Designing additional GHGs observations network over Korea using Lagrangian inversion model

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Introduction

- *Uncertainty in anthropogenic emissions is a fundamental science question*
  - The aim of this work is to propose new additional GHGs (CO2) candidate sites, which will enable us to improve GHGs emissions at fine spatiotemporal scales over Korea.

- *We need to have*
  - simulated footprints (e.g., KIM-STILT model), together with Bayesian inverse modelling framework
  - Meteorological deriving fields are obtained from KIM (*Korean Integrated Model*)
  - prior and true GHGs emissions data at high spatiotemporal resolution,
  - defined model-data mismatch errors, priori flux uncertainties, and error correlations

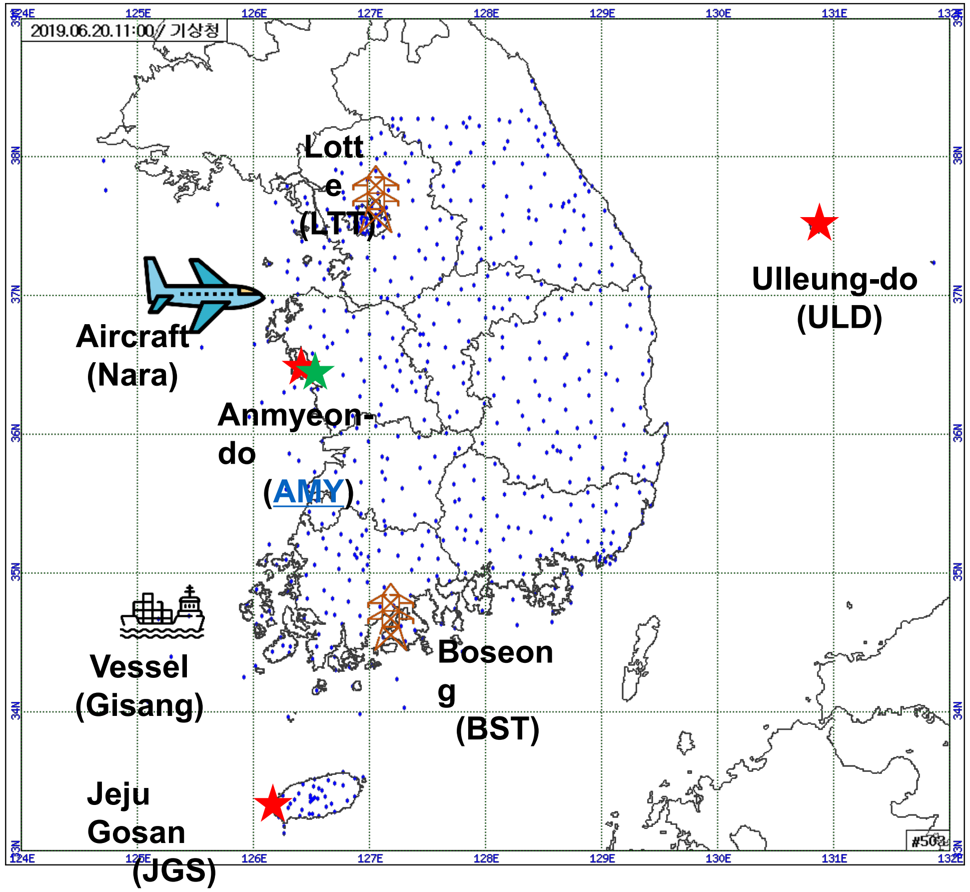
Measurement activities operated by NIMS

- Platform description
  - In situ surface (AMY, JGS, ULD)
  - Tall tower (LWT, BST)
  - Mobile (Vessel, Aircraft)
  - Remote observation (FTS, mobile FTS)
  - *Low cost sensors are under developing stage*

- Measurement details
  - $CO_2/CH_4/N_2O/SF_6$

- Data Visualization
  - Observation data
  - Model data

GHG monitoring network in Korea



★ In-situ surface

★ Ground FTS

❑ Korea CO_2 emission sectors based on EDGAR data

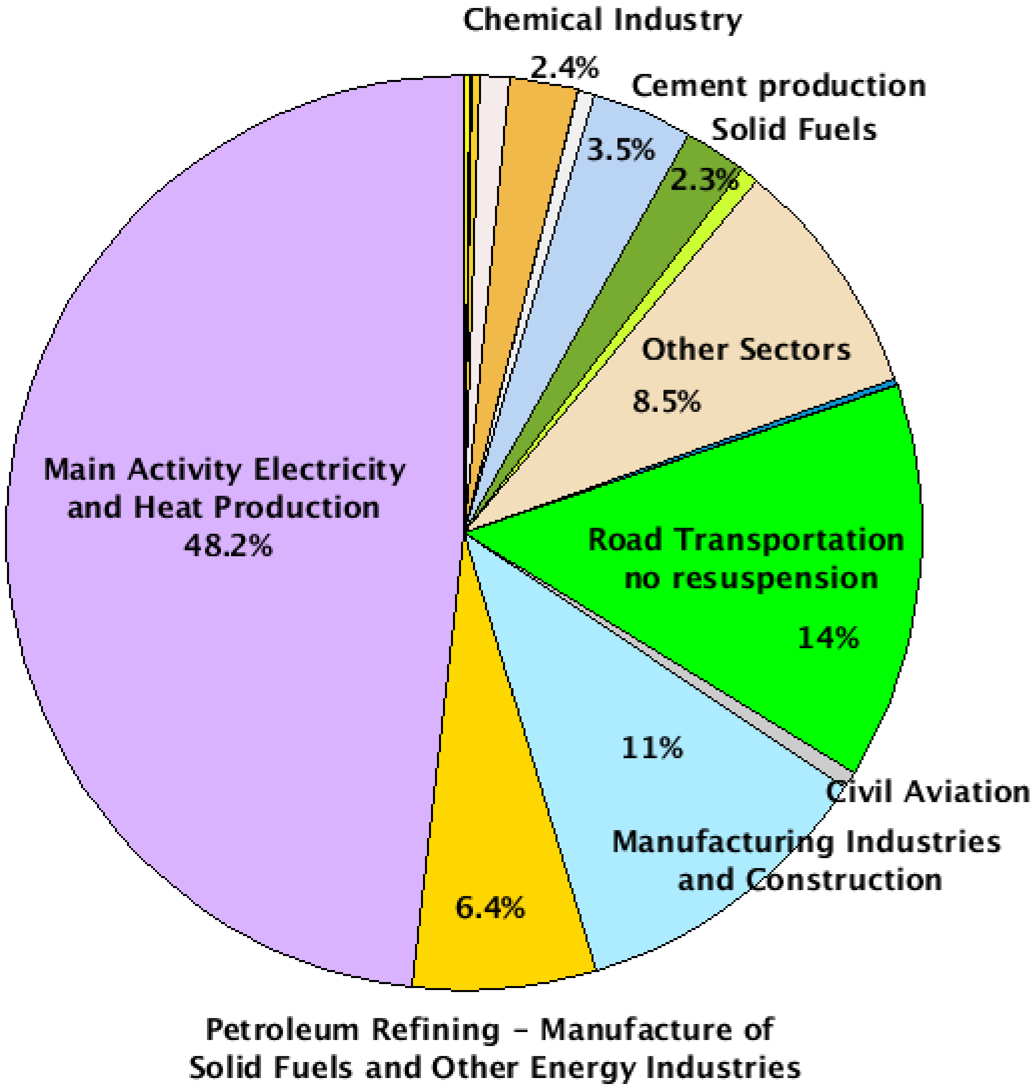
Major contributions

i. Main Activity Electricity and Heat Production 48.2%

ii. Road Transportation no resuspension 14%

iii. Manufacturing Industries and Construction 11%

iv. Other sectors 8.5%



Footprints

- **STILT** (*Stochastic Time Inverted Lagrangian Transport,* Lin et al. 2003)
  - horizontal resolution - 0.1˚ x 0.1˚ lat-lon
  - Temporal resolution - 1-hour
  - Number of particle - 500
  - Backward time – 3 days

- **The footprint** – quantifies the influence of upwind surface fluxes on the concentrations measured at the receptor and is computed by counting the number of particles in surface-influenced volume and the time spent in that volume.

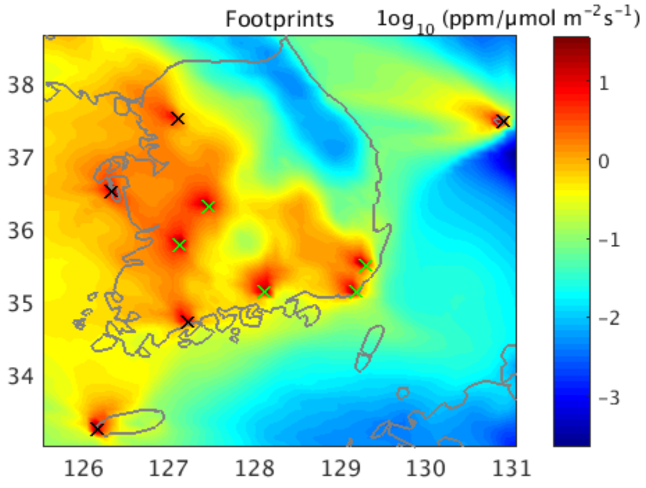


Figure 1. KIM-STILT aggregated footprints of 10 sites located in Korea, December 2020 (2-7 UTC).

- **KIM** (*Korean Integrated Model, Hong et al., 2018*) for meteorological data
  - horizontal resolution- 0.125˚ x 0.125˚ lat-lon
  - Temporal resolution - 3-hour
  - Vertical levels - 31

Table 1. List of GHG observation sites including existing and new candidate sites over Korea.

No	Site	Lat. (˚N), lon. (˚E),	STILT height (m.a.g.l)
1	Anmyeondo (AMY)	36.538576, 126.330071	40
2	Gosan (JGS)	33.29382, 126.16283	12
3	Ulleungdo (ULD)	37.48, 130.90	10
4	Lotte World Tower (LWT)	37.5126, 127.1025	550
5	Boseong Tower (BST)	34.76, 127.21	140
6	Ulsan (ULS)	35.52636, 129.293686	20
7	Busan (BSN)	35.1573, 129.1797	40
8	Jeonju (JOJ)	35.8026, 127.1182	40
9	Daejeon (DJN)	36.3359, 127.4576	40
10	Jinju (JNJ)	35.16425, 128.10732	40

Bayesian Inverse Method

Posterior emission estimates are optimized through the minimization of the cost function

$$L_s = \frac{1}{2}(z - Hs)^T R^{-1}(z - Hs) + \frac{1}{2}\left(s - s_p\right)^T Q^{-1}\left(s - s_p\right) \quad (1)$$

$$z = Hs_{truth} + \in \quad (2)$$

$z -$ observed enhancments, s_p $-$prior emissions, $s -$ true emissions,

R- covariance of model-mismatch error, Q-covariance of prior emissions,∈ -error

The posterior best estimate of emissions, ŝ, is expressed as:

$$\hat{s} = s_p + (HQ)^T(HQH^T + R)^{-1}(z - Hs_p) \quad (3)$$

Posterior uncertainty covariance matrix $V_{\hat{s}}$, is given as:

$$V_{\hat{s}} = Q - (HQ)^T(HQH^T + R)^{-1}(HQ) \quad (4)$$

❑ CO_2 emissions

- EDGAR v6
  - horizontal resolution - 0.1˚ x 0.1˚ lat-lon
  - Temporal resolution - monthly
  - the latest available data is December 2018
  - Constructed as a prior emission
  - Diurnal scaling factor (from Nassar Emissions Scale Factors) is applied

- GRACE2021 (*Dou et al. 2023*)
  - horizontal resolution - 0.1˚ x 0.1˚ lat-lon
  - Temporal resolution - daily
  - near-real-time daily national CO_2 emissions estimates (Carbon monitor), multi-source spatial activity data emissions
  - Satellite NO_2 data for time variations
  - Diurnal scaling factor (from Nassar Emissions Scale Factors) is applied
  - Constructed as a true emission

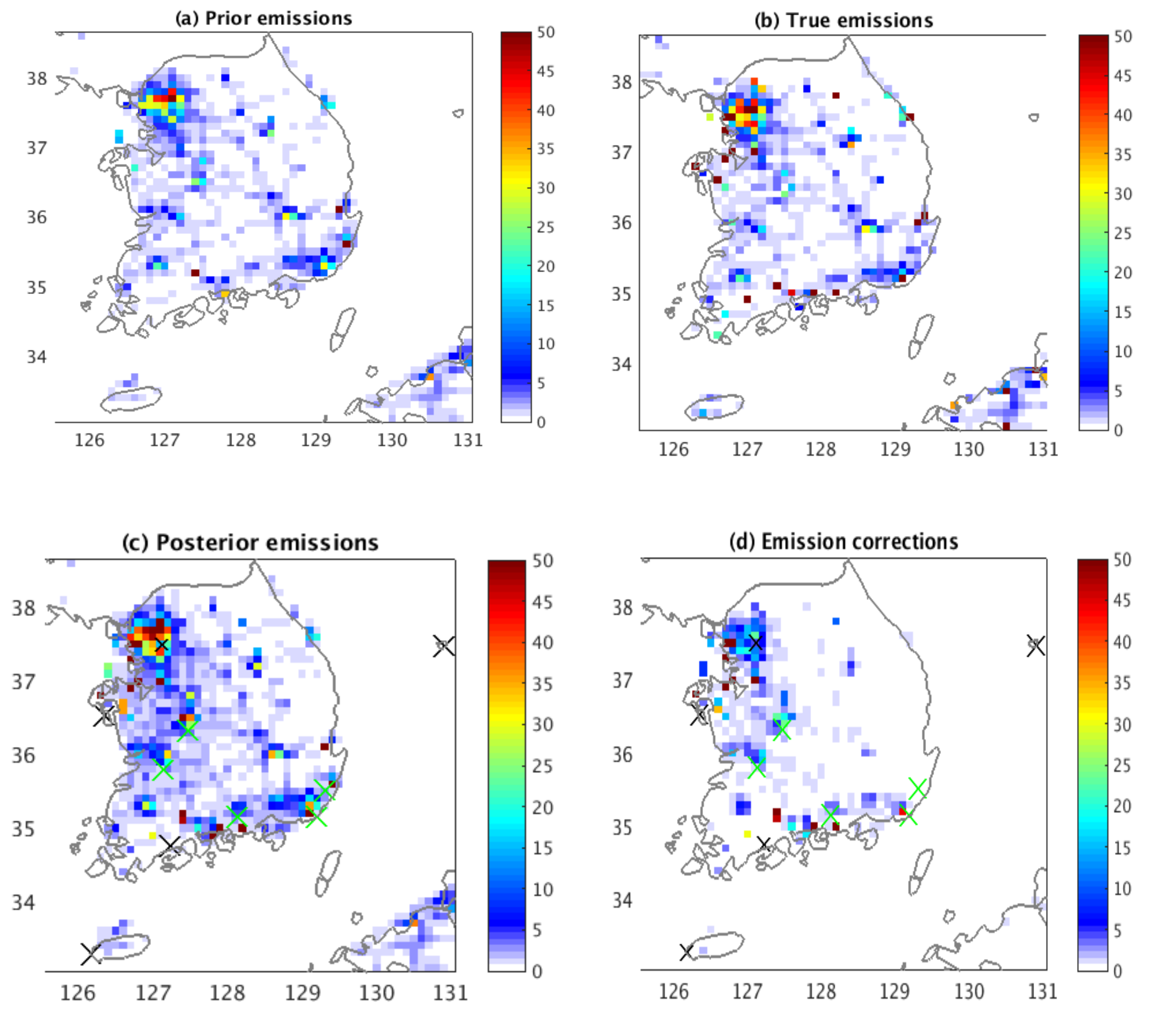


Figure 2. CO_2 emissions for December 2020. Unit for emission is μmol m^{-2} s^{-1}.

Error covariance parameters

Prior error covariance (Q) describes both variance in prior emissions uncertainty and spatial and temporal correlation of these uncertainties. $Q = I_\sigma(D \otimes E)I_\sigma$

Exponential decay equations

$E = \exp(-\frac{x_s}{l_s})$ $D = \exp(-\frac{x_\tau}{l_\tau})$

- horizontal length scale = 45 km, temporal length scale = 5 days

Model-data mismatch (R)

- R typically reflect inaccuracies in the transport, prior fluxes, and measurements
- *Vertical mixing layer height error* is approximated of 7% mean enhancement adopted from Gerbig et al. (2008), representing error for afternoon time period only.
- *Horizontal wind error* is assumed to be 35% of mean enhancement (Kunik et al., 2019), with a correlation time scale of 2.8 hours (Mallia et al., 2017)
- *uncertainty in STILT based on the finite number of particles* released is considered 0.1 ppm (Mallia et al., 2017; Kunik et al.,2019)
- *Error introduced by aggregating spatially and temporally heterogeneous fluxes* into one homogeneous grid cell and timesteps (followed Kunik et al. (2019) approach)

Uncertainty reduction

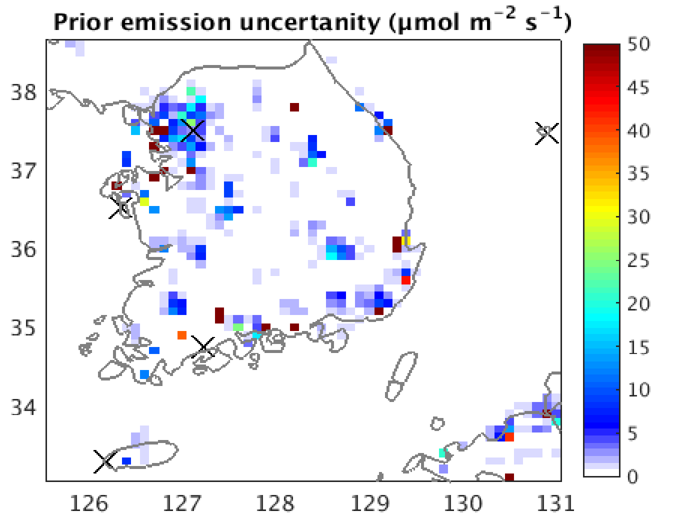
- Prior uncertainty from absolute difference of prior minus true emission
- The assigned model-mismatch values are ranging between 2.44 ppm and 3.28 ppm
- ULD site only does not have influence on the uncertainty reduction

$$\text{Uncertainty reduction (\%)} = \left(1 - \frac{\sigma_{predicted}}{\sigma_{prior}}\right) x\ 100$$

✓ Daytime (2-7 UTC) uncertainty reduction =

✓ **19.1 %** **(5 sites)** → **29.7 %** **(10 sites)**

Reduced $\chi^2 = 0.926$



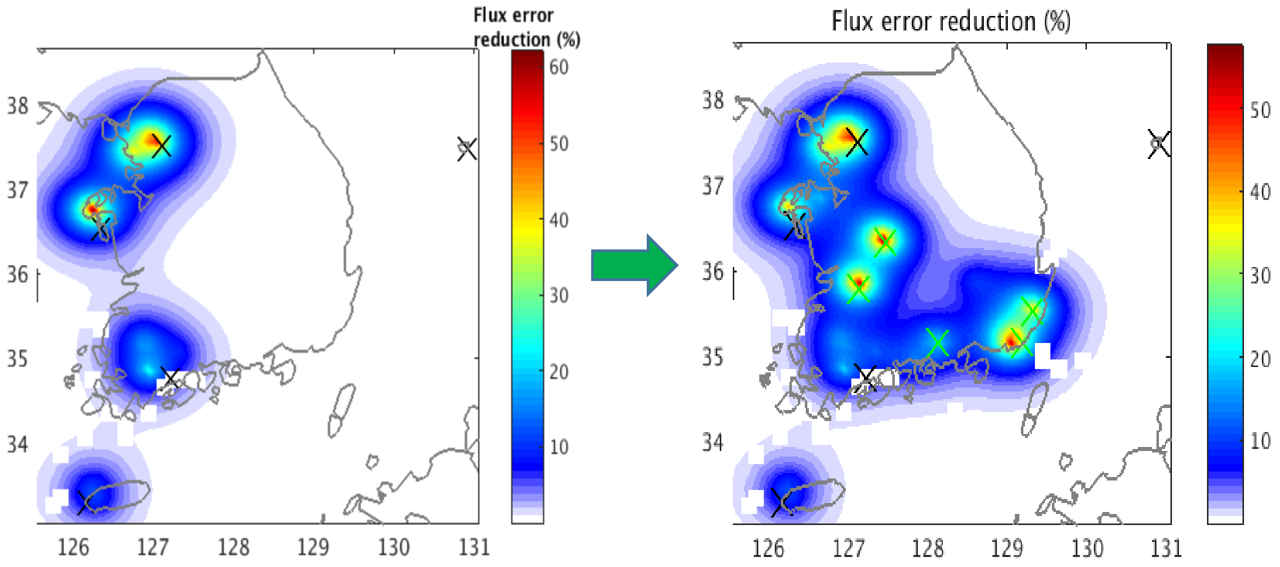


Figure 3. Prior uncertainty and uncertainty reduction maps. Unit for emission is μmol m^{-2} s^{-1}.

Undergoing work: *sensitivity analysis and method validation*

- Influence of spatial and temporal correlation length
- Ranking the site influence in terms of uncertainty reduction
- Investigate the impact of inlet heights, backward time of the trajectory

Thank you!