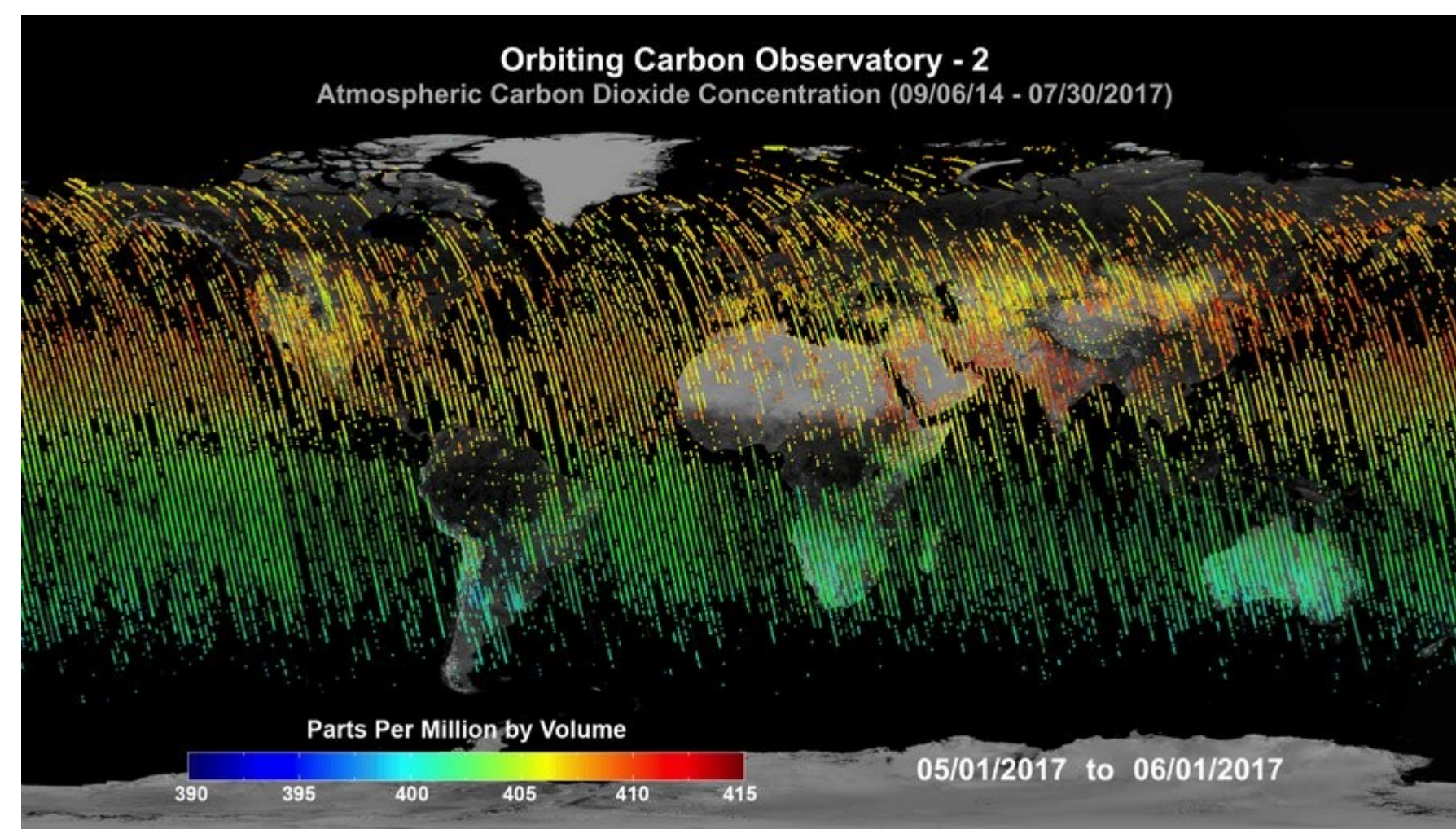
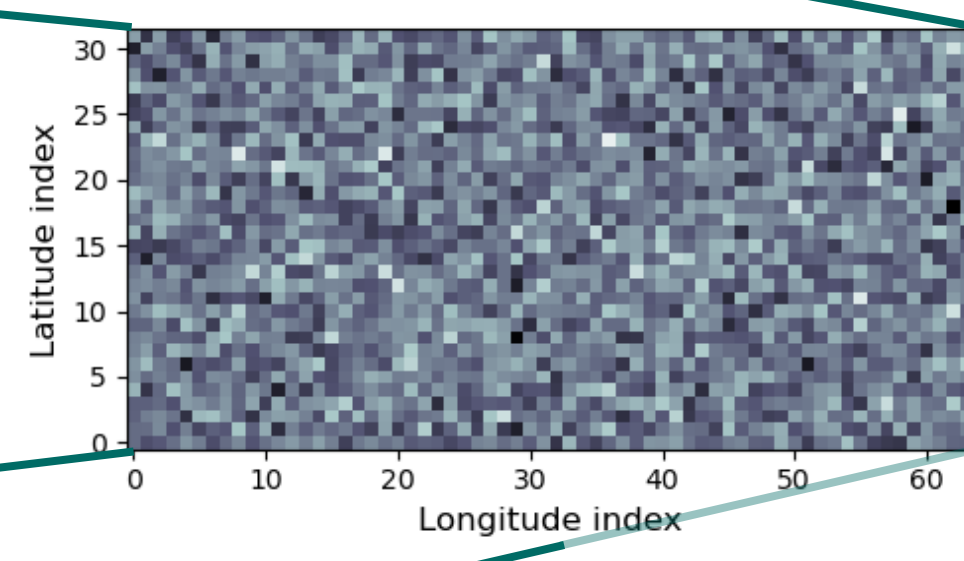


# Reconstructing Atmospheric CO<sub>2</sub> with Flow Matching Models

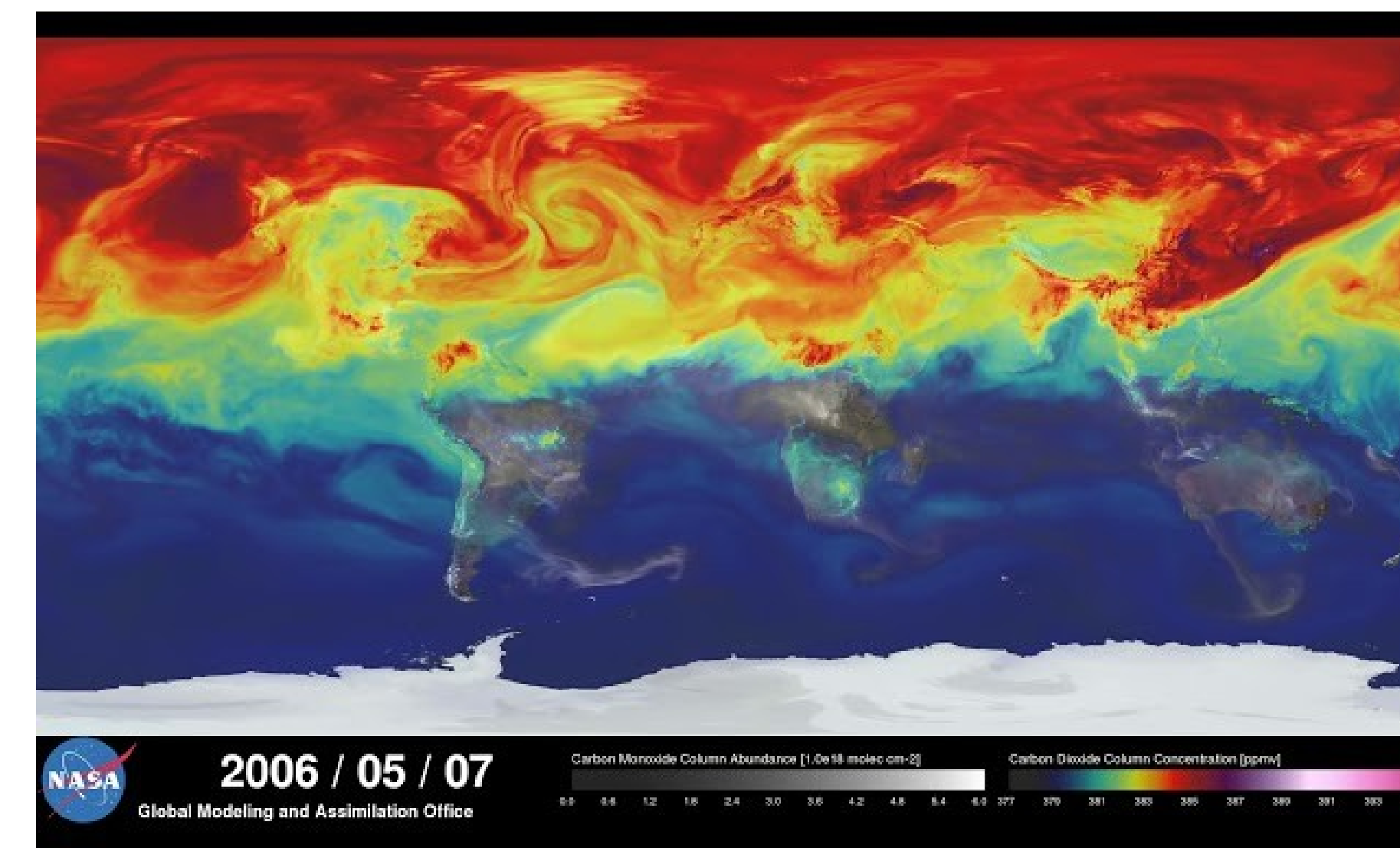
Jonathan Groß, Vitus Benson, Maurício Lima, Alexander Winkler, and Christian Reimers



1. OCO-2



Flow Matching



2. NASA | A Year in the Life of Earth's CO<sub>2</sub>

## Significance

Accurate observations of atmospheric carbon dioxide are essential...



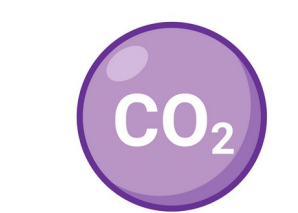
to evaluate and enforce international climate agreements



to pinpoint emitters

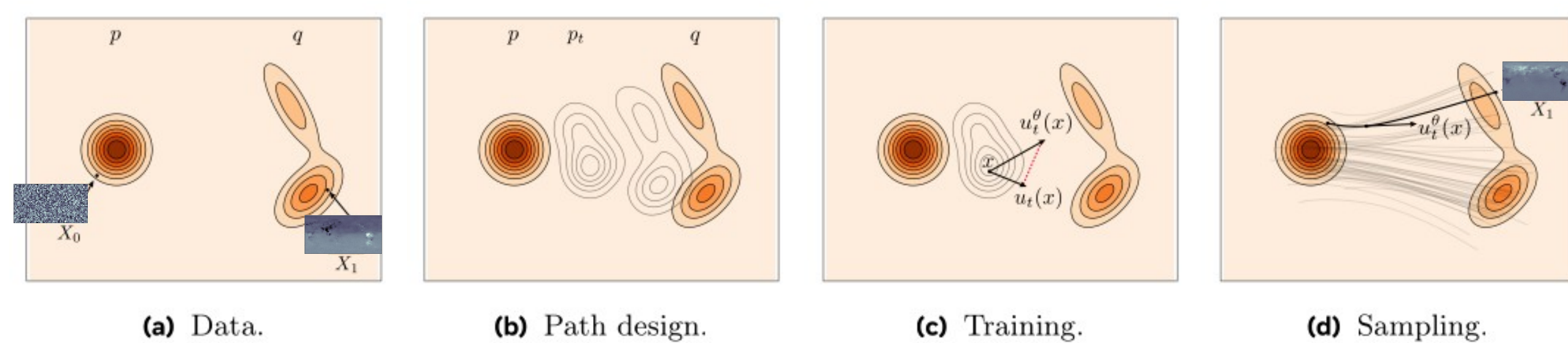


for monitoring efficacy of mitigation policies and tracking anthropogenic emission



to infer fluxes from short-time intervals

## Flow Matching



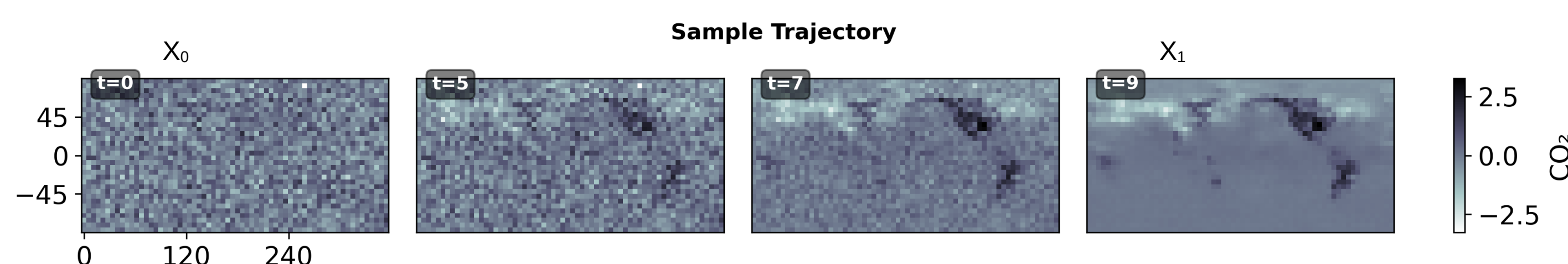
**(a)** Goal: map sample  $X_0$  from known source or simple noise distribution  $p$  to target  $X_1$  from an unknown probability distribution  $q$ .

**(b)** A continuous probability path  $p_t$  transforms the distribution into one another.

**(c)** During training the vector field  $u_t$  that determines a flow which gives rise to  $p_t$  is estimated.

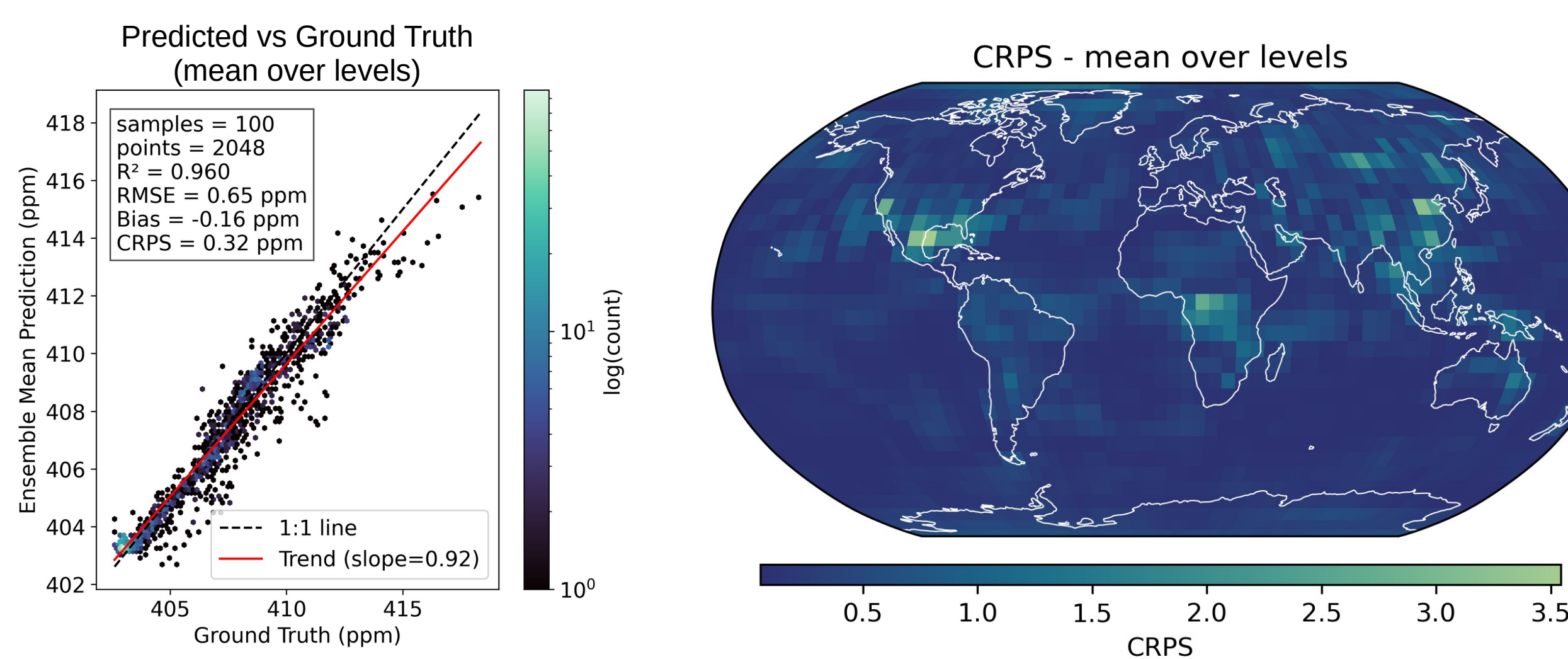
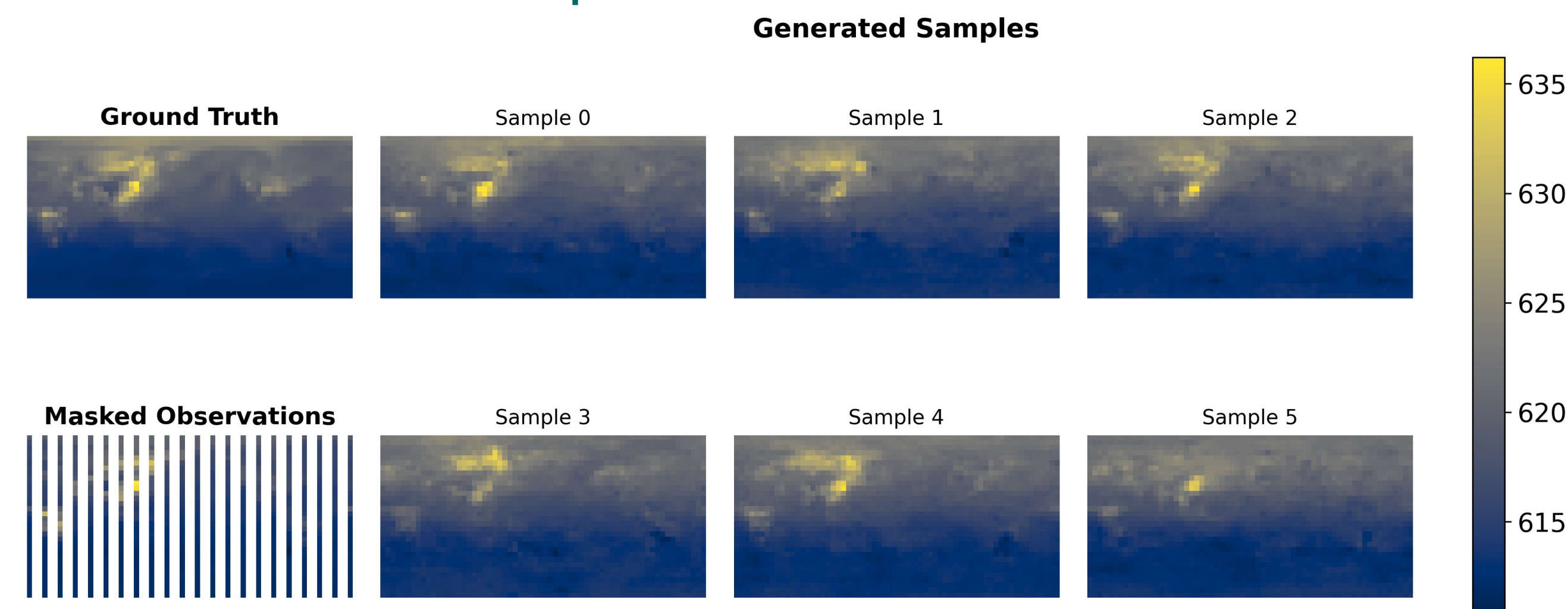
**(d)** A novel target sample is created via the trained vector field by integrating from a novel source sample.

3. Lipman et al. (2024)

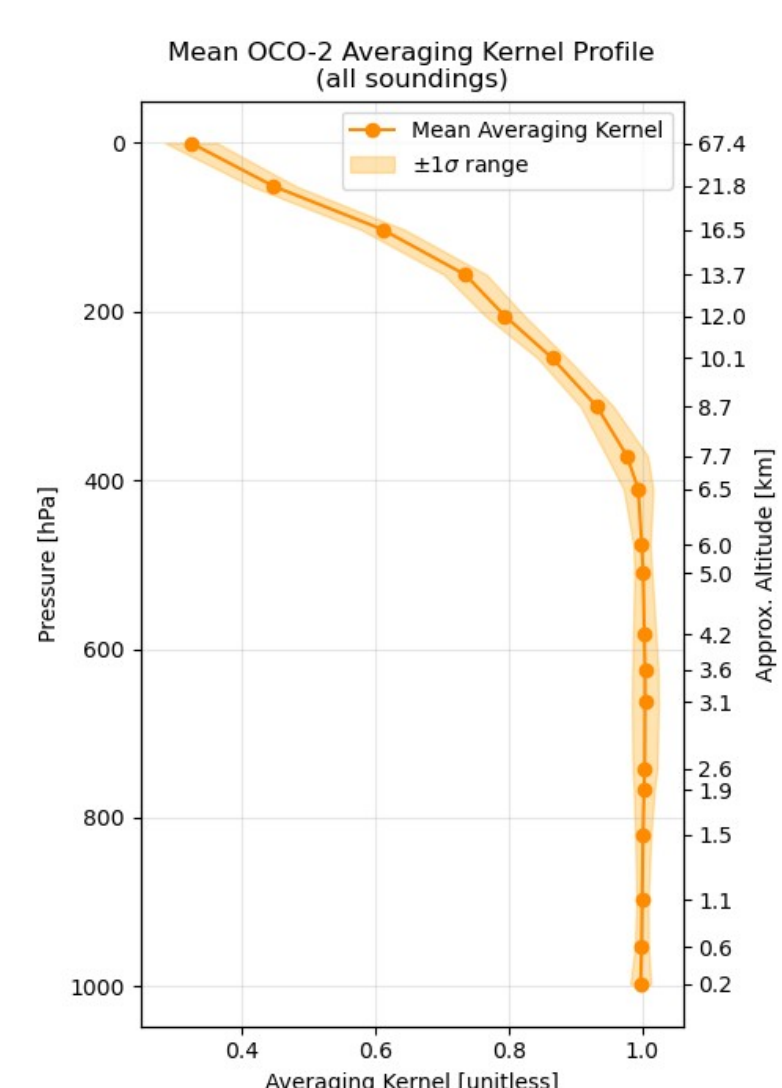


## Results

### Proof of Concept with Artificial Observations



### Next Steps: CO<sub>2</sub> → XCO<sub>2</sub> → CO<sub>2</sub>



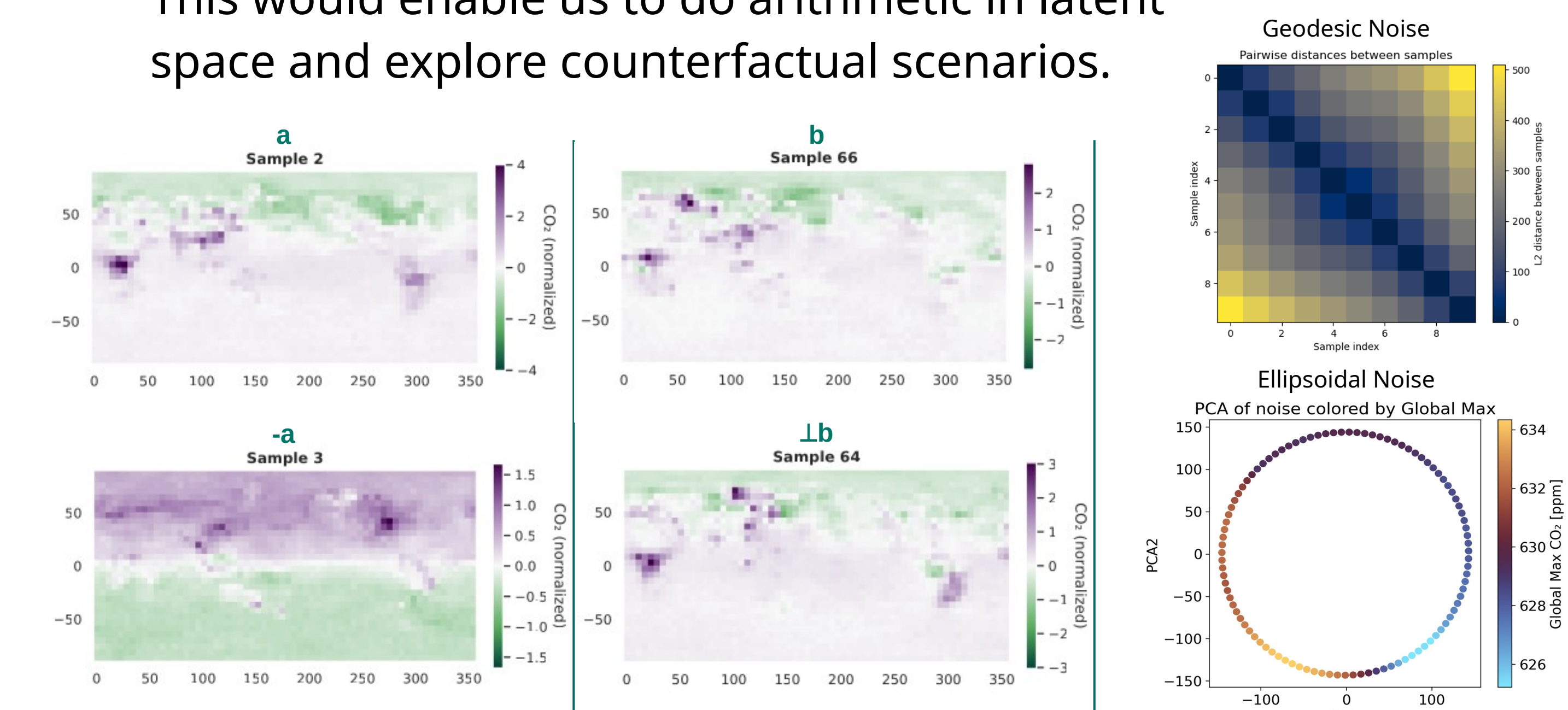
$$X_{model} = X_{prior} + \sum_{i=1}^n a_{k_i} \cdot (C_{model,i} - C_{prior,i})$$

- Obtain vertical profile from 2D observations via 3D training data → equifinality.
- Deliver CO<sub>2</sub> data product:
  - Grid: 3° × 2° lat/lon
  - Temporal: 3-daily
  - Time span: 2014-2026
  - Samples: 10 per time step
- Calculate fluxes as the difference of CO<sub>2</sub> at surface level between small timescales

## Noise

### Exploring the Noise Space:

- Small changes in the noise space → small changes in the target space
- The reverse is not true. The high dimensional noise space has redundancy. Some regions also explode.
- How to identify which areas in the noise space correspond to which features? → Eigenvalue Decomposition (→ PCA). This would enable us to do arithmetic in latent space and explore counterfactual scenarios.

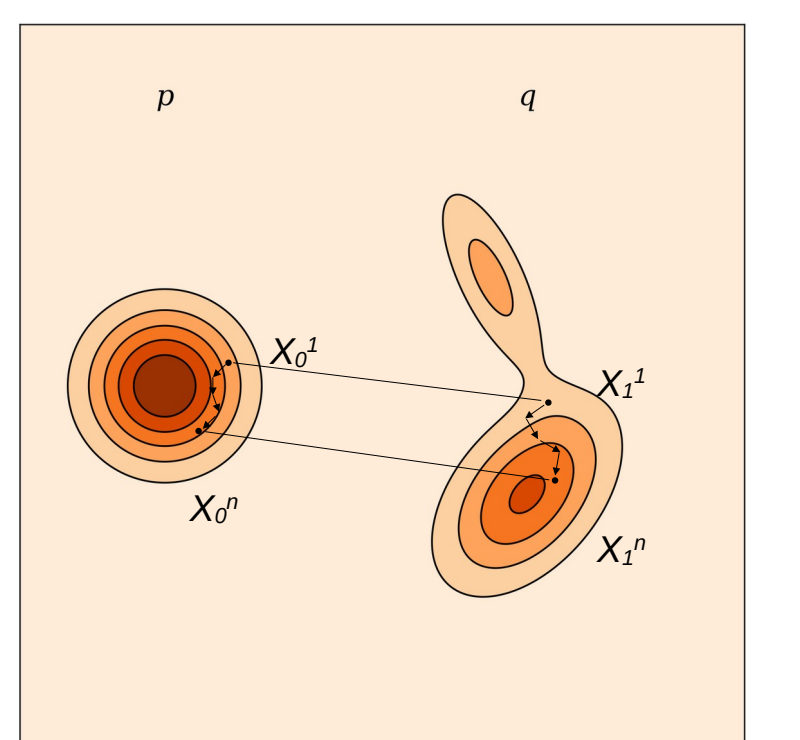


## D-Flow

**Posterior Conditioning:** Differentiating through the flow, by making noise a learnable parameter, the target sample can be steered during the generation process. → allows to condition on observations.

Drawback: introduced iteration slows down the generation process, but is still faster than diffusion.

4. Ben-Hamu et al. (2024)



## Data

Observational data:	OCO-2	Training Data:	CarbonTracker
Measurements:	ColumnCO <sub>2</sub> (XCO <sub>2</sub> )	Measurements:	CO <sub>2</sub>
Grid:	2.25 x 1.29 km <sup>2</sup>	Grid:	5.625° lat/lon
Dates on orbit:	2014-2028	Time span:	2000-2021
Temporal:	16 day cycle	Temporal:	3-hourly

Observational data XCO<sub>2</sub> is in truth (XCO<sub>2</sub>)<sub>t</sub>  
 For  $t$  small → no data  
 For  $t$  large → data ignores atmospheric transport

5. Benson et al. (2025)

