NN4CAST: UNA APLICACIÓN DE RED NEURAL DE EXTREMO A EXTREMO PARA PREDICCIONES CLIMÁTICAS ESTACIONALES

NN4CAST: AN END-TO-END NEURAL NETWORK APPLICATION FOR SEASONAL CLIMATE FORECASTS

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SUMMARY

Seasonal climate prediction is critical for decision-making across sectors, but current dynamical models have limitations. Traditional statistical and recent data-driven approaches offer promise but face challenges. NN4CAST is a specialized Python library, which applies deep learning techniques to address these challenges by enabling nonlinear statistical analysis of teleconnections in climate data. This tool represents a significant advancement in seasonal forecasting, with potential applications in practical decision-making. Examples demonstrate its effectiveness in predicting key variables impacting the Iberian Peninsula.

Predicting climate variables at seasonal time scales plays a crucial role in planning and decision-making across various sectors, from agriculture to water resource management and natural disaster preparedness Robertson et al., 2015). The implications of accurate prediction at these time scales are enormous, as they allow better preparation for extreme weather events, optimization of agricultural practices and effective management of natural resources. However, current dynamical models used for seasonal prediction face significant challenges due to the inherent complexity of climate processes and the correct modelling of different sources of predictability with low signal-to-noise (Eade et al., 2014). Taking this into account, there have been different traditional statistical approaches to seasonal forecasting, taking advantage of relationships between different fields, not only on different places though the processes called teleconnections, but also on different time lags, making them available for an operationally system of seasonal forecasting (Cohen at al., 2019).

Thanks to the recent computational advancements and the availability of vast meteorological datasets, numerous data-driven prediction models have emerged in meteorology, especially for short-range weather forecasts (from hours to days) (Lam et al, 1022). These models leverage complex machine learning and deep learning techniques to capture the complicated nonlinear relationships in climate data, offering the potential for more accurate forecasts with less computational cost than traditional dynamical methods. Regarding seasonal prediction, the potential of these techniques is even higher due to the limited skill of dynamical predictions in some regions, such as the Euro-Atlantic sector. However, the lack of data at these scales may be a tipping point, certainly not allowing the application of very complex artificial intelligence models, which would require a long period of data for training.

In this context, we have developed a specialized Python library, based on the application of deep learning in the prediction of climate variables on seasonal time scales using the information of atmospheric teleconnections. Figure 1 depicts the Flow Chart of the application of this library. It provides a versatile tool both for operational prediction and for the study of new sources of predictability through the modelling of non-linear processes at a fairly low computational cost. In this way, this library facilitates nonlinear statistical analysis of teleconnections in an accessible and straightforward manner, enabling researchers to make the most of advances in deep learning to improve the accuracy and understanding of seasonal forecasts. This tool represents a significant step forward in the ability of forecasting long-term weather events, which has the potential to have a significant impact on a wide range of practical applications and climate-based decisions.

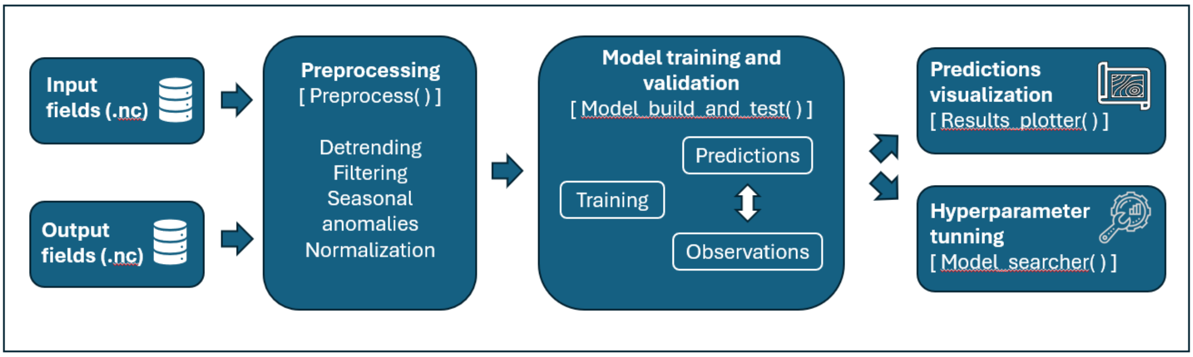

Figure 1- Flowchart describing the methodology and application setup using the NN4Cast API

In the presentation, some examples of the usefulness of this library in predicting key variables impacting the Iberian Peninsula (IP) will be shown. Concretely, Figure 2 represents the model output metrics of its performance when predicting the anomalous sea level pressure field over the Euro-Atlantic sector for November-December, with the information of the anomalous sea surface temperature from the Pacific Ocean in October as its predictor. It can be seen how the model captures the atmospheric teleconnection associated to sea surface temperature forcings from the Pacific, achieving a moderately good skill in the regions of action of important weather regimes over the IP.

Preference is expressed for an oral presentation of the results.

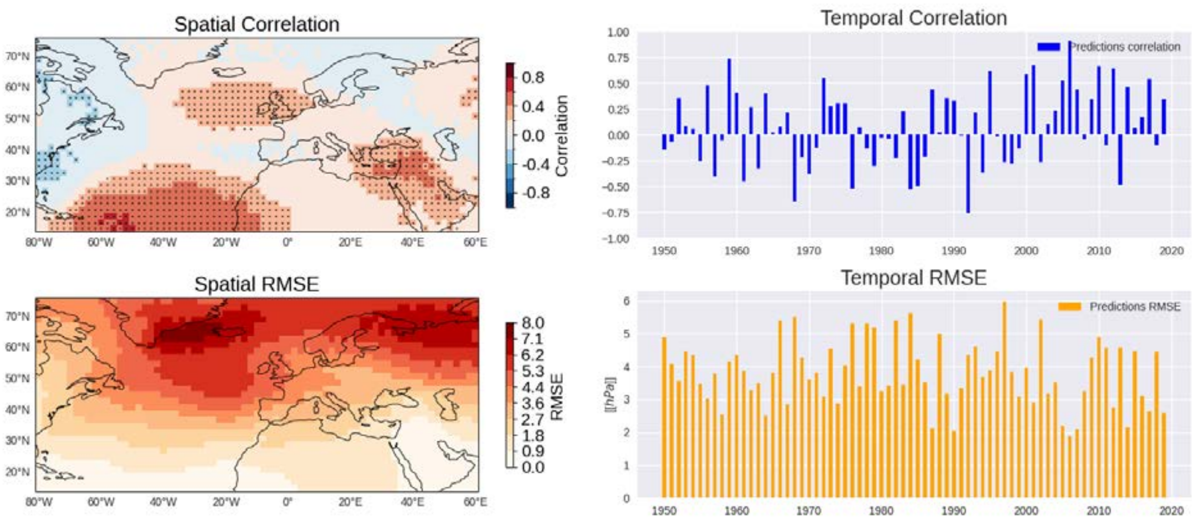

Figure 2 - Comparison of model performance for different metrics in predicting anomalous sea level pressure over the Euro-Atlantic sector for November-December, using October anomalous sea surface temperatures from the Pacific Ocean as the predictor.

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