



## **CH<sub>4</sub> flux gap-filling approaches for eddy covariance data: a comparison of three machine learning algorithms and marginal distribution sampling method with and without principal component analysis**

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Within the past decade, flux towers which incorporate methane flux (FCH<sub>4</sub>) measurements have increased following the development of a robust and low-power CH<sub>4</sub> gas analyzer. As is the case with other trace gases, CH<sub>4</sub> flux data based on the eddy covariance technique commonly includes data gaps due to unsuitable atmospheric conditions and system failures, with FCH<sub>4</sub> often having more gaps than CO<sub>2</sub> and H<sub>2</sub>O fluxes. However, there is still no consensus on FCH<sub>4</sub> gap-filling method. Some researchers have applied a marginal distribution sampling (MDS) algorithm for FCH<sub>4</sub> gap-filling, which is a standard gap-filling method for CO<sub>2</sub> and water fluxes. Others have tested and applied machine learning (ML) algorithms like artificial neural networks to gap-fill FCH<sub>4</sub> data.

One of the major challenges in FCH<sub>4</sub> gap-filling using both MDS and ML algorithms concerns selection of input variables. Since MDS has been widely used in the Fluxnet community by virtue of a robust online algorithm and an R package, standardizing the selection of MDS input variables for gap-filling FCH<sub>4</sub> is important. Nevertheless, discussions in the literature on MDS input parameters are rare. Likewise, use of ML algorithms for FCH<sub>4</sub> gap-filling has increased with limited discussions on input selection. At present, we are also not aware of a comprehensive comparison between commonly used ML algorithms such as artificial neural networks (ANN), support vector machine (SVM), and random forest (RF) for FCH<sub>4</sub> gap-filling.

In this study we compare performance of MDS and the three ML algorithms (ANN, SVM, RF) using different combinations of ancillary parameters. In addition, we applied principal component analysis (PCA) as an input to the algorithms to resolve multi-parameter dependency of FCH<sub>4</sub>. We applied this approach to 5 benchmark FCH<sub>4</sub> datasets from temperate and tropical wetlands and rice paddies. For performance evaluation, various artificial gap scenarios were added to FCH<sub>4</sub> data and then gap-filled using MDS and ML algorithms, with and without PCA. Performance of the algorithms was measured using Taylor diagrams, and residual analysis was also conducted to understand limitations of each algorithm and input decision. Results indicate that PCA improves the performance of MDS compared to traditional MDS inputs (i.e. global radiation, air temperature, and vapour pressure deficit) and alternative MDS inputs (i.e. soil temperature, water table height, and net ecosystem exchange). On the other hands, all of the ML algorithms show better performance without PCA when all available biophysical variable are selected as inputs. As for the comparison among ML algorithms, RF was found to outperform other techniques for the 5 benchmark sites and all gap scenarios. In this presentation, we also discuss how annual CH<sub>4</sub> budgets vary in relation to gap-filling methods based on biases introduced through the various gap-filing approaches.