A Scalable Approach for Non-Gaussian Bayesian **Emissions Inference**

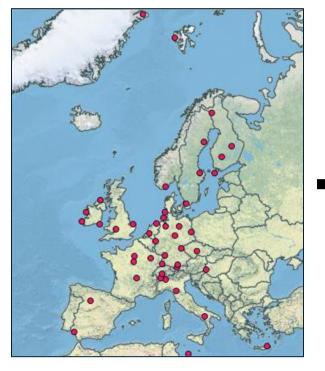
Stephen Pearson^{*}, Luke Western[†], Anita Ganesan^{*}, Matt Rigby[†] *School of Geographical Sciences University of BRISTOL [†]School of Chemistry Atmospheric Chemistry Research Group

The problem

- Non-Gaussian methods needed for inference of non-CO₂ emissions
- Model hierarchy allows for "uncertainties in uncertainties" to be incorporated, leading to more complete estimates
- Posterior sampling methods (MCMC) are flexible, but computationally expensive and so *dimension reduction required*
- They rely on "batch" data usage, which is problematic with growing volumes of remotely sensed data

The inversion

- Surface fluxes are inferred from mole fraction observations
- Large volumes of remotely sensed data not compatible with inferential frameworks designed for in-situ measurements



observations completed roughly once daily.

New methods required

Why non-Gaussian?

Gaussian emissions prior:

- Non-zero probability of negative surface fluxes
- Light tailed, may not account for extreme pollution events
- Lognormal emissions prior:
 - Non-negative and heavy tailed

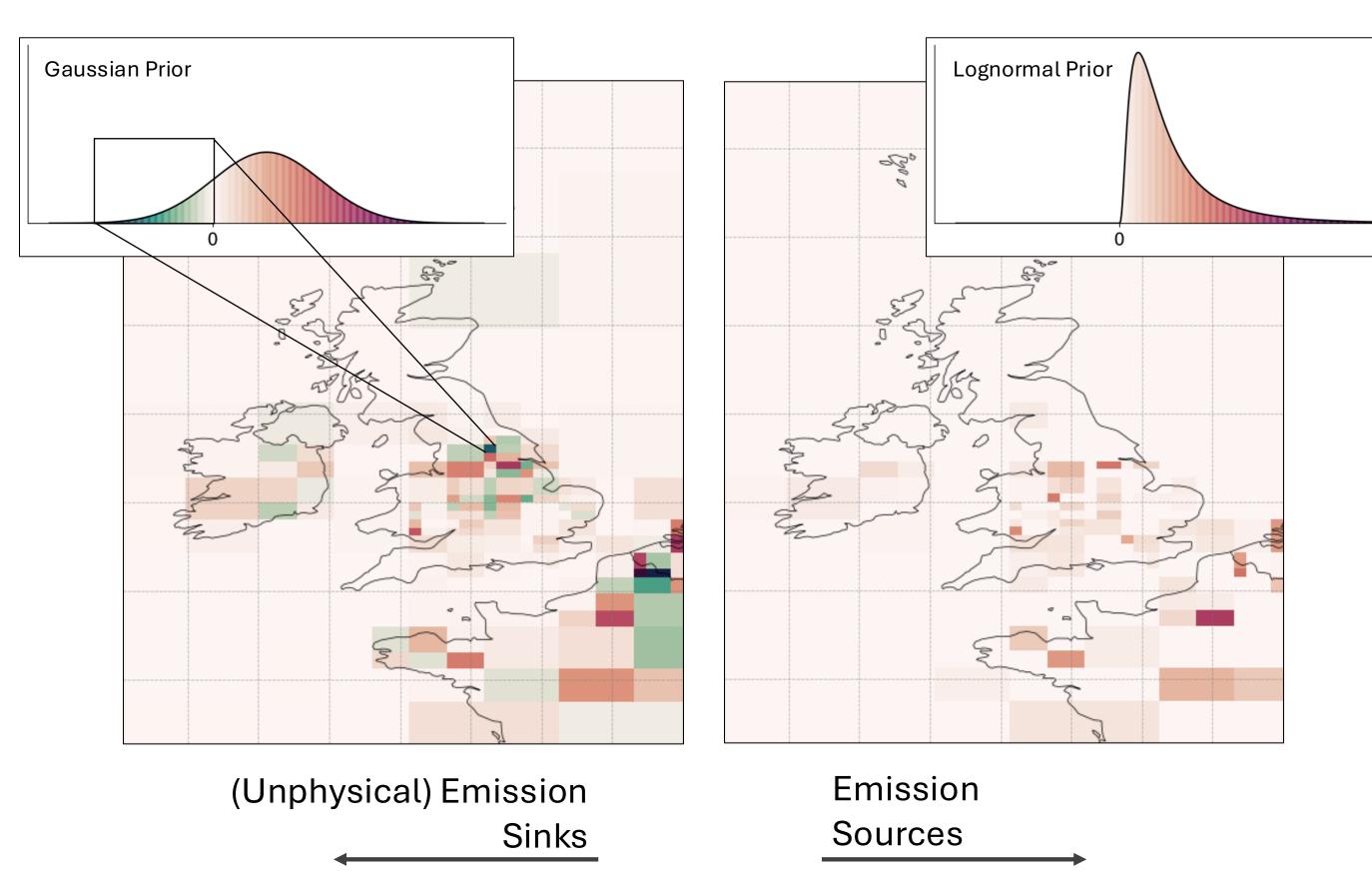


Fig.2. Inferred mean emissions field for a single month, demonstrating the impact of a Gaussian emission prior distribution. Negative surface fluxes are unphysical for many greenhouse gases and ozone depleting substances.

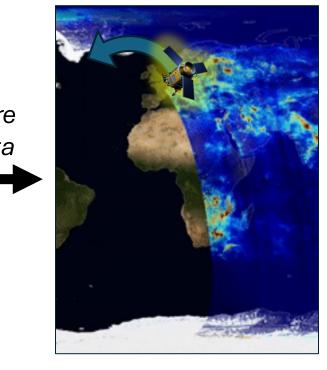
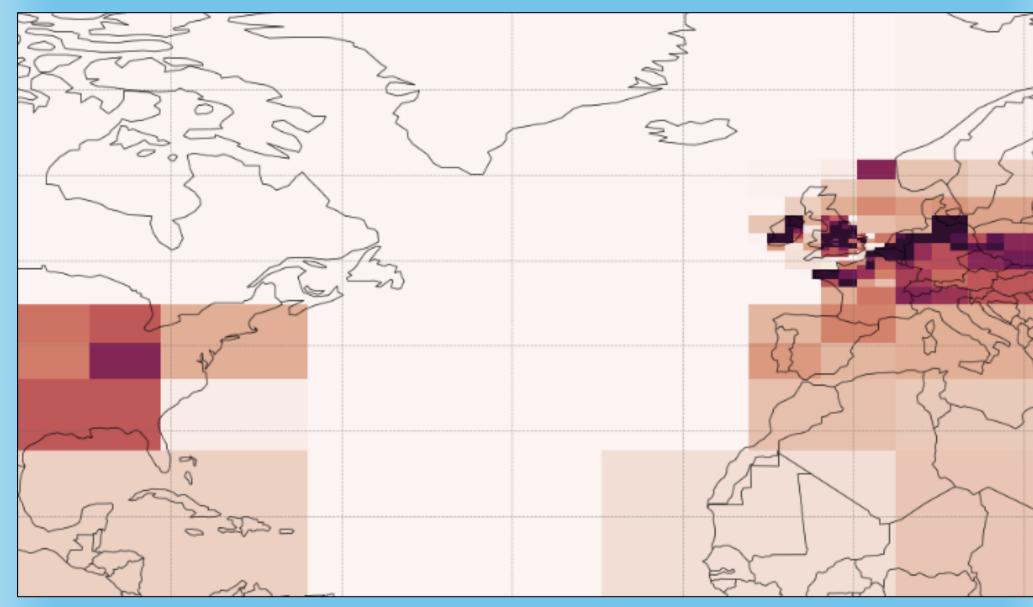
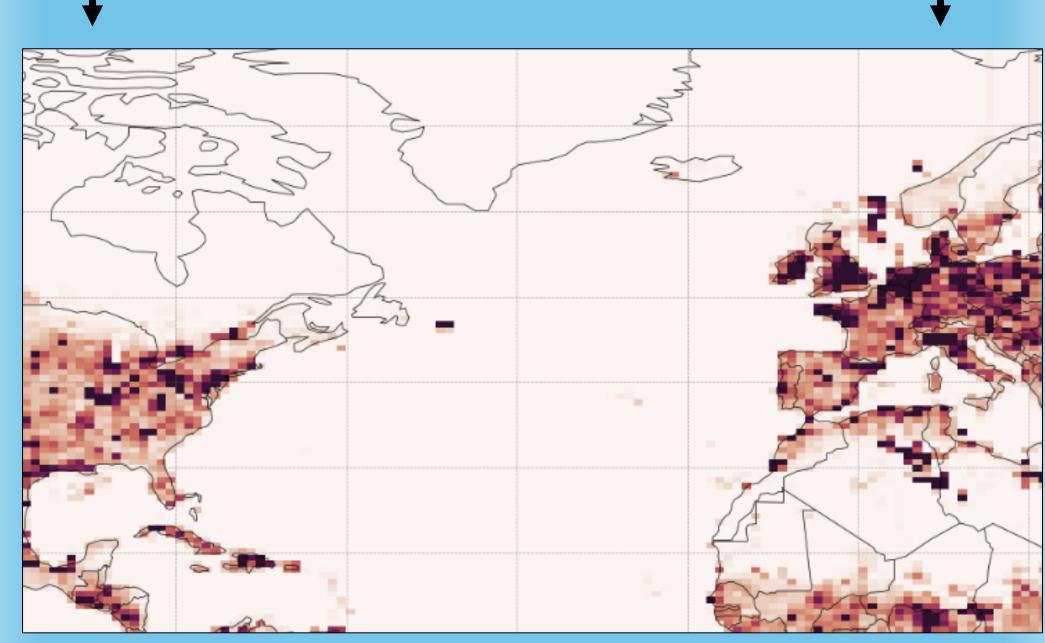


Fig.1. Left: ICOS Atmosphere network², providing high frequency in-situ measurements of greenhouse gas concentrations. Right: TROMOPI³ satellite observations, with a full set of global

This enables efficient, highresolution, non-Gaussian emissions Inference



250 Emissions Regions



10,000 Emissions Regions

Mixed Gaussian-Lognormal Sequential Approach

- Kalman filter (MXKF)
- standard Gaussian Kalman filter is maintained
- Gaussian inference
- the forecast uncertainty (no data filtering or smoothing)

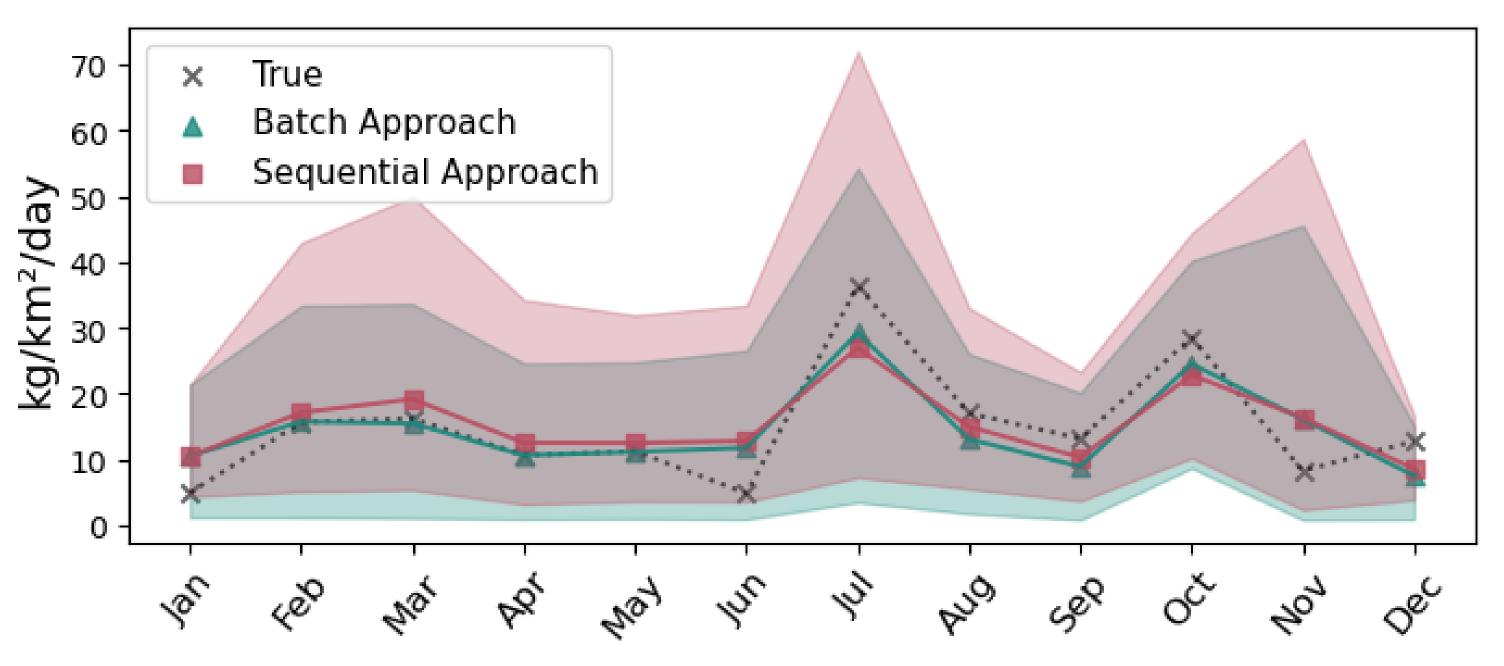


Fig.3. To enable validation, pseudo data is used to simulate mole fraction CH_4 observations for 4 in-situ UK sites. Shown here are the inferred monthly mean emission fluxes for a region in Lancashire. A conventional stochastic batch approach (NUTs MCMC) is shown, alongside a sequential approach based on the MXKF derived by Fletcher et al.

Advantages of Kalman filtering

- Kalman filters are highly efficient recursive estimators
- Temporal correlation implicitly included in the forecast step
- effectively

Regions	Observations	Batch MCMC time	Sequential solver time
9	7,960	16 mins	< 1 s
50	8,230	19 mins	2 s
50	43,865	~1.5 hrs	36 s
250	43,865	~11.5 hrs	46 s
500	43,865	~36.5 hrs	47 s
1,000	43,865	~88 hrs	56 s
10,000	43,865	N/A	41 mins

Fig.4. This table demonstrates the significant time savings associated with the sequential lognormal solver. This approach avoids any posterior sampling, and instead directly calculates the posterior mean and standard deviation

Next Steps

- observational data
- Introduce spatiotemporal correlations
- correlations



Get in touch!

¹Ganesan et al. (2014) Characterization of uncertainties in atmospheric trace gas inversions using hierarchical Bayesian methods. Doi: 10.5194/acp-14-3855-2014 ²ICOS. (n.d.). Atmosphere stations. Integrated Carbon Observation System. Available from: <u>https://www.icos-cp.eu/observations/atmosphere/stations</u> ³Aeronomie.be. (2021). *Three years TROPOMI measurements*. [online] Available from: <u>https://www.aeronomie.be/en/news/2021/three-years-tropomi-measurements</u> ⁴Fletcher et al. (2023) Lognormal and Mixed Gaussian–Lognormal Kalman Filters. *Monthly Weather Review*. Doi: 10.1175/MWR-D-22-0072.1







Fletcher et al.⁴ derived equations for a mixed Gaussian-lognormal

By propagating the median state in log-space, the form of the This provides a pseudo-analytical sequential framework for non-

As a proof of concept, a lognormal prior distribution was used as

Data assimilated sequentially, well suited to handle large volumes Does not rely on posterior sampling and so can be scaled more

Implement full mixed Gaussian-lognormal Kalman Filter with

Explore hierarchical methods to estimate uncertainties and

If you have any suggestions or would like a chat, please drop me a line - **s.pearson@bristol.ac.uk**