Using Time Series Foundation Models for Atmospheric CO_2 Concentration Forecasting

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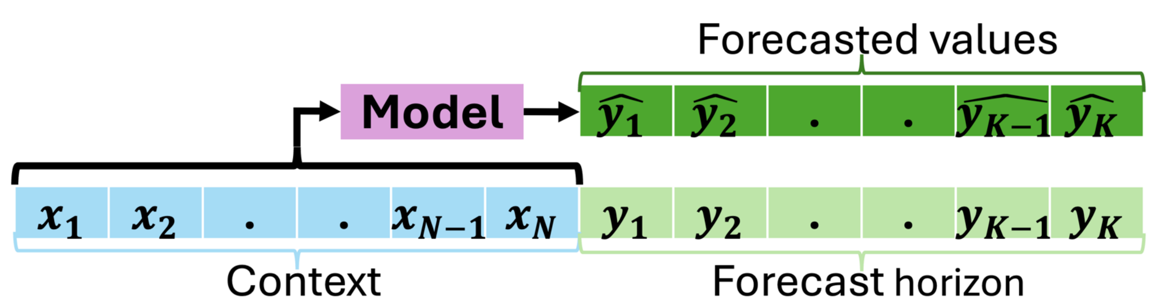
NEURAL INFORMATION PROCESSING SYSTEMS

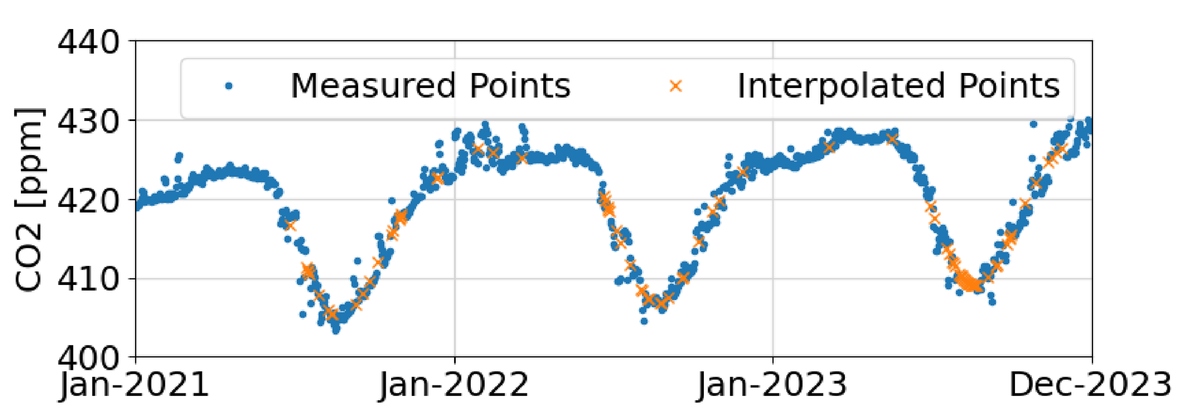
TSFM: Time Series Foundational Models

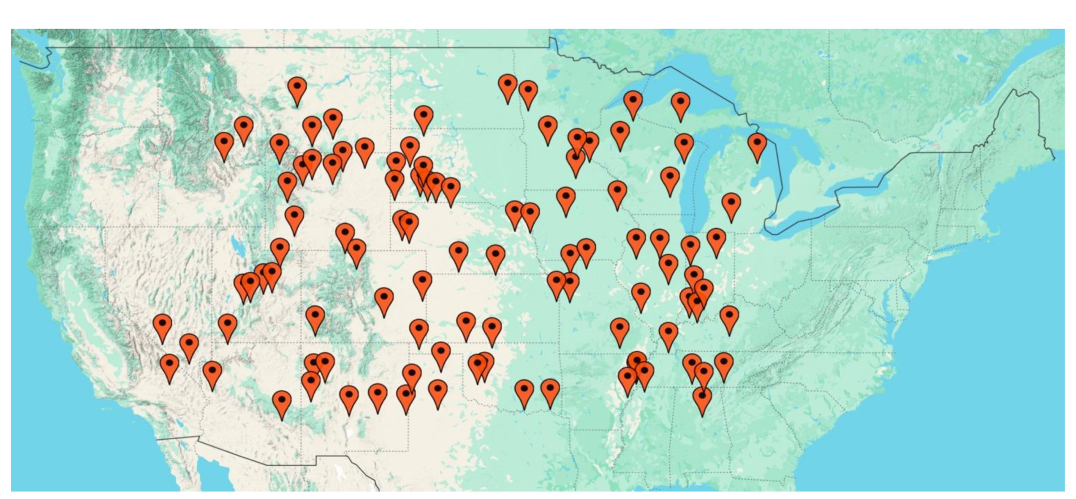
Time series foundation models pre-trained on public timeseries data have demonstrated generalizability in forecasting across multiple domains. They rely on the strengths of architecture to learn generalized representations of time-series data. TSFMs can leverage transfer learning capabilities to forecast in diverse locations by fine-tuning on data from just one location, thus enabling scalable and accurate CO_2 forecasting.



Key contribution of the paper

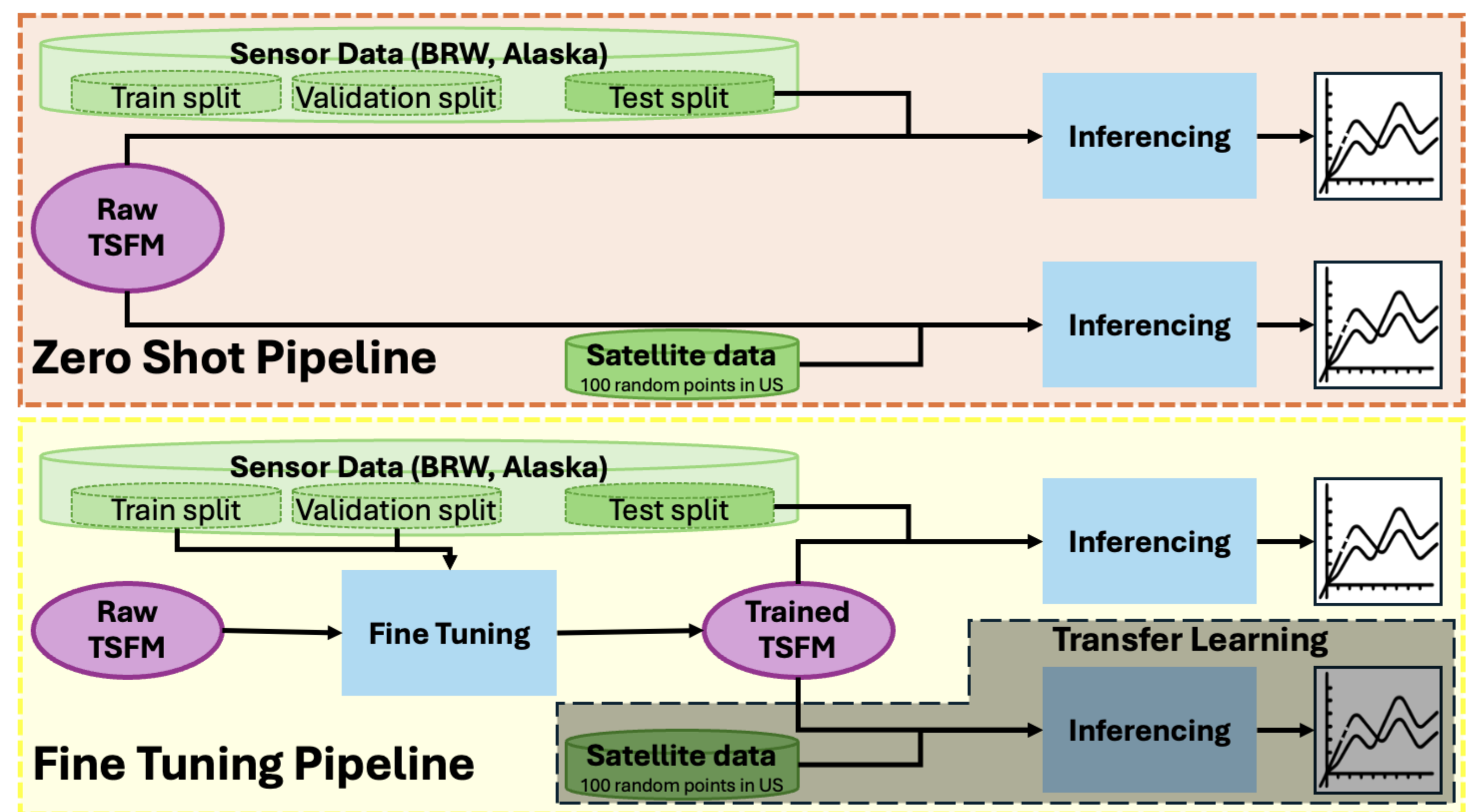
- Evaluating TSFMs to forecast CO_2 data from NOAA sensor in zero-shot and fine-tuned settings.
- Comparing TSFMs with traditional models as baseline, namely: Prophet, Theta-Forecaster, & Seasonal Naive model
- Evaluating spatial transfer learning capability of TSFMs by using fine-tuned models to forecast X-CO_2 concentrations from satellite-based timeseries (OCO-2 and OCO-3) across various geographic regions (100 random locations in USA).





Experimental Setup

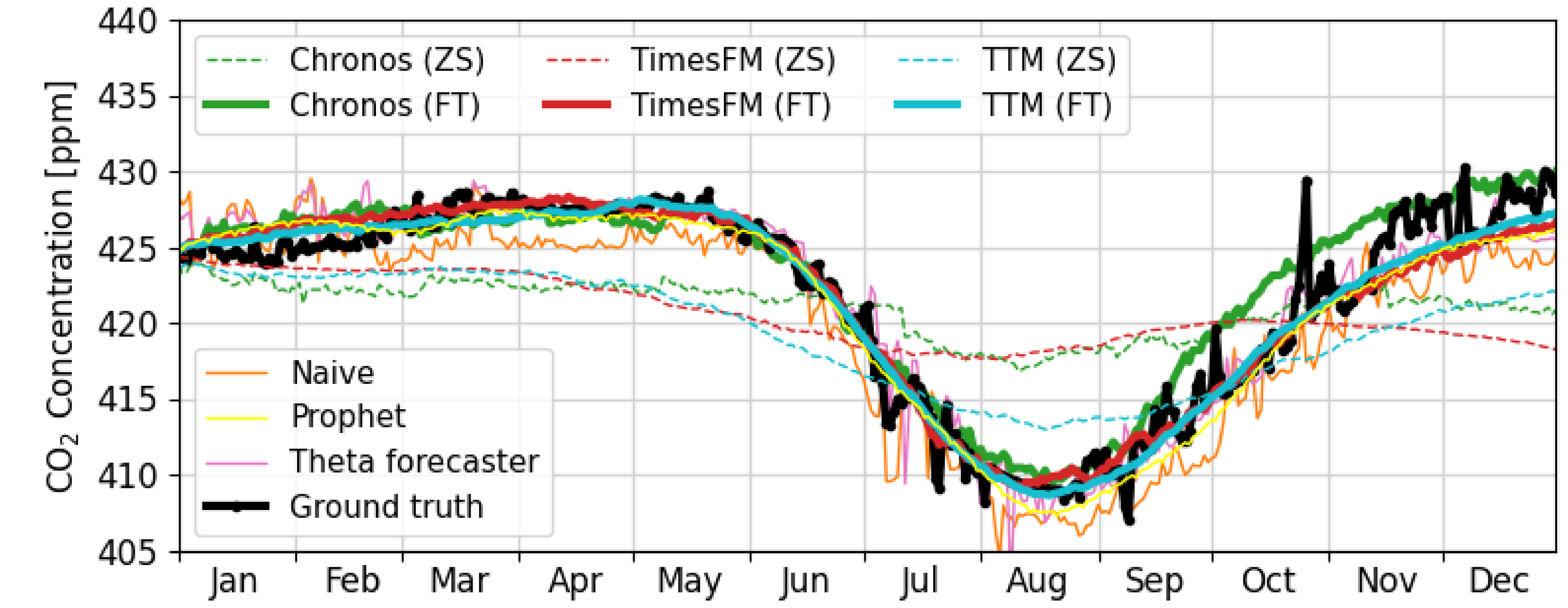
We evaluate the performance of both traditional forecasting models and TSFMs under various settings. We also explore how well the TSFMs generalize across spatial domains to assess the benefits of transfer learning.



- Two evaluation pipelines for TSFMs: Zero-shot & Fine-tuning
- **Zero-Shot(ZS)**: TSFMs are evaluated on NOAA sensor data to assess models' generalization capabilities to a new domain
- **Fine-Tuning (FT)**: TSFMs are fine-tuned using train split of NOAA sensor data; performance is evaluated on test split to quantify improvements through fine-tuning on in-domain data.
- **Transfer Learning**: TSFMs fine-tuned on train split of NOAA sensor data is evaluated on OCO-2 & OCO-3 derived X-CO_2 data for 100 locations in USA to assess transfer learning

Dataset	Model		Parameters	Transfer Learning
CO_2 data from NOAA ground sensor, Barrows, Alaska, USA for 1974 to 2023	TTM	TSFMs are evaluated in two settings for Alaska location: 1. Zero-Shot (ZS) 2. Fine-Tuning (FT)	Context: 1024, Forecast: 365	Fine-tuned model on Alaska data is evaluated on CO_2 derived from satellite for 2019-2023 for 100 locations in USA
	Chronos			
	TimesFM			
	Prophet forecaster		Default params sp = 365	Transfer learning is not applicable for traditional machine learning models
	Theta forecaster			
	Seasonal naive forecaster			

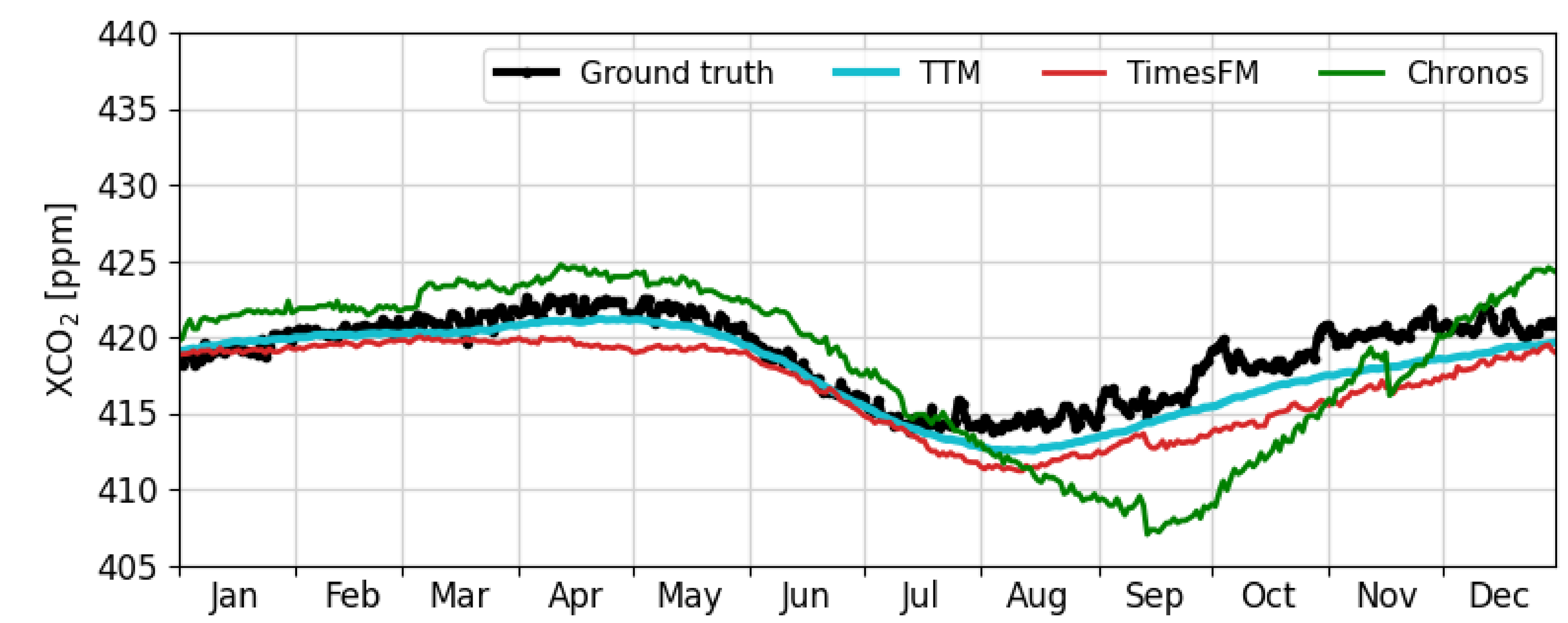
Results: CO_2 forecasting on NOAA sensor data



	Baselines			Chronos		TimesFM		TTM	
	Theta	Naive	Prophet	ZS	FT	ZS	FT	ZS	FT
RMSE	1.85	2.84	1.72	5.16	2.04	5.65	1.55	4.36	**1.37**
MAE	1.33	2.40	1.31	4.59	1.54	4.91	1.09	3.81	**0.95**
MASE	0.47	0.84	0.46	1.61	0.54	1.72	0.38	1.34	**0.34**

- Zero-Shot TSFMs are worse than traditional baselines
- Fine-Tuned TSFMs are better than traditional baselines
- TTM is the best performing model among TSFMs

Results: Transfer learning for XCO_2 for OCO-2/3 derived data for 100 random locations in USA



Transfer Learning		
Chronos	TimesFM	TTM
3.63	2.49	**1.46**
2.93	2.13	**1.19**
1.20	0.87	**0.49**

- Transfer learning is slightly worse than finetuned TSFMs
- TTM performs best under transfer learning setting