Seasonal forecasting for renewable energy management

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Abstract: Renewable energy's most abundant forms, solar and wind power, depend on weather conditions. Weather forecasts can thus assist energy resilience and security. The ability of the European Centre for Medium-Range Weather Forecasts fifth generation seasonal forecast system SEAS51 to predict wind and solar resource variability at the monthly timescale (up to 6 months ahead) is assessed, using forecasts for the period 2017-2024 and the ERA5 reanalysis as the observational verification. It is found that SEAS51 can be used to generate improved probabilistic predictions compared to climatology of both solar and wind monthly resource. Skill decreased with lead time. Skill varied by region, and was generally greatest over parts of the tropics.

Keywords: Resource assessment, Seasonal forecasting, Teleconnections, Grid management.

1. Introduction

Seasonal meteorological outlooks are based on ensembles of weather models initialized with current conditions and on observed regular seasonal-scale patterns such as El Niño Southern Oscillation (ENSO) (Troccoli, 2010). While seasonal forecasts usually focus on temperature and precipitation, there are opportunities for aiding renewable energy grid integration and system operation by forecasting additional variables such as sunniness and windspeed (Krakauer and Cohan, 2017). Because seasonal forecasts have substantial uncertainty, forecasts should be probability distributions that quantify their degree of confidence (Aizenman et al., 2016).

Here, monthly mean downward solar radiation (W m^{-2}) and windspeed (m s^{-1}) are to be forecast 0.5 to 5.5 months in advance (e.g., the August value is forecast at the beginning of August [for 0.5 month lead], going back to the beginning of March [for 5.5 month lead]) based on the currently-operational European Centre for Medium-Range Weather Forecasts fifth generation seasonal forecast system SEAS51, which has released monthly forecasts or hindcasts of a 23 to 51 member ensemble going back to 1981 (Johnson et al., 2019). The performance of several methods for generating probabilistic solar and wind forecasts from the SEAS51 ensemble averages over the period 2017-2024 is evaluated, compared to probabilistic forecasts based only on previous years' solar and wind values (climatology) without any special insight based on this year's conditions. Actual values are assumed to be given by the ERA5 reanalysis (available since 1940 and regridded from 0.25° to the 1° spatial resolution of SEAS51 output), based on billions of observations each month and shown to reasonably represent large-scale weather patterns (Soci et al., 2024). To generate probabilistic forecasts, year-to-year variability in solar and wind monthly means were taken to follow normal distributions, leading to a *t* probability distribution for the forecast.

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2. **Probabilistic forecast methods**

The methods tested (Table) were studied previously for seasonal temperature forecasts (Krakauer, 2017):

Climatology:

C: forecast distribution is based on an ERA5 climatology period, 1981-2010

MA: forecast distribution is based on the most recent 30 years in ERA5

EW: forecast distribution is based on greater weighting of the more recent years, using an exponential kernel with 30-year decay period

EW-a: same as EW, but with a shift of the mean based on a global spline fit to better correct for any climate-related trend

SEAS51:

M: forecast distribution is based on the SEAS51 ensemble mean, with an intercept term determined by linear regression

MS: also include a linear trend term in the linear regression to allow for time-varying model bias

MT: include a scale factor multiplying the SEAS51 ensemble mean to allow for possible over- or under-prediction of the magnitude of anomalies

MST: include both trend and scale factor terms

3. **Measures of forecast performance**

The main measure for assessment of forecast quality (Krakauer, 2017) was the mean negative log likelihood (NLL) of the observed solar or wind value in the forecast probability distribution, where lower values correspond to a better forecast, averaged over all forecast months and grid cells (weighted by cell area), and also separately computed for land and ocean. Additional measures computed were mean bias and root mean square error (RMSE) between the forecast expectation and the observed value, and continuous ranked probability score (CRPS), a mean square difference between the observed and the forecast cumulative distribution functions.

Information gain (IG) was defined as the improvement (reduction) in NLL of a SEAS51-based probabilistic forecast relative to a climatology-only (reference) forecast, with units of information (1 nat ≈1.44 bits). A forecast that outperforms climatology should have positive IG.

Table: Skill measures for solar and wind forecast methods, 2017-2024, with lag-1.5 month SEAS51 predictions used as inputs. NLL, RMSE, Bias, CRPS are defined in the text..

	Solar						Wind					
Method	NLL	NLL-land	NLL-ocean	RMSE	Bias	CRPS	NLL	NLL-land	NLL-ocean	RMSE	Bias	CRPS
C	3.7483	3.8237	3.7828	13.0430	0.9947	6.6435	0.9502	0.2044	1.1719	0.7527	-0.1390	0.3953
MA	3.7218	3.8011	3.7577	12.7194	0.2537	6.4750	0.9325	0.1869	1.1559	0.7318	-0.0249	0.3857
EW	3.7216	3.7993	3.7566	12.7648	0.5595	6.4933	0.9274	0.1830	1.1492	0.7342	-0.0781	0.3860
EW-a	3.7236	3.8080	3.7573	12.7631	-0.2167	6.5011	0.9424	0.2588	1.1481	0.7310	0.0171	0.3862
M	3.6789	3.7700	3.7088	12.1950	0.0896	6.2072	0.9013	0.1758	1.1024	0.7057	-0.0343	0.3725

MT	3.6793	3.7708	3.7088	12.1965	-0.0093	6.2091	0.9036	0.1847	1.1014	0.7052	0.0188	0.3727
MS	3.6758	3.7691	3.7026	12.1643	0.1248	6.1902	0.8967	0.1656	1.1009	0.7041	-0.0363	0.3714
MST	3.6761	3.7700	3.7027	12.1659	0.0442	6.1919	0.8996	0.1761	1.1005	0.7036	0.0201	0.3717

4. **Results**

Looking at the measures of forecast performance at lag 1.5, using the more recent years as a baseline (MA method) outperforms a fixed climatology period (C) (Table). An exponential weighting of previous years (EW) slightly improves the forecast further, especially for wind, while a global bias adjustment (EW-a) is unhelpful, presumably because unlike for temperature, there is no clear global trend in solar radiation or windspeed. The model-based forecasts outperform all the climatology-based ones. Adding a trend term to the model mean (MT) does not broadly improve the forecast over M, but scaling the model mean (MS) does provide some further improvement.

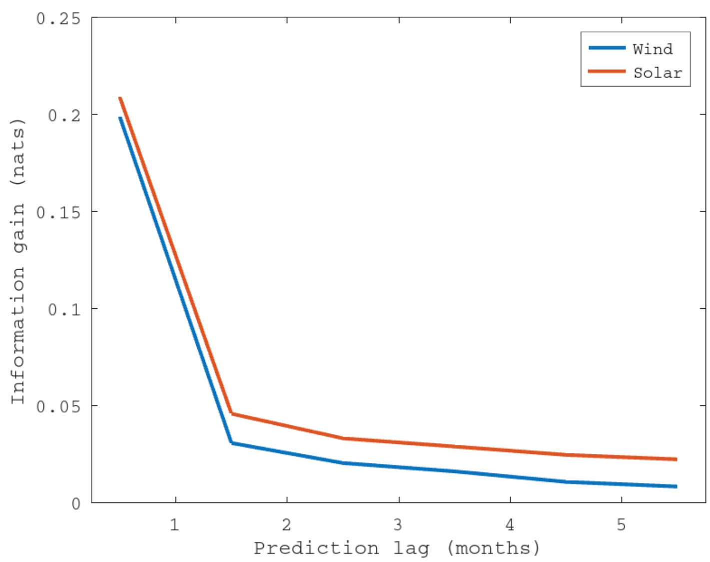

Figure 1: Information gain from using the SEAS51 ensemble to make probabilistic solar radiation and wind speed forecasts, compared to a climatology-based forecast, for 0.5 to 5.5 month lead times.

Based on this evaluation, IG can be defined as the difference between the NLL for MS and EW (Figure 1). Mean IG drops sharply after the initial 0.5 month lead, which includes the first few days after the forecast initialization during which weather models are highly skillful, and more gradually thereafter, but shows an improvement over climatology even at 5.5 month lead time, suggesting that SEAS51 is able to capture some seasonal-scale sources of predictability such as ENSO.

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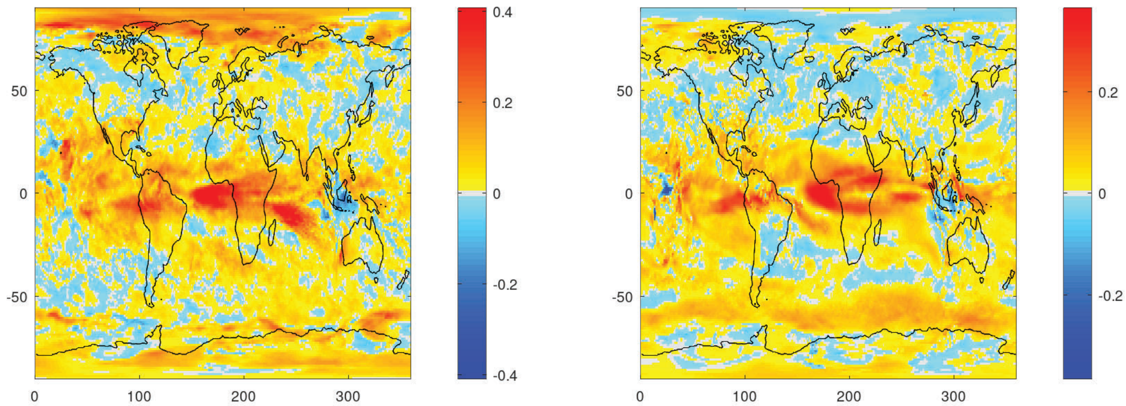

Figure 2: Mean information gain (nats) of MS over EW solar (left) and wind (right) forecasts at 1.5 month lead.

Geographic patterns in forecast skill can also be visualized by mapping IG (Figure 2). Interestingly, the areas of most skill are similar between solar and wind, and include especially tropical Africa and South America and the oceans around them. These are areas with limited but rapidly expanding renewable-energy deployments. Mexico and the southern United States show some skill from SEAS51 for both solar and wind, while the Arctic shows skill for solar but not for wind seasonal forecasts.

5. Conclusions

Variability in wind and solar resource is considerable and can affect producer revenues and regional energy security. Here, it is demonstrated that the seasonal forecast ensemble SEAS51 can be used to improve probabilistic predictions of monthly mean surface solar radiation and wind speed one or more months in advance, with variability in forecast skill geographically and probably also seasonally and by ENSO phase. Additional input data and more sophisticated forecast processing methods could be tried to improve performance further.

6. References

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