We started the first stage on the same day we manually collected CH4 ebullition and generated daily water temperature forecasts from FLARE for a 16-day forecast horizon (Thomas et al. 2020). Additionally, we accessed the observed water temperature observations measured at the dam site every 10 minutes by thermistors at 2 and 3 m depth (NexSens Technology, Inc.; Fairborn, Ohio, USA; Carey et al. 2020*b*; Figure 1). When we collected the CH4 ebullition samples at the upstream transect, we also manually downloaded 10-minute SWI temperature data from four HOBO temperature loggers (HOBO Pendant Temperature/Light Data Logger; Bourne, MA, USA) deployed just above the SWI below each trap. More information on the downloads and workflow of the SWI temperature linear scaling model can be found in Supporting information A.

Finally, The data assimilation stage consisted of using the observed transect-level ebullition rates to update the forecasting model parameters weekly via data assimilation that refit Eqn. S1 and Eqn. 2 using all existing data. When new observations of CH4 ebullition rates, deep site water temperatures, and upstream transect SWI temperatures became available, they were used to update the SWI temperature and CH4 ebullition models in a Bayesian framework (following Dietze 2017*a*), which generated new parameters for the SWI temperature scaling model (Eqn. S1) and the CH4 ebullition model (, , , and ), respectively. The Bayesian framework used three Monte Carlo Markov Chain simulations with 50,000 samples to generate the new parameter estimates that would be used for the next CH4 ebullition rate forecasts. We assessed for convergence of the chains using Gelman-Rubin diagnostics (Gelman and Rubin 1992). This framework ensured both forecast models (Eqn. S1 and 2) were probabilistic and accounted for initial conditions, parameter, and model process uncertainty (Dietze 2017*b*). We used the ‘rjags’ and ‘R2jags’ package (Plummer 2019) within the R statistical environment for the Bayesian analyses (R Core Development Team 2020).

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To account for initial conditions uncertainty, the standard error of the mean CH4 ebullition rates among at each ebullition trap () was used as initial conditions for the forecast, with uncertainty represented by a set of 210 random draws from a normal distribution which had a mean equal to the most recent observations and a standard error from the most recent observations. (How best do I describe the daily latent initial conditions?) To account for parameter uncertainty, the ebullition forecast model sampled 210 different parameter values each from the three posterior distributions of , , and (Eqn. 2). To account for process uncertainty, random noise ( from Eqn. 2) was added to each ensemble member, drawn from a normal distribution with a mean of zero and a standard deviation equal to . Finally, driver data uncertainty was represented by randomly sampling 210 different forecasted SWI temperatures () derived from the temperature scaling model and FLARE.

Suggesting theuggesting that data assimilation substantially improved the forecasted mean CH4 ebullition rates. Additionally, the Dpl similarly highlighted the higher skill of the CH4 ebullition forecasts with data assimilation (Table 1). The Dpl of the forecasts with data assimilation was 1230 while the forecasts without data assimilation and the persistence null model was 6630 and 3660, respectively, also indicating that data assimilation substantially improved the forecast skill during the forecasting period.

In addition to the successful NSE and Dpl of the forecasts with data assimilation, the seasonally summed CH4 from the forecasts with data assimilation were closer to the observations than the seasonally summed CH4 from forecasts without data assimilation and the persistence null model (Table 1). The mean seasonally summed observed CH4 ebullition over the forecasting period (143 days) was 60000 g CH4, while the forecasts with data assimilation predicted a seasonal sum of 65000 g CH4, an 8% overestimate. In comparison, the forecasts without data assimilation estimated a total of 52000 g CH4, and the null persistence model estimated 89000 g CH4, representing a 14% underestimate and 39% overestimate, respectively.