EGU24-12600, updated on 16 Sep 2024
https://doi.org/10.5194/egusphere-egu24-12600
EGU General Assembly 2024


# Autoencoder-based model for improving reconstruction of heat waves using the analogue method

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The Analogue Method (AM) is a classical statistical downscaling technique applied to field reconstruction. It is widely used for prediction and attribution tasks. The method is based on the principle that two similar atmospheric states cause similar local effects. The core of the AM method is a K-nearest neighbor methodology. Thus, two different states have similarities according to the analogy criterion. The method has remained unchanged since its definition, although some attempts have been made to improve its performance. Machine learning (ML) techniques have recently been used to improve AM performance, however, it remains very similar. An ML-based hybrid approach for heatwave (HW) analysis based on the AM is presented here. It is based on a two-step procedure: in the first step, a non-supervised task is developed, where an autoencoder (AE) model is trained to reconstruct the predictor variable, i.e. the pressure field. Second, an HW event is selected, and then the AM method is applied to the latent space of the trained AE. Thus, the analogy between the fields is searched in the encoded data of the input variable, instead of on the original field. Experiments show that the meaningful features extracted by the AE lead to a better reconstruction of the target field when pressure variables are used as input. In addition, the analysis of the latent space allows for interpreting the results, since HW occurrence can be easily distinguished. Further research can be done on including multiple input variables.