PLANETTE

Leveraging CESM2 data for machine learning based S2S forecasting

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AI Foundation Models

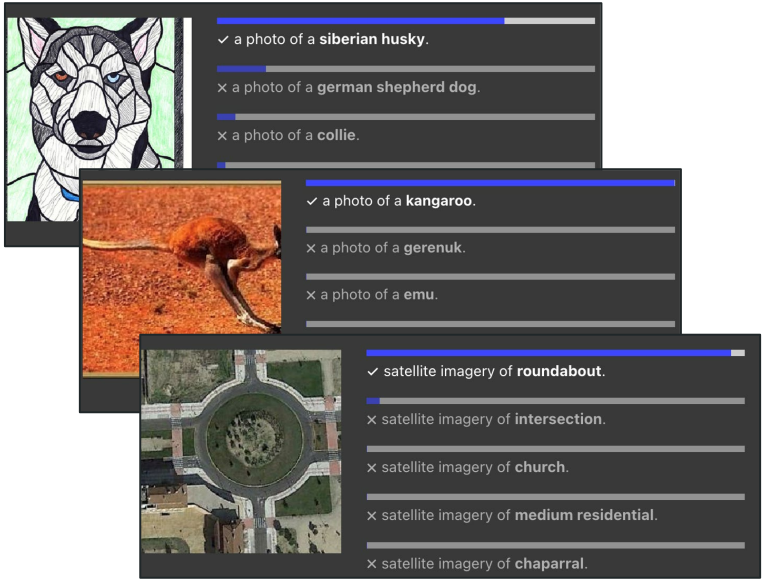
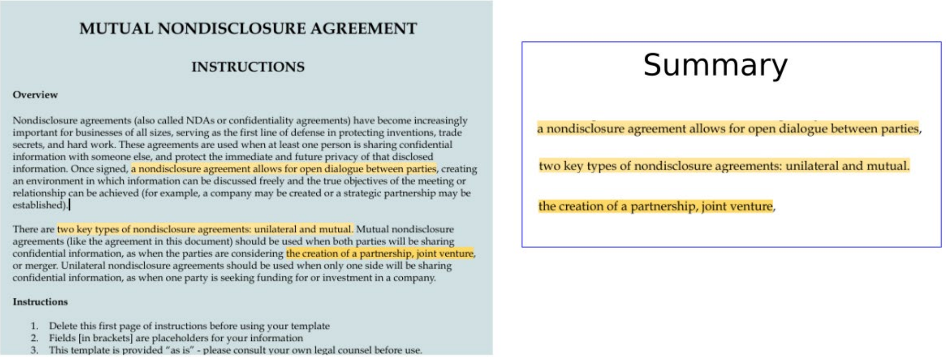


Image Classification [1]

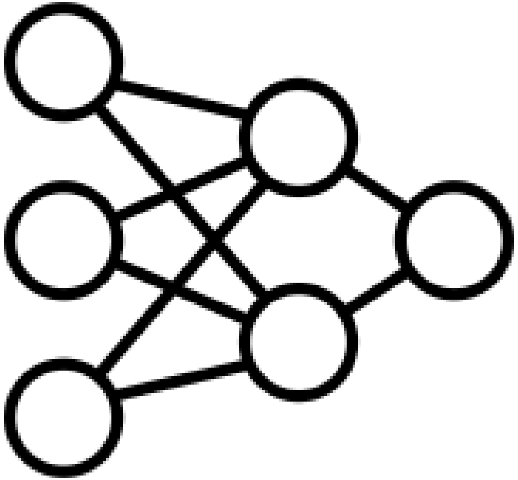
Image Segmentation [2]



Text Summarization [3]

Pretrain Broad ⟶ Finetune Precise

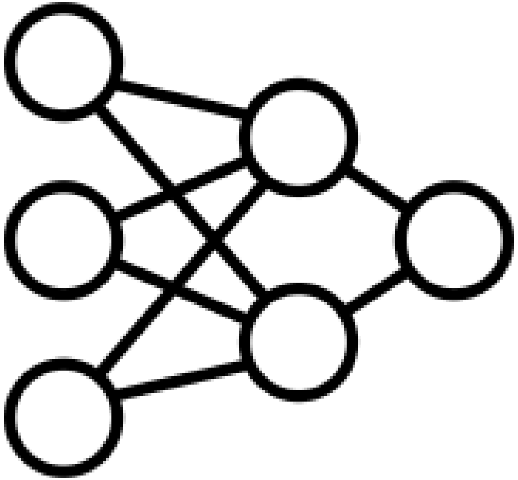
Data ~ 5M datapoints



Simple Objective/
Same as Finetuning
Objective

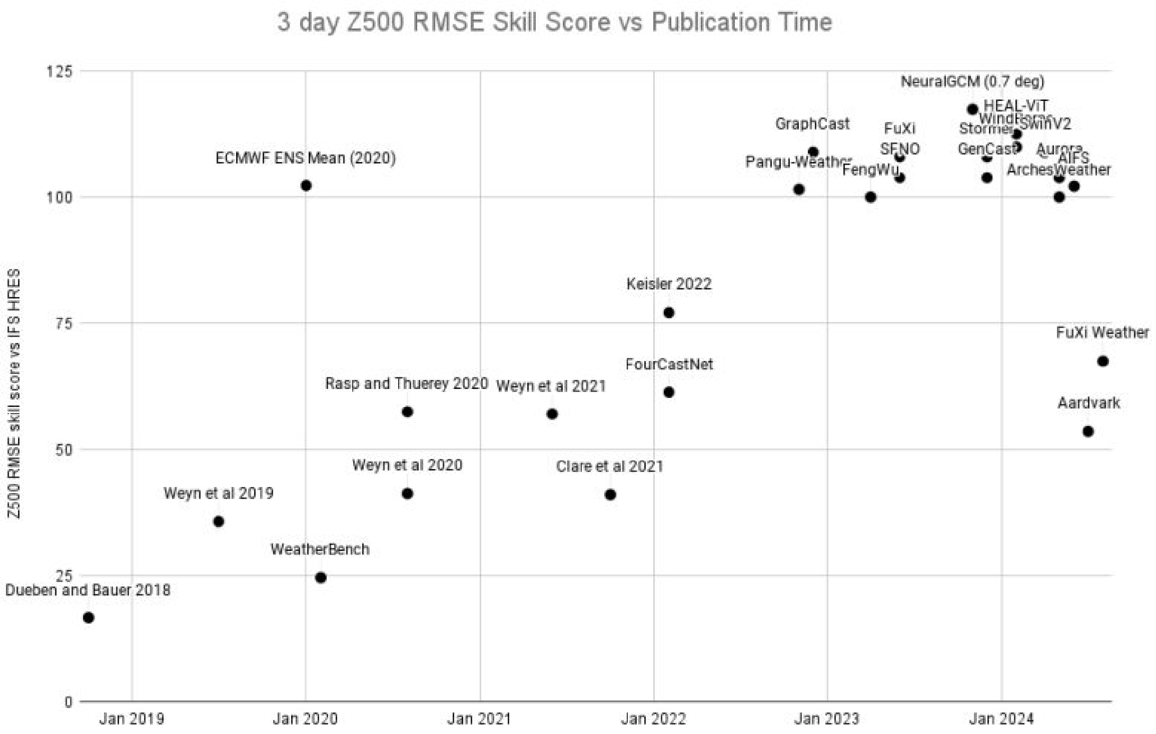
Pretrain Broad → Finetune Precise

Task Specific Data ~ 500



Specific Task

AI Based Weather Modelling



AI Weather model skill [4]

Data Source - ERA5

Temporal Scale - Hourly

Multiple Downstream Tasks

AI Based S2S Forecasting - Challenges

TASK COMPLEXITY ↑

DATA AVAILABILITY ↓

ERROR BUILDUP ↑

AI based **S2S** forecasting is **difficult** compared to AI based weather forecasting

Increased **task complexity** and additional constraints

Earth System Model Data to the rescue !

ERA5

- 1980 (1940) - 2024
- 527 months
- 1 ensemble member

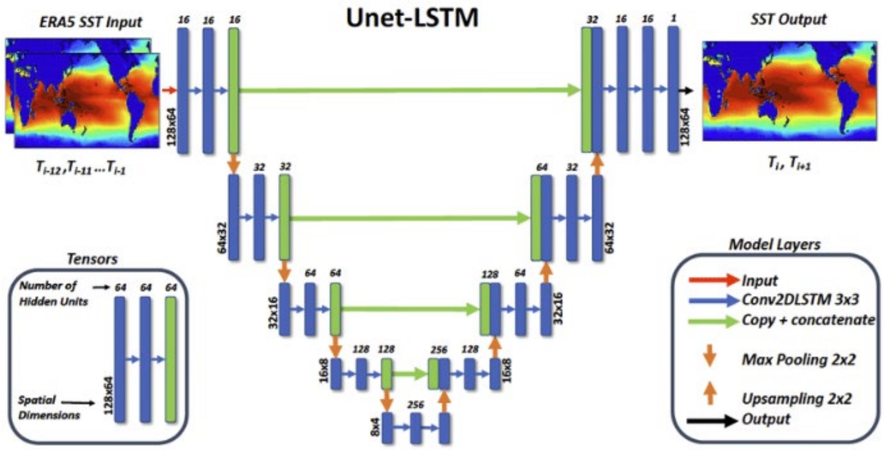
Total Data Points - **527**

CESM2

- 1850 - 2100
- ~3000 months
- 100 ensemble members

Total Data Points - **300,000** !

Our Model

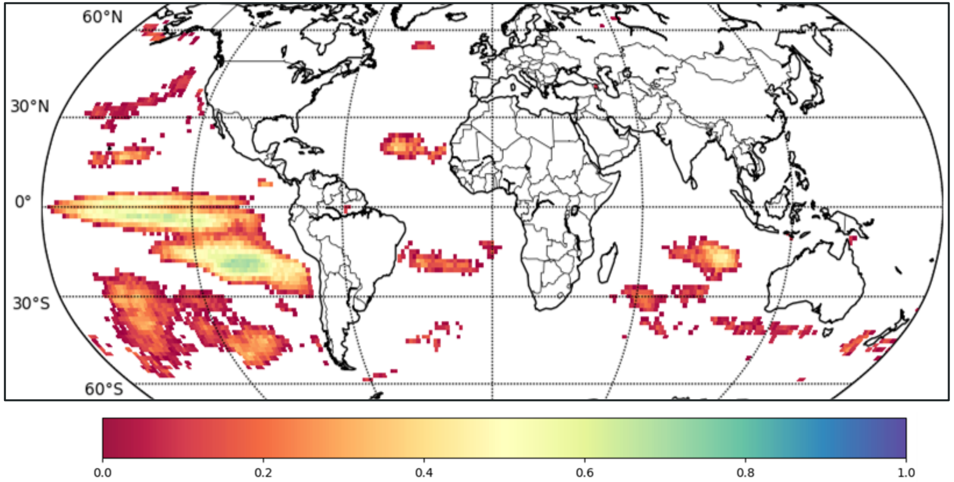


UnetLSTM architecture [5]

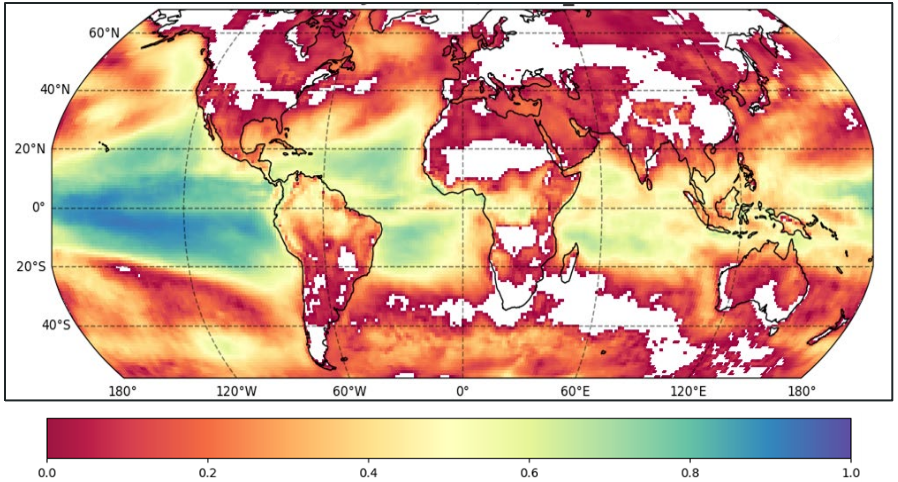
- **Unet-LSTM** - Spatiotemporal
- **Quantile Regression**
- Training Data - **CESM; 1850 - 1922**
- Test Data - **ERA5; 2008 - 2024**
- Grid Resolution - **0.9° x 1.25 °**
- Grid - **60°S to 60°N** , 180°W to 180°E
- Input - **11** variables
- Output - **T2M, Precip**
- Lead Times - **{0,1,2,3} months**
- **Metric -** Anomaly R2 ↑

Effect of Training Data on ERA5 Test set

T2M Anomalies



Trained on ERA5



Trained on CESM2

CESM data helps the model learn important large scale features such as ENSO

Lead - 0 month

Increasing Ensemble Members

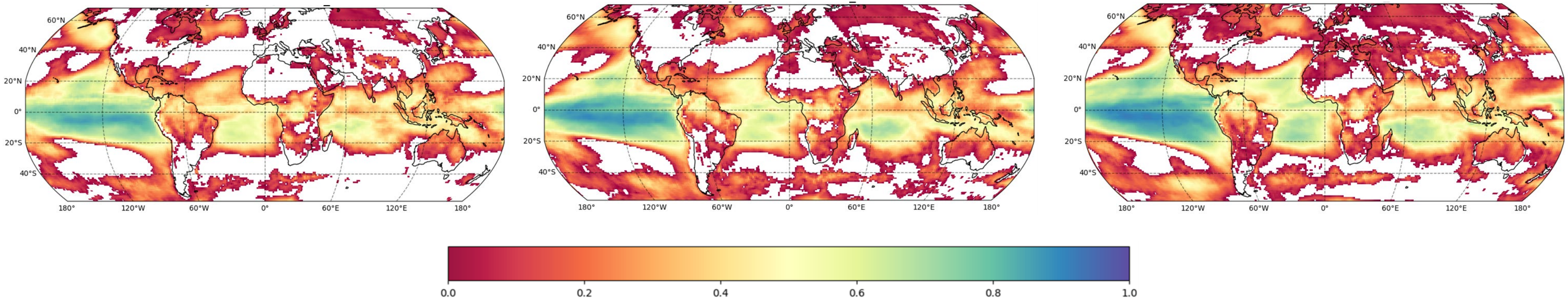
T2M Anomalies

Ensemble Members →

10

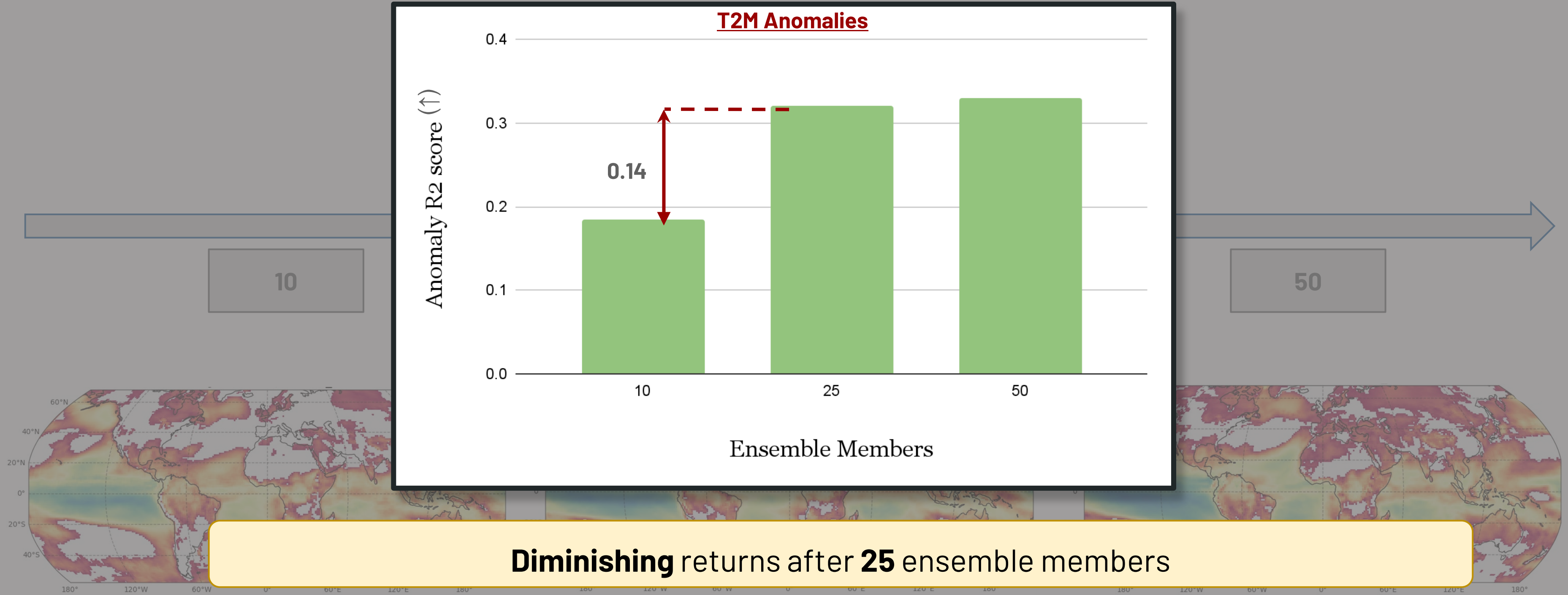
25

50



Lead - 0 month

Increasing Ensemble Members

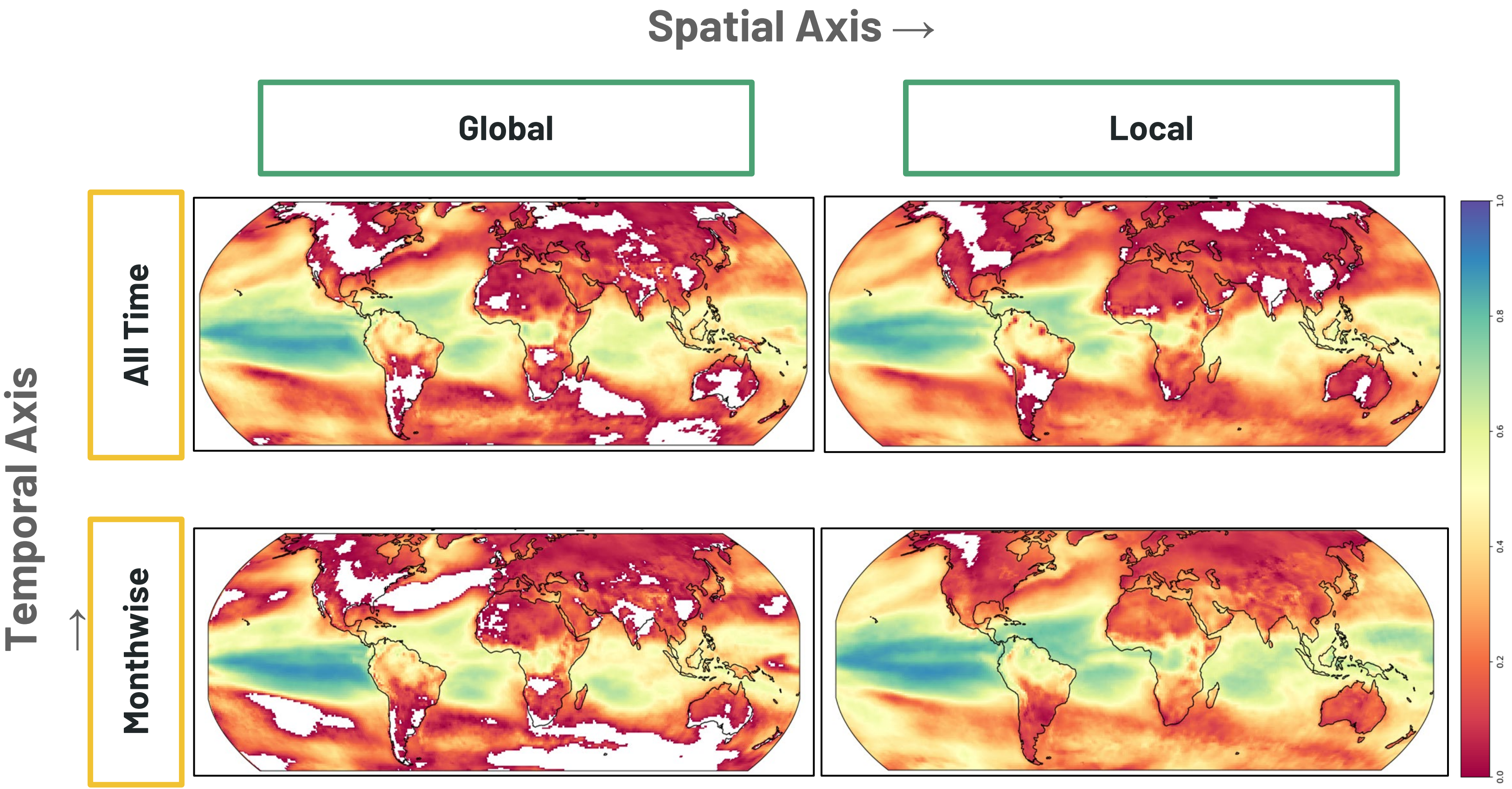


Diminishing returns after **25** ensemble members

Additional ensemble members contribute **minimally** to **unlearned large scale** variability

Capturing **additional patterns** from the noise requires a more **complex model** → **NIVA**

Effect of Data Normalization Strategies on **T2M Anomalies**



Lead - 0 month

Effect of Data Normalization Strategies on T2M

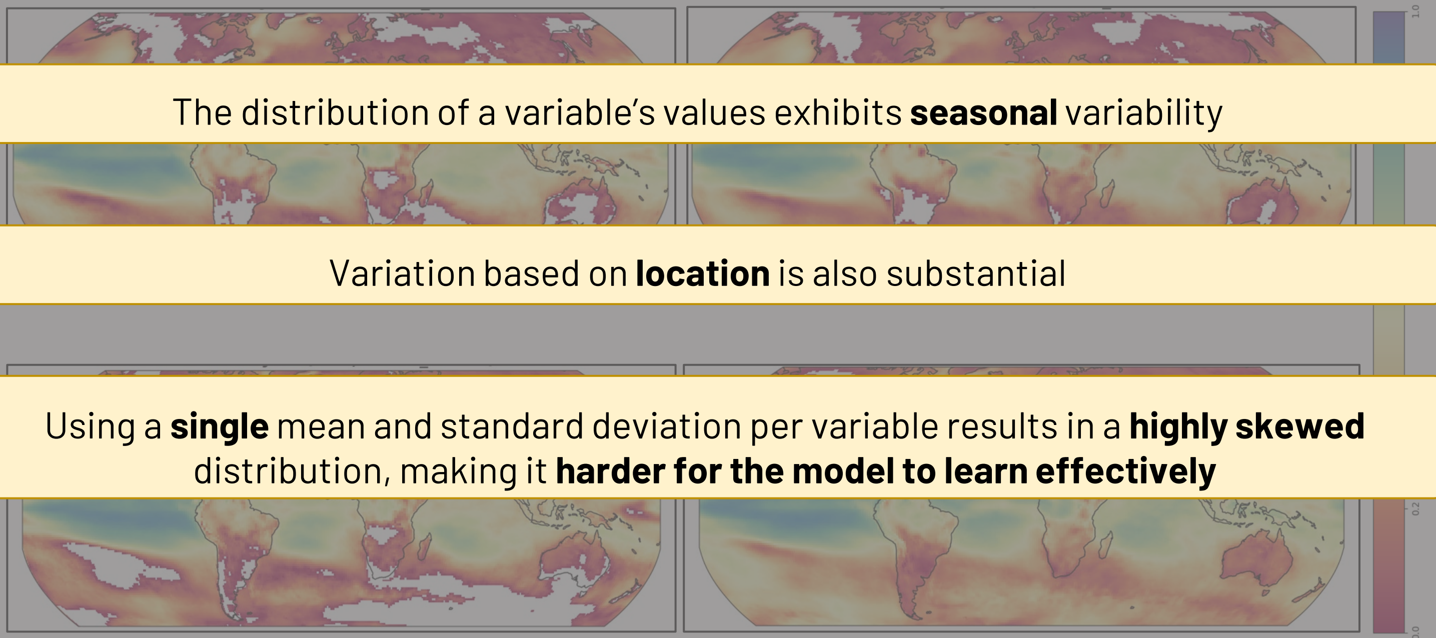
Spatial Axis →

Global | Local

Temporal Axis ↑

All Time

Monthwise



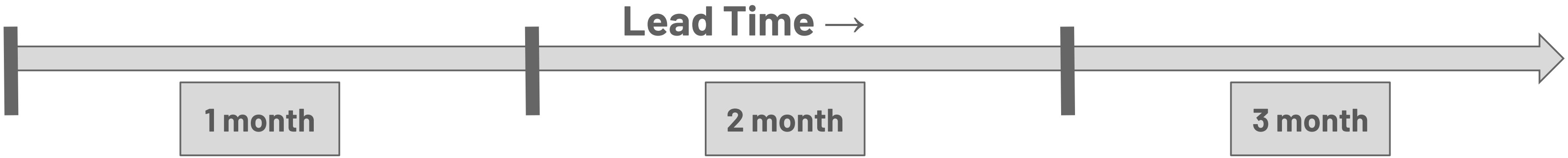
The distribution of a variable's values exhibits **seasonal** variability

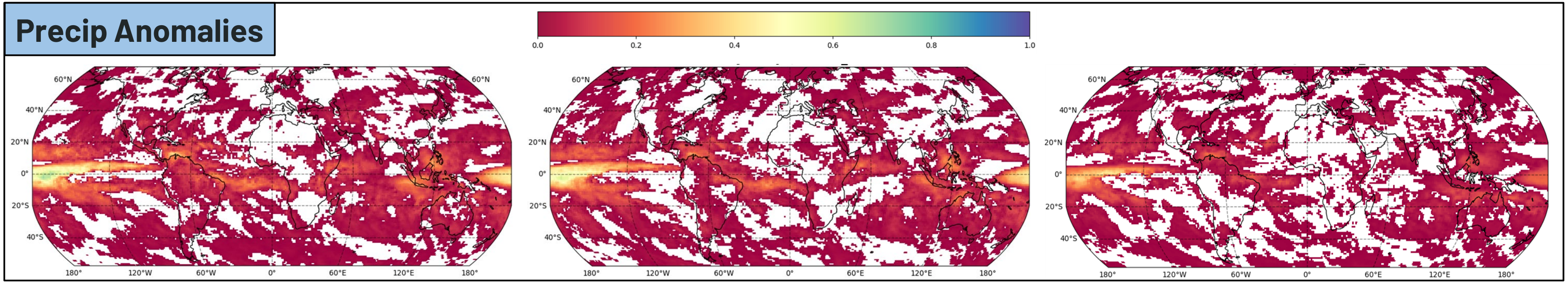
Variation based on **location** is also substantial

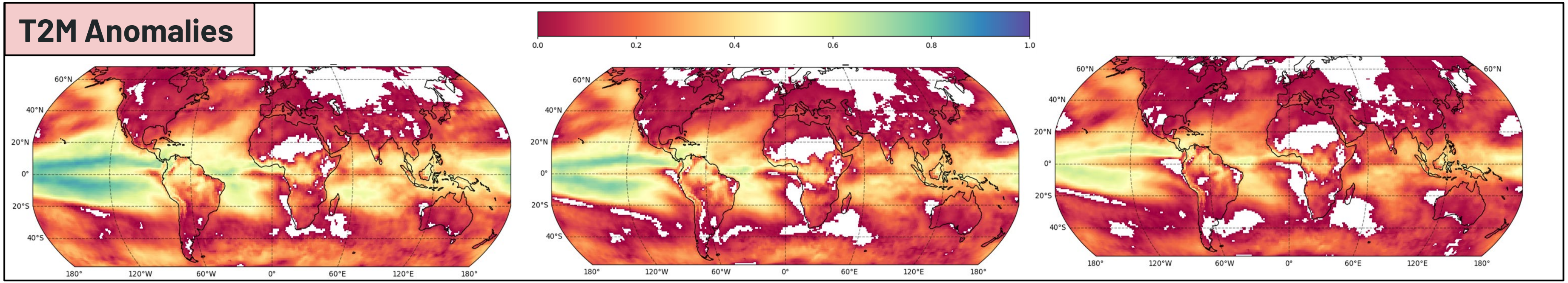
Using a **single** mean and standard deviation per variable results in a **highly skewed** distribution, making it **harder for the model to learn effectively**

Lead - 0 month

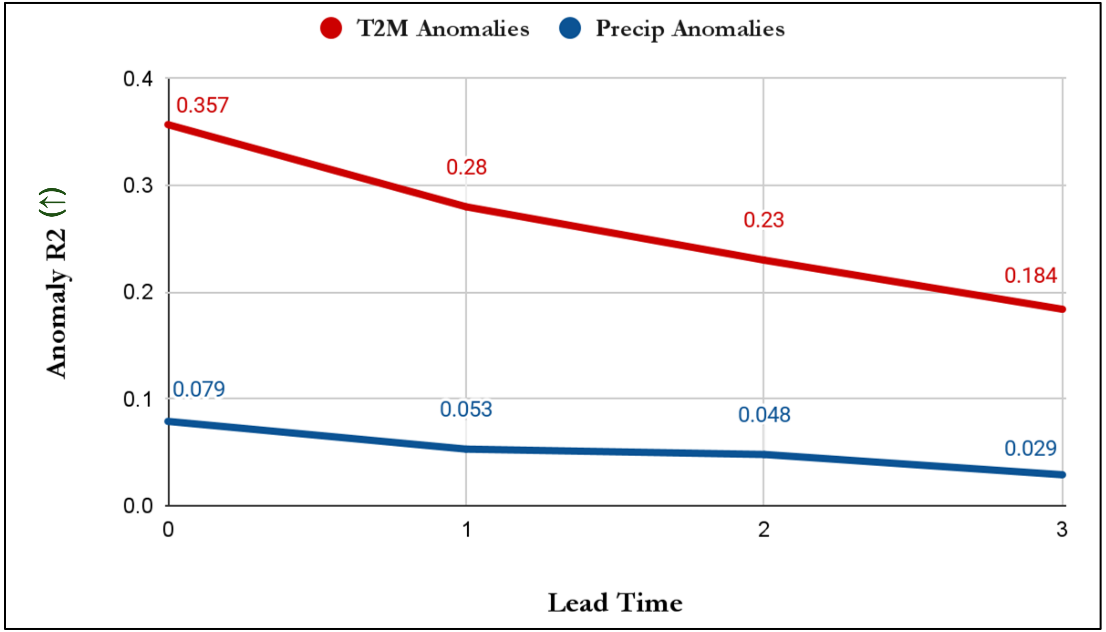
Different Lead Times







Different Lead Times



Model demonstrates greater skill in predicting **temperature** than precipitation

Predictive skill **declines with lead time**, but not as sharply as anticipated.

Key Takeaways

CESM2 data can help create the **next generation of AI foundation models** for S2S scale

Performance is very **sensitive the distribution of data** - picking the right normalization scheme is important

More data is beneficial but **model complexity** also needs to be scaled accordingly

References

[1] Radford, A., Kim, J. W., Hallacy, C., Ramesh, A., Goh, G., Agarwal, S., … Sutskever, I. (2021). Learning Transferable Visual Models From Natural Language Supervision. *arXiv [Cs.CV]*. Retrieved from http://arxiv.org/abs/2103.00020

[2] Kirillov, A., Mintun, E., Ravi, N., Mao, H., Rolland, C., Gustafson, L., … Girshick, R. (2023). Segment Anything. *arXiv [Cs.CV]*. Retrieved from http://arxiv.org/abs/2304.02643

[3] Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. *arXiv [Cs.CL]*. Retrieved from http://arxiv.org/abs/1810.04805

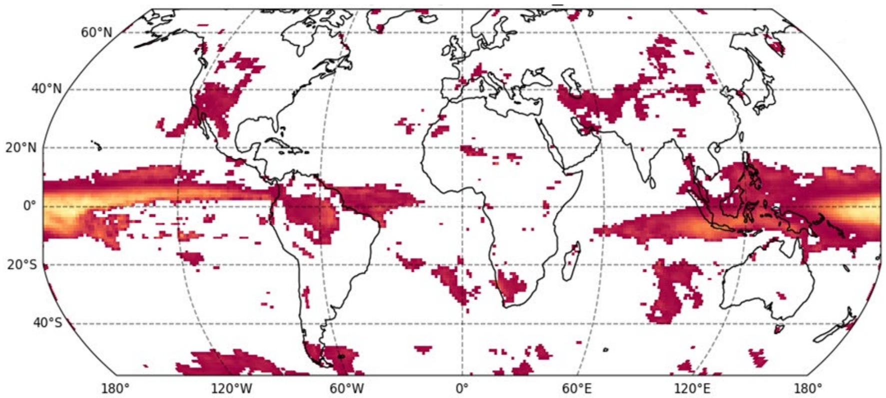
[4] Rasp, S. (2024, November 13). *Here is an updated version of my chart showing the progress of AI-weather. . . | Stephan Rasp | 22 comments [Online forum post]*.https://www.linkedin.com/posts/stephan-rasp-4154481aa_here-is-an-updated-version-of-my-chart-showing-activity-7262397352424992770-7TJU

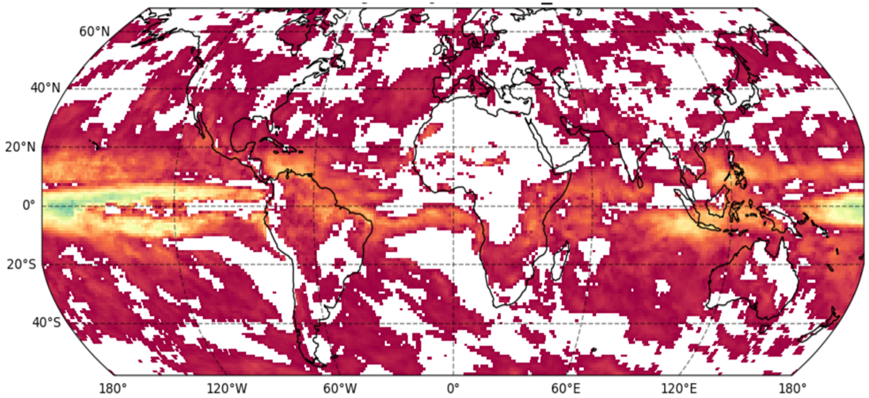
[5] Taylor J and Feng M (2022) A deep learning model for forecasting global monthly mean sea surface temperature anomalies. *Front. Clim.* 4:932932. doi: 10.3389/fclim.2022.932932

Thank You !
Any Questions ?

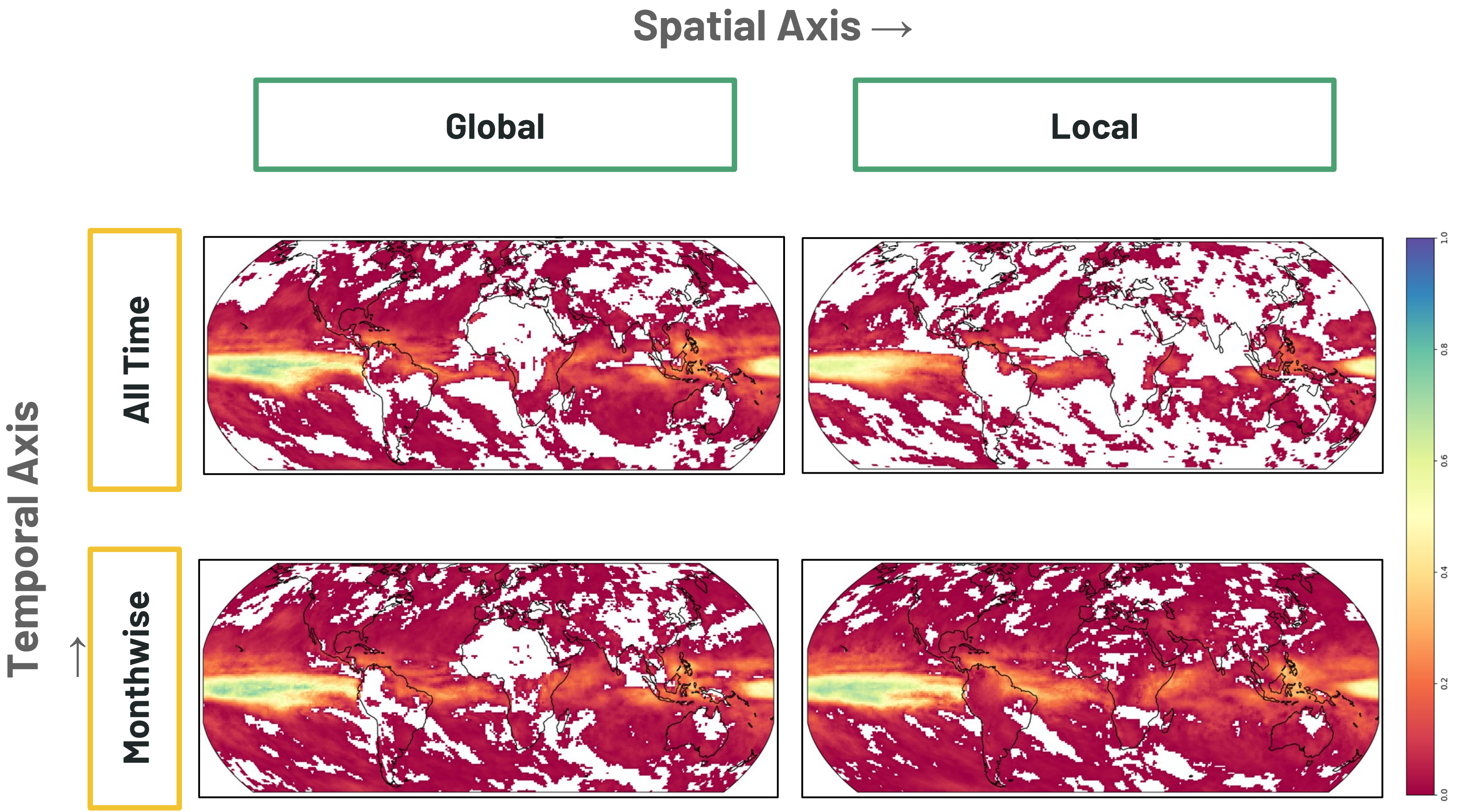
Extra Slides

Effect of Training Data





Effect of Data Normalization Strategies on **Precipitation**

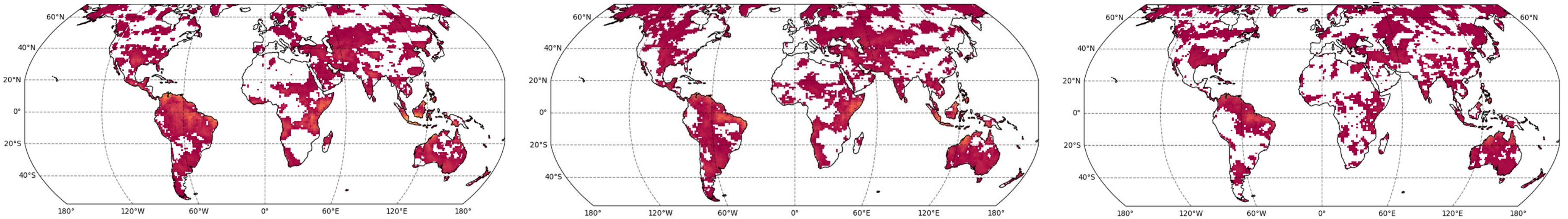


Zero Shot vs Fine Tuning **Precipitation (Land)**

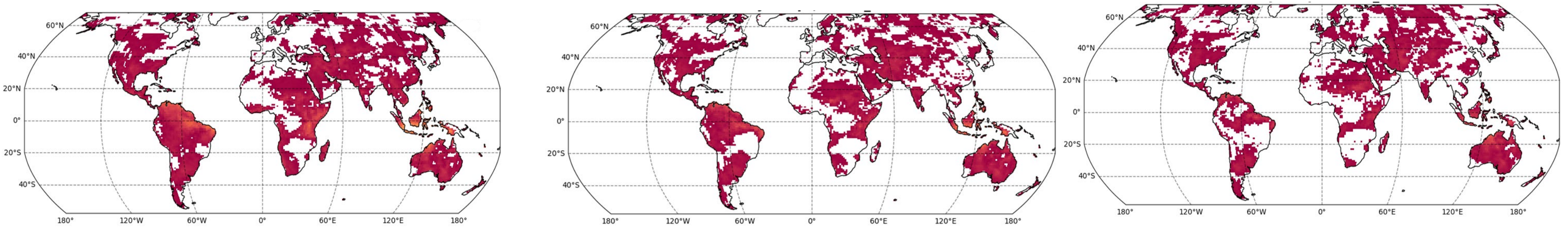
Lead Time →

1 month | **2 month** | **3 month**

Zero Shot



Fine Tuned



Zero Shot vs Fine Tuning T2M (Land)

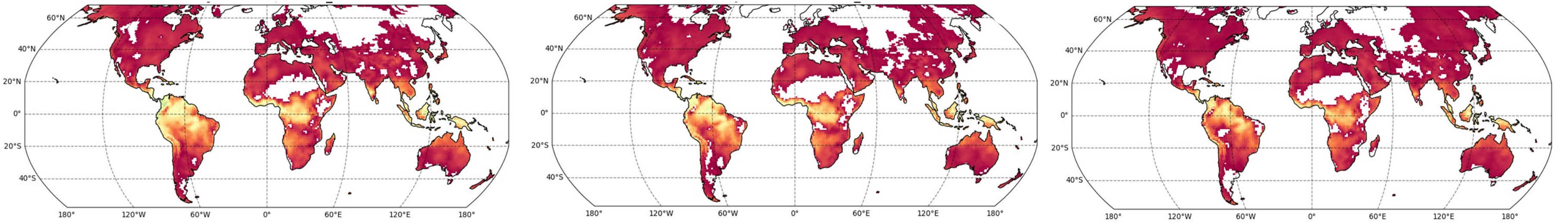
Lead Time →

1 month

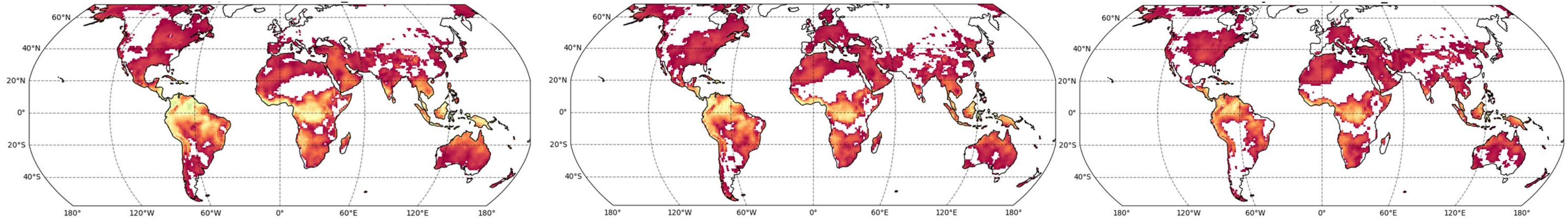
2 month

3 month

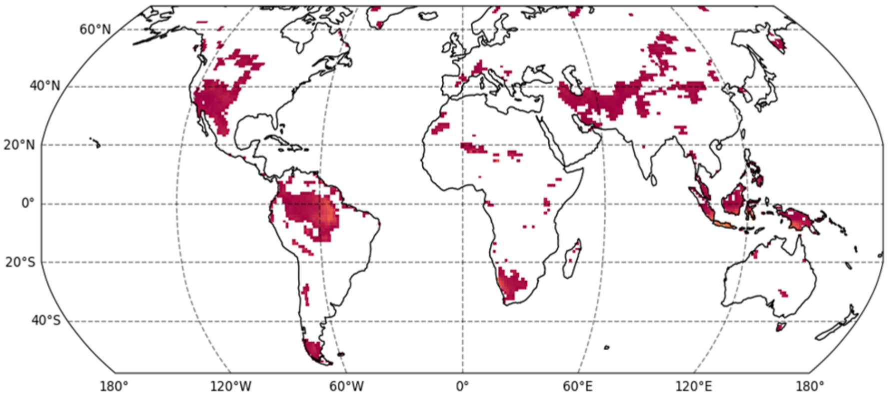
Zero Shot

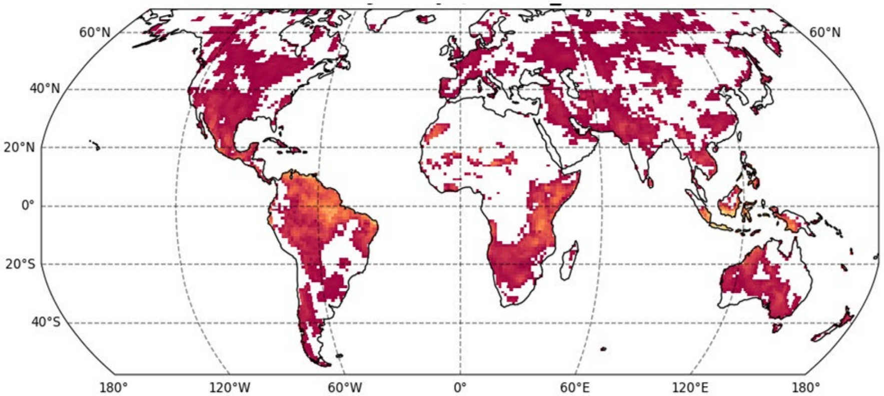


Fine Tuned

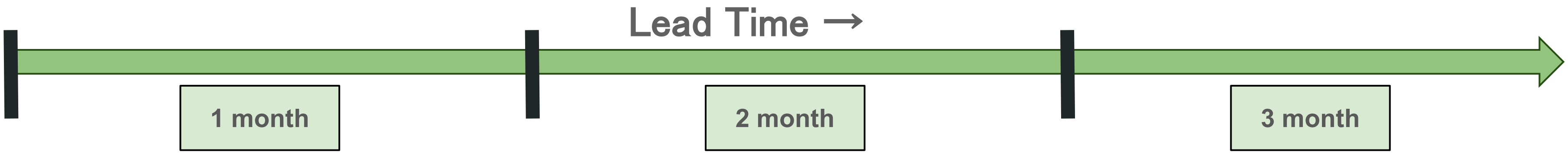


Effect of Training Data

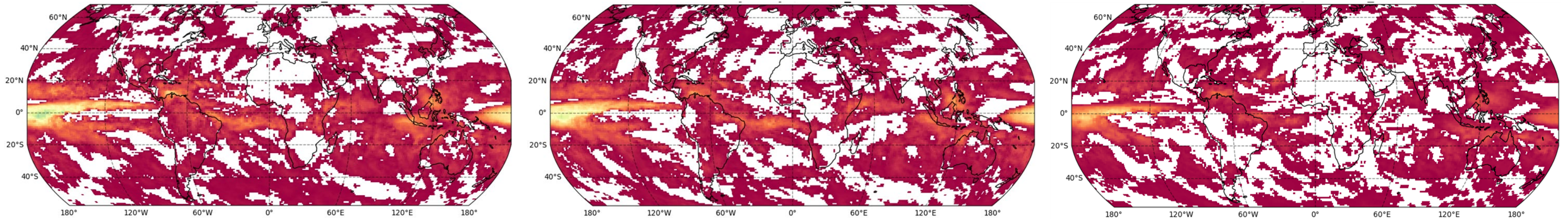




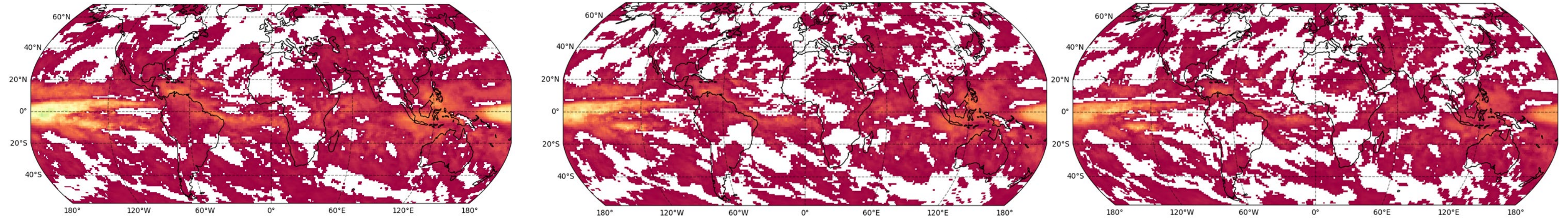
Zero Shot vs Fine Tuning Precipitation



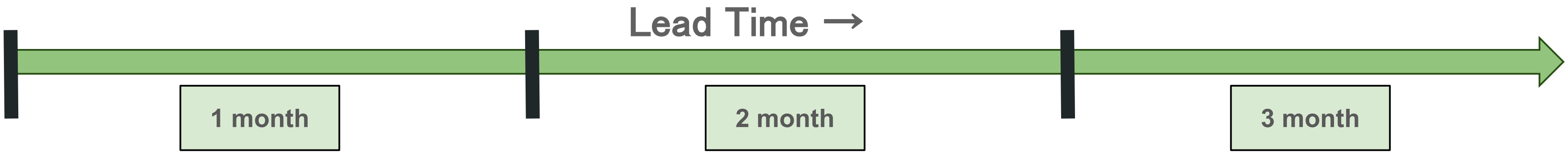
Zero Shot

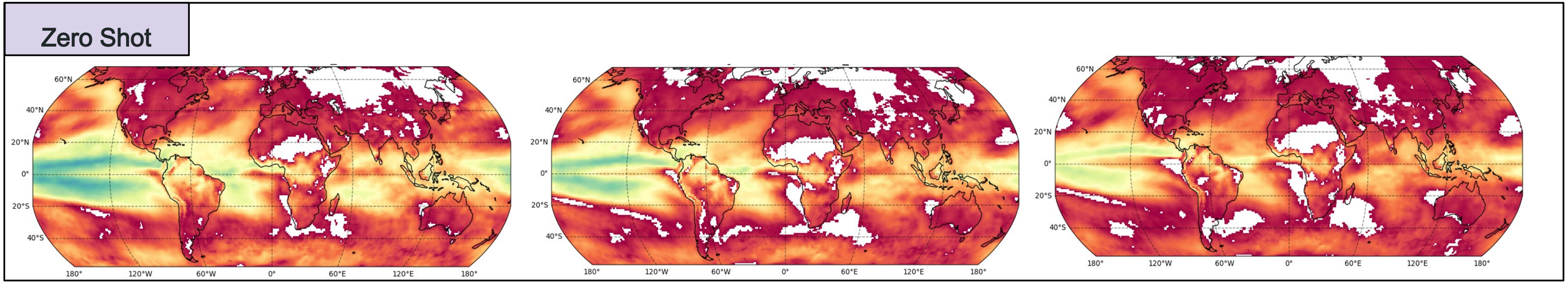


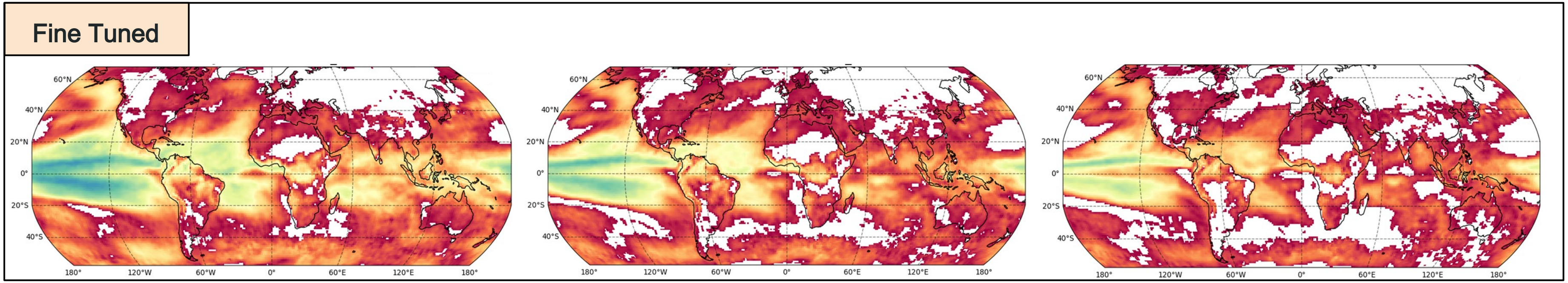
Fine Tuned



Zero Shot vs Fine Tuning T2M







Values

		Precip (All)			
1 month		2 month		3 month	
Zero Shot	Fine Tuned	Zero Shot	Fine Tuned	Zero Shot	Fine Tuned
0.053	0.054	0.048	0.049	0.029	0.036

		Precip (Land)			
1 month		2 month		3 month	
Zero Shot	Fine Tuned	Zero Shot	Fine Tuned	Zero Shot	Fine Tuned
0.043	0.0375	0.035	0.032	0.021	0.0311

Values

		T2M (All)			
1 month		2 month		3 month	
Zero Shot	Fine Tuned	Zero Shot	Fine Tuned	Zero Shot	Fine Tuned
0.28	0.3	0.23	0.24	0.184	0.2

		T2M (Land)			
1 month		2 month		3 month	
Zero Shot	Fine Tuned	Zero Shot	Fine Tuned	Zero Shot	Fine Tuned
0.16	0.18	0.13	0.15	0.116	0.12