Improving the predictions of ML-corrected climate models with novelty detection

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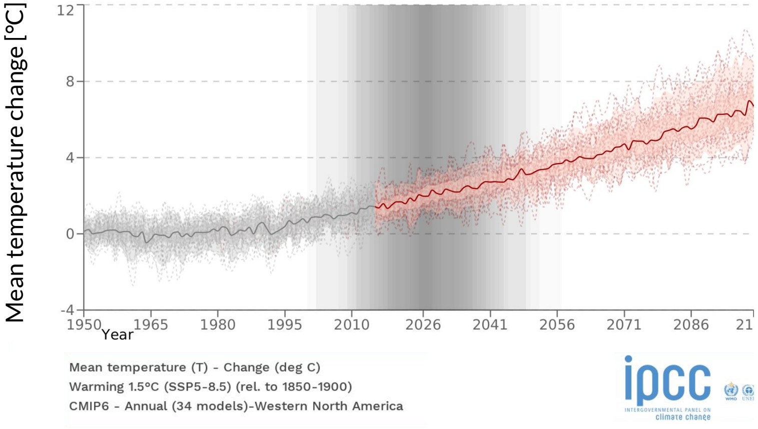
AI2

Why are we doing this?



IPCC AR6 Atlas (CMIP6 models)

Western North America **temperature**

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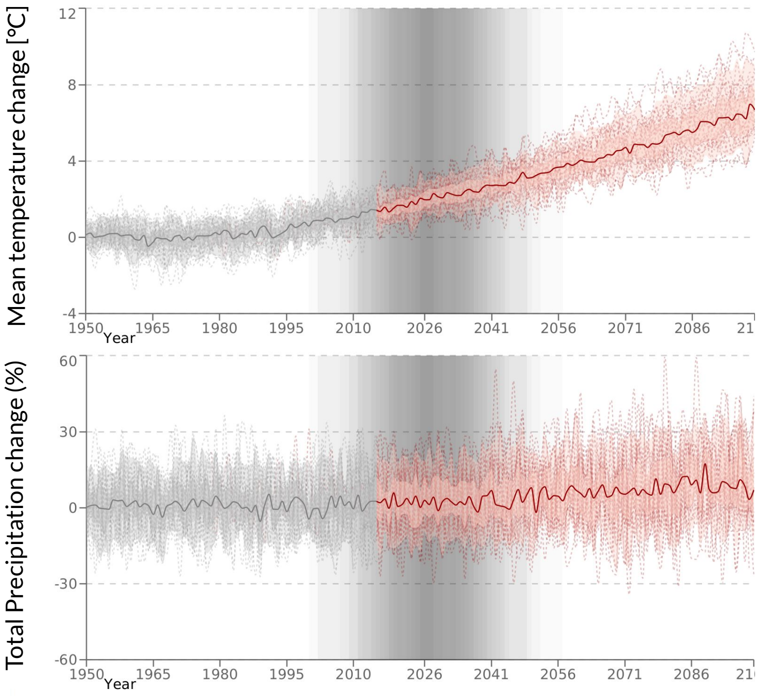


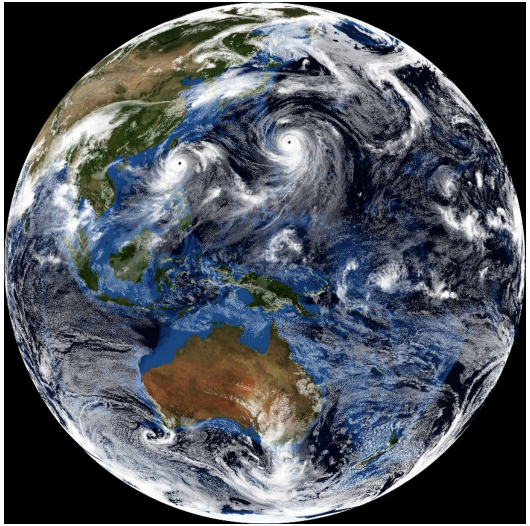
Total precipitation (PR) - Change (%)
Warming 1.5°C (SSP5-8.5) (rel. to 1850-1900)
CMIP6 - Annual (33 models)-Western North America

Western North America **temperature** and **precipitation**

Models have **less agreement** about future local precipitation trends compared to temperature. This matters!

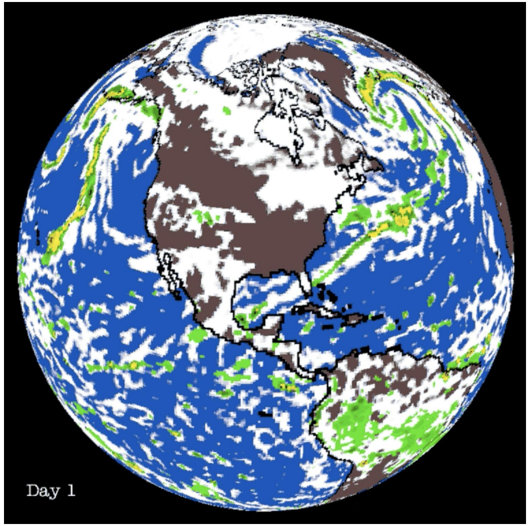
ML Goal: Improve coarse-model simulations

High fidelity reference
reanalysis or
fine-grid (~3km) simulation



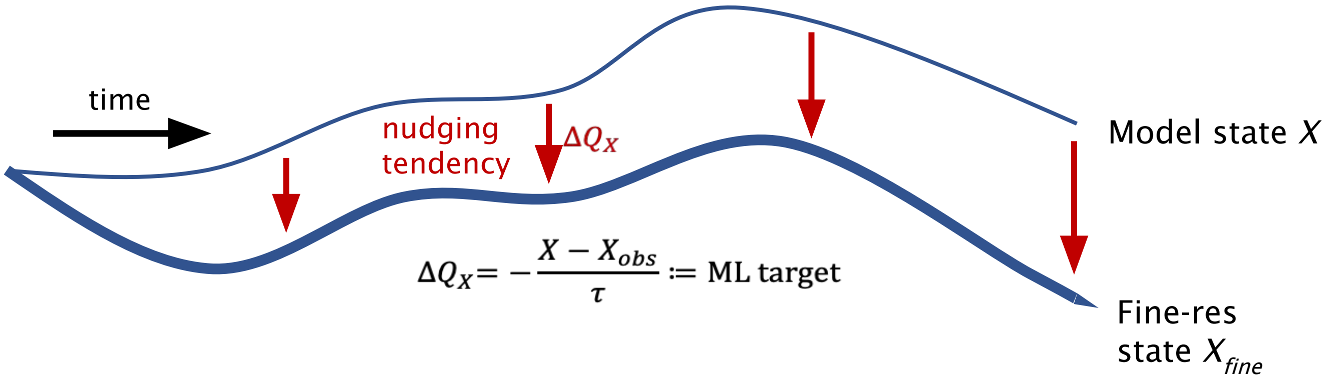
Use machine learning to make coarse model behave more like reference

Climate model (25-200 km)



Corrective approach

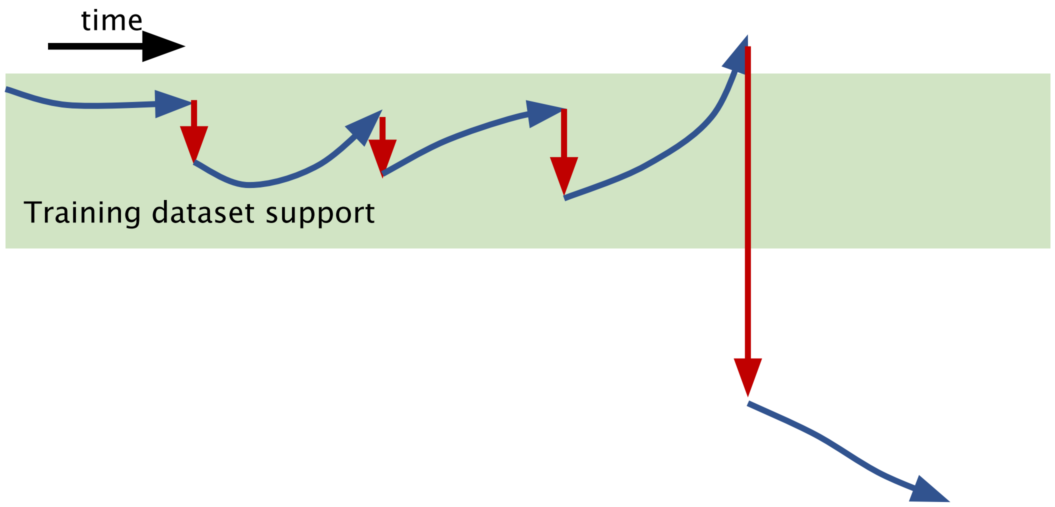
1. Nudge coarse-resolution model towards reference dataset
2. Train ML to predict nudging tendencies with input coarse-resolution state
3. Run coarse-resolution model, with ML corrective tendency at each step



Limitations of corrective approach

- ML corrective tendencies inaccurate & unstable outside training dataset
- Simulation is an online process and can produce out-of-sample data

ML-corrected simulations behave erratically & perform poorly (especially when winds included)



Stabilization with novelty detection

- **Novelty detection** is a branch of self-supervised learning that predicts whether a sample belongs to a distribution given draws from distribution

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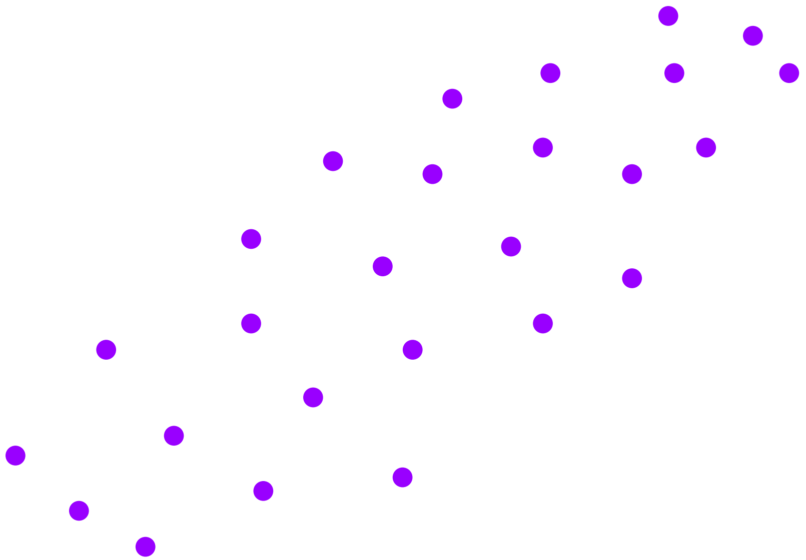

Training sample

Stabilization with novelty detection

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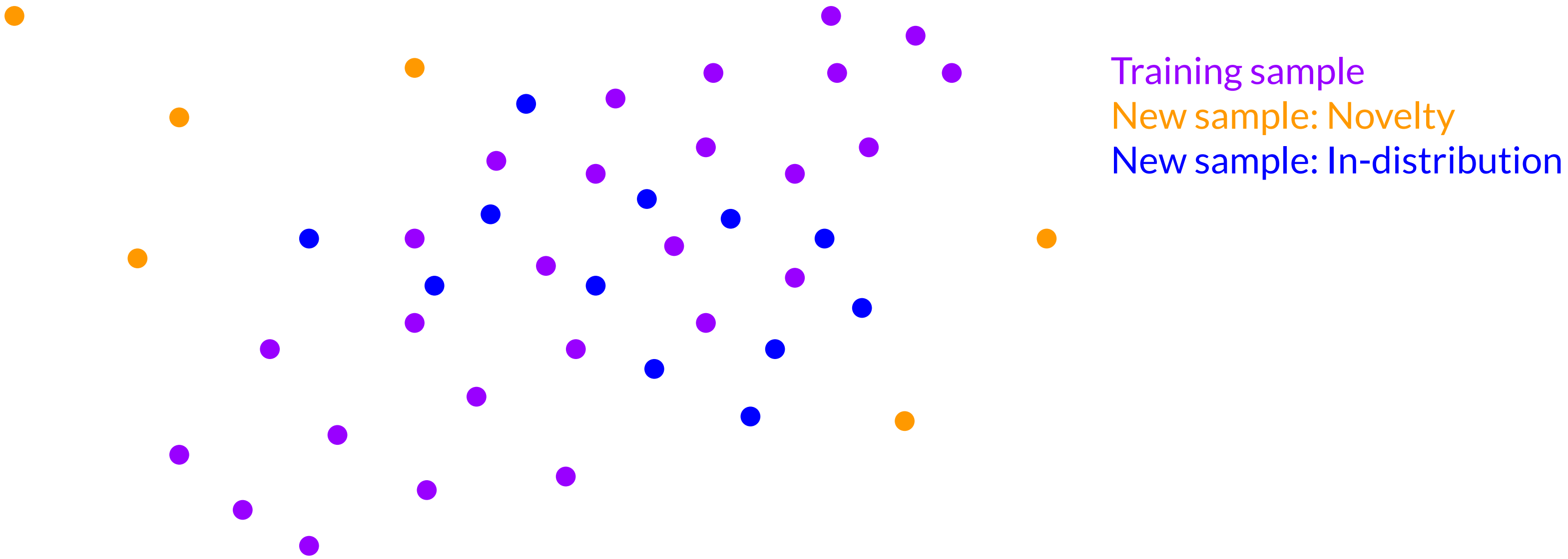

Stabilization with novelty detection

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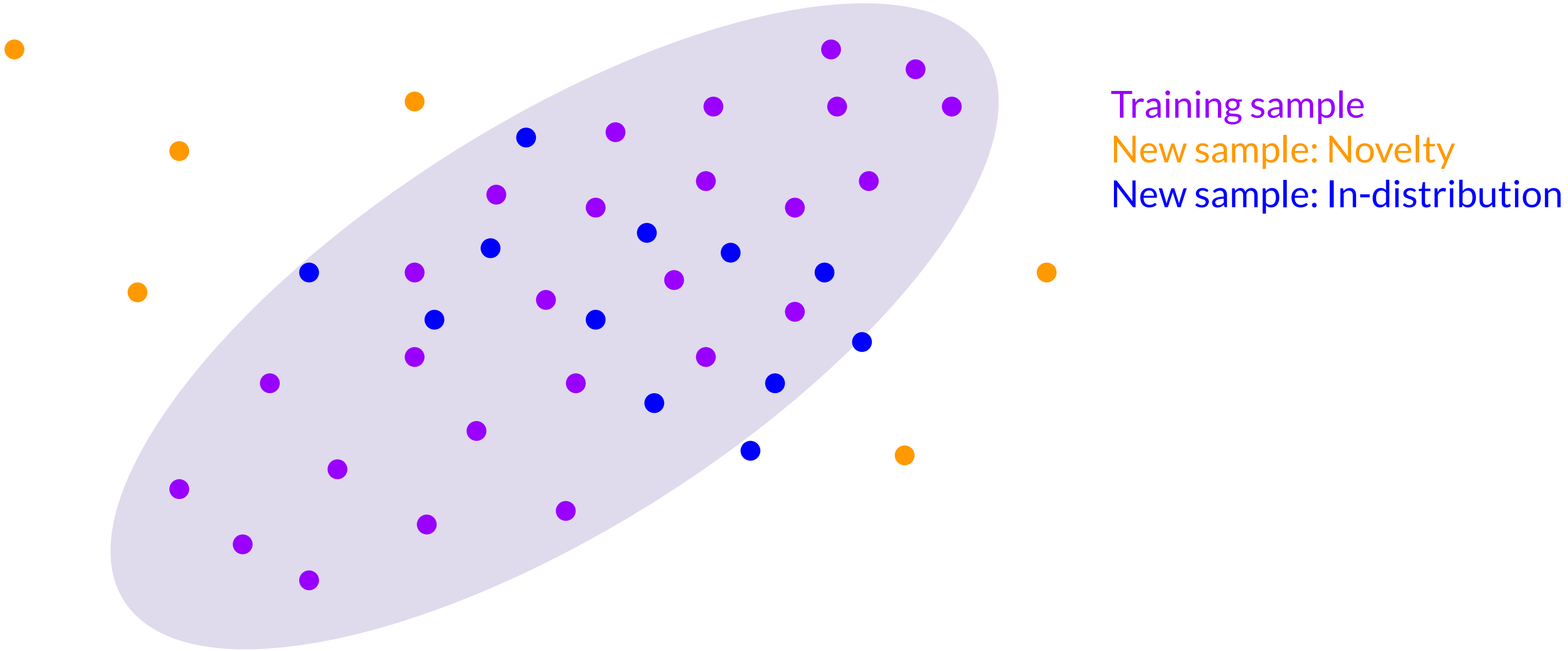
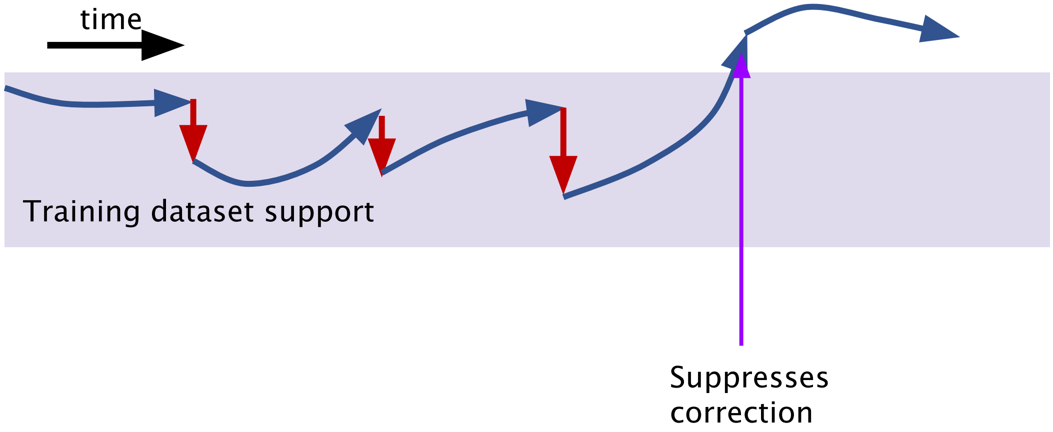


Stabilization with novelty detection

- **Novelty detection** is a branch of self-supervised learning that predicts whether a sample belongs to a distribution given draws from distribution
- Idea: If simulation drifts out-of-sample, disable ML correction

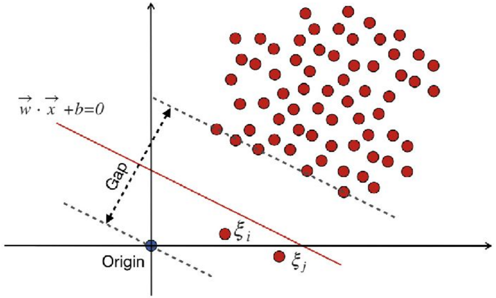


One-Class Support Vector machine (OCSVM)

- **Idea:** Directly estimate support of distribution by identifying compact region that contains all samples
- Maximize distance between dataset $\{x_1, \ldots, x_n\} \in \mathbb{R}^d$ and the origin under feature mapping $\Phi: \mathbb{R}^d \to F$
- Radial basis function (RBF) kernel
- **Alternatives:** covariance estimation, local outlier factor, other kernels

$$\min_{w \in F, \xi \in \mathbb{R}^n, \rho \in \mathbb{R}} \quad \frac{1}{2}\|w\|^2 + \frac{1}{\nu n}\sum_i \xi_i - \rho$$

$$\text{subject to} \quad (w \cdot \Phi(\mathbf{x}_i)) \geq \rho - \xi_i, \quad \xi_i \geq 0.$$



Our findings

- OCSVM novelty detection improves temperature and precipitation predictions over baseline and ML-corrected simulations

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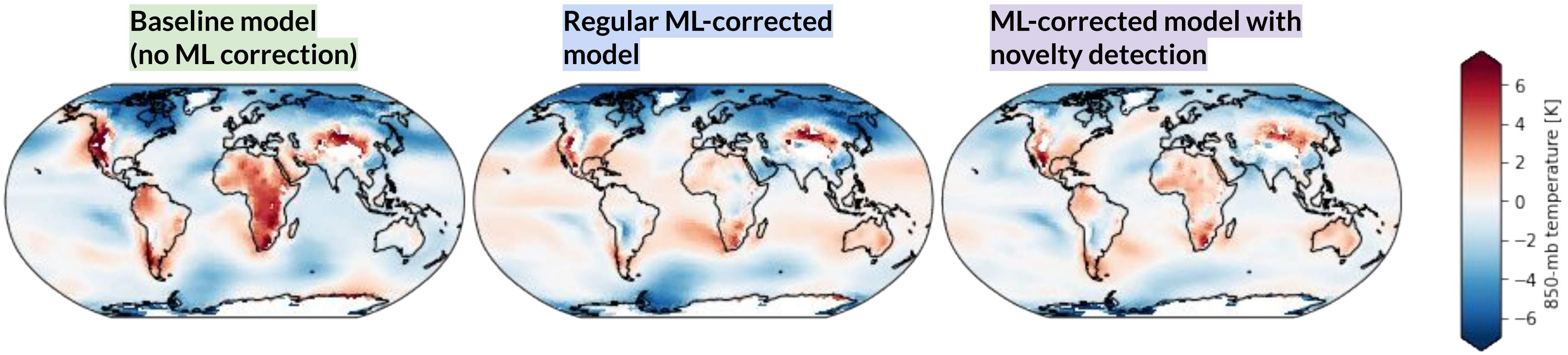
Time-averaged Near-surface Temperature Bias [K]



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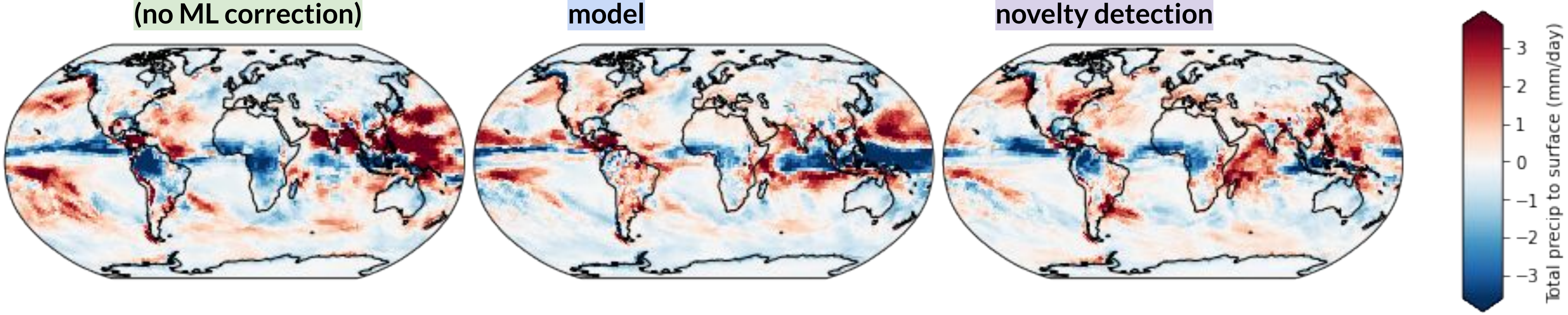
Time-averaged Surface Precipitation Rate Bias [mm/day]

Baseline model (no ML correction)

Regular ML-corrected model

ML-corrected model with novelty detection



Our findings

- OCSVM novelty detection improves temperature and precipitation predictions over baseline and ML-corrected simulations

	Run	T (K)	SP (mm/day)	PWAT (kg/m^2)
1	Baseline (1)	2.09	1.78	2.79
2	ML-corrected (2) with g_{Tq}	1.86	1.43	3.31
3	ML-corrected with g_{Tquv}	2.43	3.39	5.33
4	ND ML (3) with $g_{\mathrm{Tq}}, \eta_{\mathrm{T,OCSVM}}$	1.97	1.49	3.65
5	ND ML with $g_{\mathrm{Tquv}}, \eta_{\mathrm{T,minmax}}$	5.15	3.57	10.14
6	ND ML with $g_{\mathrm{Tquv}}, \eta_{\mathrm{T,OCSVM}}$	1.58	1.40	2.66
7	ND ML with $g_{\mathrm{Tquv}}, \eta_{\mathrm{Tq,OCSVM}}$	**1.53**	**1.24**	**2.37**

Conclusion

- **Developed a pipeline for incorporating novelty detection into an ML-corrected climate model.**
- **Novelty detection improves temperature & humidity prediction of coarse-grid ML-corrected climate models.**
- Future work: build on this proof-of-concept and experiment with other novelty detectors, parameters, and ML correction approaches.
- A version of this appeared at the NeurIPS 2022 “Tackling Climate Change with ML” workshop and is on arXiv. Check it out →
- Submission planned to JAMES journal, with some experimental changes due to upstream bug fix.

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