Kriging-based Mapping of Space-borne CO_2 Measurements by Combining Emission Inventory and Atmospheric Transport Modelling

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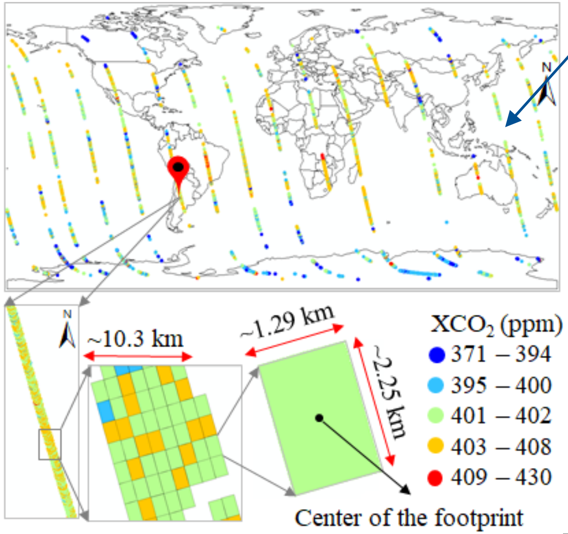
Outline

- Problem definition and objectives
  - Sparse sampling of OCO-2 measurement (including XCO_2)
  - Regional mapping of XCO_2
- Solution approach
  - Multivariate kriging with STILT-based atmospheric transport modeling
- Results
- Conclusions and future works

Problem Definition

- The Orbiting Carbon Observatory-2 (OCO-2) is offering unprecedented accuracy for the space-based measurements of atmospheric CO_2 concentration

- Problem: The Level-2 retrieval is irregular in space and time
  Sparse sampling, gap between two OCO-2 swaths on a single day: **~2558 km**, missing footprints in 8 cross-track

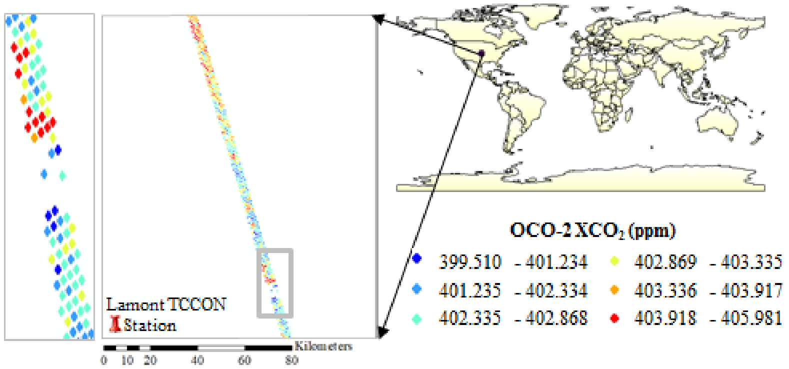


OCO-2 measurements on October 14, 2017, i.e., a single day retrieval

A Small Regional Scenario

- Measurements on October 13, 2017
- Area of the region 92 km × 135 km
- Number of samples: 464
- **Almost 89% of the total area is unmeasured**

Bounding box (lower-left, upper-right): [(36.57, -97.51); (37.79, -96.47)]



Objectives

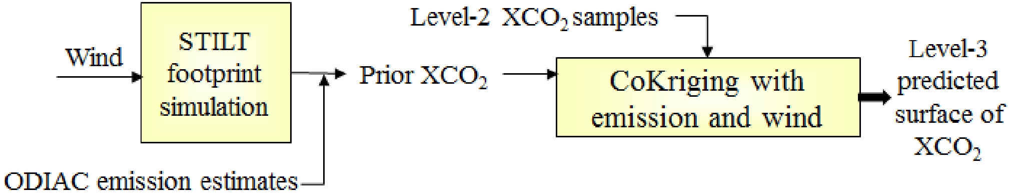
- Mapping of available XCO_2 measurements for local regions: Generate Level-3 product

- Solution approach: Mapping with the help of densely sampled correlated information

  For example:
  - **ODIAC monthly CO_2 emission estimates** (Bhattacharjee and Chen, 2020)
  - **ODIAC + Wind transport (STILT)**

Method

- Geostatistical interpolation method: Traditional Kriging/ Cokriging



ODIAC: Open-source Data Inventory for Anthropogenic CO_2, **STILT:** Stochastic Time-Inverted Lagrangian Transport model

CoKriging

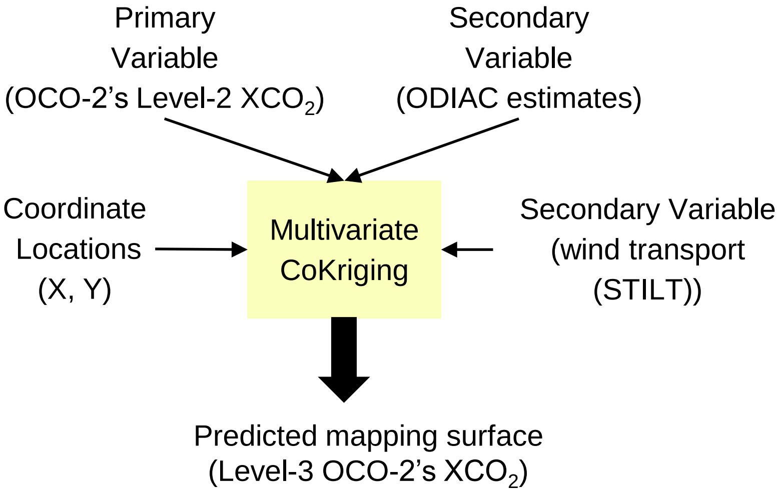
- XCO_2 interpolation = *f*(Euclidean distance, Emission estimates, Atmospheric transport)

  Semivariograms: Lag distance vs. primary variable

  Cross-variograms: Lag distance vs. (primary + secondary) variables

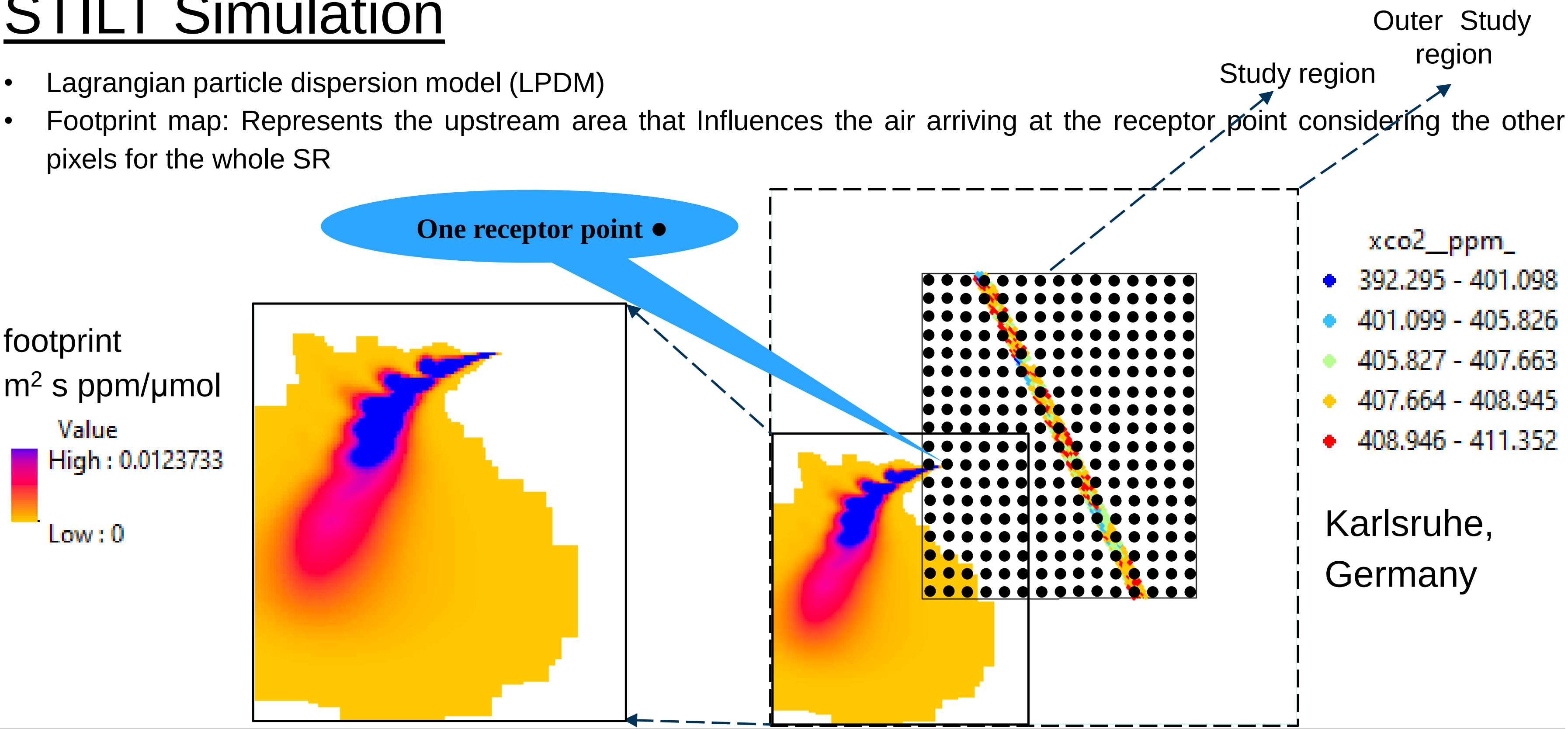
- Advantage
  - Additional domain knowledge for the estimation process
  - Higher prediction accuracy

Method	Kriging	Cokriging
Input	Level-2 XCO_2	Level-2 XCO_2 ODIAC emission STILT footprint
Output	Level-3 XCO_2 mapping	



STILT Simulation

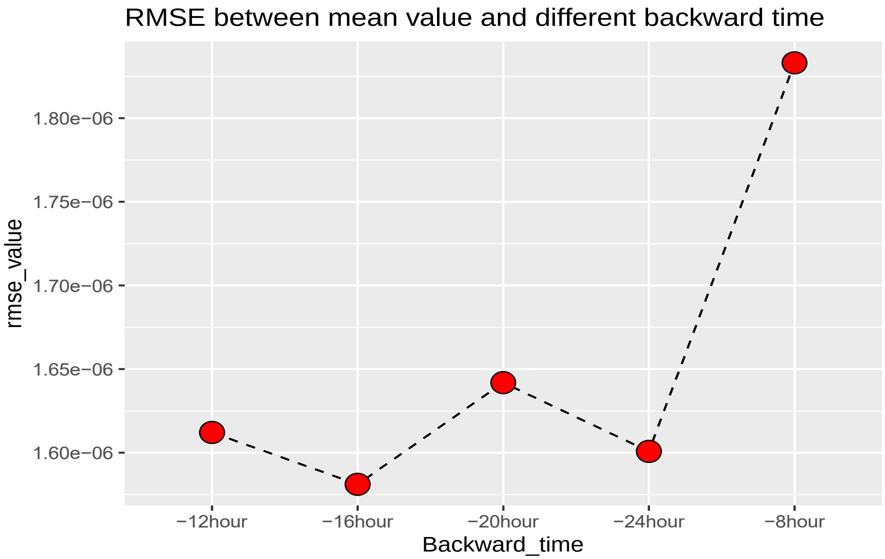
- Lagrangian particle dispersion model (LPDM)
- Footprint map: Represents the upstream area that Influences the air arriving at the receptor point considering the other pixels for the whole SR

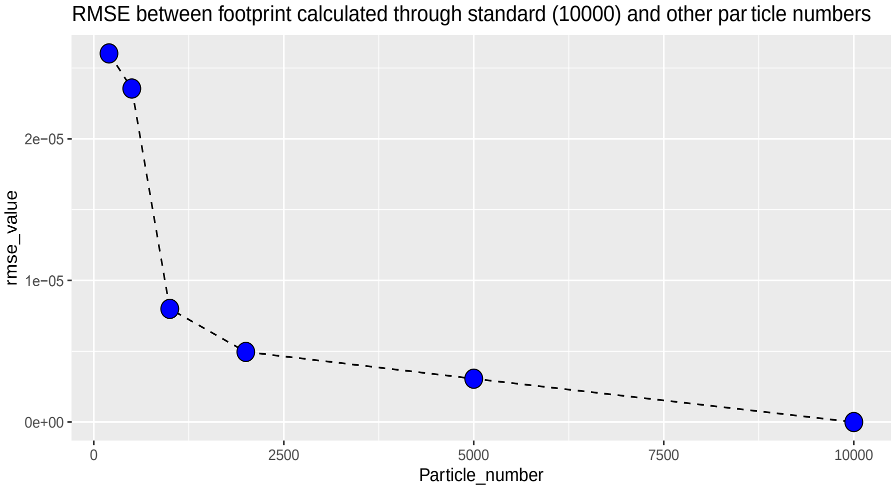


Optimization of STILT Parameters

- Wind data sources (Default: ERA5)
- Backward time
- Particle number

Lamont, USA





Study Regions

- Chosen as per the availability of the Total Carbon Column Observing Network (TCCON) measurement data for validation

SR	Locations	Date
Lamont, USA	36.604 N, 97.486 W	20171013
Karlsruhe, Germany	49.1002 N, 8.4385 E	20170421
Lauder, New Zealand	45.038 S, 169.684 E	20170123
Ascension, Island	7.933333 S,14.416667 W	20170130
Rikubetsu, Japan	43.4567 N,143.7661 E	20170605

STILT Parameters

SR	Wind Data Sources	Backward time	Particle number
Lamont, USA	GDAS (0.5 degree)	-16h	2500
Karlsruhe, Germany	ERA5 (31 km)	-12h	1000
Lauder, New Zealand	GDAS (0.5 degree)	-16h	1500
Ascension, Island	GDAS (0.5 degree)	-24h	3000
Rikubetsu, Japan	GDAS (0.5 degree)	-12h	2000

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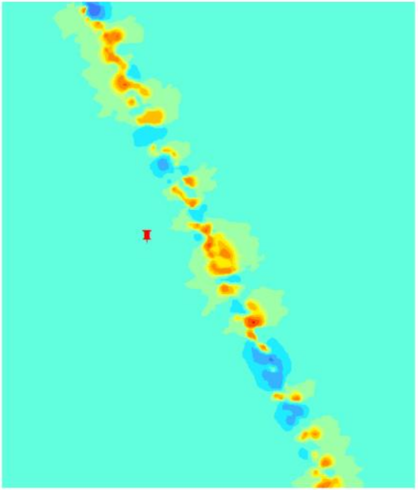
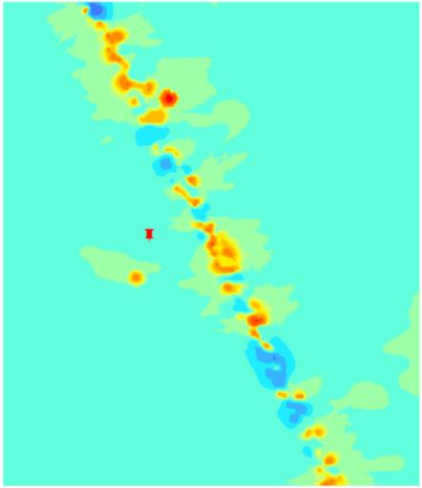
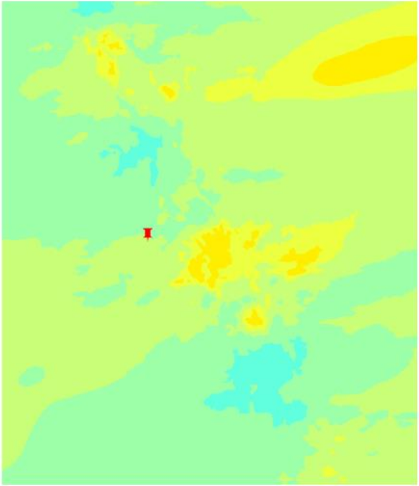
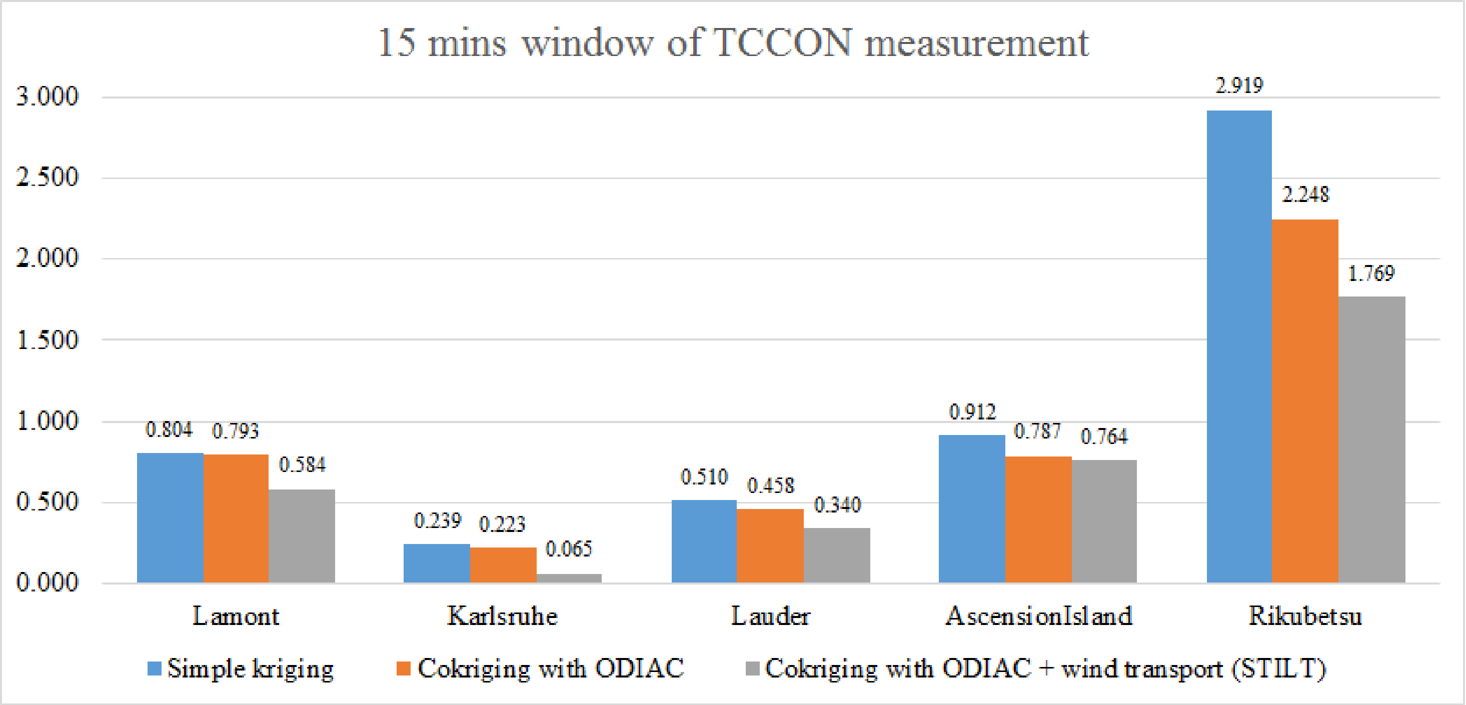
Result: Study Region: Karlsruhe, Germany

SR	(I) Predicted by Simple Kriging	(II) Predicted by Cokriging with ODIAC estimates	(II) Predicted by Cokriging with ODIAC + wind transport (STILT)	Legends (predicted XCO_2 in ppm)
Karlsruhe, Germany				392.295 – 399.374 399.374 – 403.388 403.388 – 405.664 405.664 – 406.955 406.955 – 407.687 407.687 – 408.102 408.102 – 408.337 408.337 – 408.47 408.47 – 408.546 408.546 – 408.679 408.679 – 408.915 408.915 – 409.333 409.333 – 410.061 410.061 – 411.352

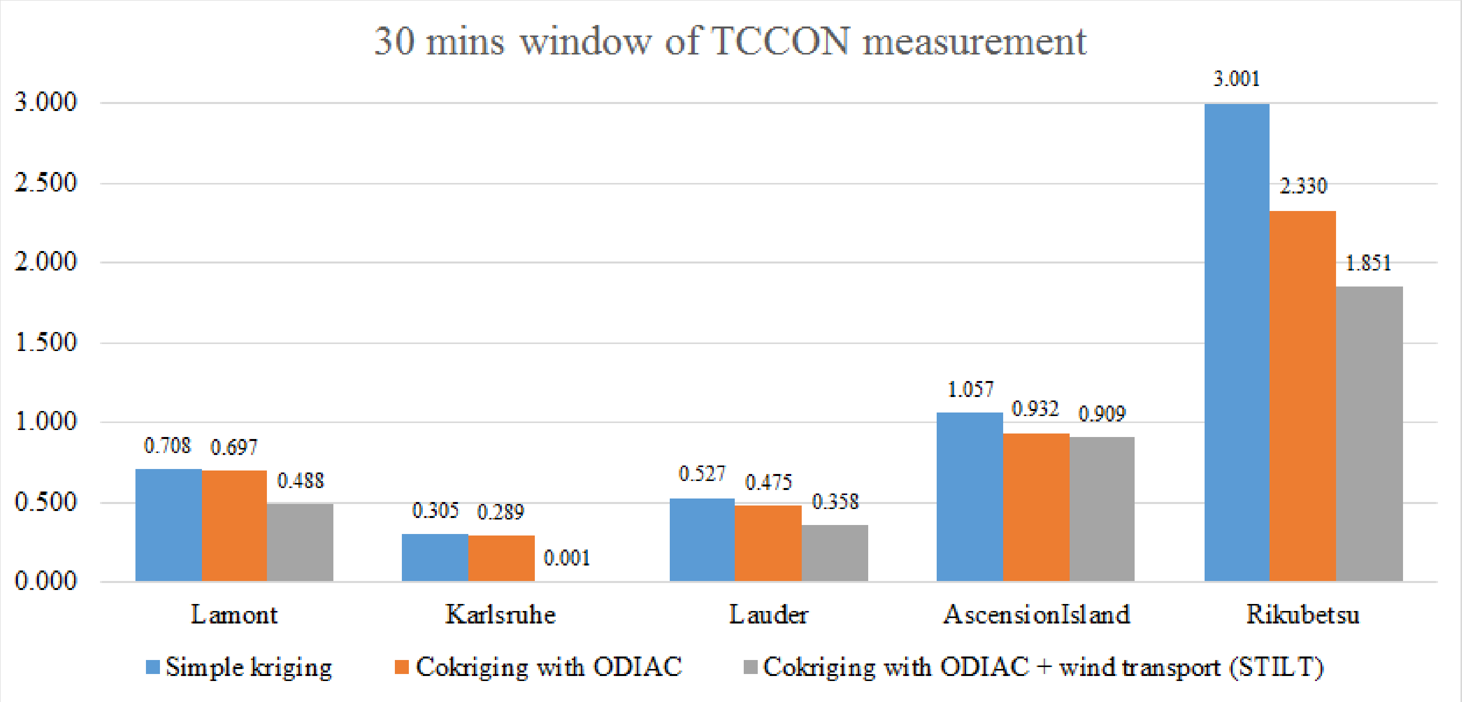
Result Summary: All Study Regions: Prediction Error

- Comparison using Root Mean Square Error (RMSE): 15 mins window of TCCON measurement



Result Summary: All Study Regions: Prediction Error

- Comparison using Root Mean Square Error (RMSE): 30 mins window of TCCON measurement



Conclusions

- We have developed a cokriging method using emission inventories and atmospheric transport information (footprints)
- This new approach is more accurate compared to the univariate mapping
- Mainly suitable for the extrapolation in the whole study region
- Extrapolated results agree well with TCCON measurements

References

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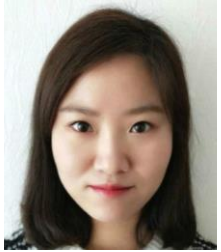

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- **Shrutilipi Bhattacharjee** and Jia Chen, "*Prediction of Satellite-based Column CO_2 Concentration by Combining Emission Inventory and LULC information*", IEEE Transactions on Geoscience and Remote Sensing, (accepted), April 2020 [DOI: 10.1109/TGRS.2020.2985047]

- **Shrutilipi Bhattacharjee**, Jia Chen and Soumya K. Ghosh, "*Spatio-temporal Prediction of Land Surface Temperature using Semantic Kriging*", Wiley Transactions in GIS, vol. 24, no. 1, pp. 189-212, January 2020 [DOI: 10.1111/tgis.12596]

Thank you for your attention...

Any question?