From Super-Resolution to Downscaling

An Image-Inpainting Deep Neural Network for High Resolution Weather and Climate Models

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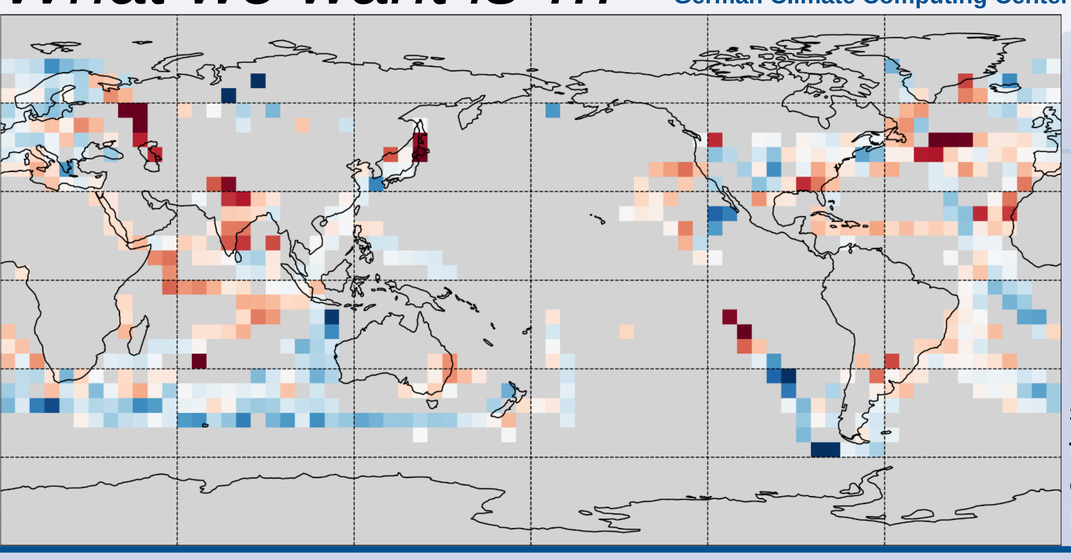
What we want is …



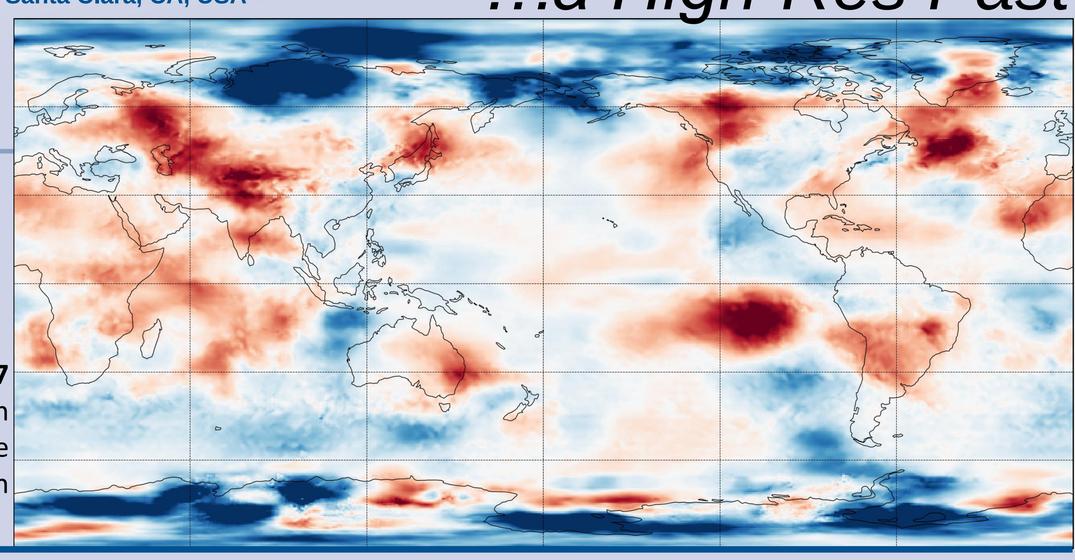
Inpainting

CRAI²

Downscaling

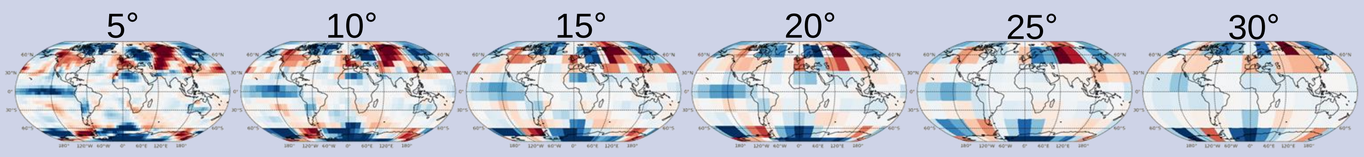
HadCRUT5 Observations July 1877 show a very strong **El Nino** in **temperature anomalies**. *Left* the original dataset. *Right* never seen before 0.5° resolution.

…a High-Res Past

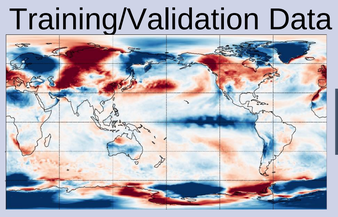


How?

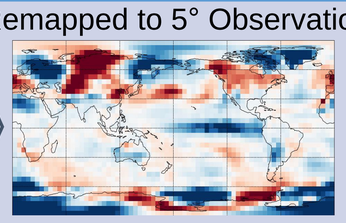
We gathered all available climate models with at least **0.5°** (~55km) grid resolution in the CMIP6 HighResMIP (Haarsma et al) historical experiments. The inpainting technology by Kadow et al. got shifted towards a **Super-Resolution Convolutional Neural Network** (SR-CNN) (Liu et al.). Tested and evaluated is the trained CNN on one left out member of the HighResMIP. Starting with the **5°** (~550km) from observations HadCRUT5 up to **30°** (~3,300km)**.** Example: **temperature.**



Training/Validation Data



Remapped to 5° Observational Grid



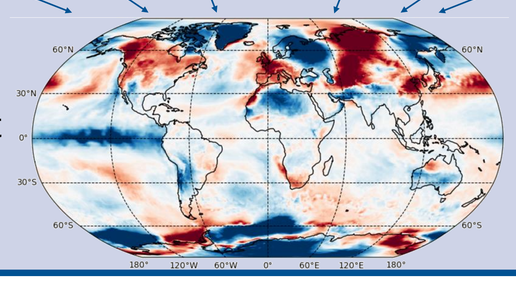
Train

CRAI²

Climate Reconstruction AI (CRAI)²

U-Net
+
Partial Convolutions[3]
+
Complex Loss Function[3]

Target

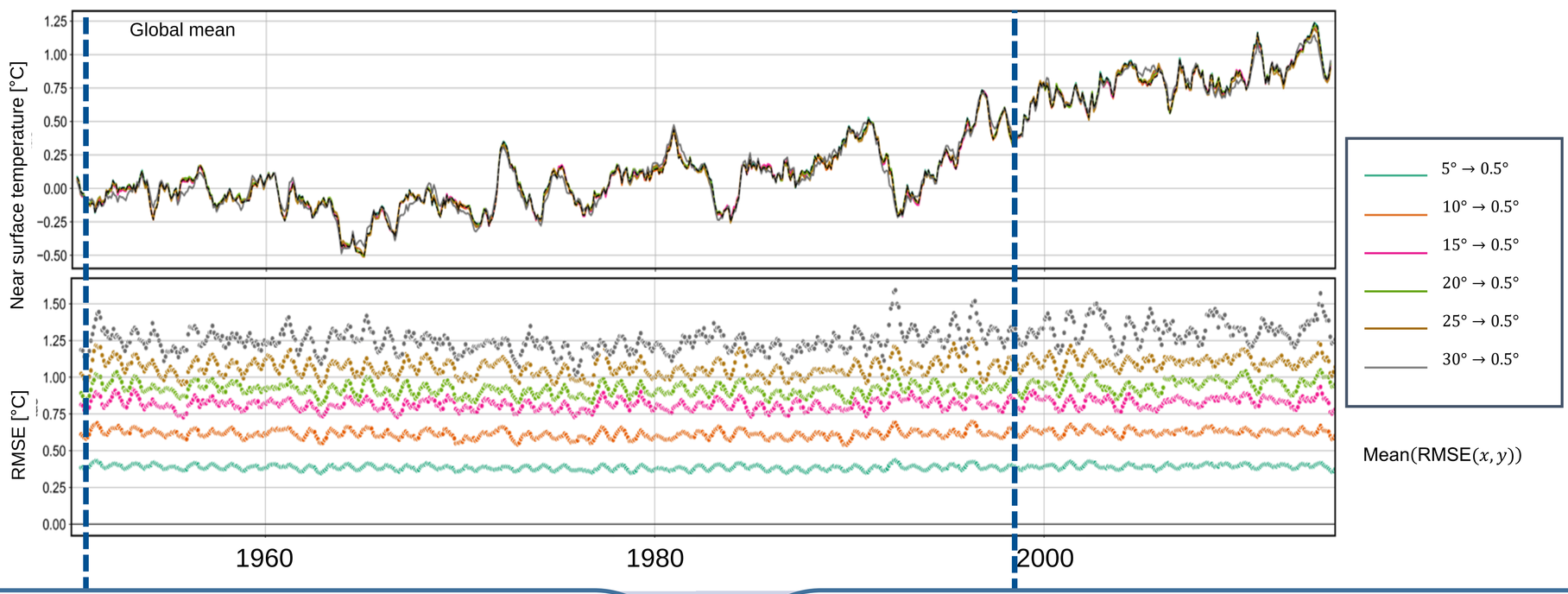


HighResMIP (1950-2014)

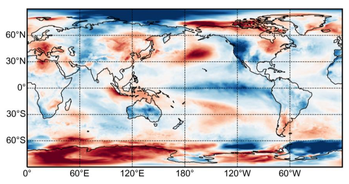
Training: 10.920 steps
Validation: 1.560 steps
Hold-out (1 model): 780 steps

Reconstruction

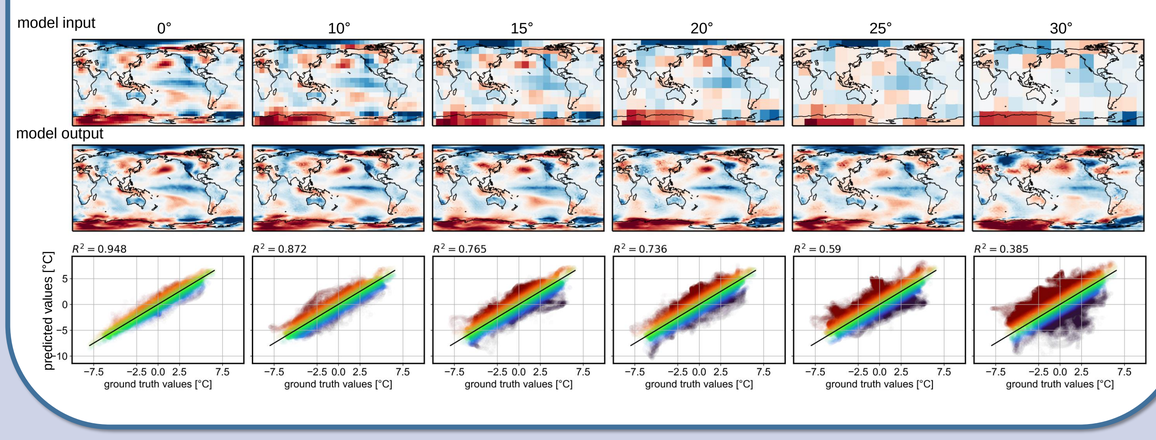
How good?



September 1951

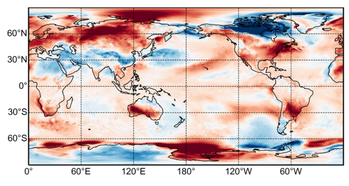


ground truth

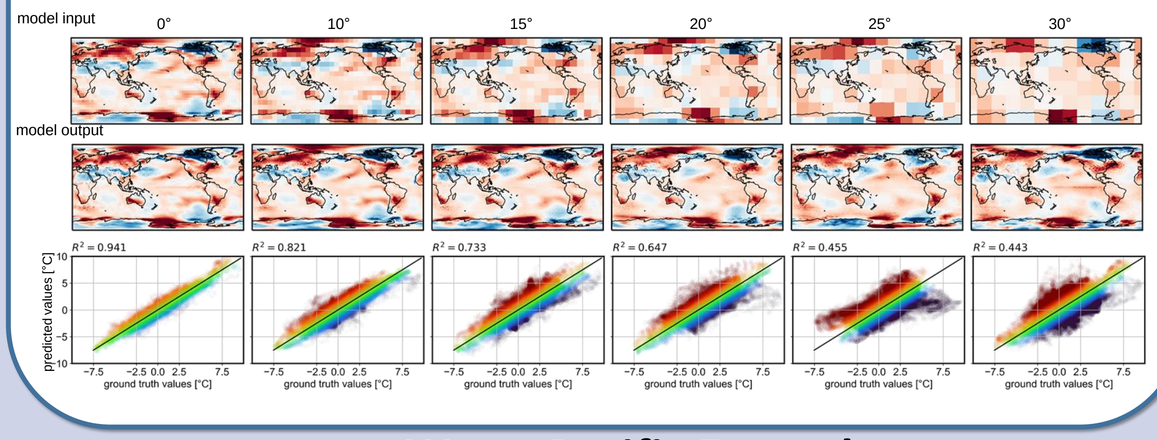


Cold Pacific Example

April 1999



ground truth

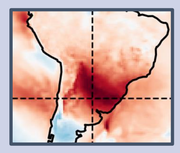


Warm Pacific Example

How good can it get?

- Remarkable performance in predicting **learned climate patterns**
- Very good general reproducibility in the temporal development of the global mean
- **Linear effect with decreasing** resolution shown in spatial error (RMSE) and spatial correlation (R^2) metrics
- However, **uncertainty** is unknown. Investigation is following...
- **In future**:
  Predict distributions + sample highly realistic patterns + include physics
  Diffusion models using this CNN for potential improvements

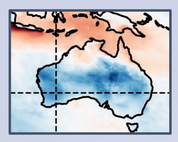
Accurate prediction



ground truth

30° upsampled downscaled

Inaccurate prediction



ground truth

30° upsampled downscaled

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DEUTSCHES KLIMARECHENZENTRUM

References

[1]Haarsma, R. J., et al. **High Resolution Model Intercomparison Project (HighResMIP v1.0) for CMIP6**, Geosci. Model Dev., 9, 4185–4208, https://doi.org/10.5194/gmd-9-4185-2016, 2016

[2]Kadow, C. et al. (2020) **Artificial intelligence reconstructs missing climate information**. *Nat. Geosci.* **13**, 408–413

[3]Liu, G. et al. (2018). **Image Inpainting for Irregular Holes Using Partial Convolutions**. In: Ferrari, V., Hebert, M., Sminchisescu, C., Weiss, Y. (eds) Computer Vision – ECCV 2018. ECCV 2018. Lecture Notes in Computer Science(), vol 11215. Springer, Cham

[4]Morice, C.P., et al. (in press**) An updated assessment of near-surface temperature change from 1850: the HadCRUT5 dataset**. Journal of Geophysical Research (Atmospheres) doi:10.1029/2019JD03236

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