Artificial intelligence reconstructs missing climate information

From missing measurements to higher resolution

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OVERVIEW

Historical temperature measurements are the basis of global climate datasets like HadCRUT4. This dataset contains *many missing values*, particularly for periods before the mid-twentieth century, although recent years are also incomplete.

Here we demonstrate that **artificial intelligence can skilfully fill these observational gaps when combined with numerical climate model data via transfer learning.**

We performed this analysis from NVIDIA 1080Ti (17 it/s) to A100/80 (56 it/s), where these *HPCs keep this effort within 4 hours, while a laptop would need weeks.*

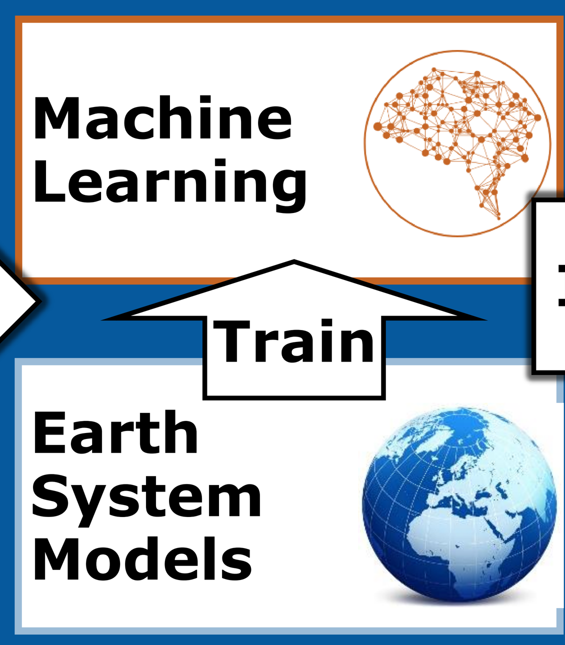
Transfer Technology

NVidia Image inpainting on irregular holes using deep 'partial' convolutional neural networks and an updated mask (Liu et al. 2018).

Method

Transfer Learning

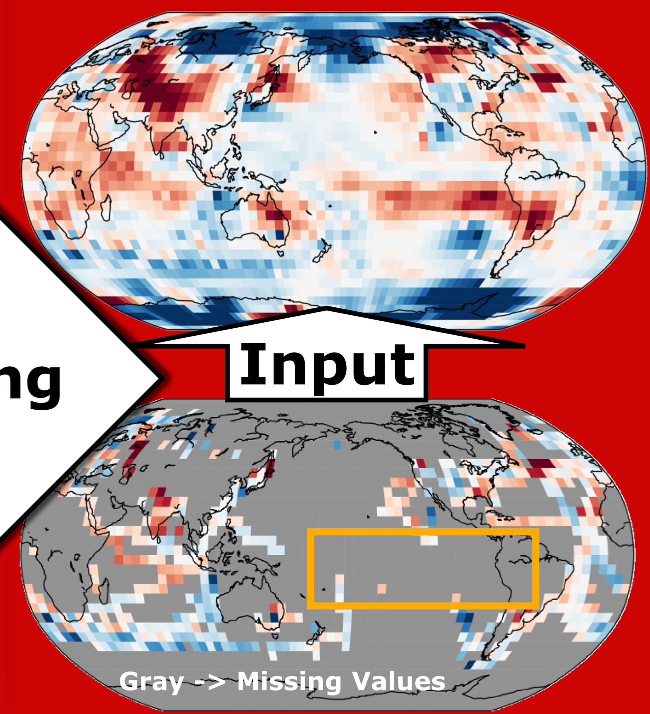
Neural networks get trained with CMIP5 and 20CR reanalysis data which are completly independent to allow cross-validation.



Infilling

Transfer Climate Data

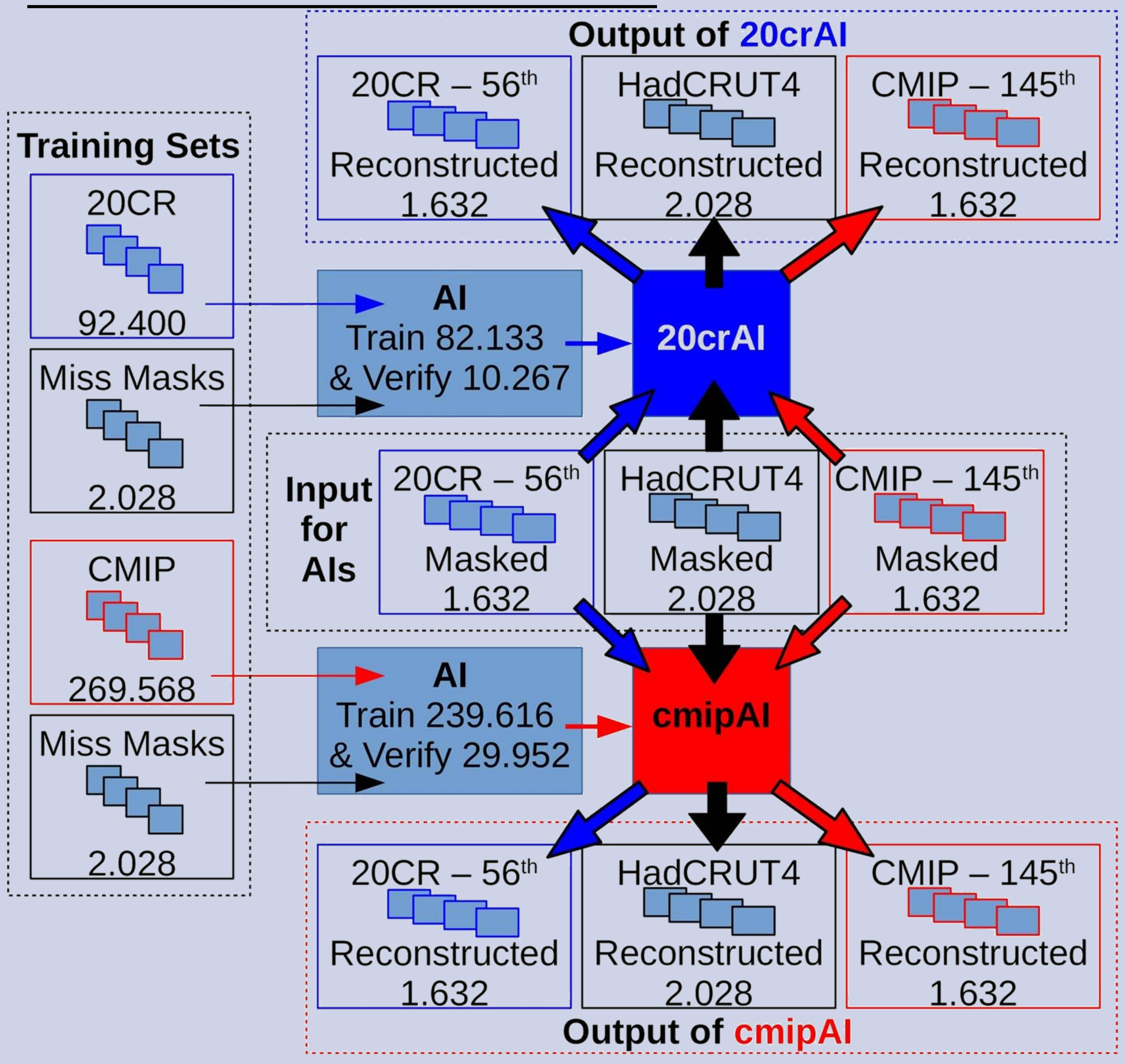
Observational climate data sets are research treasures with missing values – which can be infilled by inpainting.



Research Challenge

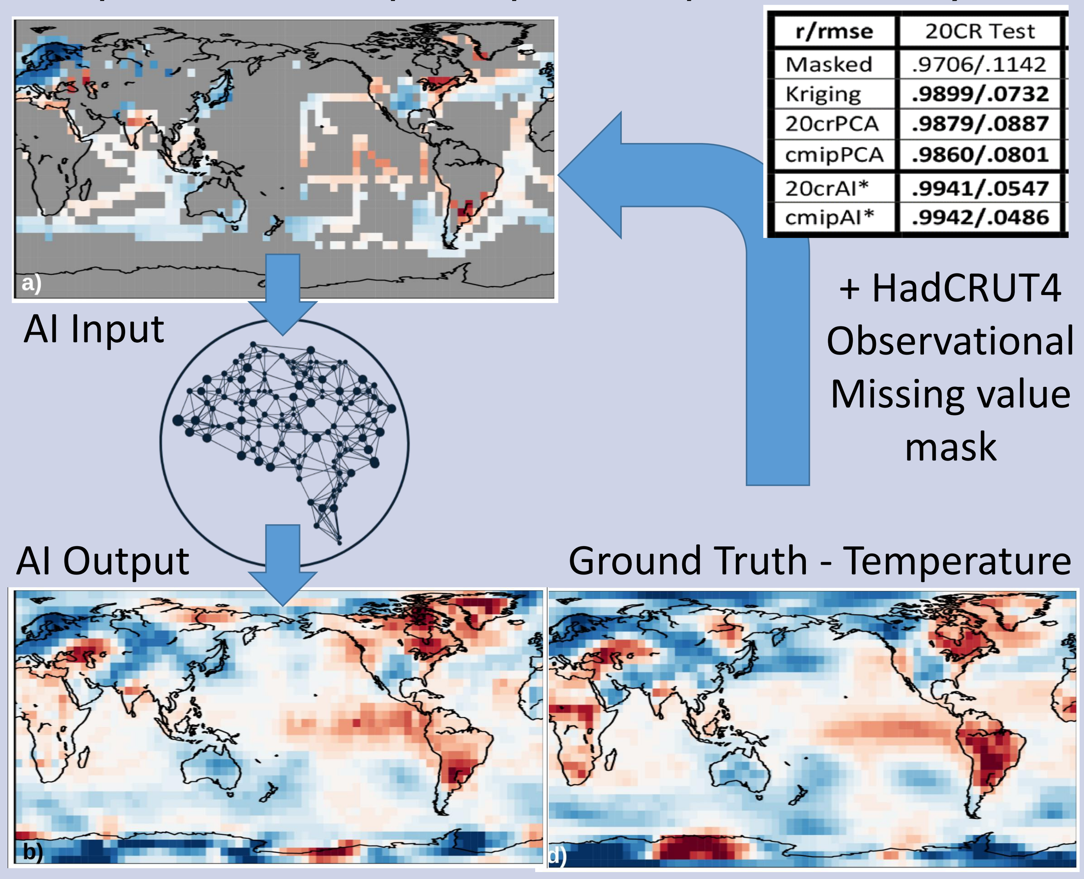
FROM: Kadow, C., Hall, D.M. & Ulbrich, U. Artificial intelligence reconstructs missing climate information. *Nat. Geosci.* 13, 408–413 (2020). https://doi.org/10.1038/s41561-020-0582-5

Scientific Scheme



Example

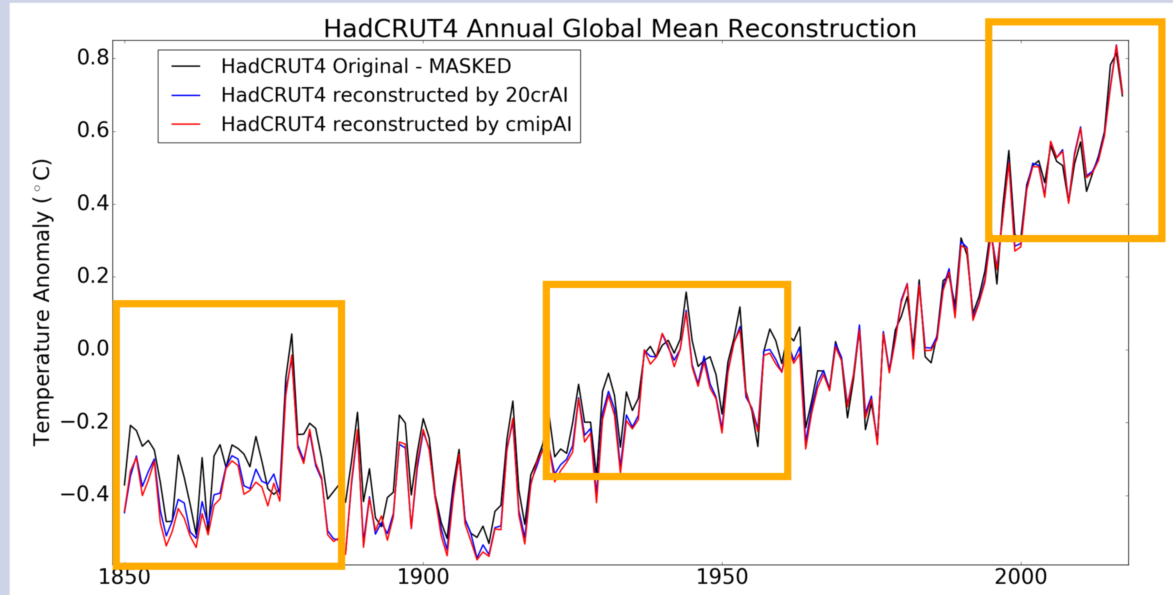
The resulting global annual mean temperature time series exhibit high correlation (≥0.9941) and low errors (≤0.0547). It provides advantages relative to *state-of-the-art kriging interpolation and principal component analysis.*



r/rmse	20CR Test
Masked	.9706/.1142
Kriging	.9899/.0732
20crPCA	.9879/.0887
cmipPCA	.9860/.0801
20crAI*	.9941/.0547
cmipAI*	.9942/.0486

Input for the AI models, training of the models, and their output. HadCRUT4 data in black, CMIP data or AI in red, 20CR data or AI in blue. Numbers on the bottom of the boxes represent the number of 'images' / months / time steps, which are used as input or result as output. Example reconstruction of a warm pacific case in 20CR masked with missing values.

Reconstution of Observations

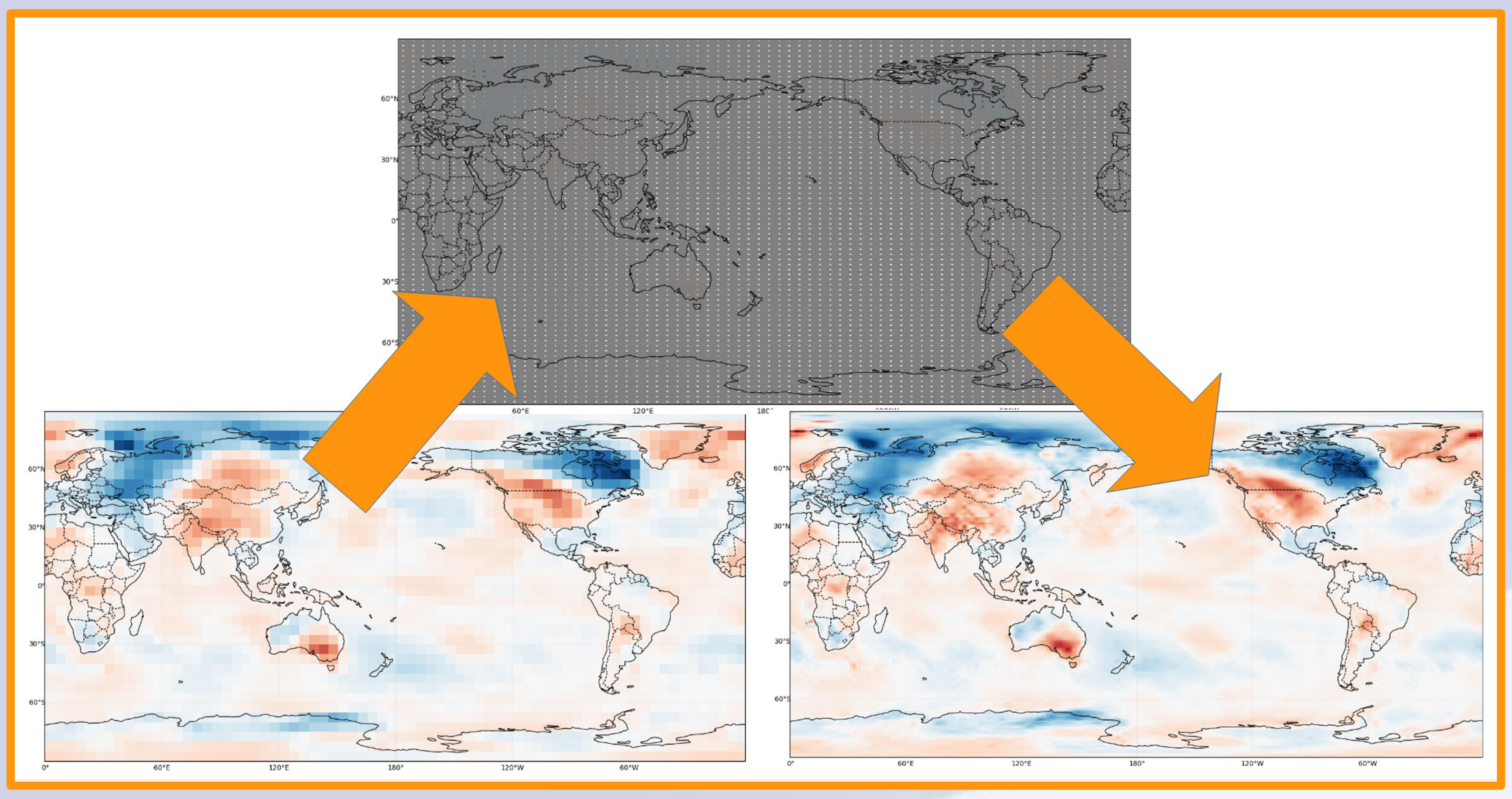


When applied to **HadCRUT4**, our method restores a missing spatial pattern of the documented **El Niño from July 1877** [SEE RED BOX *Transfer Climate Data*]. With respect to the global mean temperature time series, a HadCRUT4 reconstruction by our method points to

- a cooler nineteenth century,
- a less apparent hiatus in the twenty-first century,
- an even warmer 2016 being the warmest year on record and
- a stronger global trend between 1850 and 2018 relative to previous estimates.

Super-Resolution and Downscaling

Liu et al. 2018 basically introduced missing values around available pixels to upscale the information – and then infill using again image inpainting. ***We transformed this*** approach into the climate model setup comparable to the climate reconstruction of missing values. We obtained a valid strategy for **super-resolution** of climate data, which is basically **downscaling** in climate research. As the scientific transfer learning idea is also valid here, we are able to downscale also the observational data sets HadCRUT4/5.



Conclusion

Within this study, we are able to combine two very important tasks for climate research to investigate climate change:

1. Missing measurements & 2. Downscaling

It is important to connect the communities for further research to investigate the important challenges humanity is facing in the upcoming decades. ***Climate scientists can use this technology to related research with more accuracy and for faster results.***

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REFERENCE / ACKNOWLEDGEMENT

Guilin Liu, Fitsum A. Reda, Kevin J. Shih, Ting-Chun Wang, Andrew Tao, Bryan Catanzaro; Proceedings of the European Conference on Computer Vision (ECCV), 2018, pp. 85-100

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