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Optimising the deployment of renewable resources for the Australian NEM (National Electricity Market) and the effect of atmospheric length scales

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ABSTRACT

This study sheds new light on the variability of wind power across the Australian NEM (National Electricity Market) and in doing so gives an insight on the potential network configuration for a high RE (Renewable Electricity) future. We present idealised cost-minimised simulations for the NEM utilising onshore wind, large-scale solar, pumped hydro and OCGT (open cycle gas turbines) technologies. A model using gridded meteorological data from the regional ACCESS-R (Australian Community Climate and Earth-System Simulator) simulates wind and solar technology output along with generation from OCGT to meet demand in the NEM for the period 2010–2011. A cost for connecting each location to the nearest major load centre is introduced and a base scenario created from an initial connection cost of $1 M/km. A sensitivity study reveals that a cost of $8 M/km results in the contraction of all renewable resources to four major wind installations. Compared to the base scenario the four major wind locations share much of the variability in renewable energy output, demonstrating that the NEM region has four distinct wind regimes. Separated by 1,400 km these four wind installations provide an optimisation-based decorrelation length for the NEM. This information is particularly useful for long-term planners of large-scale energy infrastructure.

1. Introduction

Recent studies suggest that a very high penetration of RE (Renewable Electricity) into the Australian NEM (National Electricity Market) is possible while maintaining reliability standards ([1,2]). Both [1] and [2] were able to demonstrate that combinations of large-scale wind (onshore), solar (PV (Photovoltaic) and Concentrating Solar Thermal), hydro and to a lesser extent biogas and geothermal were able to meet 99.998% of energy demand. If Australia is to one day have such a renewable based NEM the balancing of wind and solar resources across large areas and many different time scales is going to be an important consideration. Studies from Sweden ([3]), Spain ([4]) and the USA ([5]), among others, have already shown the importance of spatio-temporal balancing of wind and solar resources in maximising the contribution from renewables. If Australia is to rely on renewable energy, knowledge of the influence that such large-scale covariances can have on renewable output will need to be considered.

Currently in Australia, large-scale installations of solar technology are not common. The largest PV installation is a 102 MW power plant operating at Nyngan in New South Wales ([6]). Wind power technology has undergone a dramatic growth over recent decades; growing at 21% p.a. over the last 10 years, wind power is one of the fastest growing technologies in the world ([7]). In Australia the state of South Australia has a significant investment in wind power (more than 30% of generation capacity ([8])). Ultimately though, the inherently variable nature of renewable energy production prevents any single renewable resource from being used for large-scale electrical purposes, without significant storage/dispatchable capacity.

To overcome issues associated with the hourly-daily variability of energy sources like wind and solar power, the strategic placement of resources is often explored as a way of smoothing out net energy production [9]. reported significant advantages in geographically dispersing wind farms so long as in combination the total area covered by all farms increases. The interconnecting of wind farms did not guarantee that moments of low output were

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Acronyms

RE	Renewable Electricity
NEM	National Electricity Market
AEMO	Australian Electricity Market Operator
PV	Photovoltaic
DSR	Downward Shortwave Radiation
ACCESS-R	Australian Community Climate and Earth-System Simulator-Regional
OCGT	Open Cycle Gas Turbine
GA	Genetic Algorithm

avoided but instead the combined output started to resemble a single farm with steady wind speeds [10]. utilised only existing wind farm sites in their study of the NEM [10]. noted that output from the current set of wind farms was highly correlated, which in turn restricted further investment in wind due to the limited demand not already met the existing set of wind farms [1]. also found that incorporating RE output from a wide range of locations across the NEM was critical for maintaining the supply-demand equilibrium. However, the extent to which such advantages could be gained for the NEM, and at precisely what separation distances are necessary for independent output is not well published. What is also not clear is whether or not dispersing renewable resources, presumably into remote locations, is cost effective given the infrastructure needed to support such installations.

This study presents an analysis of the cost and net output implications when strategically locating non-dispatchable renewable resources across large distances for the Australian NEM region. The energy system is purposely simplistic in order to allow flexibility in resource location and the results are geared towards understanding the difference between aggregated and dispersed renewable capacity. The study is broken up into sections as follows: Section 2 outlines the data and methods used, Section 3 the results of cost-minimised scenarios are presented and discussed, before conclusions are made in Section 4.

2. Data and methods

2.1. Data

The meteorological data used in this study come from the Australian Bureau of Meteorology. The regional version of the ACCESS-R (Australian Community Climate and Earth-System Simulator) has spatial resolution 0.11° longitude/latitude and was sampled hourly for the 2010–2011 period. The fields used in this article from the ACCESS-R model were the wind speed at model levels and the DSR (Downward Shortwave Radiation) at the surface. The model level wind speed output was interpolated to 80 m above the surface using a cubic spline (cubic polynomial line of best fit) through the first four vertical levels, which vary in height from 10 m to 250 m depending on location and atmospheric conditions. The wind speed output were instantaneous samples at each hour but the DSR an average from the preceding hour and 80 m was used as this is the approximate hub height for a 2.5 MW turbine. The demand data used in the energy model come from the AEMO (Australian Electricity Market Operator) and are half-hourly resolved. The data for each NEM region are aggregated and the NEM-wide demand for electricity utilised at an hourly resolution. The aggregation of demand follows the copper-plate model whereby the demand for electricity can be instantaneously met by any of the suppliers of electricity, irrespective of their location or of power flow restrictions that might prevent the supply reaching the demand.

2.2. Methods

RE studies often utilise optimisation techniques when trying to solve for the optimum combination of resources to meet a required goal–this might be increasing the penetration of renewable resources or reducing carbon emissions from the electricity sector. Optimisation techniques offer the advantage of being able to incorporate computer resources to solve complicated and multifaceted problems in a relatively short amount of time.

An optimisation problem is also more amenable to minimising if it can be given to the solver in a succinct version. Due to the resolution of the ACCESS-R model output at adjacent locations contain very similar meteorological information. Sub-sampling the model domain reduces the complexity of the problem without loosing important spatial variance. In this article we undertook a pre-optimisation site selection process, including only locations from the ACCESS-R model that were within the state boundaries of the NEM (Tasmania, Victoria, South Australia, New South Wales, Australian Capital Territory and Queensland). Each location was also separated by a minimum distance (120 km for wind and 250 km for solar) within the decorrelation length of each atmospheric variable (not shown). Locations that were unavailable due to existing land use (National Parks/urban areas etc.) were also omitted from the selection process—based on a Geoscience

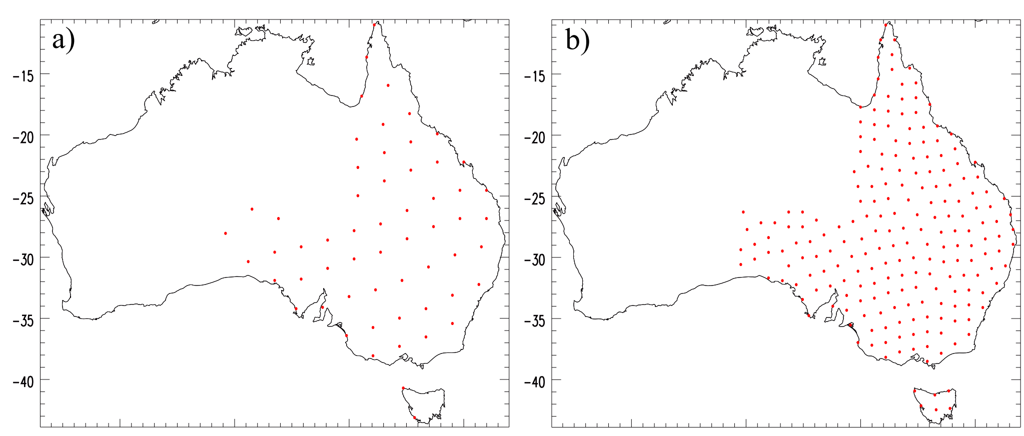

Fig. 1. Red dots representing the locations from within the ACCESS-R grid that have had their a) DSR and b) wind speed data utilised in the article. Vertical axes are degrees latitude and horizontal axes degrees longitude. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

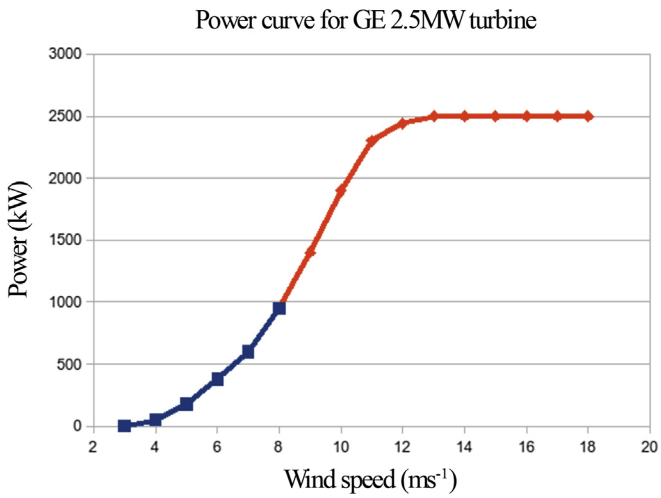

Fig. 2. Wind speed to power conversion curve for a General Electric 2.5 MW wind turbine. The curve is constructed using two quadratics (upper and lower) along with the constant values at 0 MW for wind speeds below cut-in and 2.5 MW for wind speeds at or above the rated power output.

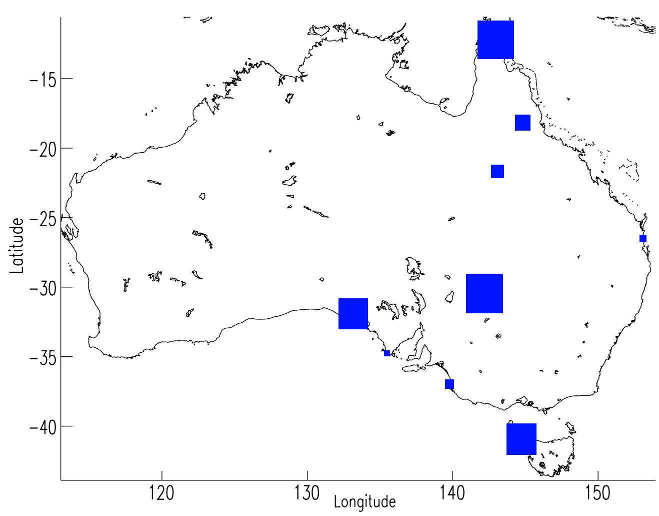

Fig. 3. Distribution of installed capacity for the base scenario. Blue squares represent wind capacity relative in size to 19.4 GW and where the largest installation in the base scenario is 14.6 GW. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Australia GIS (Geographical Information Systems) data-base. Fig. 1 illustrates the locations utilised throughout the article.

The 80 m wind speed data at each location were then converted to power using the wind speed power conversion curve for a General Electric 2.5 MW turbine (Fig. 2). The DSR was not converted to power output using conversion factors, instead the output from the solar stations was proportional to the incoming DSR. The maximum DSR from the 2010–2011 ACCESS-R output was 1180 W/m^2 and all values are a fraction of this. Over annual time-scales or longer DSR has been shown to be a good estimate of grid-connected PV output ([11]).

The energy model in this article balances the output of each given technology, combines the costs involved into a single dollar amount and then informs an optimisation algorithm of the total cost of each evaluation of the solution space. The energy model ensures that demand is met by the mixture of technologies at each timestep and the total cost varies based on the capital expenditure and 20 year fuel costs (in the case of OCGT (open cycle gas turbines)) that each resource utilises (a similar process was used in Ref. [12]). A description of the hydro and OCGT models can also be found in Ref. [12]. The algorithm used in the article is a GA (Genetic Algorithm) and the implementation process is outlined in Ref. [13]. The GA, like all optimisation techniques, aims to minimise a cost function. In the case of the current study the cost function is a combination of costs assigned to each of the available technologies (onshore wind, large-scale solar PV, pumped hydro storage and OCGT back-up). The GA approach allows for a relatively quick calculation of an optimised system, but does not guarantee an absolute least cost system. The short run marginal costs for each technology define the order in which the technologies are dispatched. For all simulations examined in this article the effective dispatch order is renewable energy (wind and solar), followed by hydro and then OCGT. The variables being optimised are the number of installations at each location (wind turbines or utility scale PV installations) and the amount of back-up resources (hydro and gas) to use in order to meet demand, while aiming to minimise total cost.

The renewable energy costs follow an economies-of-scale model whereby the cost per additional turbine/solar farm approaches the manufacturing cost (plus an additional capital expenditure for the first installation). Hydro was given a value of zero for capital expenditure as it is assumed that the current pumped hydro infrastructure would be utilised. For each location considered there was also a connection cost applied to penalise locations that were further away from the demand centres. Each location that had installed capacity had a cost of $1 M/km to the nearest capital city added to the cost of the system (although this is increased later). Power flow was not considered due to the complexity of incorporating it into the optimisation at each iteration of the search space. Instead, the proximity cost was used as a deterrent for remote locations. The figure of $1 M/km was used because it is an approximate value for high-voltage transmission cabling ([14]).

3. Results

3.1. Base scenario

The base scenario presents results from the idealised optimisation of the NEM locations (Fig. 1). The scenario presented was that which had the lowest cost function from a set of different randomised initialisations. Fig. 3 illustrates the least-cost configuration of renewable capacity that meets demand for the base

Table 1
Costs and GA (Genetic Algorithm) parameters used in the base scenario.

GA Params:	Value:	Capex:	Value ($M/MW):	Hydro Params:	Value:	OCGT Params:	Value:
Iterations	10,000	Wind	1.2	Dam capacity	10 GL	Carbon price	$80/Tonne
Base_mute	0.002	Solar	1.0	Max generation	5 GW	Fuel price	$25/MWh
Gene_mute	0.1	Hydro	0	Starting level	5 GL		
Pop. size	500	OCGT	1.0	Round-trip efficiency	80%		
Mortality rate	0.5	Connection Cost	1.0 ($M/Km)				

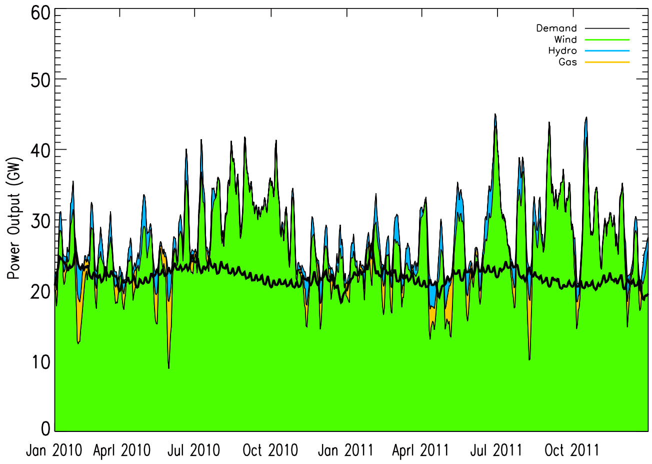

Fig. 4. Cumulative time series output for the optimised network (hydro plotted on top of OCGT, which is on top of wind). Output is daily averaged and hydro output above demand (black curve) indicates the pumping of water uphill while the reverse (release of water downhill) is true for hydro below the demand curve.

scenario. The costs used to reach the solution seen in Fig. 3 are outlined in Table 1. The GA was allowed to evolve over a 500-member, 10,000 iteration search of the solution space and the population with the lowest cost function value was said to be 'optimal'. In the case of the current study 10,000 iterations was enough to converge on an effectively un-changing cost function value. The resulting time series of wind plus solar, OCGT and hydro is shown in Fig. 4. The resource statistics for the base scenario are outlined in Table 2.

It is evident from Fig. 3 that large-scale PV without storage is not competitive with the prices used. Solar was made intentionally cheap in comparison to current prices and in relation to wind in order to encourage its use. At 2012 costs utility scale PV costs roughly \$3.8 M/MW and onshore wind \$2.5 M/MW ([15]), rather than the \$1 M/MW and \$1.2 M/MW, respectively, used here (in optimisation terms the exact costs are less important than the proportionality of the costs). It is surprising though that there appears to be no solar resource close enough to a capital city to warrant some installed capacity. On average the solar resource does not have a large spatial variance across the Australian continent (not shown). The advantage in having any large-scale solar PV installed in the NEM without storage capacity in high penetration renewable energy scenarios is therefore questionable.

3.2. *Increased transmission connection cost scenarios*

The connection cost sensitivity study aims to test the quality of remote locations utilised in the base scenario by incrementally increasing the cost of connecting each location to the nearest capital city. In this section three increased connection costs are tested: \$2 M/km, \$4 M/km and \$8 M/km. In each case the only difference in the configuration of the energy model is the increased connection cost for each possible location.

Fig. 5 depicts the optimal distribution of installed capacity using the distance to nearest capital city cost of \$2 M/km, \$4 M/km and \$8 M/km connection cost scenarios (hereafter referred to the 2X, 4X and 8X simulations). What is clear from Fig. 5 is that the increase from \$1 M/km to \$2 M/km has not significantly altered the optimised configuration. In the 2X simulation the same broad regions still contain wind capacity, while no solar capacity is utilised in either case. Table 2 also illustrates a negligible difference in total installed capacity of each resource, as well as the capacity factor of those resources in total, when compared to the base scenario.

In terms of the wind installations the 4X scenario is again almost identical to the 2X scenario—thus also a similar broad distribution to the base case. Seven wind installations are used in the 4X scenario, six of which are the same locations as 2X. The resources statistics are also very similar between the 4X and 2X scenarios (Table 2). The only noticeable shift in resource usage thus far is the slight increase in OCGT output in the 2X and 4X scenarios when compared to the base case (little change in the installed capacity but an increase in the capacity factor from 4.1% to 5.5%).

What is clear from Fig. 5c is that the connection cost of \$8 M/km crosses a threshold whereby the optimisation chooses to, as much as possible, limit the number of wind sites (five locations, from seven). This contraction of resources to four main regions (combining Northwest Tasmania and Melbourne) indicates that any advantage gained by having smaller contributing wind sites in earlier scenarios is lost if the cost of connecting those sites is high

Table 2
Total installed capacity and C.F (capacity factors) for each resource in the increased connection cost scenarios, as well as the base scenario.

	Wind		Solar		Hydro		OCGT	
	Capacity (GW):	C.F (%):	Capacity (GW):	C.F (%):	Capacity (GW):	C.F (%):	Capacity (GW):	C.F (%):
Base	71.6	37.1	0	0	5	27.2	20.1	4.1
2X	70.8	37.8	0	0	5	26.7	20.7	5.5
4X	71	38	0	0	5	26.8	20.9	5.5
8X	69.2	38	0	0	5	28.3	25.6	6.4

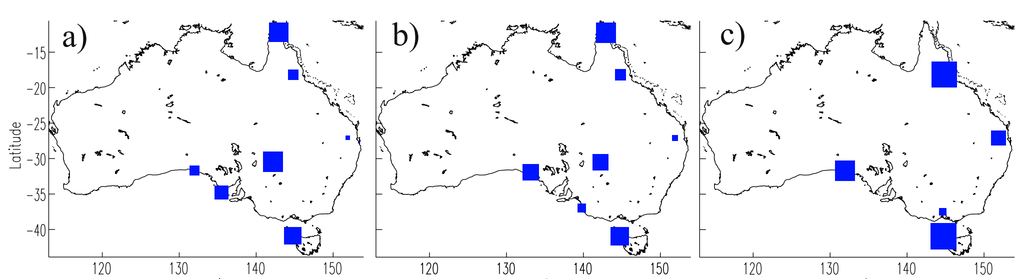

Fig. 5. Installed capacity, as per Fig. 3, except for the a) 2X, b) 4X and c) 8X simulations. Largest installation is 19.4 GW (north west Tasmania).

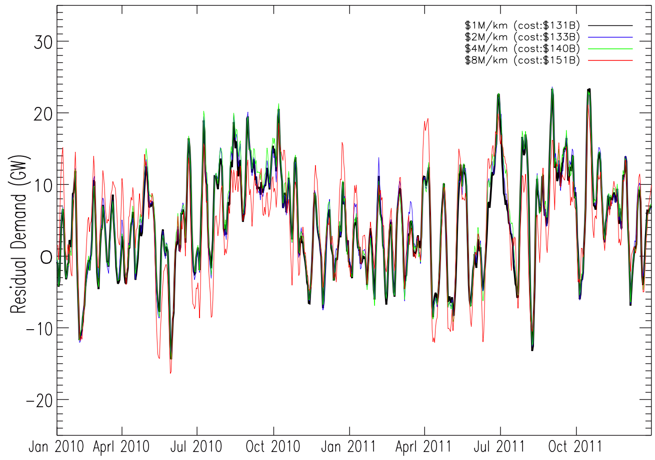

Fig. 6. Residual demand (RE output minus demand) for all simulations, but where the base scenario is in bold black for comparative purposes. Cost indicates the total cost of the optimised solution for each scenario.

enough—covered by an increase in OCGT back-up (Table 2). In all scenarios the hydro capacity is utilised, but with no clear trend in the total use of hydro (increase or decrease) when considering the capacity factors.

What is also clear is that despite the increase in reliance on OCGT when the connection cost is increased the difference between RE output and demand for all two-year scenarios presented is minimal (Fig. 6). Fig. 6 demonstrates that the NEM region as a whole is affected by the same large-scale wind events and that no amount of strategic resource placement is able to avoid exposure to such synoptic scale phenomena. The total installed capacity and capacity factor of wind throughout the scenarios, which remained quite invariant (Table 2), also indicates the same broad sampling of the NEM wind resource across the scenarios. What Fig. 6, in combination with Fig. 5c and Table 2, shows is that the NEM region can be split into four distinct wind regions–the four largest stations in Fig. 5c. The largest correlation between any of the four large wind installations from 8X is 0.09 (between the site near Townsville and the site near Brisbane), while Fig. 7 shows how these four locations correlate with the rest of the continental domain.

4. Discussion/conclusions

Despite the idealised nature of the network design the results presented have been able to identify four distinct wind regimes for the NEM. The four major wind installations from the 8X simulation were all uncorrelated to each other and the average distance to the nearest neighbour indicates that decorrelation in the NEM wind field occurs at roughly 1,400 km. The ability to get independent wind output from a set of dispersed and aggregated wind installations has implications for the optimal network design in a future highly renewable energy dependent NEM. As was outlined in Refs. [10] and [1] diversity in output from renewables is a key consideration for future increases in penetration and on the large-scale this can be achieved in the NEM with wind. Planning the future NEM should recognise that complimentary wind resources exist, but that such complementarity might only be possible at the extremities. The current NEM does not have the transmission line capacity to support the wind installations seen in the 8X simulation. But as the network evolves it should be considered that a high penetration of wind may only be possible by exploiting the separation distance found here, and that this would require investment in infrastructure to support it.

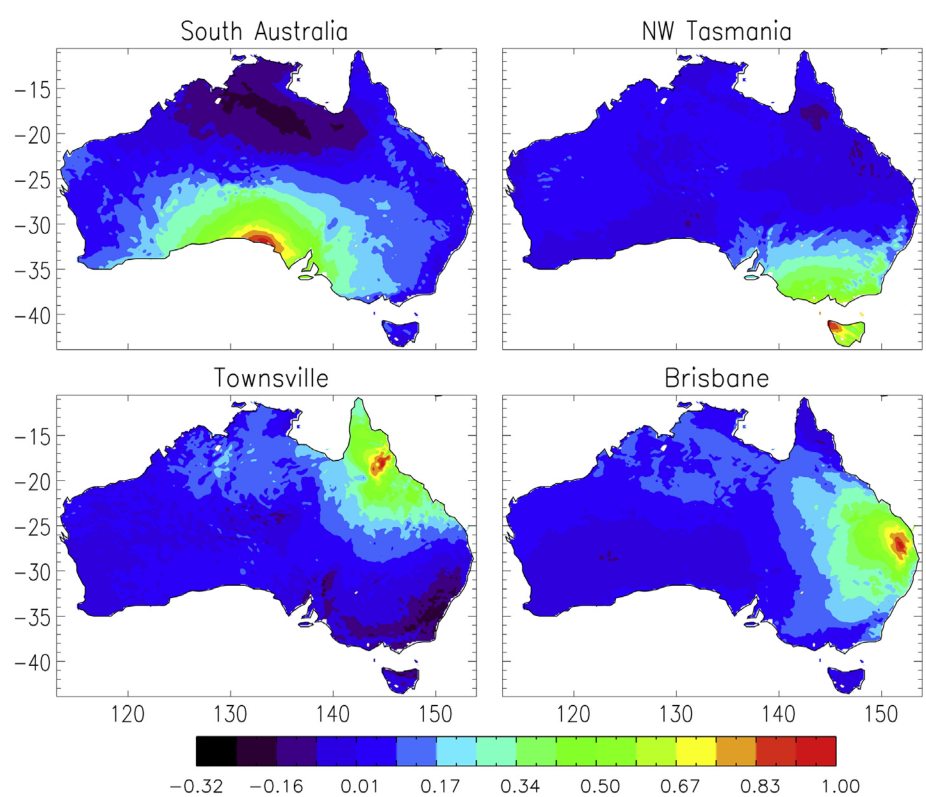

Fig. 7. Point correlation maps using the central point in each map as one of the four major wind installations from the 8X simulation. Variable being correlated is the interpolated 80 m wind speed from the 2010–2011 ACCESS-R output.

Similar aggregated and dispersed results could not be achieved with large-scale solar PV. To achieve higher penetration from solar, alternatives should be considered (for instance, large-scale PV with storage, concentrating solar thermal or simulations of distributed rooftop PV). Future studies should also include power flow constraints to further investigate the usefulness of aggregated and distributed large-scale wind power.

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References

[1] AEMO. 100 per cent renewables study—modelling outcomes. 2013. Melbourne.
[2] Elliston B, MacGill I, Diesendorf M. Least cost 100% renewable electricity scenarios in the Australian National Electricity Market. Energy Policy 2013;59:270–82.
[3] Widén J. Correlations between large-scale solar and wind power in a future scenario for Sweden. IEEE Trans Sustain Energy 2011;2:177–84.
[4] Santos-Alamillos FJ, Pozo-Vázquez D, Ruiz-Arias JA, Lara-Fanego V, Tovar-Pescador J. Analysis of spatiotemporal balancing between wind and solar energy resources in the southern Iberian Peninsula. J Appl Meteorol Climatol 2012;51:2005–24.
[5] Short W, Diakov V. Matching Western US electricity consumption with wind and solar resource. Wind Energy 2013;16:491–500.
[6] Clean Energy Council. Clean Energy Australia Report 2014. 2014. p. 66.
[7] Global Wind Energy Council. Global Wind Report Annual Market Update 2013. 2014.
[8] AEMO. South Australian Generation Information for August 13 2015. 2015.
[9] Archer CL, Jacobson MZ. Supplying baseload power and reducing transmission requirements by interconnecting wind farms. J Appl Meteorol Climatol 2007;46:1701–17.
[10] Elliston B, Diesendorf M, MacGill I. Simulations of scenarios with 100% renewable electricity in the Australian National Electricity Market. Energy Policy 2012;45:606–13.
[11] Perpiñan O, Lorenzo E, Castro MA, Eyras R. On the complexity of radiation models for PV energy production calculation. Sol Energy 2008;82:125–31.
[12] Huva R, Dargaville R, Caine S. Prototype large-scale renewable energy system optimisation for Victoria, Australia. Energy 2012;41:326–34.
[13] Rayner PJ. Optimizing CO_2 observing networks in the presence of model error: results from TransCom 3. Atmos Chem Phys Discuss 2004;4:413–21.
[14] Humpert C. Long distance transmission systems for the future electricity supply - analysis of possibilities and restrictions. Energy 2012;48:278–83.
[15] Syed A. Australian Energy Technology Assessment 2013 Model Update. 2013.