CT capacity.

This study does not examine the effect of solar generation on system costs in the SAPP, but it is expected to alter net demand patterns. We relied on 1 y of modeled wind-speed data, which may have interannual variability. However, previous analysis using 10 y of mesoscale wind data shows that the wind regime during peak hours in the region is stable (34), although wind patterns may change in the future. Such potential changes underscore the importance of incorporating multicriteria analysis in siting decisions on an ongoing basis. Due to limited power systems data availability across multiple countries, our model examines only the extreme ends of SAPP’s future—either complete grid isolation with no energy trade or complete interconnection such that the entire SAPP region operates like a coordinated, single balancing area without transmission constraints. Because generator-specific time series and constraint data needed for a production cost model and capacity expansion model could not be acquired across multiple countries, our model does not account for flexibility or responsiveness of other generators in the system. For the same data limitation reasons, we could use a capacity expansion model or a model that minimizes system costs to generate a scenario that balances conventional capacity and energy trade-offs.

Conclusions

Results demonstrate the large potential for utility-scale wind and solar energy development in many EAPP and SAPP countries,

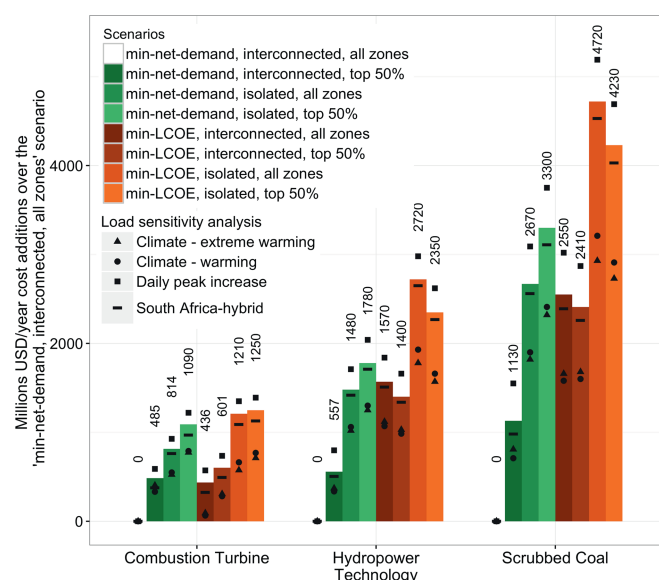


Fig. 5. System cost additions compared with the least-cost scenario. For each technology, the bars show the difference in system costs between each scenario and the least-cost scenario (Min-Net-Demand, Interconnected, All-Zones). System costs include the additional energy and/or conventional capacity required in each scenario. The set of four points for each bar shows results from load sensitivity analyses of four plausible future load growth scenarios (*SI Appendix*, Figs. S10 and S11).

with particular countries possessing sufficient no-regrets–low-cost, accessible, and low-impact–potential sites that can rapidly provide low-carbon electricity. However, the most competitive resources are spatially heterogeneous, underpinning the need for regional coordination and transmission infrastructure to enable resource sharing. Our study demonstrates how spatiotemporal models can be used to assess opportunities and address barriers for renewable energy development in countries where data are limited and where the load growth trajectory is highly uncertain.

By providing the institutional structure for electricity trade, the power pools in Africa can lay the groundwork for power plant siting that minimizes regional system costs. Currently, the emphasis on large hydropower in a small handful of EAPP and SAPP countries could result in a set of interconnection plans that fail to support the development of plentiful no-regrets solar and wind options across multiple countries. Our results show that wind and solar electricity can be cost competitive and have a much larger role to play in Africa's energy transition, especially if the benefits of strategic siting and international interconnections are considered.

Materials and Methods

MapRE Model Overview. To estimate renewable resource potential and spatially specific criteria important for site selection, we developed the MapRE spatial model, using Python and R programming languages and the arcpy spatial analysis module (*SI Appendix, Fig. S5*). The framework is founded in previous resource assessment and zoning studies (14, 35, 36), but improved and adapted to account for data availabilities of the study region. We used a combination of global or continental data and country-provided datasets that can be broadly categorized into the following: physical (slope, elevation), socio-economic (population density, built areas), technical (resource quality), and environmental (land cover, protected areas) (*SI Appendix, Table S2*). We applied thresholds and buffer distances used in previous studies (14, 35, 36) (*SI Appendix, Table S2*), but adjusted within an economically viable range for each country, depending on the projected demand and the resource quality (*SI Appendix, Table S3*). We created maps of suitable areas for renewable energy development and further divided large areas into 5 × 5-km spatial units or project opportunity areas (POAs). For each POA, we estimated multiple-siting criteria values, including component and total LCOE. Using a statistical regionalization technique (Spatial Kluster Analysis by Tree Edge Removal), we spatially clustered POAs into "zones" (30–1,000 km² in size) based on the homogeneity of resource quality (W/m²) of

each POA. We then area weighted averaged POA siting criteria to generate zone criteria values.

Criteria Estimates. We estimated the following site selection criteria for each POA and zone: slope; elevation; population density; resource quality; distance to nearest major load center, transmission line, substation, road, surface water body, and existing and proposed wind, solar, and geothermal energy projects; land cover type; total land area; and human footprint score (*SI Appendix, section S1.2.1 and Table S4*). We collected country-specific transmission and substation spatial data and, where unavailable, we used the continental dataset from the African Infrastructure Country Diagnostic initiative (*SI Appendix, Table S5*). In addition, load center locations were collected from countries individually. These criteria values were then used to calculate the following additional criteria for each POA and zone: capacity factor (*SI Appendix, section S1.2.2*), annual electricity generation, transmission or substation LCOE, generation LCOE, road LCOE, and total LCOE. Cost estimates relied on various assumptions about fixed and variable costs specific to the technology and subtechnology (*SI Appendix, section S1.2.3 and Table S6*).

Wind Build-Out Scenarios for 2030. To understand the implications of different zone selection approaches and availability of interconnections, we modeled various wind energy build-out scenarios for SAPP in 2030 (*SI Appendix, section S1.3*). We acquired hourly wind-speed profiles from Vaisala Inc. for 233 wind locations and solicited at least one year (2013) of hourly electricity demand data from each country to create 2030 load forecasts (*SI Appendix, section S1.3.1 and Table S7*). Using these two datasets, we constructed a linear optimization problem to select wind zones that minimize the hourly peak net demand (Min-Net-Demand) with and without interconnections. We compared the results of this approach to a scenario that minimizes wind LCOE. For each scenario, we compared the maximum net demand (i.e., the installed capacity required in addition to wind power), total annual net demand (i.e., the generation required in addition to wind power), average wind LCOE, and approximate system costs (*SI Appendix, section S1.3.3*).

ACKNOWLEDGMENTS. We thank Gauri Singh and the International Renewable Energy Agency for the opportunity to conduct this research and Crescent Mushwana, Naim Dargouth, Andrew Mills, Nikit Abhyankar, Nicholas Fichaux, Asami Miketa, Justin Kitzes, and Cornelius Van der Westhuizen for helpful comments on the zoning methodology. G.C.W. was supported in part by a National Science Foundation Graduate Research Fellowship. R.D. was supported by a Link Foundation fellowship. D.S.C. and D.M.K. was supported in part by the NSF CyberSEES Grant 1539585.

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Supporting Information

Strategic siting and grid interconnections key to low-carbon future in African countries

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SI Text

S1 Materials and Methods

S1.1 Data inputs

A comprehensive zoning process requires various types of physical, environmental, economic, and energy data in both specific spatial and non-spatial formats. We relied on a combination of global or continental default spatial data (Table S2) and country-provided datasets. The former serve the purpose of filling in missing country data and provide spatial uniformity for critical physical characteristics (e.g., elevation, wind speed). Country-specific datasets ensure consistency with similar past and ongoing national efforts, and in some cases, greater accuracy. We collected these data for 21 participating countries in the Eastern and Southern Africa Power Pools through a combination of stakeholders and country contacts at government agencies, utilities, and industries. The full zoning analysis could not be completed for Libya and Djibouti (both part of the Eastern Africa Power Pool) because these countries lacked requisite country-specific datasets (e.g., transmission infrastructure). As a result, we examined the Southern Africa Power Pool in more detail for the site selection process, using countries for which we could collect both transmission and demand data.

Data access Nearly all globally datasets in Table S2 are freely available and downloadable using the website links provided. LandScan (gridded global population density) and Vaisala’s hourly wind data are the two exceptions, but data may be purchased by contacting the vendor directly via the website links provided. A free and open source alternative to LandScan is Worldpop (<http://www.worldpop.org.uk/>). Hourly demand data and transmission or substation data were acquired for each country individually. Data availability and sources are tabulated for each country in Appendix A of the MapRE report [1] and Table S5.

S1.2 Project opportunity area and zone criteria estimates

S1.2.1 Human Footprint Score

The Human Footprint Score is a metric for degree of human influence in a defined land area, and it is used in this study as a proxy for degree of human “disturbance” from natural, unaltered states [2]. We estimated this metric following Sanderson et al.’s (2002) methods [2], 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 S4). We did not include the power infrastructure criteria in Sanderson et al. (2002), which relies on nighttime light visibility spatial data. Assumptions about electric power infrastructure’s use as a proxy for population distribution and correlation with human settlements is based on developed countries’ widespread electricity availability, which is not the case for many parts of our study region.

We summed the scores for each dataset to create a Human Influence Index. These scores were normalized within global terrestrial biomes [3], 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 of the maximum value. For example, a score of 1 within the Central Zambezian Miombo woodlands suggests that the area is the top 1% least disturbed or most wild area within the ecoregion. Since we calculated the

human footprint score for each 500 m grid cell, we averaged the scores across every grid cell in each project opportunity area.

S1.2.2 Capacity factor estimation

Solar PV To estimate solar PV capacity factors (r_{solar}), we extracted and spatially averaged the resource quality (q) (solar irradiance W/m^2) of each project opportunity area for solar PV (Eq. 1). Since land use factors that we applied are specified for MW_{ac} , we further applied outage rates (η_o), and inverter and AC wiring efficiencies (η_i) to estimate the capacity factor for solar PV (Table S6). We assume an incident power density of $1000 \text{ W}/\text{m}^2$ to produce an output at the rated capacity of the plant.

$$r_{solar} = \frac{(1 - \eta_o)(1 - \eta_i)q}{1000} \quad (1)$$

Solar CSP Apart from the type of collector technology (parabolic trough, compact linear Fresnel reflector or heliostat solar tower), the capacity-based land use factor (e.g., MW/km^2) of solar CSP depends on two interdependent variables: the solar multiple and thermal storage. The design capacity of the solar CSP plant is based on the design output of the power turbine block. The solar multiple is the ratio of the actual size of the power plant’s solar field to the size of the solar field that would be required to drive the turbine at its nominal design capacity assuming standard solar irradiance of $1 \text{ kW}/\text{m}^2$ at standard temperature and pressure.

Thermal storage can significantly improve the capacity factor of the plant and its ability to generate when the value of electricity is greatest, which is the greatest advantage of thermal storage. Thermal storage can enable a CSP plant to store heat during high solar insolation hours and generate electricity during the evening, night or other hours when the sun is not shining. Power plants with thermal storage can have solar multiples of up to 3-5 [4]. While such plants have a higher cost per MW due to the additional thermal storage equipment and a larger solar field (i.e., higher solar multiple), they have higher capacity factors compared to plants without thermal storage. CSP plants with no storage are typically designed to have a solar multiple between 1.1 – 1.5 [4], which is greater than 1 in order to generate electricity during the morning and evening hours when insolation is lower than threshold requirements, at the expense of losing some excess energy during the peak sun hours.

More thermal storage results in higher capacity factors (CF), but it reduces the land use factor (MW/km^2) due to the increasing solar multiple required. Given the near linear trade-off between thermal storage and land use factor, the generation-based land use factor (MWh/km^2) should be invariant to thermal storage assumptions. Nonetheless, we estimate CFs assuming both storage and no storage. Due to lack of empirical land use factor data for thermal storage systems, we use average empirical land use factors for no-storage CSP plants examined in the USA, which are more robust (as measured by number of data samples), and applied the ratio of storage to no-storage solar multiples to estimate land use factors for CSP plants with thermal storage (Table S6) [5].

Models of CSP power plant generation are complex and difficult to approximate using only design calculations and average direct normal insolation (DNI) values. Instead, we used the National Renewable Energy Laboratory’s System Adviser Model [6] to simulate the CF for 45 locations throughout the study region in Africa and five locations in California and Arizona (in order to achieve greater representation of higher DNI regions) 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. Weather data for both U.S. and African locations were available from the U.S. Department of Energy Simulation Software database, a compilation of weather

data from multiple sources [7]. We linearly regressed each location’s CF against its DNI, wind speed, temperature, and latitude, and determined that DNI was the only statistically significant explanatory variable for trends in CF. 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 S6). We used these fitted equations (Figure S6) 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.

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 used spatially-averaged shape and scale parameters for the Weibull distribution provided by 3Tier Inc. (now Vaisala Inc.) to generate a wind speed probability distribution per 3.6 km grid cell (the resolution of 3Tier data).

Air density is inversely related to elevation and temperature. It decreases with increasing elevation or temperature, and as a result, can significantly affect the power in the wind for a particular wind speed regime. Wind turbine power curves provided by manufacturers typically assume an air density of 1.225 kg/m³, which is the air density at sea level and 15°C. An increase in elevation from sea level to 2500 m can result in 26% decrease in air density. Changes in temperature produce a smaller yet significant effect on air density compared to elevation. A temperature increase from 0°C to 25°C can result in a drop of 8% in air density. To account for the effect of air density on power generation, we first estimated the air density for each grid cell, and then applied power curves modified for different air densities to the wind speed distributions.

For air density, we first estimated the pressure (p) for each grid cell from the elevation and temperature of those grid cells (see Table S2 for data sources), the air pressure at sea level (p_o : 101325 Pa), the gravitational acceleration (g : 9.807 kg/m³), and the gas constant (R : 287.04 J/kg-K) (Eq. 2) [8]. We then estimated the air density (ρ) from the estimated pressure (p), the gas constant and temperature of the grid cell (Eq. 3).

$$p = p_o \cdot e^{\frac{-Zg}{RT}} \quad (2)$$

$$\rho = \frac{p}{RT} \quad (3)$$

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 [9] (see Figure S7), and scaled these to a 2000 kW rated wind turbine. Adopting an approach similar to [10], we assumed the IEC Class III and II turbines to be viable in sites up to the reference wind speeds of 7.5 m/s and 8.5 m/s respectively, as defined by the IEC. For sites with average wind speeds above 8.5 m/s, we assumed the IEC Class I turbine to be suitable. In reality, depending on the site-specific gust, turbulence, and air density, IEC Class II and III turbines could be placed at sites with higher average wind speeds than those assumed in our analysis, in order to extract more energy from the wind [10].

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 [11] [12]. In Equation 4, v_{adj} is the adjusted wind speed, v_{std} is the wind speed from the standard power curve, ρ_{std} is

the standard air density of 1.225 kg/m^3 , and ρ_{adj} is the estimated air density of the grid cell.

$$v_{adj} = v_{std} \left(\frac{\rho_{std}}{\rho_{adj}} \right)^{1/3} \quad (4)$$

Since the resulting power curve (v_{adj} , P_{std}) is evaluated at the adjusted wind speed values, v_{adj} , we needed to interpolate the P_{adj} at discrete wind speed values (v_{std}) in order to plot the air-density-adjusted power curve (v_{std} , P_{adj}) [12]. The resultant adjusted power curves show that air density can significantly affect the wind turbine power curves, and subsequently, the expected capacity factors at a site (Figure S8).

To compute the capacity factor for each 3.6 km grid cell, we selected the appropriate air-density-adjusted power curve given the average wind speed, which determines the IEC class, and the air density, which determines the air-density adjustment within the IEC class. For each grid cell, we then discretely computed the power output at each wind speed given its probability (determined by the Weibull distribution parameters provided by 3Tier) and summed the power output across all wind speeds within the turbine's operational range to calculate the mean wind power output in W (\bar{P}). The capacity factor (r_{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. 5).

$$r_{wind} = \frac{(1 - \eta_a) \cdot (1 - \eta_o) \cdot \bar{P}}{P_r} \quad (5)$$

S1.2.3 Levelized cost of electricity (LCOE) calculations

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. Using the size (km^2) (a_x) of the project opportunity area x and its associated land use factor (l_t) for technology t , land use discount factor (f_t) for technology t , distance to nearest substation (or transmission line; $d_{i,x}$) and road ($d_{r,x}$) from area x , and economic parameters listed in Table S6, we calculated the generation, interconnection and road components of the levelized cost of electricity (LCOE in USD/MWh). Note that the size (km^2) of a project opportunity area (a) and its associated land use factor (l_t) and land use discount factor (f_t) cancel out in the LCOE equations, but are included for completeness to show the ratio of cost to electricity generation (Eqs. 6 - 8).

Road LCOE was estimated using a fixed capital cost per km of additional road needed to service the project, and is expressed per unit of electricity output from the project. Since road capital costs do not scale according to installed capacity of a project, unlike generation and interconnection costs which increase with each additional MW of capacity, the size of a project opportunity area affects the road cost. That is, a POA within 10 km of existing road infrastructure will have a higher road cost than another POA within the same distance of the nearest road if it is comparatively smaller in land area. In order to allow road LCOEs to vary only by each POA's road connection distance and resource quality, we assumed 50 MW of capacity per POA regardless of size (Eq. 8). We assumed that one road will be built for every 50 MW capacity project, which is a reasonable size for a utility-scale project, and roughly equal to the potential capacity of a project opportunity area.

Total LCOE is simply the sum of the generation, interconnection, and road cost components. We prioritize distance to nearest substation in estimating transmission LCOE when high quality spatial data for sub-

stations were available, but we also estimated transmission LCOE costs based on distance to the nearest transmission line. Refer to Table S6 for values used in LCOE calculations.

$$LCOE_{generation,t,x} = \frac{a_x l_t (1 - f_t) (c_{g,t} i_{cr} + o_{f,g,t})}{8760 \cdot a_x l_t (1 - f_t) r_{t,x}} + o_{v,g,t} \quad (6)$$

$$LCOE_{interconnection,t,x} = \frac{a_x l_t (1 - f_t) (d_{i,x} (c_i i_{cr} + o_{f,i,t}) + c_s i_{cr})}{8760 \cdot a_x l_t (1 - f_t) r_{t,x}} \quad (7)$$

$$LCOE_{road,t,x} = \frac{d_{r,x} (c_r i_{cr} + o_{f,r})}{8760 \cdot r_{t,x} \cdot 50MW} \quad (8)$$

Where $c_{g,t}$ is the capital cost of generation for technology t ; c_i is the capital cost of interconnection (i); c_s is the capital cost of substation (s); c_r is the capital cost of road; $r_{t,x}$ is the capacity factor of technology t and area x ; $o_{f,g,t}$ is the fixed operations and maintenance cost of generation for technology t ; $o_{f,i,t}$ is the fixed operations and maintenance cost of interconnection (i) for technology t ; $o_{v,g,t}$ is the variable (v) operations and maintenance cost of generation (g) for technology t ; $o_{v,i,t}$ is the variable (v) operations and maintenance cost of interconnection (i) for technology t ; $o_{f,r}$ is the fixed (f) operations and maintenance cost of roads (r). The capital recovery factor (i_{cr}) converts a present value to a uniform stream of annualized values given a discount rate and the number of interest periods (Eqn. 9). We have assumed a real discount rate (i) of 10% that reflects the high cost of capital in Africa. n is the number of years in the lifetime of a power plant.

$$i_{cr} = \frac{i(1+i)^n}{(1+i)^n - 1} \quad (9)$$

Although LCOE assumptions were selected to be as representative of current conditions and costs, these LCOE estimates are best used to compare costs within a single technology since LCOE values may be higher or lower than others reported in the literature given the dynamic nature of the industry. Further, the discount rate can significantly affect the LCOE, and can vary across countries.

System integration costs or balancing costs are not included in LCOE estimates. These can vary across countries 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 renewable energy and load (net load).

The 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.

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.

S1.3 Wind build-out scenario analysis

S1.3.1 Input load and wind generation data

We created load profiles for the year 2030 ($d_{2030,t}$) using the projected annual demand in 2030 [13], [14] by multiplying the load in each hour t ($d_{2013,t}$) by the ratio of the 2030 annual load (D_{2030} ; Table S7) to the 2013 annual load (Eq. 10). This simple load projection technique assumes that load profile shapes will remain the same between 2013 and 2030, with an equal proportional increase in energy demand across all hours. See section S1.3.4 for methods used to conduct a sensitivity analysis of load profiles.

$$d_{2030,t} = d_{2013,t} \frac{D_{2030}}{\sum_{t=1}^T d_{2013,t}} \quad (10)$$

For the Southern Africa Power Pool (SAPP) countries, we procured mesoscale modeled hourly wind generation profiles for each of 233 wind locations, selected within zone extents based on resource abundance, resource quality, representation across countries, and spatial representation within a country. Using these profiles, we created hourly capacity factor ($c_{z,t}$) profiles for all 738 wind zones in the SAPP by adjusting the hourly wind capacity factor ($c_{m,t}$) of the mesoscale modeled profile using the ratio of zones' ($\overline{c_z}$) and modeled ($\overline{c_m}$) profiles' annual average capacity factors (Eq. 11). We matched each zone to the nearest location for which we acquired mesoscale modeled wind profiles.

$$c_{z,t} = c_{m,t} \frac{\overline{c_z}}{\overline{c_m}} \quad (11)$$

S1.3.2 *Min-net-demand* site selection approach

To select wind zones and the amount of capacity to install in each zone (x_z), we minimized the maximum hourly net demand, or the difference between the hourly load and the hourly wind generation (Eq. 12). This hourly net demand is the amount of energy non-wind generators would need to supply each hour. Therefore, the maximum hourly net demand within a year is the amount of non-wind installed capacity that must be available to ensure that demand is met across all hours of the year. The objective function (Eq. 12) was minimized subject to installing a specified amount of wind capacity across the region or country (Eq. 13) (Table S7) and selecting no more than the available potential capacity of each zone (Eq. 15). We used the projected 2030 demand (Table S7) to calculate the target wind capacity (i), assuming wind will generate 30% of total annual electricity demand and have an average capacity factor of 30%. The resulting target installed capacity (i) of 61 GW across all of SAPP was consistent across scenarios.

The integer optimization problem was programmed in Python using the Pyomo module and solved using IBM CPLEX. We used this optimal wind site selection method for the following four scenarios: 30% wind penetration for each country in SAPP using only domestic wind zones (*Isolated* scenario), and 30% wind penetration across the entire SAPP region (*Interconnected* scenario), and the *Isolated* and *Interconnected* scenarios using only the top 50% of zones across three selection criteria (see the results section of the main text).

Linear optimization

Indicies

z	Zone identifier $\in \{z...Z\}$
t	Hour $\in \{1, ..., 8760\}$

Variables

x_z	Capacity to install (MW) in zone z
-------	--------------------------------------

Parameters

$c_{z,t}$	Capacity factor of zone z hour t
$d_{2030,t}$	Electricity demand (MWh) of hour t in year 2030
p_z	Potential installed capacity (MW) of zone z
i	Target capacity (MW)

Objective function

Minimize

$$\max(d_{2030,t} - \sum_{z=1}^Z c_{z,t}x_z) \quad (12)$$

Constraints

Subject to

$$\sum_{z=1}^Z x_z = i \quad (13)$$

$$x_z \geq 0 \quad \forall z \in \{z, ..., Z\} \quad (14)$$

$$x_z \leq p_z \quad \forall z \in \{z, ..., Z\} \quad (15)$$

S1.3.3 Scenario comparisons

Peak net demand calculations. Typically, conventional generation capacity is sized to meet demand. Because wind power plants are “must-run” generators, conventional generation capacity is instead sized to meet the net demand, or the difference between the demand and amount of wind generation in each hour. Therefore, to meet demand in all hours, conventional generation capacity must equal the annual peak net demand. For the *Interconnected* scenario, the conventional generation capacity is simply the coincident peak net demand, W_c (Eq. 17), or the peak net demand calculated by adding the net demand across all countries for each hour. For the *Isolated* scenarios, both coincident and non-coincident peak net demand were calculated (Eq. 16, Eq. 17). Non-coincident net demand, W_{nc} , represents the total amount of conventional capacity across the SAPP needed if each country met its net demand separately (16). Non-coincident net demand is always greater than or equal to the coincident net demand. The difference between these two values represents the avoided conventional capacity due to interconnection alone, as opposed to the balancing of wind variability through optimal site selection. This value is represented by the gray bars (“Avoided capacity due to coincident net demand”) in Fig. 3B in the main text. Therefore, the coincident

peak net demand represents the conventional capacity needed to balance the net demand due to the wind profile variability.

$$W_{nc} = \sum_{y=1}^Y [\max(w_{y,t}) \quad \forall y \in \{y \dots Y\}] \quad (16)$$

$$W_c = \max[\sum_{y=1}^Y w_{y,t} \quad \forall t \in \{1 \dots 8760\}] \quad (17)$$

where

$$w_{y,t} = d_{y,2030,t} - \sum_{z=1}^Z c_{y,z,t} x_{y,z} \quad (18)$$

y	country $\in \{y \dots Y\}$
$w_{y,t}$	net demand of country y for hour t
W_{nc}	non-coincident peak net demand across all countries in the SAPP
W_c	coincident peak net demand across all countries in the SAPP
$x_{y,z}$	Capacity installed (MW) in zone z in country y
$c_{y,z,t}$	Capacity factor of zone z hour t in country y
$d_{y,2030,t}$	Electricity demand (MWh) of hour t in year 2030 for country y

Cost difference calculations. To compare approximate system costs, we monetized differences in (1) energy needs and (2) conventional capacity needs between scenarios. For (1), we assumed that any additional energy needs would be generated using hydropower or coal technologies, using the marginal cost of electricity (Table S8). Because additional energy is needed in the *min-net-demand* scenarios and its supply curve shows that the extra energy needed is during low-net-demand or baseload hours (Fig. 3C in the main text), it is more likely that coal or hydropower, rather than natural gas, will be used to supply the extra energy required. For (2), we assumed that any extra conventional capacity needed could be met using natural gas combustion turbine (CT), hydropower, or coal (see Table S8 for cost inputs). We use the non-coincident net peak demand (see Eq. 16) to represent the needed conventional capacity. We represent cost additions or savings relative to the amortized annual capital cost of wind power, which is consistent across scenarios.

Interconnection cost estimates. A bottom-up estimate of interconnection infrastructure costs rely on knowing the lengths and voltages of new lines. A high resolution spatio-temporal ‘capacity-expansion’ model of the power pool’s entire power system (current and future generators, their locations, and current and future transmission availability and capacity) would be needed to generate such estimates. To approximate these interconnection infrastructure costs given the lack of access to data needed to build a power systems model, we use a top-down approach that relies on the interconnection costs reported for energy trade within the SAPP. Using the MWh of energy traded in the SAPP and the revenue from wheeling charges reported in the SAPP annual reports (<http://www.sapp.co.zw/areports.html>), we calculated the wheeling cost per MWh. These wheeling costs are \$2.46/MWh for 2014 - 2015, \$2.31/MWh for 2012-2013, and \$2.62/MWh for 2011 - 2012. [15], [16]. Wheeling is the transport of electricity from within a grid to serve demand outside of the grid. One of the central reasons for wheeling charges is to recover the capital and maintenance costs of transmission infrastructure. For each *Interconnected* wind build-out scenario, we calculated the net energy traded in the SAPP by summing the difference between wind electricity generated under the *Isolated* and the *Interconnected* scenarios for each country and halving the total amount. We applied the range of wheeling fees charged by the SAPP (\$2.31/MWh - \$2.62/MWh) to calculate the wheeling charges per scenario. We then represented the wheeling charges as percentage of the amortized annual capital cost of wind power in

order to compare interconnection costs with conventional energy and conventional capacity cost differences (see section S1.3.3 above).

S1.3.4 Load profile sensitivity analysis

We created four load growth scenarios that maintain the same level of energy consumption but differ in the load profile shapes. See Fig. S10 for each scenario’s hourly load profiles averaged across each month and Fig. S11 for the load duration curve across an entire year for all four scenarios. A load duration curve is the load for each hour sorted from highest to lowest. We modified each country’s load profiles separately and aggregated them to create the Southern Africa Power Pool-wide load profile. The scenarios are as follows:

- “Climate – warming”: relative to baseline, peak summertime (November through March) demand increases by 5% and wintertime (May through September) demand decreases by an appropriate amount to maintain the same level of energy across the year. For most SAPP countries, the annual peak demand occurs in the winter, during the months of July or August, due to heating demand and other appliance usage. Previous studies have shown that load in South Africa is extremely sensitive to climate [17], and under likely climate change scenarios, wintertime and summertime temperatures are expected to increase [18], [19]. This scenario represents greater air conditioning load increase in response to rising summer temperatures under climate change. According to Eskom, South Africa’s largest utility, air conditioning load is fairly uniformly across all day-time hours and some early evening hours. Therefore, we uniformly increased summertime load from 10:00 to 22:00 from November to March. These modifications create monthly hourly average profiles that have similar daily peak demand across the year (see Fig. S10d) and reduce the annual peak demand (see Fig. S11). Tanzania’s and Mozambique’s load profiles were not altered in this scenario because their load profiles do not show a seasonal pattern, unlike that of the remaining seven SAPP countries.
- “Climate – extreme warming”: relative to baseline, peak summertime demand increases by 8% and wintertime demand decreases by an appropriate amount to maintain the same level of energy across the year. Like the “Climate - warming” scenario, this scenario also anticipates strong summertime warming and increased AC load. The greater increase in summertime load inverts the current, baseline seasonal trend of annual peak load occurring in the wintertime for most SAPP countries (Fig S10a) to one that shows annual peak demand occurring in the summer (Fig S10e). This has the effect of slightly reducing the annual peak demand relative to baseline, but not as significantly as in the “Climate - warming” scenario (Fig. S11).
- “South Africa - hybrid”: the daily hourly profiles averaged across a month for each country are combined with that of South Africa’s using 50%-50% weighted averaging. This scenario represents economic structural growth in load curves to resemble that of South Africa’s (Fig. S10c and S11). Although the monthly average hourly load profiles and the load duration curve do not appear to differ from that of the baseline scenario, this is primarily because South Africa contributes 85% of the demand in the SAPP. Differences in load profiles at the country-level are more discernible.
- “Daily peak increase”: Increase in daily peak hours by 5-7% across all days of the year (Fig. S10b). This scenario represents increased electrification leading to increased load from appliance ownership and usage. It also represents reduced curtailment, as load shedding typically occurs during both summer and wintertime peak hours, despite summertime peak demand being less than wintertime peak demand. According to Eskom, this is because less capacity is available in the summer due to scheduled maintenance. This scenario effectively increases the annual peak demand (Fig. S11).

Each of the future load growth scenarios were generated by modifying each monthly average hourly demand profile. This was done by calculating the difference between each hour’s demand and the unmodified monthly

average for that hour and then adding this difference to the growth scenario's generated monthly average for that hour.

S2 Supporting figures and tables

S2.1 SI Figures and Tables for results

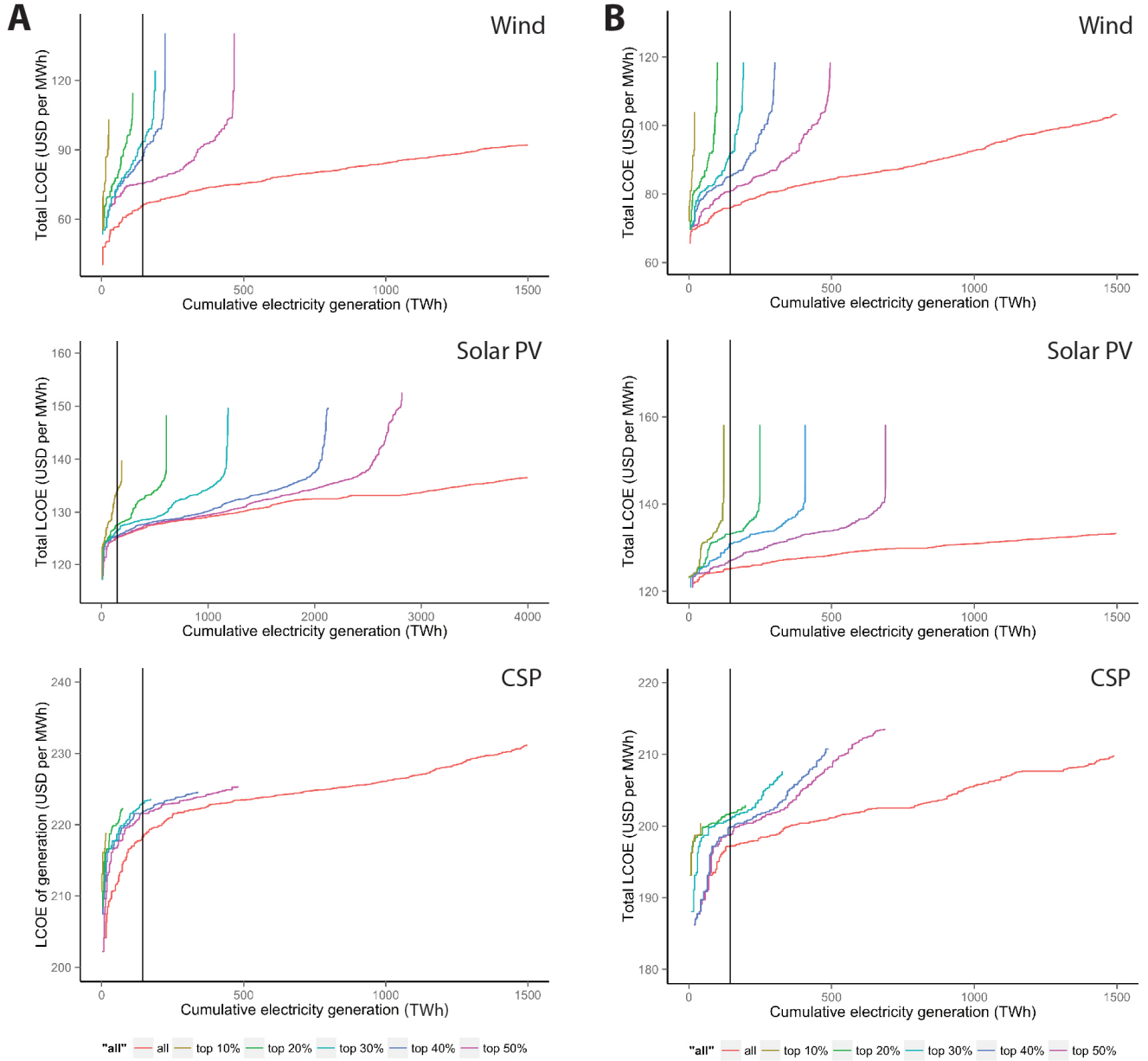


Fig. S1: Technology supply curves for the Eastern (A) and Southern (B) Africa Power Pools. For each technology, each supply curve shows all project opportunity areas and those that meet the top 10% - 50% of siting criteria values (shortest distance to transmission infrastructure, shortest distance to load center, and greatest human footprint score). The black vertical lines show 25% of the projected demand in 2030 [13], [14]. Supply curves show whether it is possible to achieve a particular generation target in each power pool under particular levels of siting criteria constraints and at what marginal total levelized cost of electricity.

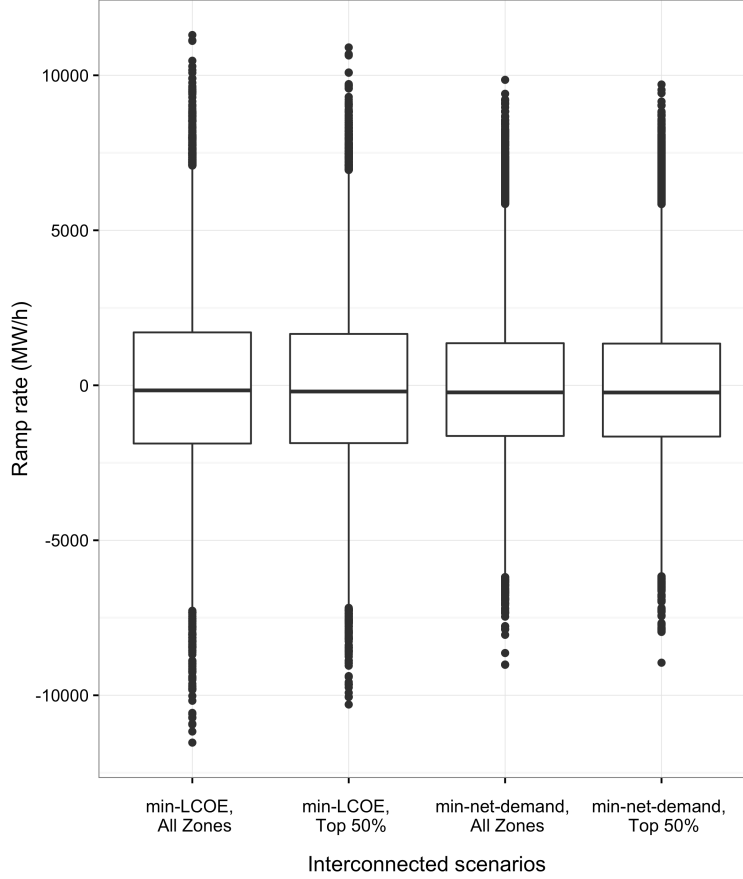
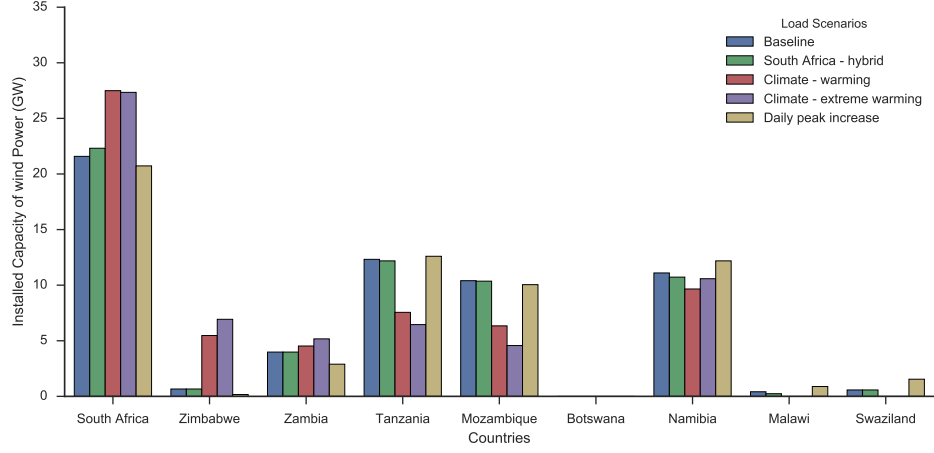
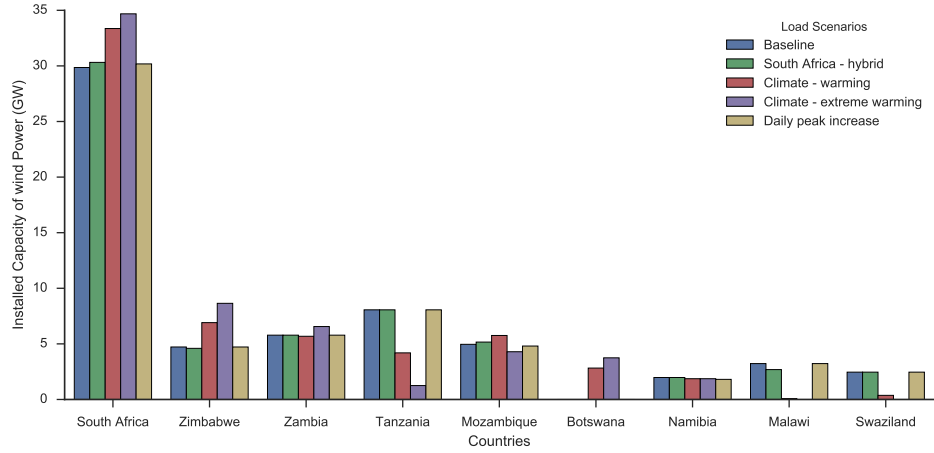


Fig. S2: Distribution of hourly ramp rates for the Interconnected wind build-out scenarios. Ramp rates were calculated by taking the inter-hourly differences in net demand. They indicate the amount of energy that conventional generators need to produce or reduce hour-to-hour to balance the variability of wind generation. Given the range of ramp rates of conventional generators (2%/min for coal, 5% for combined cycle, and 8.3% for gas turbine [20]), 100% of available up-ramp capacity can be dispatched within an hour. If day-ahead scheduling commits enough capacity to meet the forecasted daily peak demand, there will be sufficient capacity to ramp up, regardless of the ramp requirement calculated for each scenario. However, a wider distribution of ramp rates indicates the need for more conventional generation flexibility and cycling, increasing the rate of wear-and-tear on conventional generators and increasing the system costs due to a higher demand for flexibility services.



(a)



(b)

Fig. S3: Distribution of installed wind capacity among countries in the SAPP using the baseline load profile and four future load growth profiles for “Interconnected, min-net-demand, all zones” (a) and “Interconnected, min-net-demand, top 50%” scenarios (b). See Figure S10 and S11 and section S1.3.4 for descriptions of future load growth profiles.

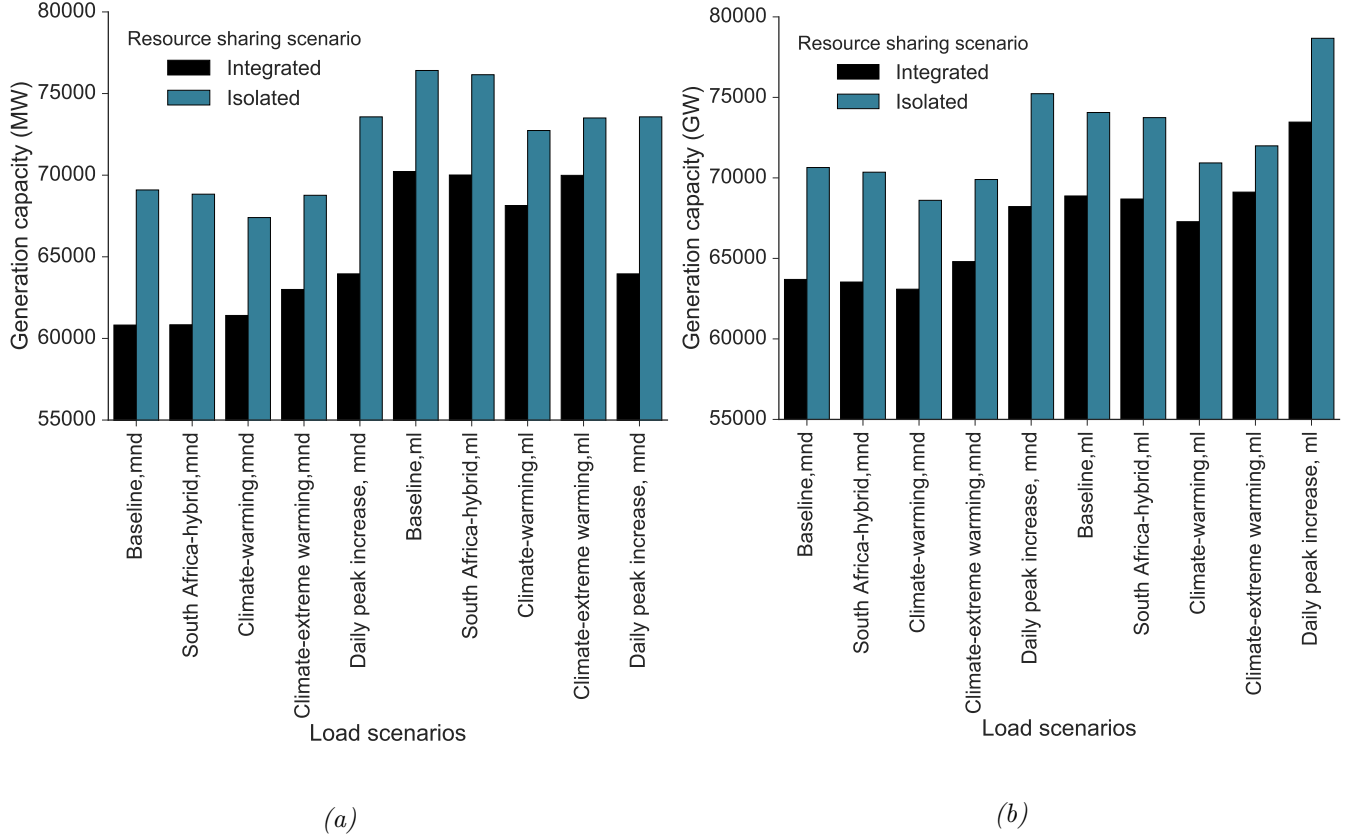


Fig. S4: Conventional installed capacity needed to meet the highest hourly net demand within a year using baseline load profiles and four load growth projections for “all zones” (a) and the “top 50%” of zones (b). Note that the range of the y-axis does not begin at zero in order to highlight the differences between scenarios. See Figures S10 and S11 for details on the load growth scenarios. “mnd” = “min-net-demand” and “ml” = “min-LCOE”.

Table S1: Transmission costs for “Interconnected” wind build-out scenarios

Scenario	Annual wheeling fees (Million USD)	Wheeling fees as percentage of annual wind capital costs	Fraction of wind energy traded	Net energy traded (TWh)
Min-net-demand, all zones	210 - 240	1.6 - 1.8%	40.4%	91
Min-net-demand, top 50% zones	140 - 160	1.0 - 1.2%	28.2%	60
Min-LCOE, all zones	52 - 59	0.40 - 0.44%	9.1%	23
Min-LCOE, top 50% zones	42 - 48	0.32 - 0.36%	8.2%	18

S2.2 SI Figures and tables for methods

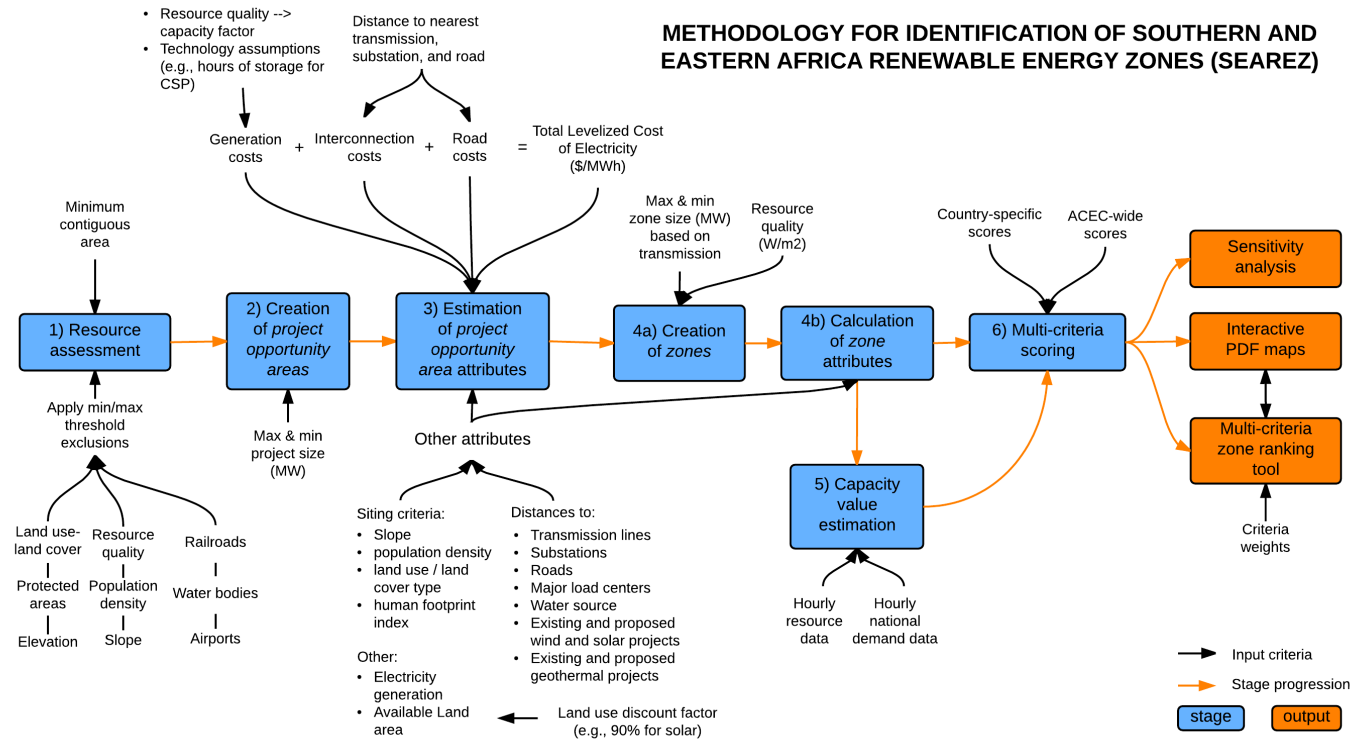


Fig. S5: *The MapRE zoning methodology flow chart.* The chart shows the stages of analysis and the required inputs. Interactive PDF maps and zone ranking tool outputs are available on <http://mapre.lbl.gov>.

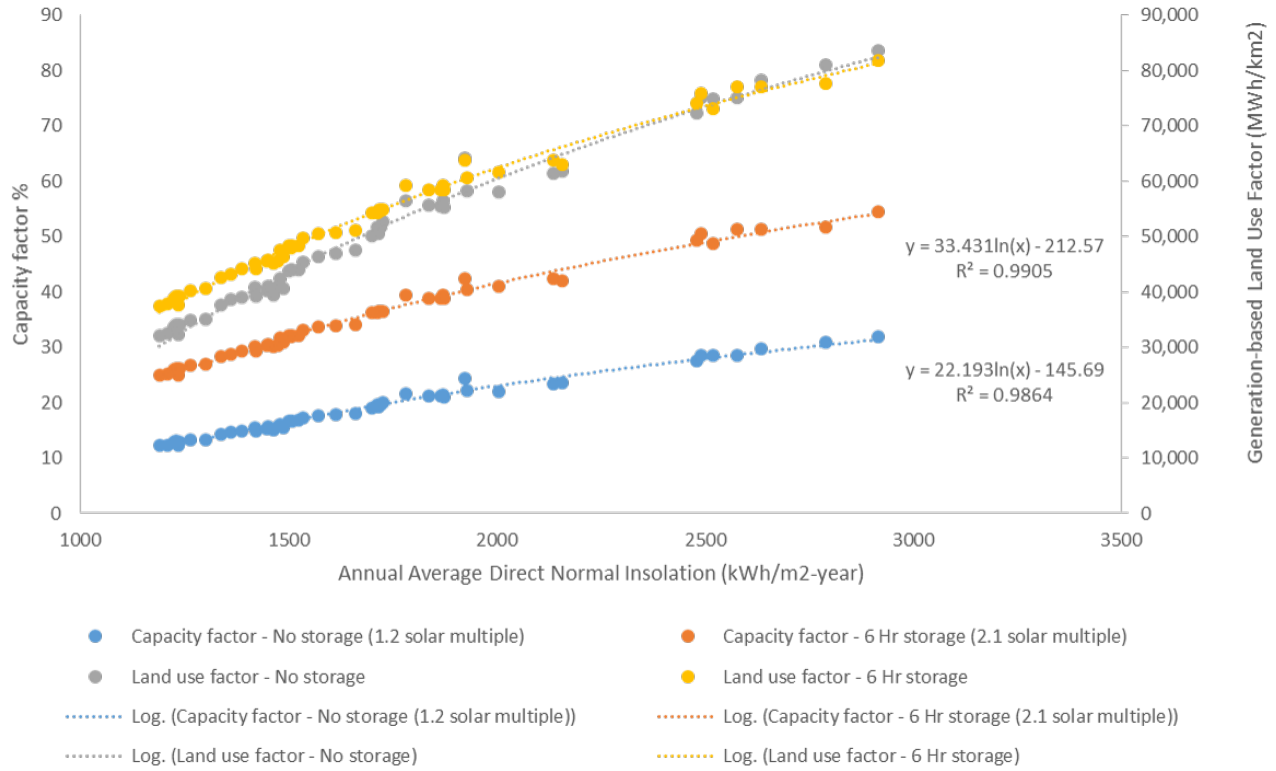


Fig. S6: Relationship between capacity factor, land use factor, and Direct Normal Insolation (DNI) for CSP. Capacity factors were simulated using specifications for a generic CSP plant in the National Renewable Energy Laboratory's System Adviser Model for 45 locations throughout the study region in Africa and five locations in California and Arizona, USA. Logarithmic equations were fit to the simulated capacity factor data to statistically model the relationship between capacity factor and DNI. Land use factors (MW/km^2) on the secondary axis were estimated for each location's capacity factor assuming an installed capacity land use efficiency of $30 \text{ MW}/\text{km}^2$ for no storage and $17 \text{ MW}/\text{km}^2$ for 6 hours of storage.

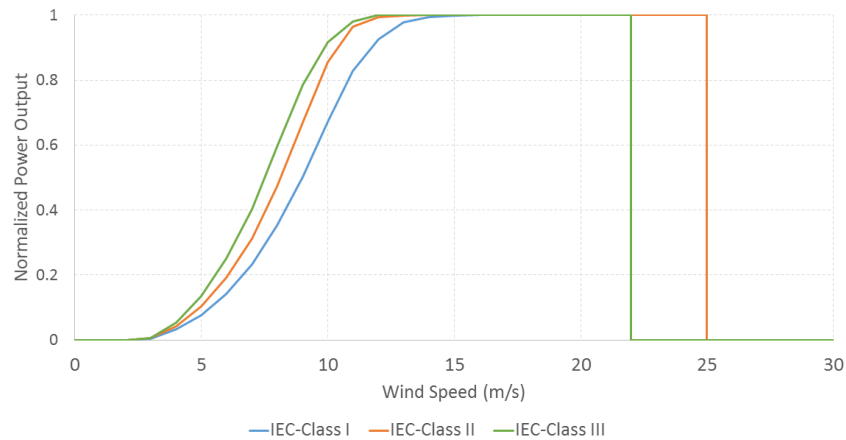


Fig. S7: Normalized wind turbine power curves for different IEC class turbines reproduced from [9].

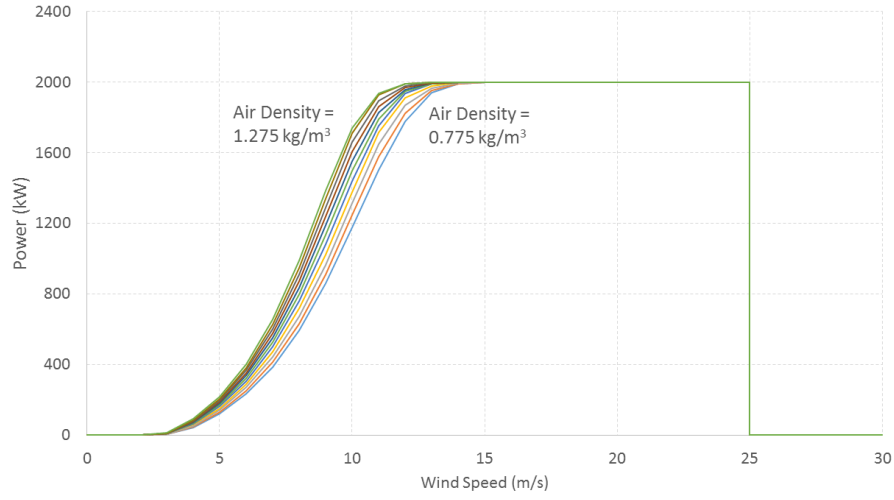


Fig. S8: Adjusted IEC Class II turbine wind power curves for air densities ranging from 1.275 kg/m^3 to 0.775 kg/m^3 (from left to right, respectively).

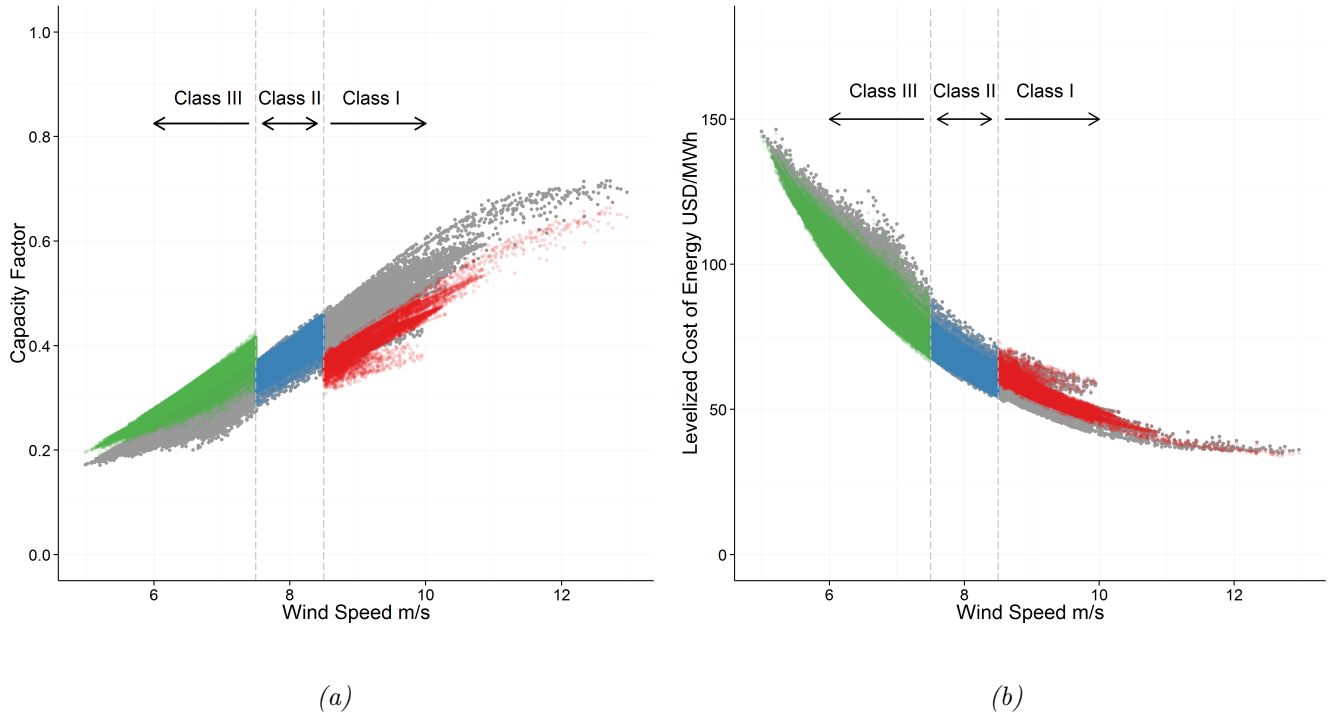


Fig. S9: Relationship between average wind speed and estimated capacity factor (A) and levelized cost of energy for wind (B) across the Eastern and Southern Africa Power Pools. Capacity factors and LCOEs estimated using the wind-speed-appropriate Class I, II and III turbine power curves are represented by red, blue and green points respectively. Capacity factors and LCOEs estimated using just the Class II turbine power curve are also represented by grey points across the wind speed regimes.

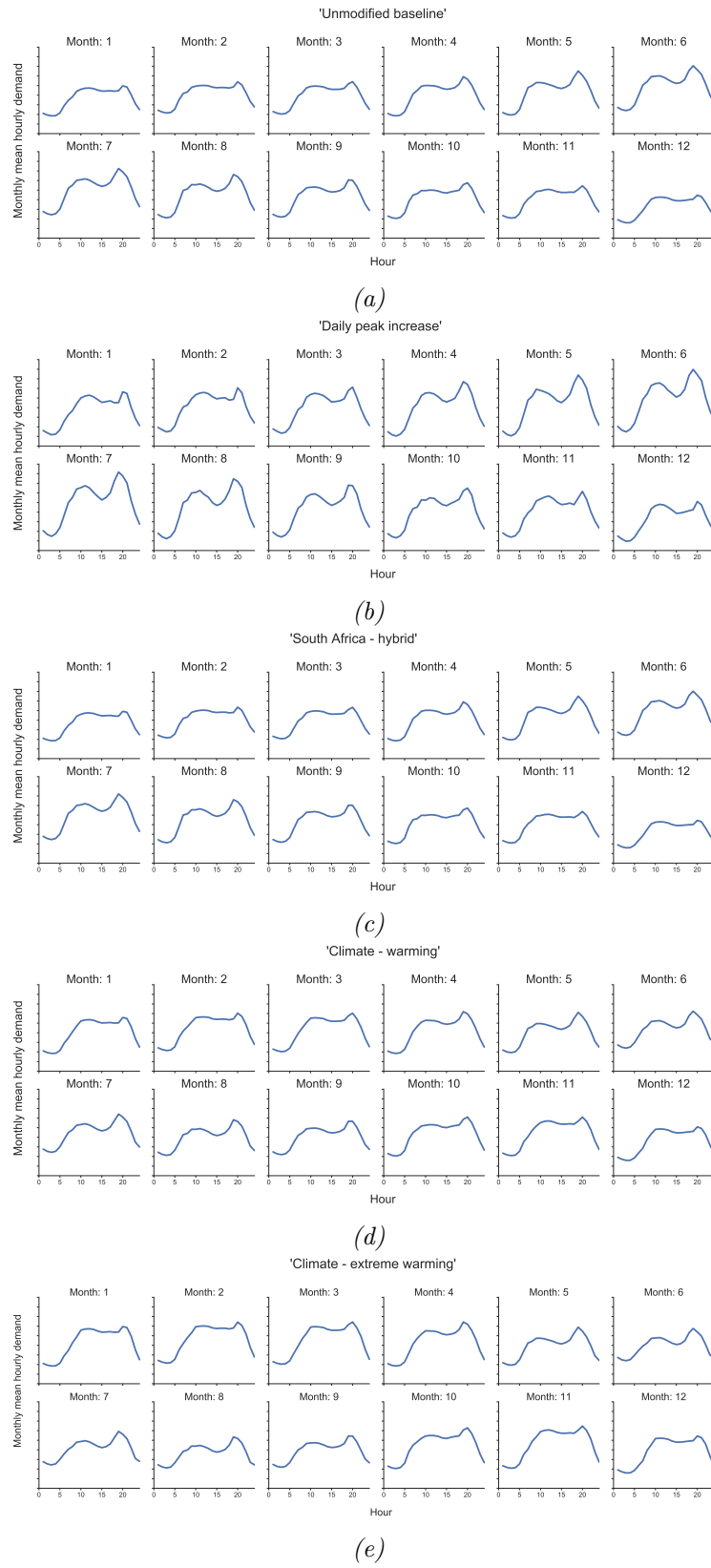


Fig. S10: Unmodified monthly mean daily load profiles of the Southern Africa Power Pool (A) and modified load profiles under the following growth scenarios: (B) increase in the daily peak hours, (C) 50% structural shift in individual country load shapes to resemble South Africa's, (D) climate warming that increases peak summertime demand by 5%, (E) climate warming that increases peak summertime demand by 8%. The total demand is the same across load growth scenarios. The y-axis of all load curves have the same scale.

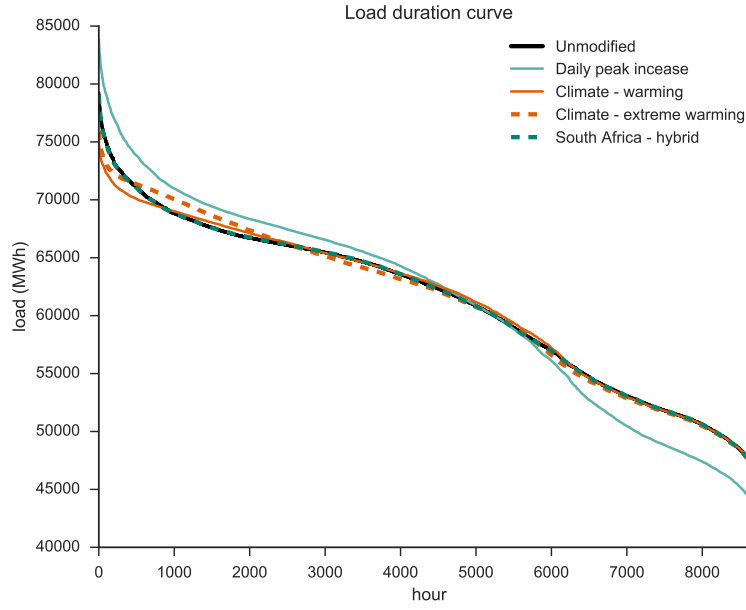


Fig. S11: Annual load duration curves for the Southern Africa Power Pool under various load growth scenarios. A load duration curve is the load for each hour sorted from highest to lowest. “Daily peak increase” shows greater growth in the daily peak hours, “South Africa - hybrid” shows a 50% structural shift in individual country load shapes to resemble South Africa’s, “Climate - warming” shows increases in peak summertime demand by 5%, “Climate- extreme warming” shows increases in peak summertime demand by 8% in countries that have seasonally varying load profiles. The total demand is the same across load growth scenarios.

Table S2: Data sources and resource assessment thresholds

Stage of analysis	Category	File type	Source	Description	Year	Default exclusion thresholds
Resource assessment	Boundaries	Vector	Global Administrative Database (GADM) v2	GADM is a spatial database of the location of the world's administrative areas (or administrative boundaries) for use in GIS and similar software. Administrative areas in this database are countries and lower level subdivisions. http://www.gadm.org/country	2012	
Resource assessment	Elevation	Raster	Shuttle Radar Topographic Mission (SRTM) - CGIAR-CGI Digital Elevation dataset v4.1 SRTM - CGIAR	Produced by NASA originally, the SRTM is a major breakthrough in digital mapping of the world and provides a major advance in the accessibility of high quality elevation data for large portions of the tropics and other areas of the developing world. 3 arc seconds (approx. 90 m) resolution. http://srtm.csi.cgiar.org/	2000	>1500 m (all technologies)
Resource assessment	Slope	Raster		Created from elevation dataset using ArcGIS 10.2 Spatial Analyst.	2000	>5% (solar); >20% (wind)
Estimation of Project opportunity area attributes	Temperature	Raster	WorldClim	WorldClim is a set of global climate layers (climate grids) with a spatial resolution of about 1 square kilometer.	1950 - 2000	
				Hijmans, R.J., S.E. Cameron, J.L. Parra, P.G. Jones and A. Jarvis, 2005. Very high resolution interpolated climate surfaces for global land areas. International Journal of Climatology 25: 1965-1978.		
Resource assessment	Land use/land cover (LULC)	geotiff	ISGCM - Global Map V.2 (Global Version)	http://www.worldclim.org/formats The Global Land Cover by National Mapping Organizations (GLCNMO) is the data of 500m (15 arc seconds) grid with 20 land cover items. The data were created by using MODIS data observed in 2008 (Terra & Aqua Satellites) with the co-operation of NMOs of the world in providing training data and validation. The classification is based on LCCS developed by FAO. Download data via: https://www.iscgm.org/gmd/	2008	See Table 2 in [1]
Resource assessment and Project opportunity area attributes	Water bodies	vector	World Wildlife Federation Global lakes and wetlands database	Comprises lakes, reservoirs, rivers and different wetland types in the form of a global raster map at 30-second resolution. We excluded the following categories: lake, reservoir, river, freshwater marsh, floodplain, swamp forest, flooded forest, coastal wetland, brackish/saline wetland, and intermittent wetland/lake from. http://www.worldwildlife.org/pages/global-lakes-and-wetlands-database	2004	<500 m buffer

Stage of analysis	Category	File type	Source	Description	Year	Default exclusion thresholds
Project opportunity area attributes	Rivers	vector	Natural Earth	Natural Earth is a public domain map dataset featuring both cultural and physical vector data themes. The rivers datasets are originally from the World Data Bank 2. All rivers received manual smoothing and position adjustments to fit shaded relief generated from SRTM Plus elevation data, which is more recent and (presumably) more accurate. http://www.naturalearthdata.com/downloads/	Unknown (version 3.0.0)	
Resource assessment	Population density	raster	LandScan (Oak Ridge National Laboratory)	ORNL's LandScanTM is the community standard for global population distribution. At approximately 1 km resolution (30" X 30"), it is the finest resolution global population distribution data available and represents an ambient population (average over 24 hours). https://www.ornl.gov/ornl/careersci/landscan/	2012	>100 persons km ⁻²
Resource assessment	Wind	raster	3Tier/Vaisala	Data were created from computer simulations using a meso-scale numerical weather prediction model and validated using publicly available wind speed observations from 194 meteorological stations within Africa from the National Centers for Environmental Prediction (NCEP). Annual wind speed, wind power density, and wind power output were provided at 80 m hub height and 5 km resolution for a typical meteorological year. Data can be downloaded on the Global Atlas by searching for "Vaisala Global wind dataset"; http://irena.masdar.ac.ae/	10-year model run	<300 Wm ⁻²
Resource assessment	Solar DNI	raster	3Tier/Vaisala	The dataset is based on actual, half-hourly, high-resolution visible satellite imagery observations via the broadband visible wavelength channel at a 2 arc minute resolution. Data can be downloaded on the Global Atlas by searching for "Vaisala Global solar dataset"; http://irena.masdar.ac.ae/	15 years	<250 Wm ⁻²
Resource assessment	Solar GHI				(July 1998 – last quarter) 2014	<280 Wm ⁻²
Resource assessment	Protected Areas	vector	World Database of Protected Areas (WDPA)	The World Database on Protected Areas (WDPA) is the most comprehensive global spatial dataset on marine and terrestrial protected areas available. The WDPA is a joint project of UNEP and IUCN, produced by UNEP-WCMC and the IUCN World Commission on Protected Areas working with governments and collaborating NGOs. Download data via https://www.protectedplanet.net/		<500 m buffer
Resource assessment	Protected Areas	vector	Protected Planet	Open source database that includes most WDPA locations, but also include polygon representations of the WDPA point locations (those with unknown extents/boundaries). Download data via https://www.protectedplanet.net/	2014	<500 m buffer

Stage of analysis	Category	File type	Source	Description	Year	Default exclusion thresholds
Resource assessment	Rail	vector	Africa Infrastructure Country Diagnostic (AICD) – Africa Development Bank (AfDB) and World Bank (WB)	Primary data collection efforts covering network service infrastructures (ICT, power, water & sanitation, road transport, rail transport, sea transport, and air transport) from 2001 to 2006 in 24 selected African countries. Download data via: http://www.infrastructureafrica.org/about	Variable; compiled 2011	<500 m buffer
Project opportunity area at-tributes	Roads	vector	AICD – AfDB and WB	See above rail category	Variable; compiled 2008	
Project opportunity area at-tributes	Roads	vector	gROADSv1 - Columbia University	Global Roads Open Access Data Set, Version 1 was developed under the auspices of the CODATA Global Roads Data Development Task Group at Columbia University. The data set combines the best available roads data by country into a global roads coverage, using the UN Spatial Data Infrastructure Transport (UNSDI-T) version 2 as a common data model. Download data via: http://sedac.ciesin.columbia.edu/data/set/global-roads-open-access-v1	Variable; compiled 2010 (1980-2010)	
Project opportunity area at-tributes	Transmission	vector	AICD – AfDB and WB	Transmission lines were only available for a subset of sub-Saharan African countries. In some cases, lines do not represent geographic footprint of transmission lines but are schematics depicting points of interconnection. See Appendix A of the MapRE report [1] for transmission infrastructure data sources for each country.	Variable - compiled 2010	
Project opportunity area at-tributes	Renewable energy locations	vector	AICD – AfDB and WB, Cross Border Information	Existing and proposed power plants for select sub-Saharan African countries where data were available.	Variable; compiled 2011	
Project opportunity area at-tributes	Load centers	Lat-long coordinates	Geonames	The GeoNames geographical database is available for download free of charge under a creative commons attribution license. It contains over 10 million geographical names and consists of over 9 million unique features including 2.8 million populated places and 5.5 million alternate names. Download data via www.geonames.org	2014	
Project opportunity area at-tributes	Wind speed time series	.csv	3Tier/Vaisala	Hourly wind speed, wind power density, and wind power output for 10 years (same simulated data that was used to create the typical meteorological year (TMY) average values); approximately 5 km resolution. Data must be purchased from Vaisala directly: http://www.vaisala.com/en/energy/Pages/default.aspx	10-year model run	

Table S3: Adjusted resource quality thresholds for each country.

Country	Wind W/m ²	Solar PV GHI W/m ²	Solar CSP DNI W/m ²	Eleva- tion	Slope	Popula- tion	LULC
Angola	200 (lower) ¹	250 (PP) ²	280 (PP)				
Botswana	200 (lower)	250 (PP)	280 (PP)				
Burundi	200 (lower)	230 (lower)	260 (lower)	2500 m	20% (wind and solar)	200 per- sons per km2	Include “Tree Open” cate- gory
DRC	200 (lower)	210 (PP)	260 (lower)	2500 m			
Djibouti	300 (PP)	250 (PP)	260 (lower)				
Egypt	200 (lower)	230 (lower)	270 (lower)				
Ethiopia	200 (lower)	250 (PP)	280 (PP)	3000 m			
Kenya	250 (lower)	250 (PP)	270 (lower)	2500 m			
Lesotho	200 (lower)	250 (PP)	280 (PP)	2500 m			
Libya	300 (PP)	250 (PP)	280 (PP)				
Malawi	200 (lower)	240 (PP)	260 (lower)	2500 m			
Mozambique	200 (lower)	230 (PP)	260 (lower)				
Namibia	200 (lower)	250 (PP)	280 (PP)				
Rwanda	200 (lower)	230 (lower)	260 (lower)	2500 m	10% (wind)	200 per- sons per km2	Include “Tree Open” and “Mixed Crop- land” cate- gories
South Africa	300 (PP)	250 (PP)	280 (PP)	2000 m			
Sudan	250 (lower)	250 (PP)	280 (PP)				
Swaziland	250 (lower)	210 (lower)	260 (lower)				
Tanzania	250 (lower)	250 (PP)	280 (PP)	2000 m			
Uganda	200 (lower)	250 (PP)	260 (lower)	2500 m			
Zambia	200 (lower)	250 (PP)	260 (PP)	2000 m			
Zimbabwe	200 (lower)	250 (PP)	280 (PP)				

¹Threshold that is lower than the Power-Pool-wide (PP) resource threshold indicated in Table S2

²Power-Pool-wide (PP) threshold values

Table S4: Human Influence Index scoring system for Human Footprint datasets

Dataset	Scoring system
Population density	Score increased linearly from 0 to 10 persons/km ² ; all densities greater than 10 were assigned a score of 10.
Land use land cover	10 – built environments, 9 – cropland and paddy fields, 7 – cropland/mosaic vegetation, 0 – for all other land use land cover categories
Roads and railways	Areas within 1 km of roads and railways were assigned a score of 10, and those areas between 1 and 15 km assigned a score of 4.
Oceans and rivers	Areas within 1 km of rivers or the ocean oceans were assigned a score of 10, and those areas between 1 and 15 km assigned a score of 4.

Table S5: Transmission and substation spatial data availability and sources

Country	Default transmission data	Country-specific substations	Country-specific transmission lines
Angola	AICD ³	N/A	N/A
Botswana	AICD	Botswana Power Corporation	N/A
Burundi	AICD	N/A	N/A
Djibouti	N/A	N/A	N/A
DRC	AICD	N/A	N/A
Egypt	CBI ⁴	N/A	N/A
Ethiopia	AICD	N/A	N/A
Kenya	AICD	KETRACO	KETRACO
Lesotho	AICD	N/A	N/A
Libya	N/A	N/A	N/A
Malawi	AICD	ESCOM	ESCOM
Mozambique	AICD	Ministry of Energy	N/A
Namibia	AICD	NamPower	NamPower
Rwanda	AICD	REDC	REDC
South Africa	AICD	Eskom	Eskom
South Sudan	CBI	N/A	N/A
Sudan	CBI	N/A	N/A
Swaziland	AICD	Swaziland Electricity Company (SEC)	Swaziland Electricity Company (SEC)
Tanzania	AICD	N/A	TANESCO (partially complete)
Uganda	AICD	UNEP	UNEP
Zambia	AICD	ZESCO	N/A
Zimbabwe	AICD	ZETDC	N/A

³Africa Infrastructure Country Diagnostic, an African Development Bank Initiative

⁴Cross Border Information and African Energy, 2015. African Energy Atlas 2015. <http://www.africa-energy.com/african-energy-atlas>

Table S6: Parameters in levelized cost of electricity estimates

Parameters	Wind			Solar PV	Solar CSP	
					No-storage	6 hr storage
Land use factor [MW/km ²](l)	9 ¹			30 ²	30 ²	17 ³
Land use discount factor (f)	75%			90%	90%	
Costs	Class I	Class II	Class III		No-storage	6 hr storage
Generation – capital [USD/kW] (c_g)	1250 ⁴	1450 ⁴	1700 ⁴	2000 ⁴	3700 ⁵	7400 ⁵
Generation – fixed O&M [USD/MW/y] ($o_{f,g}$)	60000 ⁴			50000 ⁴	50000 ⁴	
Generation – variable O&M [USD/MWh] ($o_{v,g}$)	-			4 ⁹	-	
Transmission – capital [USD/MW/km] (c_t)	990 ⁶			990 ⁶	990 ⁶	
Transmission – fixed O&M [USD/km] ($o_{f,i}$)	-			-	-	
Substation – capital [USD / 2 substations (new transmission)] (c_s)	71000 ⁶			71000 ⁶	71000 ⁶	
Road – capital [USD/km] (c_r)	407000 ⁷			407000 ⁷	407000 ⁷	
Road – fixed O&M [USD/km] ($o_{f,r}$)	-			-	-	
Economic discount rate (i)	10% ⁸			10% ⁸	10% ⁸	
Outage rate (h_o)	2% ⁹			4% ⁹	4% ⁹	
Inverter efficiency and AC wiring loss (h_i)	-			4% ⁸	-	
Array and collection loss (h_a)	15% ¹⁰			-	-	
Lifetime [years] (n)	25 ⁸			25 ⁸	25 ⁸	

¹ Mean of U.S. empirical values (3 MW/km²) [21] and theoretical land use factors [22]

² [21]

³ 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)

⁴ For Class II turbine: [20]. See [23] for decrease in Class I turbine cost, and [10], [24] for increase in Class III turbine costs, relative to Class I turbine costs.

⁵ [4]

⁶ [20]

⁷ [25]

⁸ [26]

⁹ Default value in the System Advisor Model (SAM) by NREL [6]

¹⁰ [27]

Table S7: Projected 2030 electricity demand

Country	2030 Demand (GWh)	Peak demand (MW)	Wind capacity to install by 2030 to meet 30% RPS (MW) ⁵
Angola	20294	-	N/A ⁶
Botswana	7730	578	882
Burundi	622	-	N/A
Democratic Republic Of Congo	21225	-	N/A
Djibouti	764	-	N/A
Egypt	455525	-	N/A
Ethiopia	21363	-	N/A
Kenya	20646	-	N/A
Lesotho	1309	-	N/A
Libya	5420	-	N/A
Malawi	3667	475.9	419
Mozambique	8840	761	1009
Namibia	5420	546	619
Rwanda	788	-	N/A
South Africa	453069	35360	51720
Sudan	58754	-	N/A
Swaziland	1952	223	223
Tanzania	10923	898.79	1247
Uganda	9313	-	N/A
Zambia	18003	1794.6	2055
Zimbabwe	25153	1621	2871

Table S8: Cost inputs for comparing wind build-out scenarios

	Natural gas combustion turbine (CT) ⁷	Scrubbed Coal ⁸	Hydropower	Wind ⁹
Capital cost (\$/MW)	922,000	2,726,000	1,500,000 ¹⁰	1450000
Fixed O&M (\$/MW-yr)	5,260	31,160	15,150 ¹¹	60000
Variable O&M \$/MWh	15.44	5	5 ¹²	-
Heating value (BTU/lb)	-	10000	-	-
Fuel cost (\$/MMBTU or \$/MT)	-	50	-	-
Heat rate BTU/kWh	-	8800	-	-
Aux Consumption (%)	-	10	-	-
Discount rate (%)	10	10	10	10
Plant lifetime (yrs)	25	25	25	25
Marginal cost of generation (\$/MWh)	-	23.2 ¹³	5 ¹⁴	-

⁵Renewable Portfolio Standard, or a target amount of renewable energy

⁶N/A: Optimal wind site selection was not performed for this country

⁷All natural gas values are from [28].

⁸All coal cost values are [28].

⁹Costs used to calculate annual amortized cost of wind capacity assume Class II turbine using values from Table S6

¹⁰From [29] (Figure 7.3, pg 118). This value is the average capital cost of African hydropower plants.

¹¹[28]

¹²[28]

¹³Calculated using the above fuel inputs

¹⁴[28]

S3 Supporting references

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