



Artificial Intelligence Reconstructs Historical Climate Extremes

Étienne Plésiat¹, Robert Dunn², Markus Donat³, Thomas Ludwig¹, and Christopher Kadow¹

¹German Climate Computing Centre (DKRZ), Hamburg, Germany

²Met Office Hadley Centre, Exeter, United Kingdom

³Barcelona Supercomputing Center (BSC), Barcelona, Spain

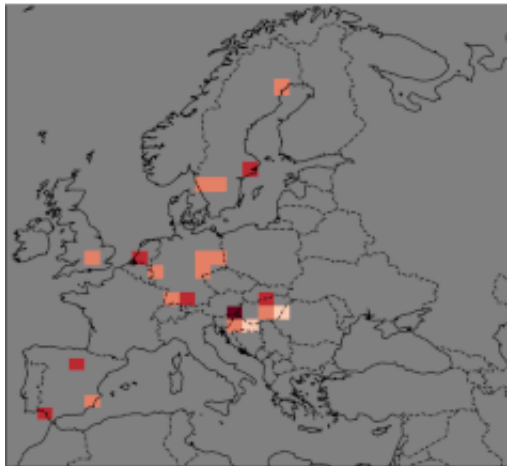
The year 2023 represents a significant milestone in climate history: it was indeed confirmed by the Copernicus Climate Change Service (C3S) as the warmest calendar year in global temperature data records since 1850. With a deviation of 1.48°C from the 1850-1900 pre-industrial level, 2023 largely surpasses 2016, 2019, 2020, previously identified as the warmest years on record. As expected, this sustained warmth leads to an increase in frequency and intensity of Extreme Events (EE) with dramatic environmental and societal consequences.

To assess the evolution of these EE and establish adaptation and mitigation strategies, it is crucial to evaluate the trends of extreme indices (EI). However, the observational climate data that are commonly used for the calculation of these indices frequently contains missing values, resulting in partial and inaccurate EI. As we delve deeper into the past, this issue becomes more pronounced due to the scarcity of historical measurements.

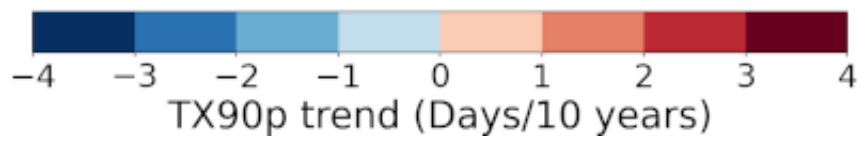
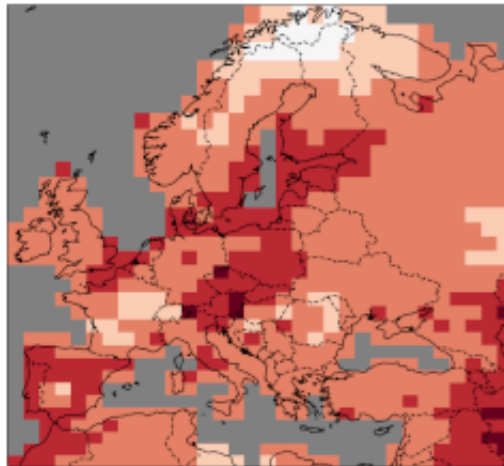
To circumvent the lack of information, we are using a deep learning technique based on a U-Net made of partial convolutional layers [1]. Models are trained with Earth system model data from CMIP6 and has the capability to reconstruct large and irregular regions of missing data using minimal computational resources. This approach has shown its ability to outperform traditional statistical methods such as Kriging by learning intricate patterns in climate data [2].

In this study, we have applied our technique to the reconstruction of gridded land surface EI from an intermediate product of the HadEX3 dataset [3]. This intermediate product is obtained by combining station measurements without interpolation, resulting in numerous missing values that varies in both space and time. These missing values affect significantly the calculation of the long-term linear trend (1901-2018), especially if we consider solely the grid boxes containing values for the whole time period. The trend calculated for the TX90p index that measures the monthly (or annual) frequency of warm days (defined as a percentage of days where daily maximum temperature is above the 90th percentile) is presented for the European continent on the left panel of the figure. It illustrates the resulting amount of missing values indicated by the gray pixels. With our AI method, we have been able to reconstruct the TX90p values for all the time steps and calculate the long-term trend shown on the right panel of the figure. The reconstructed dataset is being prepared for the community in the framework of the H2020 CLINT project [4] for further detection and attribution studies.

Original



AI reconstructed



- [1] Liu G. et al., Lecture Notes in Computer Science, 11215, 19-35 (2018)
- [2] Kadow C. et al., Nat. Geosci., 13, 408-413 (2020)
- [3] Dunn R. J. H. et al., J. Geophys. Res. Atmos., 125, 1 (2020)
- [4] <https://climateintelligence.eu/>