Uncertainty in global time-resolved methane emissions from aquatic waterbodies

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1. Focal Area(s)

This whitepaper addresses focal areas 1) uncovering key uncertainties and knowledge gaps for predictive understanding of the methane cycle and 4) automated/real-time data capture to improve uncertainty quantification.

2. Science or Technological Challenge

Quantifying global methane emissions from lakes and reservoirs (hereafter 'waterbodies') is challenged both by 1) uncertainty in areal flux rates and 2) uncertainty in the distribution and magnitude of total waterbody area. This whitepaper is concerned with constraining estimates of the latter and propagating its associated uncertainties to global methane emissions calculations. To do this, we propose creating a data pipeline for retrieving time-resolved measurements of waterbody area and using these to 'update' a methane uncertainty model, the architecture of which we describe below.

3. Rationale

Because we do not have a complete real-time census of all waterbodies, upscaling estimates of methane emissions from small waterbodies to broad spatial extents requires the use of waterbody size-abundance distributions rather than empirical measurements of area. Such waterbody-size abundance distributions are typically generated on an ad-hoc (i.e. one-off) basis that yields an over-exact estimate of total waterbody area reported with no uncertainty bounds [2]. As an alternative to the typical approach: *We propose a data assimilation workflow that combines the Bayesian sensitivity analysis method of [4] with a dynamic data pipeline for retrieving waterbody areas from remote sensing imagery [1].* Our approach is capable of producing global waterbody nowcasts of methane emissions that include the uncertainty arising from dynamic area fluctuations. Not only does our approach avoid the necessarily static estimates derived from static waterbody databases, it avoids the need to continuously create massive global water body datasets [3] out of whole-cloth. Instead, an initial estimate of methane emissions uncertainty is derived, which is then dynamically 'updated' via a data pipeline that retrieves waterbody areas from remote sensing imagery.

4. Narrative

The approach we describe below will help better define uncertainties in our predictive understanding of the methane cycle using advanced statistical tools and automated (near)real-time data capture. It involves two components:

4.1 Bayesian sensitivity analysis

Waterbody areas are typically treated as arising from a scale-invariant fractal generating process. This means that the number of waterbodies in one size class is proportional to the number of waterbodies in the preceding size class irrespective of their magnitudes [4]. The numerical form describing such a process is a power-law function. One of the statistical tools often used to model data that follow a power-law function is the Pareto distribution. The fit of any particular dataset to a Pareto distribution has associated uncertainty (Fig 1) which can be carried through to uncertainty in waterbody areas [4] and we propose to carry this uncertainty forward even further to methane emissions calculations themselves (i.e. values across the posterior interval of the underlying parameters are used for calculation instead of a single posterior median).

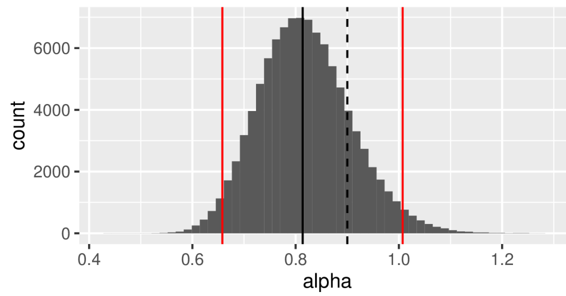

Figure 1:Median (black line) and central 95 percent interval estimates of the Pareto shape parameter alpha (red lines) from the simulation in [4]. Here the 'true' alpha is 0.9.

4.2 Automated data capture

Even after accounting for uncertainty in total waterbody area on a static basis (e.g. [4]), there remains a high degree of uncertainty with respect to dynamic fluctuations in waterbody area [1][3]. For example, new waterbodies are formed as a result of flooding, old waterbodies disappear as a result of climate change and dam removal. Therefore, we propose a data pipeline which will retrieve 'raw' remote sensing imagery, subject this imagery to water detection analysis, vectorization, and filtering for recurrency to exclude ephemeral and non-lake non-reservoir waterbodies (Figure 2). Limiting the pipeline to recurrent waterbodies will allow for temporal updating of an initial static uncertainty model (described above) and has the advantage of not requiring fully global processing. Rather, the model can be updated from limited portions of the globe as they become available in the data pipeline. When the automated data capture pipeline is fully integrated with the Bayesian sensitivity model, it will provide estimates of global methane emissions from inland waterbodies along with an associated uncertainty.

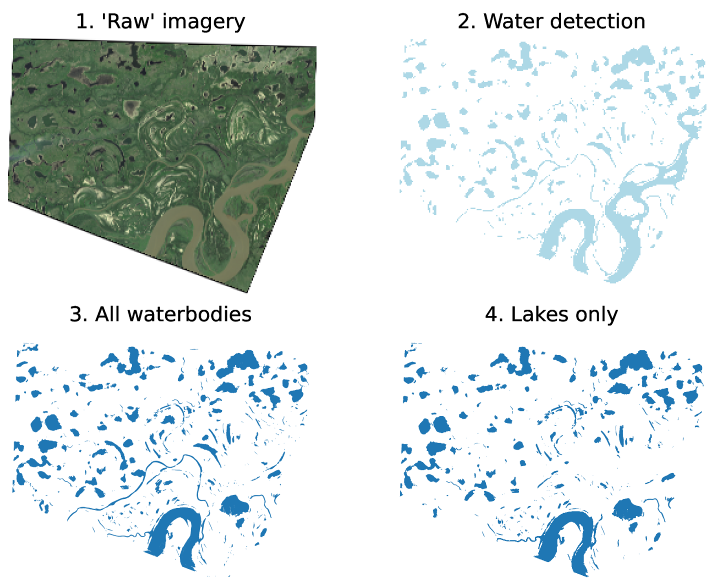

Figure 2: Workflow for automated lake identification and area measurement. 1) Imagery fetching (Image ©Planet Labs, CubeSat, 3m resolution)[7], 2) Water dectection [5], 3) 'blob' vectorization, 4) river removal [6].

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