Global High Resolution CO_2 Monitoring using Super Resolution

Andrianirina Rakotoharisoa[1,2], Simone Cenci[3], Rossella Arcucci[1,2]

[1]Department of Earth Science & Engineering, Imperial College London
[2]Data Science Institute, Imperial College London
[3]Imperial College Business School

Motivation

- Greenhouse Gases (GHGs) have caused global temperature to rise by over 1° since 1850-1900
- Monitoring concentrations and by extension emissions is crucial to their effective reduction
- Technological limitations of remote sensing devices make global high-resolution monitoring an ongoing challenge

- Machine Learning methods can improve existing datasets
- Focus on CO_2, with plans to address other GHGs in future works

Methods

- OCO-2-derived L3 data is upsampled using Super Resolution (SR)
- The model framework is derived from Haris et al. (2020) and uses up- and down-sampling modules (see Figure 1)
- Training is performed on HR LST data from MODIS

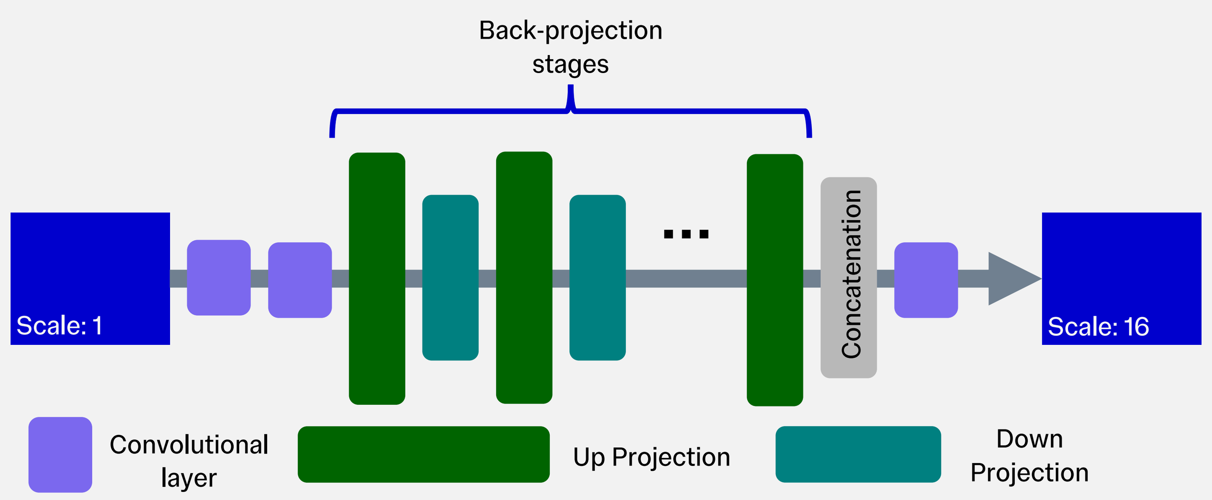


Figure 1: General architecture of DBPN exploiting densely connected projection blocks

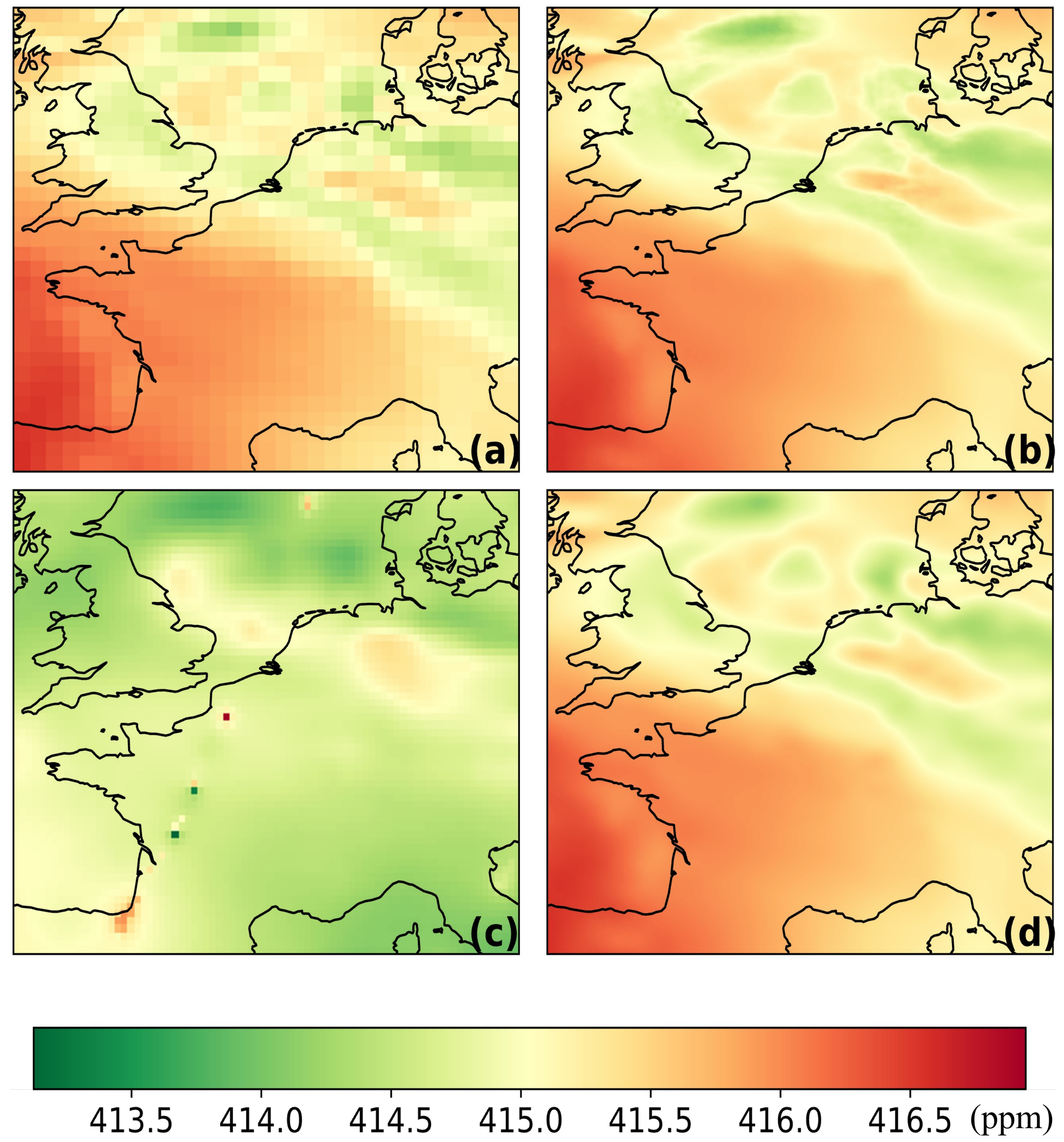


Figure 2: Visualisation of XCO_2 over western Europe according to the four datasets used for this benchmark. From top left to bottom right: (a) is the LR dataset, (b) is after SR (ours), (c) is the fusion dataset, (d) is after bicubic interpolation. On this example, we observe a general bias difference between the LR and the fusion maps

Experiments

- Perform a benchmark of our maps with existing products in the literature
- Quantify how often upsampling improves the estimations with an Improvement Ratio:

$$IR = \frac{N_{improved}}{N_{total}}$$

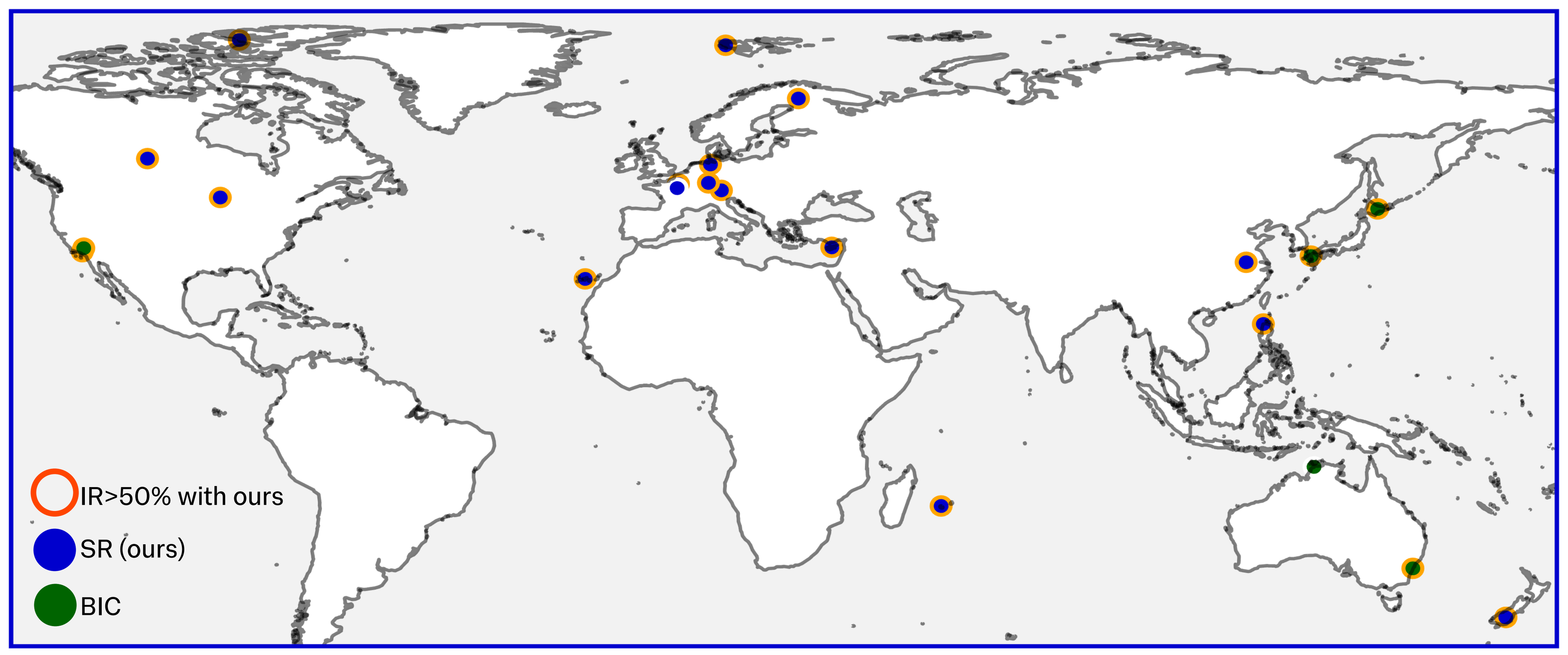
Key Takeaways

- Creation of a new dataset for global HR daily monitoring
- Method is component-agnostic
- Concentration monitoring is improved compared to other methods

	RMSE (↓)				MAE (↓)				R2 coeff (↑)			
	SR (ours)	LR	BIC	Fusion	SR (ours)	LR	BIC	Fusion	SR (ours)	LR	BIC	Fusion
America	1.002	1.076	1.071	1.226	0.795	0.865	0.856	0.973	0.934	0.915	0.916	0.917
Africa	0.592	0.596	0.598	0.698	0.464	0.468	0.468	0.532	0.976	0.976	0.976	0.968
Europe	1.039	1.053	1.066	1.317	0.844	0.855	0.870	1.039	0.945	0.943	0.942	0.911
Asia	0.919	0.976	0.883	1.281	0.732	0.779	0.702	1.047	0.927	0.915	0.934	0.862
Oceania	0.656	0.662	0.638	0.785	0.518	0.523	0.503	0.615	0.949	0.948	0.950	0.925

Table 1: Metrics comparison to ground sensors data (Best; second best). LR is the original OCO-2 L3 dataset, BIC is the dataset derived from bicubic interpolation and Fusion is the dataset from Wang et al. (2023).

Figure 3: IR comparison between our method and SR with bicubic interpolation (BIC). Our model upsamples better in 80% of cases.



Future Work

- Apply the framework to other atmospheric components
- Quantify emissions and impact from known sources
- Detect unreported emission sources

References

Haris, M., Shakhnarovich, G. and Ukita, N., 2020. Deep back-projection networks for single image super-resolution. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *43*(12), pp.4323-4337.
Wang, Y., Yuan, Q., Li, T., Yang, Y., Zhou, S. and Zhang, L., 2023. Seamless mapping of long-term (2010–2020) daily global XCO 2 and XCH 4 from the Greenhouse Gases Observing Satellite (GOSAT), Orbiting Carbon Observatory 2 (OCO-2), and CAMS global greenhouse gas reanalysis (CAMS-EGG4) with a spatiotemporally self-supervised fusion method. *Earth System Science Data*, *15*(8), pp.3597-3622.
Xiang, R., Yang, H., Yan, Z., Mohamed Taha, A.M., Xu, X. and Wu, T., 2022. Super-resolution reconstruction of GOSAT CO2 products using bicubic interpolation. *Geocarto International*, *37*(27), pp.15187-15211.

Contact: ar1619@ic.ac.uk