Abstract:

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. The footprints generated by FootNet are at approximately one-kilometer resolution. We update the architecture of the deep-learning model to improve the performance in a GHG flux inversion. Paradoxically, the updated FootNet model out-performs the full-physics model when used in a flux inversion and compared against independent observations. This improved performance is likely because atmospheric transport simulated with a full-physics transport model is not necessarily more accurate. The more simplistic representation of transport in the machine learning model helps to mitigate transport errors. This flux inversion using a machine learning surrogate model only requires meteorological data, GHG measurements, and prior fluxes. Constructing footprints using FootNet is 650× faster than the full-physics atmospheric transport model on similar hardware. This speedup allows for computation of footprints "on-the-fly'' during the GHG flux inversion (i.e., computed as needed, rather than archiving for future use) and makes near-real-time emission monitoring computationally possible. This work alleviates a major computational bottleneck with inferring GHG fluxes with next generation dense observing systems.