Towards debiasing climate simulations using unsupervised image-to-image translation networks

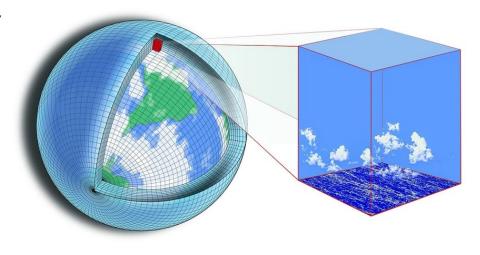
James Fulton, Ben Clarke





Motivation

- Climate simulations via GSMs are used widely for research
- They also inform policy, and legal action
- They aren't perfect representations of the world
- We need to make best use of the simulation results via post-processing



https://news.mit.edu/2018/new-climate-modeling-alliance-clima-1212

The status-quo: Quantile mapping

Quantile mapping is defined as:

$$\hat{x}_{obs} = \mathcal{F}_{obs}^{-1}(\mathcal{F}_{GCM}(x_{GCM}; \vec{\theta}); \vec{\theta})$$

where

$$\mathcal{F}_{GCM}(x_{GCM}; \vec{\theta})$$

is the cumulative distribution function calculated from the GCM (simulation) of variable x at location θ

$$\mathcal{F}_{obs}(x_{obs}; \vec{\theta})$$

is the cumulative distribution function calculated from the observations - and we use its inverse

The status-quo: Quantile mapping

Quantile mapping is defined as:

$$\hat{x}_{obs} = \mathcal{F}_{obs}^{-1}(\mathcal{F}_{GCM}(x_{GCM}; \vec{\theta}); \vec{\theta})$$

Doesn't take into account:

- Spatial correlations
- Cross variable correlations (e.g. temperature vs pressure)

We cannot have corresponding pairs

For this task, we cannot collect prediction pairs like $\{\vec{x}_{GCM}^{~i}, \vec{x}_{obs}^{~i}\}$

- Even a perfect simulator will diverge
- Pairs can only be collected for short time
- observations
 simulations
 start
- A biased simulator may never revisit of initial states where data was collected
- Cause misalign between train and test data



Unsupervised image-to-image translation networks

summer ←→ winter

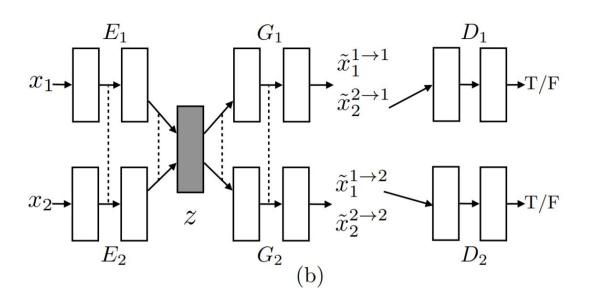
eer oto

video game ←→photo

Liu, Ming-Yu, Thomas Breuel, and Jan Kautz. "Unsupervised image-to-image translation networks." *Advances in neural information processing systems*. 2017.

Zhu, Jun-Yan, et al. "Unpaired image-to-image translation using cycle-consistent adversarial networks." *Proceedings of the IEEE international conference on computer vision*. 2017.

The UNIT network



Components of loss

- L1 loss on image reconstruction
- L1 cycle consistency loss
- GAN loss on translation

Data sources and extent

Climate simulation data source

- HadGEM3
- C20C+ archive
- Historical recreation scenario

"Observations" source

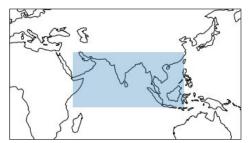
- ERA5

Time overlap

- Jan 1979 Dec 2013
- Approx. 12 000 days

Spatial extent

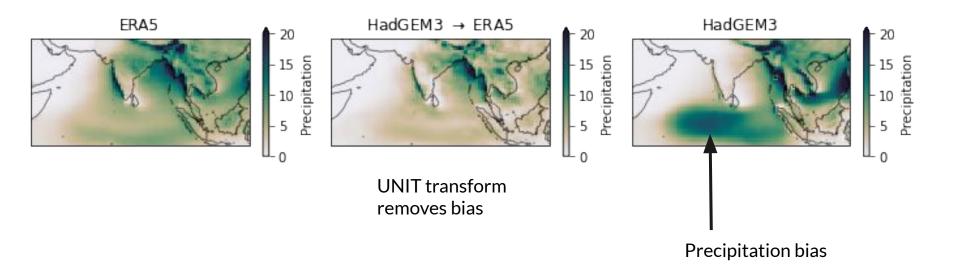
- South Asian monsoon region
- Has large known biases in GCMs
- Hard case to get correct
- 8°S 30°N
- 44°E 121°E



Physical variables

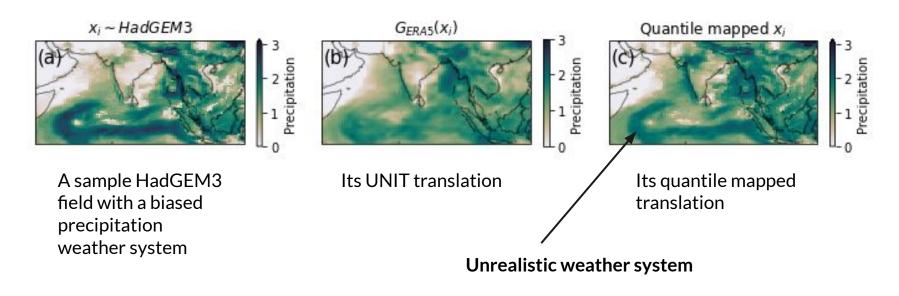
- Daily min, mean and max temperature
- Daily total precipitation
- Z500 geopotential height

UNIT improves monsoon circulation bias



Single example

For precipitation only, other 4 variables not plotted



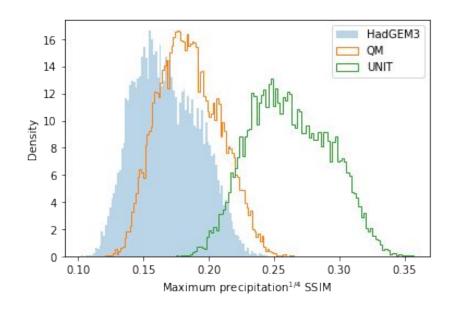
Spatial matching

To assess spatial plausibility of fields

- Take each precipitation field from HadGEM3/QM/UNIT
- Measure structural similarity index measure to all ERA5 precipitation fields
- 3. Keep score of best match

Distribution of best matches

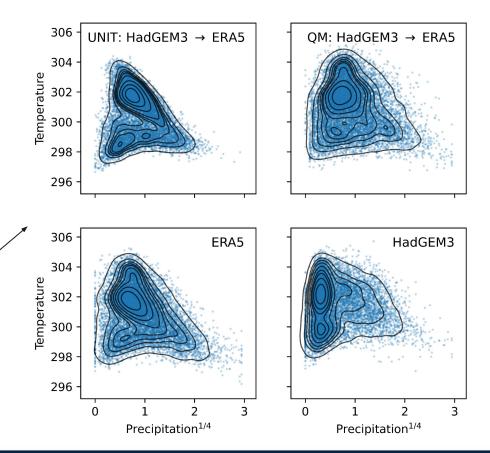
The UNIT translated HadGEM3 data had spatial structures with better matches to the ERA5 data,.



Cross-variable biases

 Joint distribution sampled from single spatial location

 UNIT captures, but over-exaggerates joint distribution structure



Conclusion

UNIT network

- Removes major bias in HadGEM3 precipitation
- Produces precipitation spatial patterns which better match the observations, when compared to baseline
- Corrects the joint distribution of variables at individual spatial locations

Further developments in techniques that would be beneficial

- Translation with distributions with long tails
- Avoid collapse towards modes in joint-distributions i.e. more diversity

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