Nonlinearity for improving sub-seasonal forecasts in Europe

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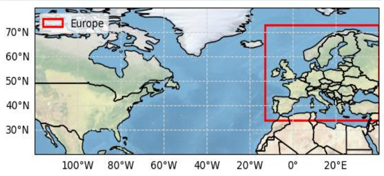
Abstract—Skillful wind speed forecasts for sub-seasonal periods, ranging from two to six weeks, are challenging for managing and balancing the energy supply and demand of wind power systems. Leveraging the higher predictability of atmospheric fields involved in large-scale dynamics offers a potential avenue for improving probabilistic wind speed forecasts. Goutham et al. (2022) improved surface wind speed forecasts by applying a linear regression model to regress surface wind speed forecasts using forecasts of higher atmospheric levels, specifically the 500 hPa geopotential height (Z500). Building on their work, our study explores the potential of non-linear supervised-learning models, such as Convolutional Neural Networks (CNN), to outperform linear models in predicting sub-seasonal wind speeds in Europe during boreal winters.

I. Methodology

This study proposes a nonlinear statistical sub-seasonal ensemble prediction approach based on applying a supervised MLR or CNN to dynamical forecasts of 500 hPa geopotential height to forecast the weekly-mean surface wind speed, with a focus on boreal winter over Europe.

As shown in Fig 1, we first evaluate the skill of a deterministic version of the MLR and CNN to regress the wind speed from the geopotential height using ERA5 reanalysis. Subsequently, we apply the same model (without retraining), member by member, to dynamical ensemble sub-seasonal forecasts from the European Centre for Medium-Range Weather Forecasts' (ECMWF) Sub-seasonal to seasonal (S2S) project, produced in the boreal winters from 2015 to 2022, for the same variables.



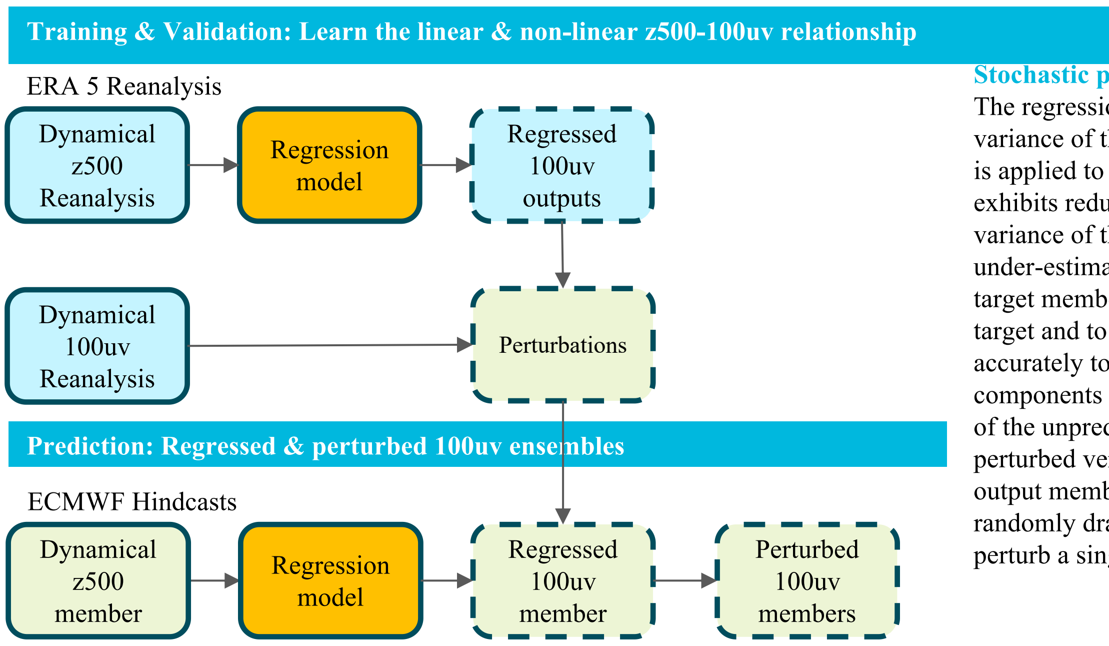


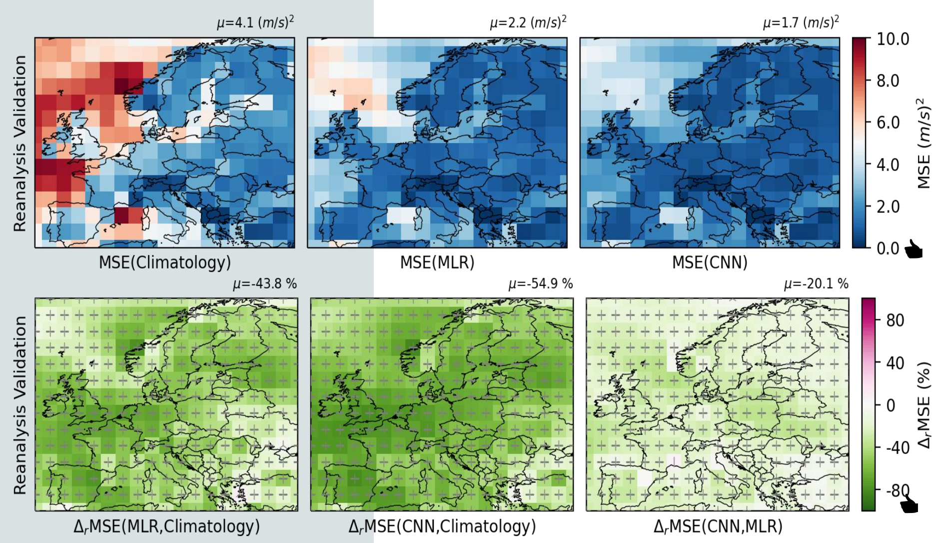
Fig 1. The workflow of our wind speed downscaling algorithm.

Stochastic perturbations

The regression model captures only a portion of the variance of the target. Consequently, when the model is applied to a probabilistic dataset, the output exhibits reduced variance relative to the expected variance of the target. This leads to a systematic under-estimation of dispersion and variability of the target members. To maintain the total variance of the target and to attribute skill improvements more accurately to the representation of the predictable components of the signal, rather than to the variance of the unpredictable components, we employ a perturbed version of the model. For each regressed output member, the stochastic perturbations are randomly drawn from the residual distribution to perturb a single regressed member.

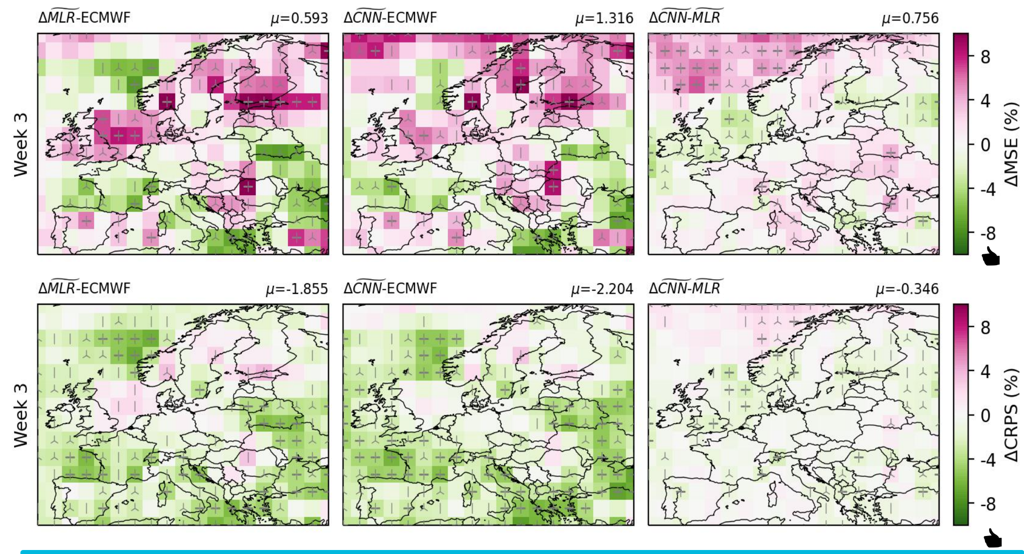
II. Results

Nonlinearity from reanalysis

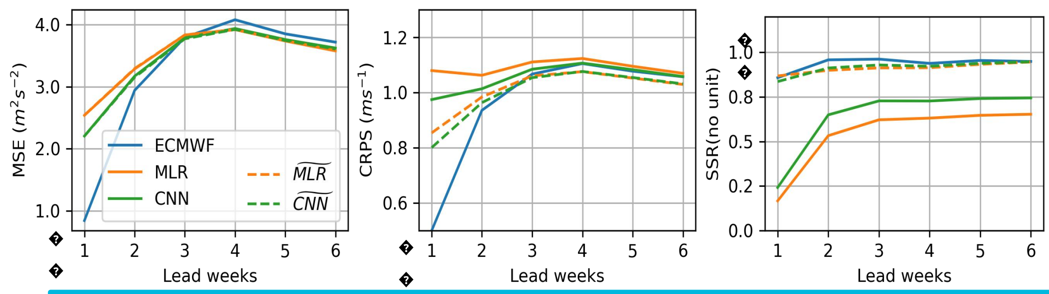


- ***Non-linearity can better model the regression relationship between Z500 and 100uv reanalysis..***

Prediction: Regressed & perturbed 100uv ensembles



- *Compared to ECMWF, both MLR and CNN show significant improvements* ***in southern France, southeastern Europe,*** *and* ***the Norwegian Sea.***
- *Compared to MLR, CNN's improvements are spatially distributed, with significant improvements in* ***the North Sea*** *and* ***Eastern Europe.***



- ***Non-linearity, compared to the linear model, achieves better CRPS.***
- ***Both non-linear and linear models are under-dispersive.***
- ***Modeling regression uncertainty can enhance the model's reliability and thus improve CRPS.***
- ***The improvement from non-linearity gradually diminishes after Week 2.***

III. Conclusions

For sub-seasonal forecasts, the non-linearity:
- **no improvement in deterministic skill,**
- **but there is an improvement in probabilistic skill.**

However, by introducing model uncertainty, probabilistic skill can be further improved, making ensembles more reliable.

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