MIA: A flexible data-driven system for climate impact modelling applied for subseasonal-to-seasonal prediction of renewable energy in Brazil.

Gabriel Perez[1], **Thomas Martin**[1]

1. MeteoIA, São Paulo, SãO PAULO, Brazil

Objective & Background

The Brazilian energy matrix is 79% renewable, thus the energy generation and commercialisation markets are directly dependent on weather and climate variations. In these markets, crucial decisions on reservoir management and trading are made on subseasonal-to-seasonal scales, where current dynamical and simple statistical modelling approaches are most deficient.

Method

In this study, we propose a purely data-driven approach to simulate precipitation, wind speed and their impacts on the variations of hydroelectric and wind power generation in a 12-month forecast horizon. Model inputs are solely based on reanalyses and observational datasets and do not depend on dynamical models outputs. Our modelling approach is based on (i) non-linear feature extraction of the global earth system physical state, such as sea-surface temperature and geopotential and (ii) specifically designed recurrent neural network architectures for encoding the past and unfolding the future sequence of the target variables.

Principal findings

We show that our precipitation predictions and the subsequent hydroelectric generation outperforms state-of-the-art dynamical model ensembles after the third week of the forecast period in most watersheds in Brazil and shows useful performance (>66% accuracy to predict monthly anomalies) for the entire forecast horizon. We also show that our approach provides useful performance to predict the monthly-mean wind potential in Northeast Brazil up until 12 months in advance.

Conclusions

The competitive advantages of the methodology in wind and hydroelectric power generation points to its potential of application in other components of the supply-chain that are also deficiently supported by traditional modelling products. These results, along with recently published data-driven models such as Google’s GraphCast and Microsoft’s ClimaX, point to a shift in the role of machine learning in climate impact modelling from simply post-processing results from dynamical models to integrating in time and predicting future states of variables sensitive to weather and climate with competitive advantages that enable planning and decision-making in crucial timescales for energy markets.