

EGU22-13008

<https://doi.org/10.5194/egusphere-egu22-13008>

EGU General Assembly 2022

© Author(s) 2022. This work is distributed under the Creative Commons Attribution 4.0 License.



Closing the Gap between Models and Observations: Deep Learning from Mismatches

Kaveh Patakchi Yousefi and Stefan Kollet

Agrosphere (IBG-3), Research Centre Jülich GmbH, Jülich, Germany

Numerical weather prediction and climate models provide important information on essential atmospheric variables and extreme events. However, due to model uncertainties arising from initial value and model errors, the simulation results do not match *in-situ* or remotely sensed measured observations to an arbitrary accuracy. Machine Learning (ML) and/or Deep Learning (DL) methods have shown to be successful tools in closing the gap between models and observations due to high generalization skills and better representation of non-linear and complex relationships. This study focused on using UNet encoder-decoder Convolutional Neural Network (CNN) for extracting spatiotemporal features from model simulations and predicting the actual mismatches between the simulations results and a reference data set. Here, the model simulations serving as input to the CNN were obtained from climate simulations over Europe with the Terrestrial Systems Modeling Platform (TSMP-G2A). The reference data set representing observations was obtained from the COSMO-REA6 reanalysis. The proposed mismatch learning framework was applied to precipitation and surface pressure representing more and less chaotic variables, respectively. The study shows that UNet is able to learn the precipitation and surface pressure mismatches with a daily average correlation coefficient of 0.68 between the actual against predicted mismatches. Seasonal and regional intercomparisons of various precipitation types (e.g., stratiform rainfall, convective rainfall, and snowfall) reveal that the UNet faces challenges in learning the convective-type precipitation mismatches, which may be due to higher random uncertainties in model-based data. After training the UNet network, the reference data is no longer needed for generating the mismatch information. Thus, the UNet weights may be used online during the simulation or as a post-processor to correct predicted variables, which is useful in impact studies. In the first validation experiments, the corrected precipitation data show a strong improvement over the original simulated model data in mean error (47 % on average), correlation coefficient (37 % on average), and root mean square error (22 % on average).