High-resolution greenhouse gas flux inversions using a machine learning surrogate model

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Poster

Quantifying greenhouse gas (GHG) emissions is critically important for projecting future climate and assessing the impact of environmental policy. Estimating GHG emissions using atmospheric observations is typically done using source-receptor relationships (i.e., "footprints"). Constructing these footprints can be computationally expensive and is rapidly becoming a computational bottleneck for studying GHG fluxes at high spatio-temporal resolution using dense observations. Here we demonstrate a computationally efficient GHG flux inversion framework using a machine learning emulator for atmospheric transport (FootNet) as a surrogate for the full-physics model. This flux inversion using a machine learning surrogate model only requires meteorological data, densely spaced measurements, and prior emission fluxes. This flux inversion framework is 84 times faster than the conventional inversion framework on a similar infrastructure such that it only takes 1.13 days to perform hourly urban flux inversions at a kilometer scale for a 3-month period on a single machine, this time includes both the construction of footprints and the GHG flux inversion. This shows the feasibility of using FootNet in the near-real-time quantification of GHG emission fluxes at a kilometer scale.

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