TITLE: Fencing farm dams to exclude livestock halves methane emissions and improves water quality

Running Title: Reducing carbon emissions from farm dams

Martino E. Malerba [1,*], David B. Lindenmayer [2], Ben C. Scheele [2], Pawel Waryszak [1], I. Noyan Yilmaz [1], Lukas Schuster [3], Peter I. Macreadie [1].

[1] Centre for Integrative Ecology, School of Life and Environmental Sciences, Deakin University VIC 3125, Australia

[2] Sustainable Farms, Fenner School of Environment & Society, The Australian National University ACT 2601, Australia

[3] Centre of Geometric Biology, School of Biological Sciences, Monash University, VIC 3800, Australia

* Corresponding author: Martino E. Malerba; m.malerba@deakin.edu.au

ORCID ID:

Martino E. Malerba – https://orcid.org/0000-0002-7480-4779.

David B. Lindenmayer – https://orcid.org/0000-0002-4766-4088

Ben C. Scheele – https://orcid.org/0000-0001-7284-629X

Pawel Waryszak – https://orcid.org/0000-0002-4245-3150

I. Noyan Yilmaz – https://orcid.org/0000-0003-0260-4708

Lukas Schuster – https://orcid.org/0000-0003-2691-9085

Peter I. Macreadie – https://orcid.org/0000-0001-7362-0882

Keywords: impoundment, sustainable farms, eutrophication, inland water, agricultural reservoirs, dugouts.

Author Contributions: M.E.M, D.B.L, B.C.S, and P.I.M. designed the research, M.E.M., P.W., and I.N.Y. collected the data, M.E.M. and L.S. analyzed the data, M.E.M. wrote the first draft, and all authors contributed to the final draft.

Competing Interest Statement: The authors declare no conflict of interest.

Acknowledgments: We thank the anonymous reviewers and the Editor for their many insightful comments and suggestions. This work was supported by the Australian Government through the Australian Research Council (project ID DE220100752) and the Alfred Deakin Fellowship scheme. We thank David Smith, Clare Cane, Dan Florance, Michelle Young, Suzannah Macbeth, Eleanor Lang, Colleen O'Malley, Angelina Siegrist, Amber Croft, and the team at Sustainable Farms for facilitating fieldwork. We are grateful to landowners who allowed us to work on their farms. We also thank Dr Tertius de Kluyver

(Dept. of Industry, Science, Energy and Resources, Australian Government) for insightful comments and suggestions.

Data availability statement: We published a public online repository with all raw data, R codes, analyses, plots, tables, and the results of the literature review on GitHub (https://github.com/martinomalerba/FarmDamEmissions) and Dryad (https://doi.org/10.5061/dryad.g1jwstqt5).

Abstract

Agricultural practices have created tens of millions of small artificial water bodies ("farm dams" or "agricultural ponds") to provide water for domestic livestock worldwide. Among freshwater ecosystems, farm dams have some of the highest greenhouse gas (GHG) emissions per m^2 due to fertilizer and manure run-off boosting methane production – an extremely potent GHG. However, management strategies to mitigate the substantial emissions from millions of farm dams remain unexplored. We tested the hypothesis that installing fences to exclude livestock could reduce nutrients, improve water quality, and lower aquatic GHG emissions. We established a large-scale experiment spanning 400 km across south-eastern Australia where we compared unfenced (N = 33) and fenced farm dams (N = 31) within 17 livestock farms. Fenced farm dams recorded 32% less dissolved nitrogen, 39% less dissolved phosphorus, 22% more dissolved oxygen, and produced 56% less diffusive methane emissions than unfenced dams. We found no effect of farm dam management on diffusive carbon dioxide emissions and on the organic carbon in the soil. Dissolved oxygen was the most important variable explaining changes in carbon fluxes across dams, whereby doubling dissolved oxygen from 5 to 10 mg L^{-1} led to a 74% decrease in methane fluxes, a 124% decrease in carbon dioxide fluxes, and a 96% decrease in CO_2-eq ($CH_4 + CO_2$) fluxes. Dams with very high dissolved oxygen (>10 mg L^{-1}) showed a switch from positive to negative CO_2-eq. ($CO_2 + CH_4$) fluxes (i.e., negative radiative balance), indicating a positive contribution to reduce atmospheric warming. Our results demonstrate

that simple management actions can dramatically improve water quality and decrease methane emissions while contributing to more productive and sustainable farming.

Introduction

Global methane emissions are rising rapidly, nearly tripling from ca. 700 ppb in pre-industrial times to 1900 ppb today (Conrad, 2009; Dlugokencky, 2022). The accumulation of artificial water bodies has contributed to the growth in atmospheric methane, with aquatic ecosystems now accounting for half of natural and anthropogenic methane emissions (Rosentreter et al., 2021). With farm dams estimated to cover a surface area >75,000 km^2 globally (Downing et al., 2006), these artificial systems are now a key part of aquatic ecosystems globally (Malerba et al., 2021; Swartz & Miller, 2021). Therefore, it is likely that farm dams are an important contributor to global carbon cycles – even though this link is often overlooked in national and global carbon inventories. Indeed, the Intergovernmental Panel on Climate Change (IPCC) recently revised their guidelines to promote the inclusion of agricultural ponds in national GHG inventories and tackle this form of anthropogenic carbon emission (IPCC, 2019).

Farm dams (or agricultural ponds) are small, human-made freshwater bodies created for the purpose of storing water for livestock or crop irrigation. These systems have some of the highest greenhouse gas (GHG) emissions per m^2 among freshwater ecosystems (Grinham et al., 2018; Ollivier et al., 2018, 2019) due to their much higher nitrogen and phosphorus concentrations than natural ponds (Westgate et al., 2022), creating the perfect conditions for methanogenesis and GHG emissions (Li et al., 2021; Peacock et al., 2021). Importantly, eutrophication appears to have a disproportionate effect on farm dams. That is, a 25% increase in nitrate concentration was observed to double the CO_2-equivalent carbon flux per m^2 of a farm dam (Ollivier et al., 2018). Hence, understanding how to reduce the emissions of millions of farm dams worldwide has the potential to make a substantial difference in mitigating climate change. Yet, there is no evidence of the effects of management practices on reducing these emissions.

Using fences to exclude livestock from farm dams improves water quality by reducing direct depositions of nutrient-rich manure and urine into the water (Westgate et al., 2022). In addition, fencing a farm dam avoids hooved livestock (ungulates) disturbing soils and promotes higher vegetation cover around the dam, acting as a filter to reduce dissolved nutrients (i.e., "phytoremediation"; reviewed in Pilon-Smits, 2005). A recent study showed that partially or fully fenced farm dams have higher vegetation cover, higher water quality (i.e., lower nutrients, turbidity, and fecal coliforms), and higher macroinvertebrate richness and abundance than unfenced farm dams (Westgate et al., 2022). Moreover, fencing farm dams is often cost-effective, with the benefits for livestock health and weight gain from higher water quality often exceeding the costs of this management intervention (Dobes et al., 2021).

In summary: (1) nutrient pollution drives high GHG emissions from farm dams; (2) excluding livestock from accessing farm dams favors vegetation growth and improves water quality; and (3) higher water quality provides benefits to livestock health, biodiversity, and aesthetic value. Based on these premises, installing fences could reduce aquatic GHG emissions from farm dams while improving agricultural productivity and biodiversity. Previous studies have already shown that excluding livestock and reducing grazing intensity can reduce methane emissions and enhance carbon sequestration and storage of freshwater wetlands (Limpert et al., 2021; Oates et al., 2008; Watkins et al., 2017). Yet, the effects of installing fences (or any other management intervention) on farm dam GHG production remain untested. Similarly, there is little evidence of the benefits of farm dam fencing on water quality (Westgate et al., 2022). Hence, we here addressed two key questions:

(1) What are the effects of fencing farm dams on water quality (i.e., total dissolved nitrogen, total dissolved phosphorus, and dissolved oxygen), soil organic carbon, and GHG fluxes of methane and carbon dioxide?
(2) What are the mechanisms linking farm dam management to aquatic GHG fluxes?

To answer these questions, we completed a cross-sectional field-based study comparing the effects of fencing farm dams on their water quality and carbon footprint. We surveyed 64 farm dams across 17 farming properties. At each property, we compared farm dams under two management regimes: “unfenced dams” where livestock have free access to the water, and “fenced dams” where water access has been controlled for at least two years using either full fencing or partial fencing (with a hardened livestock access point). We predicted that fencing a farm dam would reduce dissolved nutrients, increase dissolved oxygen, and lower GHG emissions. Testing these processes contributes to identifying novel GHG abatement methods to reduce the carbon footprint of farming practices.

Methods

Study area and experimental design

In April 2021, we sampled farm dams across 400 km of the Australian South West Slopes bioregion in south-eastern New South Wales. The study region has a warm temperate climate, with hot dry summers and cool humid winters (the largest city of Albury has an annual mean temperature of 22 °C and annual rainfall of 691 mm). Most of the area is dedicated to livestock grazing (especially beef cattle and sheep) and dryland cropping (mainly cereals and oilseed). We surveyed 64 farm dams located in pastures on 17 farming properties. Within each property, we established two experimental treatments: "unfenced" farm dams and "fenced" farm dams. At each combination of experimental treatment and farming property, we measured between 1 and 5 dams (depending on availability) on the same day. Unfenced farm dams ($N = 33$) received no management intervention to improve their ecological condition. Fenced farm dams ($N = 31$) were either entirely fenced (with a pump delivering water into drinking troughs) or partly fenced (providing water access through a hardened access point) for at least two years prior to sampling. We avoided small (< 200 m^2) farm dams because they were too ephemeral. We measured farm dam areas by tracing the most recent satellite images on Google Earth Pro (version 7.3.4).

Aquatic greenhouse gas emissions

We measured diffusive emissions of methane and carbon dioxide at each farm dam using methods described in Ollivier et al. (2018, 2019). Briefly, a white plastic floating chamber (0.021 m^3 volume and 0.14 m^2 surface area) was sealed and connected to an Ultraportable Greenhouse Gas Analyzer (UGGA, Los Gatos Research, Model 915- 0011) through two tubes (influx and outflux) on the chamber roof to create a closed circuit. We sampled methane and carbon dioxide (ppm) at 1-second intervals for 5 minutes (300 data points per sample). We measured each farm dam three times from different locations along the shore ensuring the starting concentration matched atmospheric levels.

Floating chambers can measure constant fluxes (diffusion) and stochastic releases of gas bubbles (ebullition). Here we focused only on diffusive fluxes. To do so, we excluded any trajectories showing sudden increases in gas concentration due to a gas bubble being released inside the floating chamber. We estimated the linear rate of change of diffusive gas flux from the water surface to the atmosphere (F; mg m^{-2} d^{-1}) as:

$$F = \frac{slope \times volume \times F_1 \times F_2}{F_3 \times surface} \qquad \text{(Eq. 1)}$$

where $slope$ is the linear rate of change in gas concentrations over time within the chamber (ppm s^{-1}), $volume$ is the chamber volume (0.021 m^3), F_1 is the conversion factor from ppm to µg m^{-3} for methane (655.47), F_2 is the conversion factor from minutes to day (86,400), F_3 is the conversion factor from µg to mg (1000), $surface$ is the surface area of the chamber

($0.14\ m^2$; Lambert and Fréchette, 2005). We retained all diffusive rates without applying any filtering method (e.g., R^2 threshold).

Sediment carbon stocks

At each dam, we collected two cores (45 mm diameter, 50 mm deep, 79.52 cm^3 volume) from the edge of the pond within the water (wet sediments). We preserved the cores in a freezer until returning to the lab. We dried all cores at 60°C until there was no more weight loss (approx. a week) and measured their dry weights. Finally, we ground the cores and determined the organic carbon content by analyzing 10 mg of each sample using a EuroVector MicroElemental CN Analyser (see Gulliver et al., 2020 for details). We quantified each sample's C:N ratio using Acetanilide as standards (71.09% C, 0.5-1 mg input mass; $R^2 > 0.98$). The carbon density of each core was the product of dry biomass density (g cm^{-3}) and carbon content (i.e., % C/100) in units of tons of carbon per hectare (t C ha^{-1}).

Water quality and nutrient analysis

At each site, we measured dissolved oxygen (mg O_2 L^{-1}), conductivity (µS cm^{-1}), and water temperature (°C) using a Hach HQ30D portable Multi Meter. We also filtered 50 mL of water from each farm dam using syringe filters with Filtech 483 Glass fiber filter paper (1.10 µm retention, 25 mm diameter). We froze all filtrated water samples immediately after collection and sent them to ALS Environmental (alsglobal.com, Everton Park QLD 4053 Australia) to analyze total nitrogen following APHA 4500-N_{org} / 4500-NO_3^- (method EK062G; mg N L^{-1}) and total phosphorus following APHA 4500-P (method EK067G; mg P

L^{-1}). All analyses followed standard protocols and included quality controls. Finally, we took three pH measurements at each dam using the YSI ProDSS Multiparameter Digital Water Quality Meter (Xylem Analytics, Yellow Springs, OH 45387 USA), taking measurements at 1.5 m from the water's edge and at 20 cm depth. We rinsed the sensors with demineralised water between samples and sites and always calibrated probes before use.

Statistical analyses

First, we used individual linear mixed-effects models to evaluate whether the management regime (categorical variable, either "fenced" or "unfenced") affected total dissolved nitrogen (log_{10} mg N L^{-1}), total dissolved phosphorus (log_{10} mg P L^{-1}), dissolved oxygen (mg L^{-1}), organic carbon stock (log_{10} t C ha^{-1}), rates of methane emissions (log_{10} mg m^{-2} d^{-1} + 2), and rates of carbon dioxide emissions (log_{10} mg m^{-2} d^{-1} + 1800). We added two units to methane emissions and 1800 units to carbon dioxide emissions to avoid negative values when applying the log_{10} transformation. We did not correct the p values for multiple statistical testing, yet we ensured that reducing the risk of type I error by adopting more conservative thresholds for statistical significance using the false discovery rate (Benjamini & Hochberg, 1995) did not change any of our conclusions.

Second, we used three linear mixed-effects models to quantify the statistical association of each environmental variable with fluxes of carbon dioxide, methane, and CO_2-equivalent (carbon dioxide + methane) of a farm dam. We calculated CO_2-equivalent units by combining methane and carbon dioxide fluxes using the 20-year Sustained-Flux Global Warming Potential (SGWP) metric from Neubauer and Megonigal (2015), where 1 Kg of

CH_4 traps as much infrared radiation as 96 Kg of CO_2. The SGWP calculates the decay rate assuming a sustained gas flux rate over time, and this approach is more realistic for farm dams than the one-time pulse assumed in the Global Warming Potential metric. In the models, the independent variables were farm dam surface area ($\log_{10}$ m^2), dissolved oxygen ($\log_{10}$ mg L^{-1}), pH, conductivity ($\log_{10}$ µS cm^{-1}), water temperature (°C), total dissolved nitrogen ($\log_{10}$ mg N L^{-1}), total dissolved phosphorus ($\log_{10}$ mg P L^{-1}), and organic carbon stock ($\log_{10}$ t C ha^{-1}). The initial fully parameterized model included all main effects and a 2-way interaction term to account for the potential interplay between total nitrogen and total phosphorus. To avoid bias from multicollinearity between main effects, we ensured a cut-off value of five for the maximum variance inflation factor (VIF) in the model, as recommended by Zuur et al. (2009). As a result, pH and dissolved oxygen could not be included together in the models because they are highly correlated (r = 0.72 and VIF > 5). Therefore, we used only dissolved oxygen in the mixed-effects models as this variable is associated with fluxes of both carbon dioxide and methane (whereas pH is only associated with CO_2). Finally, we quantified the importance of each statistically significant explanatory variable by calculating its contribution to the total model prediction power using a permutation approach (Niittynen & Luoto, 2018; Fisher et al., 2019; Virkkala et al., 2021). This analysis consisted of three steps. First, we extracted the predictions from the best-fitting model ($Predictions_{original}$). Second, we created simulated datasets using random permutations of each statistically significant explanatory variable to remove its explanatory power. Third, we re-fitted the model to each simulated dataset, computed model predictions, and quantified the Pearson correlation coefficient between the predictions of the original model ($Predictions_{original}$) and the predictions with the explanatory variable being permutated ($Predictions_{shuffled,v}$), as:

$$Importance_v = 1 - cor(Predictions_{original} - Predictions_{shuffled,v}) \qquad \text{(Eq. 2)}$$

Values close to -1 or 1 indicate greater importance of the shuffled variable for the model's explanatory power. We repeated this process 100 times for each variable to calculate the average importance and 95% confidence intervals.

We centred and scaled all variables before fitting the models. We also added a random intercept to account for the experimental block design where each of the 17 farming properties contained one or more fenced and unfenced dams. To analyse repeated flux measurements from the same pond, we added a nested random intercept of site within farming property. When standardized residuals showed unequal variances or a relationship with any predictor variables, we included treatment-specific variance coefficients (function varIdent) or other variance functions (functions varExp or varPower) in the model. We identified the best-fitting model using Akaike Information Criteria corrected for small sample sizes (AICc; Burnham & Anderson, 2004). We used standard diagnostics to ensure normality, homoscedasticity, and the absence of influential points or outliers.

We used the statistical software R version 4.0.3 (R Core Team, 2020) with the packages nlme (Pinheiro et al., 2020) and effects (Fox & Weisberg, 2018, 2019) for the statistical analyses, and dplyr (Wickham et al., 2018), plyr (Wickham, 2011), and ggplot2 (Wickham, 2009) for data manipulation and plotting.

Results

Effects of fencing farm dams on greenhouse gas emissions and organic carbon stocks

On average, methane emissions from fenced farm dams (3.5 mg m^{-2} d^{-1}) were 56% lower than unfenced farm dams (8.05 mg m^{-2} d^{-1}; Fig. 1a). Conversely, we found no significant difference for carbon dioxide fluxes ($p = 0.2$; Fig. 1b) or for CO_2-eq fluxes ($p = 0.08$; Fig. 1c). Finally, there was no effect of fencing on the organic carbon stock in the sediments of the farm dams ($p = 0.42$; Fig. 1d). See Table 1 for summary statistics and Table S1 for statistical scores.

Effects of fencing farm dams on water quality

Fenced farm dams recorded higher water quality than unfenced ones across all parameters measured here. Specifically, water from fenced farm dams had on average 32% less total dissolved nitrogen (from 2.4 to 1.6 mg L^{-1}; Fig. 2a), 39% less total dissolved phosphorus (from 0.078 to 0.047 mg L^{-1}; Fig. 2b), and 22% more dissolved oxygen than unfenced dams (from 6.32 to 7.74 mg L^{-1}; Fig. 2c). We found no difference in the water temperature (Fig 2d) and water pH (data not shown) of fenced and unfenced farm dams (see Table 1 for summary statistics and Table S1 for statistical scores).

Drivers of greenhouse gas fluxes

Overall, most relationships between greenhouse gas fluxes and environmental variables show a high degree of variability. Yet, the methane flux of a farm dam was statistically associated with dissolved oxygen (Fig. 3a), sediment organic carbon stocks (Fig. 3b), total dissolved nitrogen (Fig. 3c), and total dissolved phosphorus (Fig. 3d). In contrast, the carbon dioxide flux of a farm dam only showed a negative association with dissolved oxygen (Fig. 3f). The total carbon flux of a farm dam, calculated as CO_2-eq (methane + carbon dioxide) fluxes, showed statistically significant associations with dissolved oxygen (Fig. 3k), sediment organic carbon stocks (Fig. 3l), and total dissolved nitrogen (Fig. 3m). Conversely, farm dam area, conductivity, and a 2-way interaction between dissolved nitrogen and dissolved phosphorus were systematically excluded from the best-fitting models following Akaike Information Criteria.

Dissolved oxygen was the most important variable for explaining all three greenhouse gas fluxes (see Table S3 for importance scores). Specifically, doubling dissolved oxygen from 5 to 10 mg L^{-1} corresponded to a 74% decrease in methane fluxes (from 6.92 to 1.8 mg CH_4 m^{-2} day^{-1}; Fig. 3a), a 124% decrease in carbon dioxide fluxes (from 2.27 to -0.56 g CO_2 m^{-2} day^{-1}; Fig. 3f), and a 96% decrease in CO_2-eq fluxes (from 3.77 to 0.13 g CO_2-eq m^{-2} day^{-1}; Fig. 3k). Farm dams with dissolved oxygen levels higher than ca. 10 mg L^{-1} showed a switch from positive to negative CO_2-eq fluxes (i.e., negative radiative balance; Fig. 4).

Changes in both dissolved oxygen and carbon dioxide were pH related (Fig. 5). Dissolved oxygen was positively correlated with the pH ($r = 0.72$; Fig. 5a) and negatively correlated with the carbon dioxide flux ($r = -0.82$; Fig. 5b), while carbon dioxide flux was negatively correlated with pH (r = – 0.76; Fig. 5c). Conversely, we found no significant correlation between pH and methane fluxes (p = 0.39; data not shown).

Discussion

Farm dams are common in many rural landscapes worldwide and make important contributions to carbon cycles and greenhouse gas (GHG) emissions (Grinham et al., 2018; Ollivier et al., 2018; Peacock et al., 2021). We discovered that simple management practices, such as fencing off livestock from farm dams, increased water quality and dramatically lowered methane emissions. Fenced farm dams were characterized by 32% less dissolved nitrogen, 39% less dissolved phosphorus, 22% more dissolved oxygen, and 56% lower methane emissions than unfenced dams. Dissolved oxygen was the most important variable explaining changes in carbon fluxes across dams, whereby doubling dissolved oxygen from 5 to 10 mg L^{-1} led to a 74% decrease in methane fluxes, a 124% decrease in carbon dioxide fluxes, and a 96% decrease in CO_2-eq (CH_4 + CO_2) fluxes. Moreover, farm dams with very high oxygen levels (>10 mg L^{-1}) exhibited a switch from positive to negative CO_2-eq fluxes. Finally, we found a strong negative correlation between the pH of the water and both the dissolved oxygen and fluxes of carbon dioxide.

We found that fencing farm dams, on average, more than halves diffusive methane emissions to 3.56 mg CH_4 m^{-2} day^{-1} compared to 8.16 mg CH_4 m^{-2} day^{-1} of unfenced farm dams. Our fieldwork took place in the bioregion of South Western Slopes in south-eastern

Australia, an important agricultural hotspot covering 86,811 km^2. This region contains an estimated 172,000 farm dams with a cumulative surface area of 278 km^2 (Malerba et al., 2021), which is equivalent to the surface area of all lakes in the region (277 km^2; Crossman & Li, 2015). Assuming our data are representative of average yearly fluxes, we estimated that fencing farm dams in this region would avoid emissions of 468 tonnes CH_4 year^{-1}, which corresponds to 44,917 tonnes CO_2-eq year^{-1} using the 20-year Sustained-Flux Global Warming Potential (SGWP) metric. These are only ballpark estimates, and more data are needed to better estimate the opportunity for avoided emissions using farm dam restoration. Considering that most farm dams have broadly similar properties and serve the same purposes (i.e., collect water for agricultural uses), our results and qualitative mechanisms may also apply to other regions of the world – albeit with different magnitudes. Thus, an important next step is to use a cost-benefit analysis to determine if improving farm dam conditions could be a cost-effective way to help decarbonize agricultural practices at scale.

The range of diffusive carbon fluxes measured here (1 to 164 CH_4 mg m^{-2} day^{-1} and -1.7 to 14 CO_2 g m^{-2} day^{-1}) is comparable to previously published values for farm dams in Australia, Canada, India, and Sweden (Fig. 7, Table S4). Yet, our study (and most others) measured diffusive methane fluxes without accounting for other pathways of methane emissions (e.g., ebullition events; Bastviken et al., 2008; Bastviken et al., 2011). Grinham et al. (2018) quantified both ebullitive and diffusive methane fluxes from Australian irrigation and stock dams and reported higher values than ours (up to 3.6 CH_4 g m^{-2} day^{-1}; Fig. 7). It is possible that the benefits of fencing farm dams on carbon emissions are even higher than our estimates after accounting for multiple types of methane fluxes. However, research is needed to establish if fencing farm dams can influence ebullitive methane fluxes.

The two main findings of this study were: (1) that excluding livestock from farm dams improves water quality, and (2) that higher water quality corresponds to lower methane emissions. For the first finding, fenced farm dams recorded 32% less dissolved nitrogen, 39% less phosphorus, and 22% more dissolved oxygen than unfenced farm dams. Westgate et al. (2022) is the only other study on this topic and showed comparable results to ours, with a 45-50% reduction in total nitrogen and phosphorus in fenced farm dams over unfenced farm dams, together with reduced turbidity and lower fecal contamination. The similar results between two field studies from different years (2019 and 2021) and seasons (summer and autumn) suggest that the positive effects of fencing on water quality may be maintained throughout the year.

For the second finding, the higher water quality of fenced farm dams corresponded to 56% lower methane emissions. We found that total dissolved oxygen was a key driver explaining the reduced methane emissions. The strong negative effect of dissolved oxygen is consistent with our understanding of methanogenesis as a microbiological process requiring anaerobic conditions (Segers, 1998). Similarly, the positive effects of total dissolved nitrogen and sediment organic carbon stocks meet the expectation that freshwater environments rich with nutrients and labile organic materials emit more GHG (Beaulieu et al., 2019; Li et al., 2021; Peacock et al., 2021). Instead, a surprising result was the negative effect of total phosphorus on methane fluxes, particularly since phosphorus is thought to promote methane production rates (Peacock et al., 2021; Peacock et al., 2019). Phosphorus concentration only had a weak negative effect on methane fluxes but not on carbon dioxide or CO_2-eq fluxes. As shown by Nijman et al. (2022), one explanation could be that a greater phosphorus availability increases the growth and activity of methane-oxidizing bacteria, resulting in a reduction of methane emissions through the oxidation of methane to hydrogen and carbon monoxide. Yet more studies are needed to clarify the effects of phosphorus on methanogenesis in farm dams.

We found that farm dams with very high concentrations of dissolved oxygen exhibited negative CO_2-eq GHG fluxes (i.e., negative radiative balance), indicating a positive contribution to reduce atmospheric warming. Most farm dams contribute to climate change by emitting substantial amounts of atmospheric GHG (Holgerson & Raymond, 2016; Ollivier et al., 2018; Peacock et al., 2021). Yet, under certain circumstances, small freshwater systems can remove GHG from the atmosphere and act as a carbon sink (Ollivier et al., 2018; Peacock et al., 2021; Webb, Hayes, et al., 2019; Webb, Leavitt, et al., 2019). While we found negative fluxes in only a minority of cases (13 farm dams out of 64), the effect of oxygen on CO_2-eq fluxes was very predictable: every farm dam recording oxygen levels >10 mg L^{-1} also showed a carbon drawdown (at up to 1.2 g CO_2-eq m^{-2} d^{-1}). These negative fluxes are due to aquatic photosynthesis (i.e., net ecosystem production) sequestering carbon dioxide from the atmosphere at higher rates than CO_2-eq methane emissions. This finding further emphasizes the importance of farm dam management, even suggesting that increasing oxygen levels could turn farm dams into carbon sinks. Nonetheless, these results are likely to change during the night phase when plant respiration replaces photosynthesis, highlighting the importance of long-term studies on carbon dynamics in farm dams.

There is still considerable uncertainty on the net radiative balance of farm dams, as there is little data on the rates of carbon sequestration and storage in dam sediments. Yet, farm dams appear to have the highest burial rates of organic carbon among freshwater systems, ranging from 148 to 17,000 g C m^{-2} $year^{-1}$ (Downing et al., 2008; Rogers et al., 2022). Therefore, it is possible that farm dams can sequester more carbon in the sediments than what they emit to the atmosphere. Future studies should investigate if fencing farm dams can increase carbon sequestration together with decreasing methane emissions.

Dissolved oxygen was strongly positively correlated with pH and strongly negatively correlated with carbon dioxide, which is evidence that aquatic primary production is the key process regulating dissolved oxygen in the farm dams of this study. Specifically, photosynthetic activity produces oxygen and consumes carbon dioxide, which results in higher pH from faster dissociation of HCO_3^- into CO_2 and OH^- (Zang et al., 2010). Had there been no correlation between pH and dissolved oxygen (as is often the case with aquaculture systems), other factors unrelated to photosynthesis (e.g., decomposition of organic matter) may have been more likely to drive changes in dissolved oxygen (Zang et al., 2010). Importantly, the pH increase from aquatic photosynthesis is likely to further reduce the carbon emissions of a farm dam by moving the carbonate equilibria toward carbonic acid and away from gaseous CO_2. Specifically, as the system becomes more basic, the carbonate system changes from CO_2-dominated to CO_3^--dominated, with negligible carbon dioxide left at pH > 8.5 (Andersen, 2018; Drever, 1997).

Conclusions

We discovered that fencing to exclude livestock from farm dams improves water quality (i.e., fewer dissolved nutrients and higher dissolved oxygen) and reduces diffusive methane emissions. Our data also revealed a threshold in dissolved oxygen at 10 mg L^{-1} above which farm dams switch from positive to negative CO_2-eq fluxes, helping mitigate climate change. Considering avoided carbon emissions and additional economic and ecological co-benefits (i.e., higher biodiversity, increased livestock health, and capital value; Dobes et al., 2021; Hazell et al., 2001; Lewis-Phillips et al., 2019; Westgate et al., 2022), investing in better farm dam management appears to be a promising strategy for improving farming productivity and environmental sustainability. Nevertheless, carbon cycles in farm dams remain one of the least explored among freshwater systems. Promising avenues for follow-up studies include environmental work to analyze long-term cycles for several carbon pathways (e.g., methane ebullition, plant-mediated methane emissions, rate of carbon sedimentation), economic assessments to determine the best allocation of incentives for sustainable management interventions, and social studies to establish non-market benefits and farmers' willingness to adopt management interventions. This information will help deliver policy recommendations on the cost-effectiveness of investing in farm dam management as a novel carbon abatement strategy, as well as for additional co-benefits.

References

Agriculture Victoria. (2022). How much water is in my dam? https://agriculture.vic.gov.au/farm-management/water/farm-water-solutions/how-much-water-is-in-my-dam (access date 26 April 2022).

Andersen, C. B. (2018). Understanding Carbonate Equilibria by Measuring Alkalinity in Experimental and Natural Systems. *Journal of Geoscience Education, 50*(4), 389-403. doi:10.5408/1089-9995-50.4.389

Bastviken, D., Cole, J. J., Pace, M. L., & Van de Bogert, M. C. (2008). Fates of methane from different lake habitats: Connecting whole-lake budgets and CH4 emissions. *Journal of Geophysical Research: Biogeosciences, 113*(G2).

Bastviken, D., Tranvik, L. J., Downing, J. A., Crill, P. M., & Enrich-Prast, A. (2011). Freshwater methane emissions offset the continental carbon sink. *Science, 331*(6013), 50. doi:10.1126/science.1196808

Beaulieu, J. J., DelSontro, T., & Downing, J. A. (2019). Eutrophication will increase methane emissions from lakes and impoundments during the 21st century. *Nat Commun, 10*(1), 1375. doi:10.1038/s41467-019-09100-5

Benjamini, Y., & Hochberg, Y. (1995). Controlling the false discovery rate: a practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society Series B, 57*, 289-300.

Burnham, K. P., & Anderson, D. R. (2004). Multimodel inference - understanding AIC and BIC in model selection. *Sociological Methods & Research, 33*(2), 261-304. doi:Doi 10.1177/0049124104268644

Conrad, R. (2009). The global methane cycle: recent advances in understanding the microbial processes involved. *Environ Microbiol Rep, 1*(5), 285-292. doi:10.1111/j.1758-2229.2009.00038.x

Crossman, S., & Li, O. (2015). *Surface Hydrology Polygons (Regional). Geoscience Australia, Canberra.* Retrieved from http://pid.geoscience.gov.au/dataset/ga/83134 (data sourced on the 4th Feb 2022 from)

Dlugokencky, E. (2022). NOAA/GML (gml.noaa.gov/ccgg/trends_ch4/). Access date: 8 Feb 2022.

Dobes, L., Crane, M., Higgins, T., Van Dijk, A., & Lindenmayer, D. B. (2021). Increased livestock weight gain from improved water quality in farm dams: A cost-benefit analysis. *PLoS One, 16*(8), e0256089. doi:10.1371/journal.pone.0256089

Downing, J. A., Cole, J. J., Middelburg, J. J., Striegl, R. G., Duarte, C. M., Kortelainen, P., . . . Laube, K. A. (2008). Sediment organic carbon burial in agriculturally eutrophic impoundments over the last century. *Global Biogeochemical Cycles, 22*(1), n/a-n/a. doi:10.1029/2006gb002854

Downing, J. A., Prairie, Y. T., Cole, J. J., Duarte, C. M., Tranvik, L. J., Striegl, R. G., . . . Middelburg, J. J. (2006). The global abundance and size distribution of lakes, ponds, and impoundments. *Limnology and Oceanography, 51*(5), 2388-2397. doi:10.4319/lo.2006.51.5.2388

Drever, J. I. (1997). The Geochemistry of Natural Waters: Surface and Groundwater Environments. Prentice Hall. *Eaglewood Cliffs, New Jersy, USA*.

Fisher, A., Rudin, C., & Dominici, F. (2019). All Models are Wrong, but Many are Useful: Learning a Variable's Importance by Studying an Entire Class of Prediction Models Simultaneously. *J. Mach. Learn. Res., 20*(177), 1-81.

Fox, J., & Weisberg, S. (2018). Visualizing Fit and Lack of Fit in Complex Regression Models with Predictor Effect Plots and Partial Residuals. *Journal of statistical software, 87*(9), 1-27.

Fox, J., & Weisberg, S. (2019). *An R Companion to Applied Regression, 3rd Edition. Thousand Oaks, CA* <*https://socialsciences.mcmaster.ca/jfox/Books/Companion/index.html*>.

Grinham, A., Albert, S., Deering, N., Dunbabin, M., Bastviken, D., Sherman, B., . . . Evans, C. D. (2018). The importance of small artificial water bodies as sources of methane emissions in Queensland, Australia. *Hydrology and Earth System Sciences, 22*(10), 5281-5298.

Gulliver, A., Carnell, P. E., Trevathan-Tackett, S. M., Duarte de Paula Costa, M., Masqué, P., & Macreadie, P. I. (2020). Estimating the potential blue carbon gains from tidal marsh rehabilitation: A case study from south eastern Australia. *Frontiers in Marine Science, 7*, 403.

Hazell, D., Cunnningham, R., Lindenmayer, D., Mackey, B., & Osborne, W. (2001). Use of farm dams as frog habitat in an Australian agricultural landscape: factors affecting species richness and distribution. *Biological Conservation, 102*(2), 155-169.

Holgerson, M. A., & Raymond, P. A. (2016). Large contribution to inland water CO_2 and CH_4 emissions from very small ponds. *Nature Geoscience, 9*(3), 222-226. doi:10.1038/ngeo2654

IPCC. (2019). 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories.

Lambert, M., & Fréchette, J.-L. (2005). Analytical techniques for measuring fluxes of CO_2 and CH_4 from hydroelectric reservoirs and natural water bodies. In *Greenhouse gas emissions—fluxes and processes* (pp. 37-60): Springer.

Lewis-Phillips, J., Brooks, S., Sayer, C. D., McCrea, R., Siriwardena, G., & Axmacher, J. C. (2019). Pond management enhances the local abundance and species richness of farmland bird communities. *Agriculture, Ecosystems & Environment, 273*, 130-140. doi:10.1016/j.agee.2018.12.015

Li, Y., Shang, J., Zhang, C., Zhang, W., Niu, L., Wang, L., & Zhang, H. (2021). The role of freshwater eutrophication in greenhouse gas emissions: A review. *Sci Total Environ, 768*, 144582. doi:10.1016/j.scitotenv.2020.144582

Limpert, K. E., Carnell, P. E., & Macreadie, P. I. (2021). Managing agricultural grazing to enhance the carbon sequestration capacity of freshwater wetlands. *Wetlands Ecology and Management, 29*(2), 231-244. doi:10.1007/s11273-020-09780-7

Malerba, M. E., Schuster, L., & Macreadie, P. I. (In review). Global greenhouse gas emissions from agricultural ponds.

Malerba, M. E., Wright, N., & Macreadie, P. I. (2021). A Continental-Scale Assessment of Density, Size, Distribution and Historical Trends of Farm Dams Using Deep Learning Convolutional Neural Networks. *Remote Sensing, 13*(2), 319.

Neubauer, S. C., & Megonigal, J. P. (2015). Moving beyond global warming potentials to quantify the climatic role of ecosystems. *Ecosystems, 18*(6), 1000-1013.

Niittynen, P., & Luoto, M. (2018). The importance of snow in species distribution models of arctic vegetation. *Ecography, 41*(6), 1024-1037.

Nijman, T. P. A., Amado, A. M., Bodelier, P. L. E., & Veraart, A. J. (2022). Relief of Phosphate Limitation Stimulates Methane Oxidation. *Frontiers in Environmental Science, 10*. doi:10.3389/fenvs.2022.804512

Oates, L. G., Jackson, R. D., & Allen-Diaz, B. (2008). Grazing removal decreases the magnitude of methane and the variability of nitrous oxide emissions from spring-fed wetlands of a California oak savanna. *Wetlands Ecology and Management, 16*(5), 395-404. doi:10.1007/s11273-007-9076-0

Ollivier, Q. R., Maher, D. T., Pitfield, C., & Macreadie, P. I. (2018). Punching above their weight: Large release of greenhouse gases from small agricultural dams. *Glob Chang Biol, 25*(2), 721-732. doi:10.1111/gcb.14477

Ollivier, Q. R., Maher, D. T., Pitfield, C., & Macreadie, P. I. (2019). Winter emissions of CO_2, CH_4, and N_2O from temperate agricultural dams: fluxes, sources, and processes. *Ecosphere, 10*(11). doi:10.1002/ecs2.2914

Panneer Selvam, B., Natchimuthu, S., Arunachalam, L., & Bastviken, D. (2014). Methane and carbon dioxide emissions from inland waters in India - implications for large scale greenhouse gas balances. Glob Chang Biol, 20(11), 3397-3407. doi:10.1111/gcb.12575

Peacock, M., Audet, J., Bastviken, D., Cook, S., Evans, C. D., Grinham, A., . . . Futter, M. N. (2021). Small artificial waterbodies are widespread and persistent emitters of methane and carbon dioxide. *Glob Chang Biol*. doi:10.1111/gcb.15762

Peacock, M., Audet, J., Jordan, S., Smeds, J., & Wallin, M. B. (2019). Greenhouse gas emissions from urban ponds are driven by nutrient status and hydrology. *Ecosphere, 10*(3), e02643.

Pilon-Smits, E. (2005). Phytoremediation. *Annu. Rev. Plant Biol., 56*, 15-39.

Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D., & Team, R. C. (2020). nlme: Linear and Nonlinear Mixed Effects Models. R package version 3.1-150.

R Core Team. (2020). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

Rogers, M. N., Williamson, T. J., Knoll, L. B., & Vanni, M. J. (2022). Temporal patterns in sediment, carbon, and nutrient burial in ponds associated with changing agricultural tillage. *Biogeochemistry*. doi:10.1007/s10533-022-00916-w

Rosentreter, J. A., Borges, A. V., Deemer, B. R., Holgerson, M. A., Liu, S., Song, C., . . . Eyre, B. D. (2021). Half of global methane emissions come from highly variable aquatic ecosystem sources. *Nature Geoscience, 14*(4), 225-230. doi:10.1038/s41561-021-00715-2

Segers, R. (1998). Methane production and methane consumption: a review of processes underlying wetland methane fluxes. *Biogeochemistry, 41*(1), 23-51.

Swartz, T. M., & Miller, J. R. (2021). The American Pond Belt: an untold story of conservation challenges and opportunities. *Frontiers in Ecology and the Environment, 19*(9), 501-509. doi:10.1002/fee.2381

Virkkala, A. M., Aalto, J., Rogers, B. M., Tagesson, T., Treat, C. C., Natali, S. M., . . . Luoto, M. (2021). Statistical upscaling of ecosystem CO2 fluxes across the terrestrial tundra and boreal domain: Regional patterns and uncertainties. *Glob Chang Biol*. doi:10.1111/gcb.15659

Watkins, S. C., Baldwin, D. S., Waudby, H. P., & Ning, S. E. M. A. (2017). Managing rain-filled wetlands for carbon sequestration: a synthesis. *The Rangeland Journal, 39*(2). doi:10.1071/rj16077

Webb, J. R., Hayes, N. M., Simpson, G. L., Leavitt, P. R., Baulch, H. M., & Finlay, K. (2019). Widespread nitrous oxide undersaturation in farm waterbodies creates an unexpected greenhouse gas sink. *Proceedings of the National Academy of Sciences, 116*(20), 9814-9819.

Webb, J. R., Leavitt, P. R., Simpson, G. L., Baulch, H. M., Haig, H. A., Hodder, K. R., & Finlay, K. (2019). Regulation of carbon dioxide and methane in small agricultural reservoirs: optimizing potential for greenhouse gas uptake. *Biogeosciences, 16*(21), 4211-4227. doi:10.5194/bg-16-4211-2019

Westgate, M. J., Crane, M., Scheele, B. C., Crane, C., O'Malley, C., Siegrist, A., . . . Lindenmayer, D. B. (2022). Improved management of farm dams increases vegetation cover, water quality, and macroinvertebrate biodiversity. *Ecology and Evolution, 12*(3).

Wickham, H. (2009). ggplot2: Elegant Graphics for Data Analysis. Springer-Verlag New York, 2009.

Wickham, H. (2011). plyr: The Split-Apply-Combine Strategy for Data Analysis. *Journal of statistical software, 40*(1), 1-29.

Wickham, H., François, R., Henry, L., & Müller, K. (2018). dplyr: A Grammar of Data Manipulation.

Zang, C., Huang, S., Wu, M., Du, S., Scholz, M., Gao, F., . . . Dong, Y. (2010). Comparison of Relationships Between pH, Dissolved Oxygen and Chlorophyll a for Aquaculture and Non-aquaculture Waters. *Water, Air, & Soil Pollution, 219*(1-4), 157-174. doi:10.1007/s11270-010-0695-3

Zuur, A., Ieno, E. N., Walker, N., Saveliev, A. A., & Smith, G. M. (2009). *Mixed effects models and extensions in ecology with R*. New York: Springer.

Variable	Unit	Rep	Min	Mean	Median	Max
Area	m^2	64	227	1978	886	20796
Water volume (est.)	ML	64	0.21	3.05	1.13	56
Water depth (est.)	m	64	2.31	3.86	3.19	6.73
Longitude		64	146.79	147.63	147.19	149.45
Latitude		64	-36.10	-35.32	-35.86	-33.51
Total Nitrogen	mg N L^{-1}	64	0.40	2.68	2.10	9.20
Total Phosphorus	mg P L^{-1}	64	0.01	0.12	0.06	0.80
Dissolved Oxygen	mg O_2 L^{-1}	64	3.16	6.94	6.52	17.60
Water Temperature	°C	64	12.83	16.20	15.57	22.13
pH		63	6.50	7.79	7.71	9.52
Conductivity	µS cm^{-1}	64	11.89	294.3	227.5	1647
CH_4 diffusion	g m^{-2} d^{-1}	63	0.0001	0.0151	0.0034	0.1639
CO_2 diffusion	g m^{-2} d^{-1}	64	-1.6995	1.4897	0.7887	13.9746
CO_2-eq diffusion	g m^{-2} d^{-1}	63	-1.2161	2.9364	1.5619	21.3560
Sediment organic C stock	t C ha^{-}	63	0.56	6.26	4.59	28.84

Table 1: Summary of farm dam properties in this study. Water volume was estimated using the model in Fig. 1 of Malerba et al. (2022): $Water\ Volume = -3.593 + 1.237 \times Water\ Area$. Water depth was estimated using the formula $(Water\ Volume \times 1000)/(Water\ Area \times 0.4)$ (Agriculture Victoria, 2022).

Figure legends

Figure 1: Effects of farm dam fencing on (a) methane fluxes, (b) carbon dioxide fluxes, (c) CO_2-eq (methane + carbon dioxide) fluxes, and (d) organic carbon in the soil. Black point ranges represent the means $\pm$ 95% confidence intervals from the best-fitting linear models. Grey points are the raw data. All statistics are calculated on a sample size of 64 farm dams across 17 farming properties. We reported percentage changes only on statistically significant effects (see Table S1 for test statistics).

Figure 2: Effects of farm dam fencing on (a) total nitrogen, (b) total phosphorus, (c) dissolved oxygen, and (d) temperature. All statistics are calculated on a sample size of 64 farm dams across 17 farming properties. We reported percentage changes only on statistically significant effects (see Table S1 for test statistics).

Figure 3: Effects of environmental parameters (columns) on carbon fluxes (rows) from farm dams. Points in each panel represent the partial residuals of farm dams after controlling for the effects of the other fixed and random variables in the models. Lines indicate statistically significant effects following the best-fitting mixed effect models ($\pm$ 95% confidence intervals). Reported in each panel are the p-values and the importance scores of statistically significant terms (see Table S2 for all test statistics and Table S3 for importance scores).

Figure 4: Dashed lines indicate where fluxes equal zero. Also indicated in the figure is the dissolved oxygen concentration (10 mg L^{-1}) associated with a switch from positive to negative CO_2-eq. fluxes. Variables were linearised using $\log_{10}$-transformations when fitting the model, but they are presented here on an arithmetic scale (see Fig. 3K for model fits presented in log scales).

Figure 5: Statistical associations between (a) the dissolved oxygen and the pH of the water, (b) the dissolved oxygen and the CO_2 fluxes, and (c) CO_2 fluxes and the pH of the water. Each point represents the average value recorded from a farm dam. Reported in each panel are the correlation coefficient and the p-value of statistically significant relationships.

Figure 6: Effects of fencing farm dams on water quality and methane emissions. Installing fences to exclude livestock from farm dams reduces the direct deposition of nutrient-rich manure and urine into the water, avoids hooved livestock (ungulates) disturbing soil, and promotes higher vegetation cover around the dam. As a result, fenced farm dams have lower dissolved nutrients, higher dissolved oxygen, and lower methane emissions than unfenced dams. Percentages associated with fencing farm dams represent the relative change compared to unfenced dams (Fig 1 and 2), while percentages associated with CH_4 fluxes indicate the sensitivity analysis of the best-fitting model (Fig 3, Table S3).

Figure 7: Emissions of (a) CH_4 and (b) CO_2 from agricultural ponds from the scientific literature divided by land-use type. Each symbol indicates the arithmetic mean and the range of values. Reported in each panel are the overall average emissions and the average ranges. All studies measured methane diffusion, except for Grinham et al. (2018) who measured both methane diffusion and ebullition.

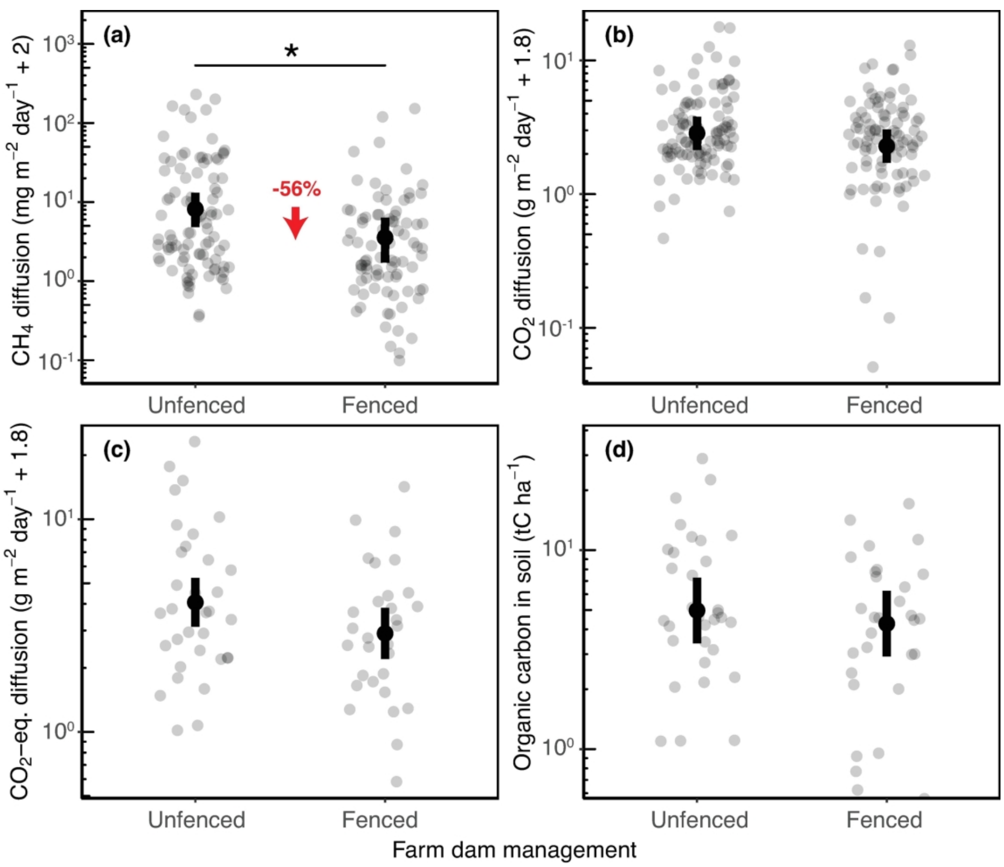

Figure 1: Effects of farm dam fencing on (a) methane fluxes, (b) carbon dioxide fluxes, (c) CO_2-eq (methane + carbon dioxide) fluxes, and (d) organic carbon in the soil. Black point ranges represent the means ±95% confidence intervals from the best-fitting linear models. Grey points are the raw data. All statistics are calculated on a sample size of 64 farm dams across 17 farming properties. We reported percentage changes only on statistically significant effects (see Table S1 for test statistics).

183x157mm (300 x 300 DPI)

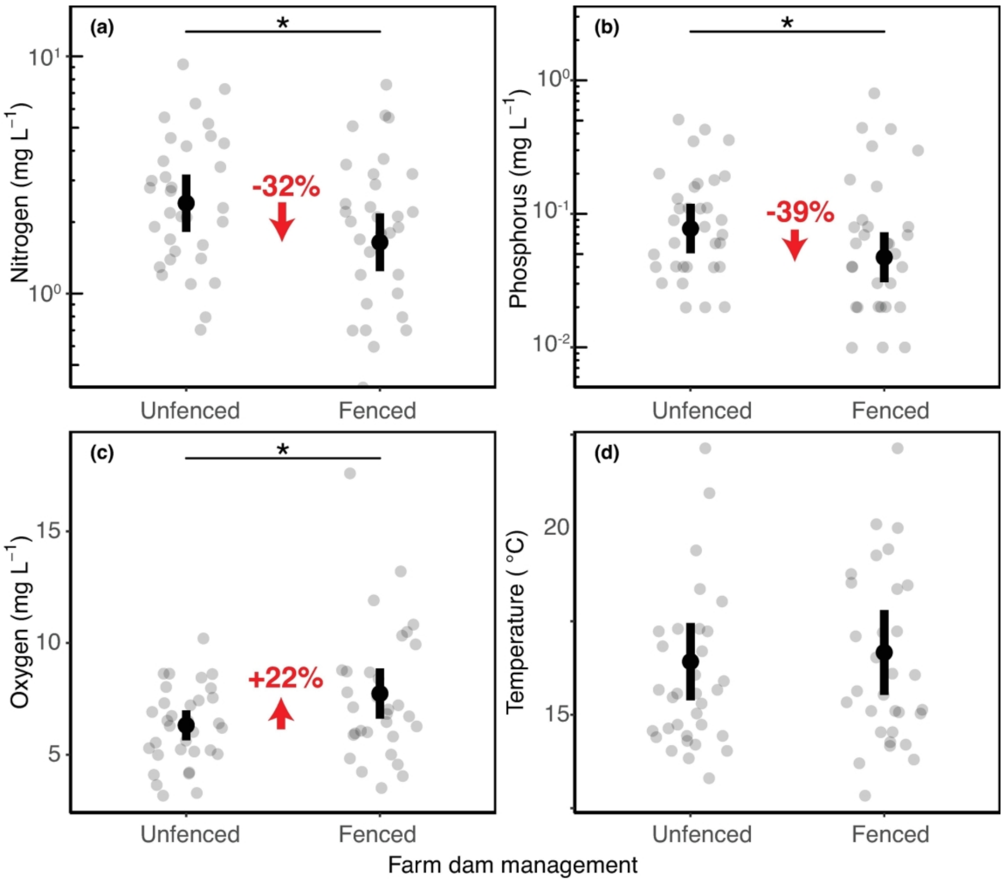

Figure 2: Effects of farm dam fencing on (a) total nitrogen, (b) total phosphorus, (c) dissolved oxygen, and (d) temperature. All statistics are calculated on a sample size of 64 farm dams across 17 farming properties. We reported percentage changes only on statistically significant effects (see Table S1 for test statistics).

180x157mm (300 x 300 DPI)

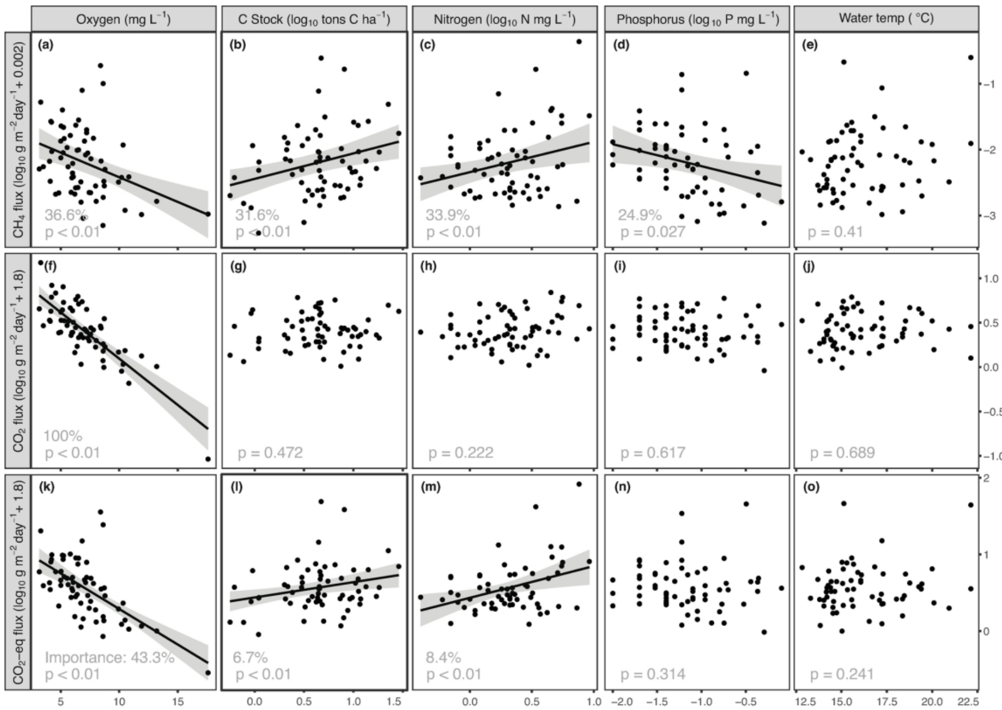

Figure 3: Effects of environmental parameters (columns) on carbon fluxes (rows) from farm dams. Points in each panel represent the partial residuals of farm dams after controlling for the effects of the other fixed and random variables in the models. Lines indicate statistically significant effects following the best-fitting mixed effect models (±95% confidence intervals). Reported in each panel are the p-values and the importance scores of statistically significant terms (see Table S2 for all test statistics and Table S3 for importance scores).

179x126mm (300 x 300 DPI)

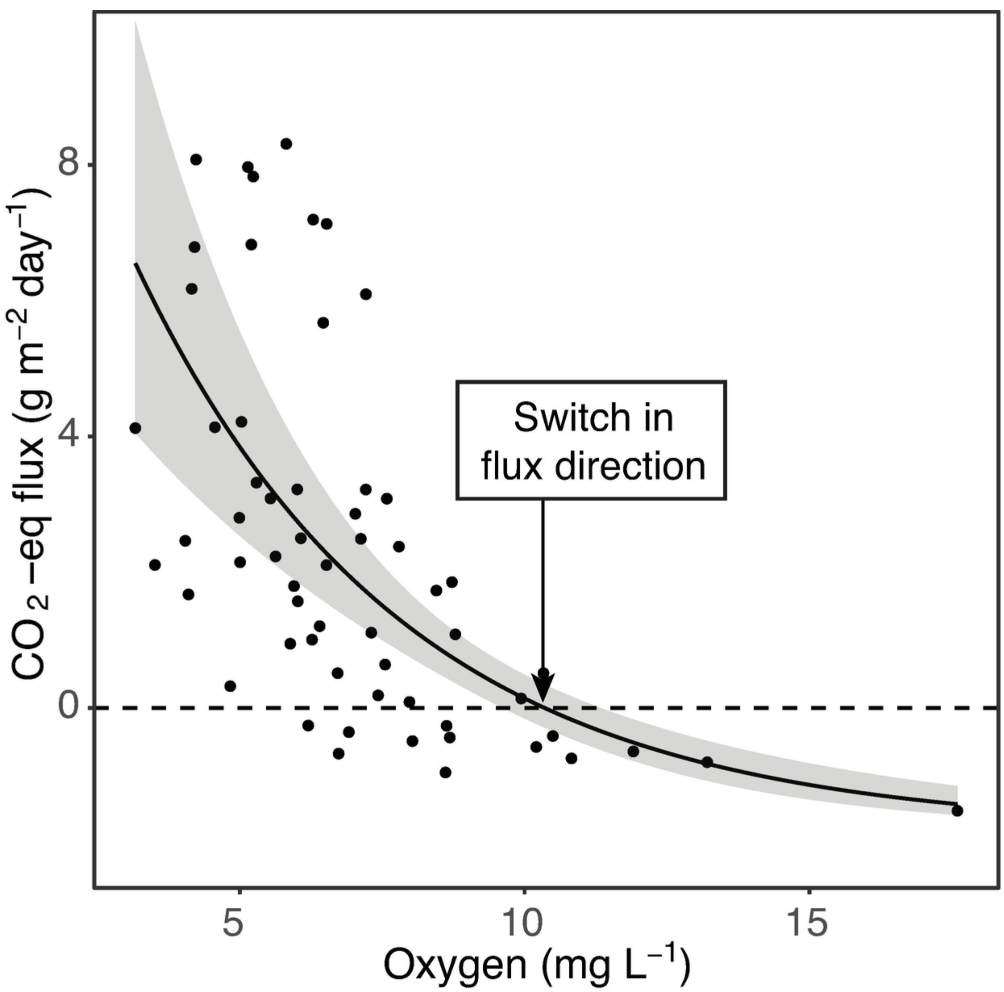

Figure 4: Dashed lines indicate where fluxes equal zero. Also indicated in the figure is the dissolved oxygen concentration (10 mg L^{-1}) associated with a switch from positive to negative CO_2-eq. fluxes. Variables were linearised using $\log_{10}$-transformations when fitting the model, but they are presented here on an arithmetic scale (see Fig. 3K for model fits presented in log scales).

105x103mm (300 x 300 DPI)

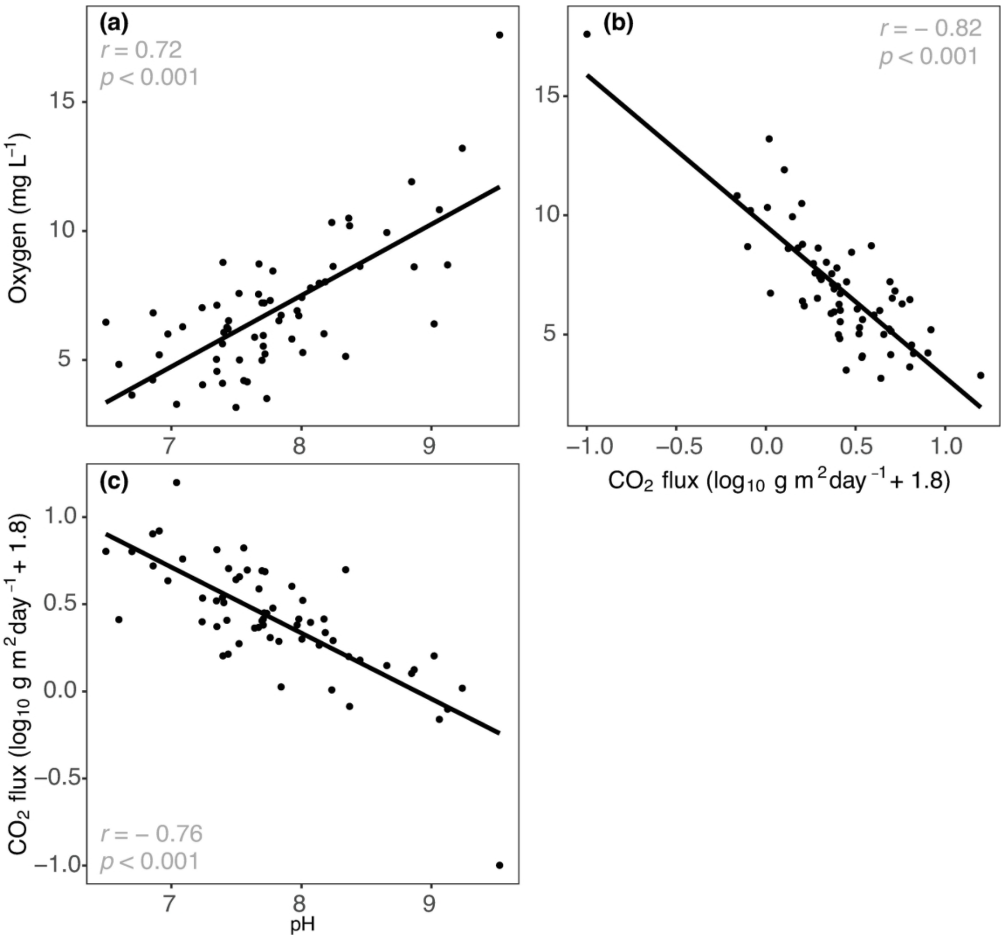

Figure 5: Statistical associations between (a) the dissolved oxygen and the pH of the water, (b) the dissolved oxygen and the CO_2 fluxes, and (c) CO_2 fluxes and the pH of the water. Each point represents the average value recorded from a farm dam. Reported in each panel are the correlation coefficient and the p-value of statistically significant relationships.

174x163mm (300 x 300 DPI)

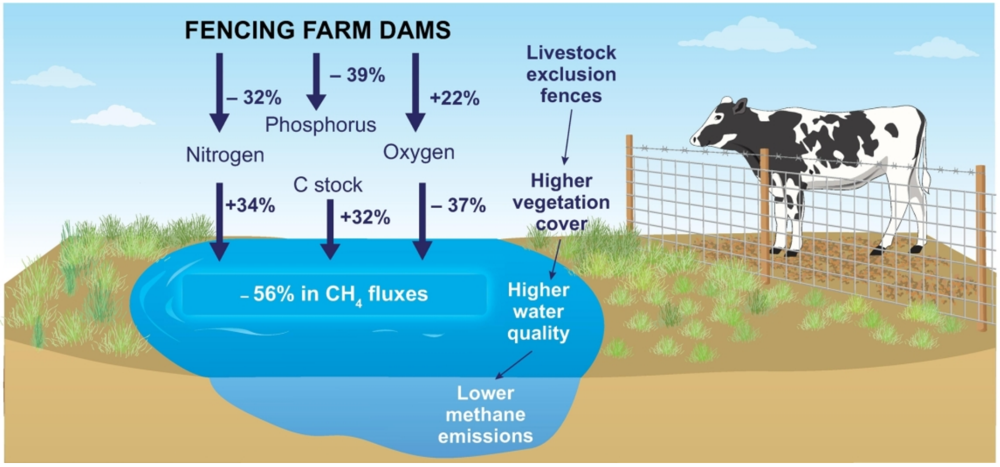

Figure 6: Effects of fencing farm dams on water quality and methane emissions. Installing fences to exclude livestock from farm dams reduces the direct deposition of nutrient-rich manure and urine into the water, avoids hooved livestock (ungulates) disturbing soil, and promotes higher vegetation cover around the dam. As a result, fenced farm dams have lower dissolved nutrients, higher dissolved oxygen, and lower methane emissions than unfenced dams. Percentages associated with fencing farm dams represent the relative change compared to unfenced dams (Fig 1 and 2), while percentages associated with CH4 fluxes indicate the sensitivity analysis of the best-fitting model (Fig 3, Table S3).

179x82mm (300 x 300 DPI)

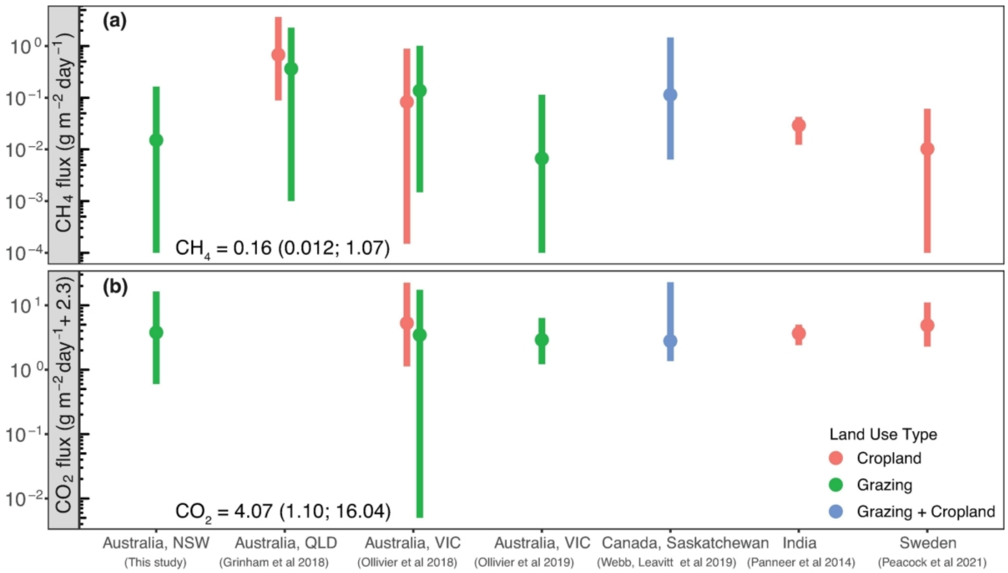

Figure 7: Emissions of (a) CH_4 and (b) CO_2 from agricultural ponds from the scientific literature divided by land-use type. Each symbol indicates the arithmetic mean and the range of values. Reported in each panel are the overall average emissions and the average ranges. All studies measured methane diffusion, except for Grinham et al. (2018) who measured both methane diffusion and ebullition.

177x100mm (300 x 300 DPI)

Explanatory Variable: Farm dam management (fenced vs unfenced)			
Dependent Variables	χ^2	df	P
a) CH_4 diffusion ($\log_{10}$ g m^{-2} d^{-1} + 2)	5.305	1	**0.021**
b) CO_2 diffusion ($\log_{10}$ g m^{-2} d^{-1} + 1800)	1.65	1	0.2
c) CO_2-eq diffusion ($\log_{10}$ g m^{-2} d^{-1} + 1800)	3.12	1	0.08
d) Sediment organic C stock ($\log_{10}$ t C ha^{-1})	0.645	1	0.42
e) Nitrogen ($\log_{10}$ mg N L^{-1})	7.399	1	**0.007**
f) Phosphorus ($\log_{10}$ mg P L^{-1})	6.589	1	**0.010**
g) Oxygen (mg L^{-1})	5.631	1	**0.018**
h) Temperature (°C)	0.417	1	0.518
i) pH	0.141	1	0.708

Table S1: Analysis of Deviance (Type II) for the best-fitting linear mixed models on the effects of fencing farm dams on carbon dynamics (a-d) and water quality (e-i). Each row reports the test statistics for a model where each environmental parameter is the dependent variable and farm dam management is the explanatory variable. All tests relied on a sample size of 64 farm dams across 17 properties. Statistically significant effects are indicated in bold.

	χ^2	df	P
(a) CO_2-eq (CO_2+CH_4) fluxes (log_{10} g m^{-2} d^{-1} + 1.8)			
Oxygen (mg L^{-1})	74.798	1	**<0.001**
Nitrogen (log_{10} mg N L^{-1})	7.710	1	**0.006**
Carbon stock in soil (log_{10} t C ha^{-1})	6.844	1	**0.009**
Water temperature (°C)	1.372	1	0.241
Phosphorus (log_{10} mg P L^{-1})	1.014	1	0.314
(b) CH_4 fluxes (log_{10} g m^{-2} d^{-1} + 0.002)			
Oxygen (mg L^{-1})	7.85	1	**0.005**
Nitrogen (log_{10} mg N L^{-1})	10.78	1	**0.001**
Carbon stock in soil (log_{10} t C ha^{-1})	8.8	1	**0.003**
Phosphorus (log_{10} mg P L^{-1})	4.915	1	**0.027**
Water temperature (°C)	0.69	1	0.41
(c) CO_2 fluxes (log_{10} g m^{-2} d^{-1} + 1.8)			
Oxygen (mg L^{-1})	91.224	1	**<0.001**
Nitrogen (log_{10} mg N L^{-1})	1.491	1	0.222
Carbon stock in soil (log_{10} t C ha^{-1})	0.517	1	0.472
Water temperature (°C)	0.160	1	0.689
Phosphorus (log_{10} mg P L^{-1})	0.250	1	0.617

Table S2: Analysis of Deviance (Type II) for the best-fitting linear mixed models on the drivers of farm dam emissions on (a) CO_2-eq (CO_2 + CH_4) fluxes, (b) CH_4 fluxes, and (c) CO_2 fluxes. Rows report the effects of each covariate on the GHG fluxes of a farm dam. All statistics relied on a sample size of 64 farm dams across 17 properties. Statistically significant covariates are indicated in bold (see Table S3 for the explanatory powers of statistically significant terms). Akaike Information Criteria selected against including farm dam area, conductivity, catchment area, and a 2-way interaction between dissolved nitrogen and dissolved phosphorus in the best-fitting models.

Model	Vars	Importanc e	LCI	UCI
CO_2-eq flux (g m^2 day^{-1})	Oxygen (mg L^{-1})	43.3%	42.9%	43.6%
	Nitrogen (N mg L^{-1})	8.4%	8.1%	8.3%
	C Stock (tons C ha^{-1})	6.7%	6.3%	7.0%
	Water temp (°C)		n.s.	
	Phosphorous (P mg L^{-1})		n.s.	
CH_4 flux (g m^2 day^{-1})	Oxygen (mg L^{-1})	36.6%	36%	37.2%
	Nitrogen (N mg L^{-1})	33.9%	33.3%	34.5%
	C Stock (tons C ha^{-1})	31.6%	31.1%	32.2%
	Phosphorous (P mg L^{-1})	24.9%	24.3%	25.5%
	Water temp (°C)		n.s.	
CO_2 flux (g m^2 day^{-1})	Oxygen (mg L^{-1})	100% (only sign. variable)		
	Nitrogen (N mg L^{-1})		n.s.	
	C Stock (tons C ha^{-1})		n.s.	
	Water temp (°C)		n.s.	
	Phosphorous (P mg L^{-1})		n.s.	

Table S3. Sensitivity analysis for the relative importance of each statistically significant environmental parameter to explain the variability in the three best-fitting models. The importance score is the contribution of a variable to the total explanatory power of the best-fitting model, calculated using eq. 2 (±95% C.I.). See Table S2 for the Analysis of Deviance.

Author	Location	Land use type	N	Arithmetic mean (mg m^{-2} d^{-1})	Min (mg m^{-2} d^{-1})	Max (mg m^{-2} d^{-1})	Median (mg m^{-2} d^{-1})	Notes
This study	Australia (NSW)	Grazing	64	CH_4: 15.1 CO_2: 1489.7	CH_4: 0.1 CO_2: -1699.5	CH_4: 163.9 CO_2: 13977	CH_4: 3.4 CO_2: 788.7	
Ollivier et al 2018	Australia (VIC)	Cropland	39	CH_4: 82.9 CO2: 2988.5	CH_4: 0.15 CO2: -1167	CH_4: 884.11 CO2: 20089	CH_4: 7.44 CO_2: 1211.8	
Ollivier et al 2018	Australia (VIC)	Grazing	41	CH_4: 137.4 CO_2: 1163	CH_4: 1.49 CO_2: -2295	CH_4: 1008.5 CO_2: 15077.8	CH_4: 20.11 CO_2: 480.24	
Ollivier et al 2019	Australia (VIC)	Grazing	12	CH_4: 6.7 CO_2: 609.7	CH_4: 0.09 CO_2: -1079	CH_4: 114 CO_2: 4055	CH_4: 3.56 CO_2: 812	
Grinham et al 2018	Australia (QLD)	Grazing	10	CH_4: 364.9	CH_4: 1	CH_4: 2261	CH_4: 203.6	
Grinham et al 2018	Australia (QLD)	Cropland	2	CH_4: 679	CH_4: 89	CH_4: 3635	CH_4: 423	
Webb et al 2019	Canada (Saskatchewan)	Grazing+ Cropland	101	CH_4: 113.9 CO_2: 488.5	CH_4: 6.4 CO_2: -937.4	CH_4: 1468 CO_2: 20517	CH_4: 51.328 CO_2: 2557	
Panneer et al 2014	India (Southeast)	Cropland	3	CH_4: 29.3 CO_2: 1363	CH_4: 12.35 CO_2: 121.03	CH_4: 42.6 CO_2: 2697		Sites: TSFP1, THKp1, and TSFP2
Peacock et al 2021	Sweden	Cropland	2	CH_4: 10.26 CO_2: 2577	CH_4: 0 CO_2: 0	CH_4: 61 CO_2: 8711	CH_4: 4.87 CO_2: 1951	Sites: Fembäcke pond N and Fembäcke pond S

Table S4: Summary statistics for carbon fluxes from farm dams reported in the literature.