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

Running Title: Reducing carbon emissions from farm dams

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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 – the second most 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. We found that fenced farm dams generated 32% less dissolved nitrogen, 39% less dissolved phosphorus, 22% more dissolved oxygen, and 56% less diffusive methane emissions than unfenced dams. The higher dissolved oxygen and the lower dissolved nitrogen underpinned the reduced CO_2-eq (methane + carbon dioxide) carbon fluxes of fenced dams. Dams with very high dissolved oxygen (>10 mg L^{-1}) showed net uptake of carbon dioxide that exceeded CO_2-eq. methane emissions (i.e., negative radiative balance), contradicting the general paradigm that farm dams are invariantly contributing to atmospheric warming. We also found a positive association between sediment organic carbon and CO_2-eq fluxes. Our results demonstrate that simple management actions can dramatically improve water quality and decrease GHG 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 an estimated 42 million farm dams worldwide covering a cumulative area comparable to Costa Rica (Malerba et al., In review), these artificial systems have replaced many natural water bodies and are a key part of aquatic ecosystems globally (Malerba et al., 2021; Swartz & Miller, 2021). Therefore, it is likely that farm dams are now 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).

Recent evidence indicates that farm dams have some of the highest greenhouse gas (GHG) emissions per m^2 among freshwater ecosystems (Grinham et al., 2018; Ollivier et al., 2018, 2019). These artificial water bodies often reach 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 can 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, 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 on 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. Yet, no previous study has quantified the effects of installing fences (or any other management intervention) on farm dam GHG production. 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 predict that fencing a farm dam would favor the growth of fringing wetland vegetation, 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. 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 (N = 33) and "fenced" farm dams (N = 31). Unfenced farm dams received no management intervention to improve their ecological condition. Fenced farm dams 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. We matched fenced and unfenced dams on a farming property to ensure they had similar characteristics (e.g., size, shape, surrounding land use). We sampled both types of dams on a given farm on the same day. We avoided small (<1 megalitre) 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, 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:

$$F = \frac{s \times V}{R \times T \times A} \times t \qquad \text{(Eq. 1)}$$

where s is the linear rate of change in gas concentrations over time within the chamber (ppm s^{-1}), V is the chamber volume (0.021 m^3), R is the universal gas constant (8.2×10^{-5} m^3 atm K^{-1} mol^{-1}), T is the temperature in the chamber that is automatically measured by the gas analyzer (in Kelvin), A is the surface area of the chamber (0.14 m^2), and t is the conversion from seconds to days and µmol to mg.

Sediment carbon stocks

At each dam, we collected two cores (45 mm diameter, 50 mm deep, 79.52 cm^3 volume) from the dam sediments on the edge of the water level. We preserved the cores in a freezer until returning to the lab. We dried all cores 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 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 filters immediately after collection and sent samples 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.

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.

Second, we used a single linear mixed-effects model to quantify the statistical association of each environmental variable with the average CO_2-equivalent (carbon dioxide + methane) flux ($\log_{10}$ g m^{-2} d^{-1} + 1.8) 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 model, the dependent variable was the CO_2-equivalent flux of the farm dam ($\log_{10}$ g m^{-2} d^{-1} + 1.8). The independent variables were farm dam surface area ($\log_{10}$ m^2), dissolved oxygen ($\log_{10}$ mg L^{-1}), 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). 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; 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:

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

Values closer 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 centered 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 both fenced and unfenced dams. 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 water quality

Fenced farm dams generated higher water quality than unfenced ones across all parameters measured here (see Table S1 for statistical scores). Specifically, water from fenced farm dams had on average 32% less total dissolved nitrogen (from 2.4 to 1.6 mg L^{-1}; Fig. 1A), 39% less total dissolved phosphorus (from 0.078 to 0.047 mg L^{-1}; Fig. 1B), and 22% more dissolved oxygen than unfenced dams (from 6.32 to 7.74 mg L^{-1}; Fig. 1C).

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. 1D). Conversely, we found no significant difference for carbon dioxide fluxes ($p = 0.2$, see Table S1), although CO_2 emissions from fenced farm dams (488 [95% C.I.: -85 to 1253] mg m^{-2} d^{-1}) were on average 54% lower than those from unfenced farm dams (1052 [347 to 1990] mg m^{-2} d^{-1}; Fig. 1E). Finally, there was no effect of fencing on the organic carbon stock in the sediments of the farm dams (Fig. 1F; see Table S1 for statistical scores).

Drivers of CO_2-eq greenhouse gas fluxes

We found a statistically significant association between the total carbon flux of a farm dam and its dissolved oxygen, total dissolved nitrogen, and sediment organic carbon stocks (Fig. 2; see Fig. S1 for linear fits on log_{10} axes). Dissolved oxygen was the most important variable in the model (see Fig. S2 for relative importance), whereby doubling dissolved oxygen from 5 to 10 mg L^{-1} corresponded to a 96% decrease in CO_2-eq fluxes (from 3.77 to 0.13 g CO_2-eq m^{-2} day^{-1}; Fig. 2A). Farm dams with dissolved oxygen levels higher than 10 mg L^{-1} even showed a switch from positive to negative CO_2-eq fluxes (i.e., negative radiative balance; Fig. 2A).

Total dissolved nitrogen and sediment organic carbon stocks were positively associated with CO_2-eq fluxes. Specifically, CO_2-eq fluxes increased by 38% (from 2.17 to 3.5 g CO_2-eq m^{-2} day^{-1}) when doubling nitrogen from 2.5 to 5 mg L^{-1} and by 21% (from 2.52 to 3.18 g CO_2-eq m^{-2} day^{-1}) when doubling organic carbon stock from 10 to 20 tons C ha^{-1} (Fig. 2 B, C). Conversely, we found no significant effects of temperature and total dissolved phosphorus on CO_2-eq fluxes (Fig. 2 D, E). Similarly, farm dam area, conductivity, and a 2-way interaction between dissolved nitrogen and dissolved phosphorus were excluded from the best-fitting model following Akaike Information Criteria.

Discussion

Farm dams are ubiquitous features of rural landscapes worldwide and can contribute disproportionately to 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 aquatic GHG emissions (see summary diagram in Fig. 3). 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. Higher dissolved oxygen and lower dissolved nitrogen were the most important variables explaining the lower CO_2-eq carbon flux of fenced farm dams. We also found a positive association between the organic carbon content in farm dam sediments and CO_2-eq fluxes (Fig. 3). Moreover, farm dams with very high oxygen levels (>10 mg L^{-1}) exhibited a switch from positive to negative CO_2-eq fluxes. Conversely, we found no significant effects of water temperature and total dissolved phosphorus in the models.

We found that fencing farm dams on average more than halves diffusive GHG emissions to 1.1 g CO_2-eq m^{-2} day^{-1} compared to 2.4 g CO_2-eq m^{-2} day^{-1} of unfenced farm dams. Our fieldwork took place 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 comparable to nearly five times Manhattan, NYC (278 km^2) (data from AusDams.org sourced on 4th Feb 2022; Malerba et al., 2021). Assuming our data are representative of average yearly GHG fluxes, we can estimate that fencing farm dams in this region would avoid emissions of up to 132,082 tonnes CO_2-eq year^{-1}. To put this into context, such an amount of potentially avoided emissions is comparable to offsetting all transport emissions in the largest town of this region (i.e., 54,000 people living in Albury, NSW, emitting 3 tons CO_2-eq year^{-1} per capita) (Charting Transport, 2022). More data are needed to confirm this first-order approximation of regional-scale emissions from farm dams. 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 (1-15 CH_4 mg m^{-2} day^{-1} and 0-2 CO_2 g m^{-2} day^{-1}) is comparable to previously published values for farm dams in Australia (e.g., 1-160 CH_4 mg m^{-2} day^{-1} and 0.4-1.3 CO_2 g m^{-2} day^{-1}) (Ollivier et al., 2018, 2019) and elsewhere (e.g., 5-8 CH_4 mg m^{-2} day^{-1} and 1.5-1.7 CO_2 g m^{-2} day^{-1})(Peacock et al., 2021). 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 systematically higher values than ours (i.e., 40-120 CH_4 mg m^{-2} day^{-1}). Therefore, it is likely that the benefits of fencing farm dams on carbon emissions are even higher than our estimates after accounting for multiple types of 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 GHG 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 phosphorous 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 increasing total dissolved oxygen substantially reduced the CO_2-eq GHG fluxes of farm dams. 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). We also found no effects of total phosphorus on CO_2-eq, which is consistent with Peacock et al. (2021) and Ollivier et al. (2018) and may indicate that other nutrients (e.g., nitrogen) limit microbial productivity and carbon dynamics in these systems.

A surprising (and encouraging) result from this study is 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 against atmospheric warming. This finding contradicts the general paradigm that farm dams are invariantly contributing to climate change by increasing atmospheric GHG (Holgerson & Raymond, 2016; Ollivier et al., 2018; Peacock et al., 2021). While we found negative CO_2-eq fluxes in only a minority of cases (13 farm dams out of 64), this effect 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. Webb et al. (2019) previously showed that farm dams could act as sinks for nitrous oxide. Yet, our study is the first documentation of farm dams showing negative diffusive CO_2-eq (methane + carbon dioxide) fluxes. 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. Also, there is still considerable uncertainty on the net radiative balance of farm dams, as there is no data on the rates of carbon sequestration and storage in the sediments.

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 financial mechanisms, 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.

Figures

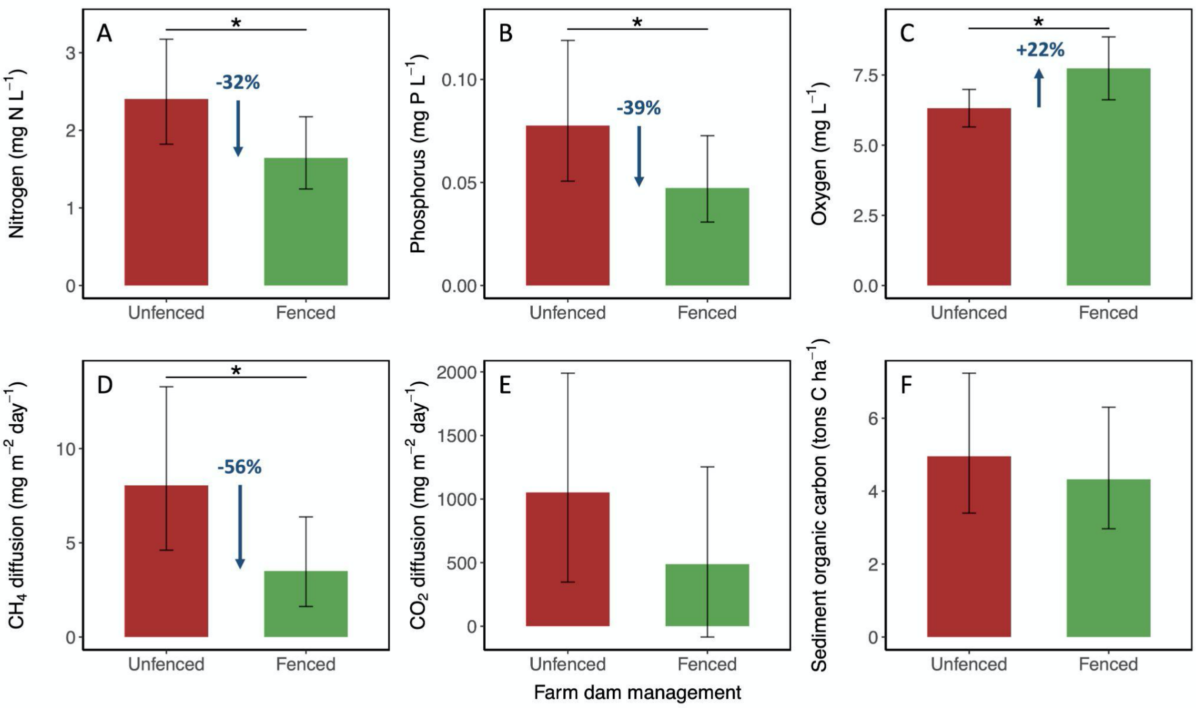

Figure 1: Effects of farm dam fencing on water quality parameters (A-C), greenhouse gas fluxes (D, E), and sediment organic carbon stocks (F). Bars represent the means (±95% confidence intervals) from the best-fitting linear models. All statistics are calculated on a sample size of 64 farm dams across 17 farming properties. We reported percentage changes only on statistically significant effects (see Table S1 for test statistics).

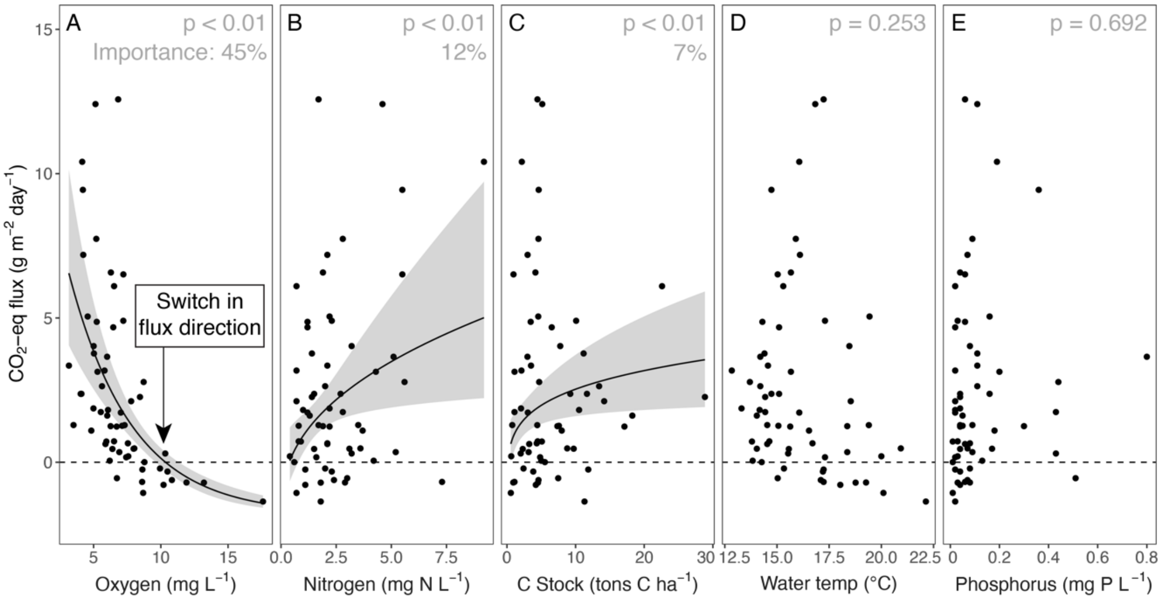

Figure 2: Effects of environmental parameters on the CO_2-eq. (methane + carbon dioxide) flux of farm dams extracted from the best-fitting model. Each point is the mean value of a farm dam. Lines indicate the statistical associations of the independent variables on carbon fluxes in the best-fitting model ($\pm$95% confidence intervals). Reported in each panel are the p-values and importance scores of statistically significant terms (see Table S2 for all test statistics and Fig S2 for importance scores). 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. S3 for model fits presented in log scales).

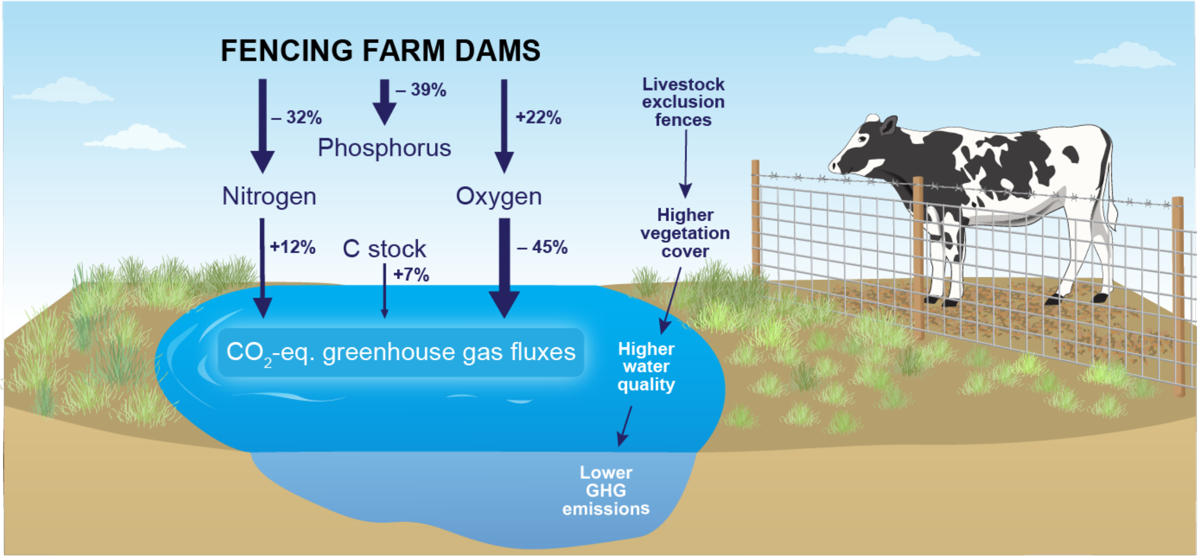

Figure 3: Effects of fencing farm dams on water quality and greenhouse gas emissions. Installing fences to exclude livestock from farm dams reduces direct deposition of nutrient-rich manure and urine into the water, avoids hooved livestock (ungulates) disturbing soil, and promotes higher vegetation cover around the dam. As a result, fenced farm dams have lower dissolved nutrients, higher dissolved oxygen, and lower aquatic GHG emissions than unfenced dams. Percentages associated with fencing farm dams represent the relative change compared to unfenced dams (Fig 1 A-C), while percentages associated with CO_2-eq fluxes indicate the sensitivity analysis of the best-fitting model (Fig S2). Arrow thickness is proportional to the magnitude of the effects.

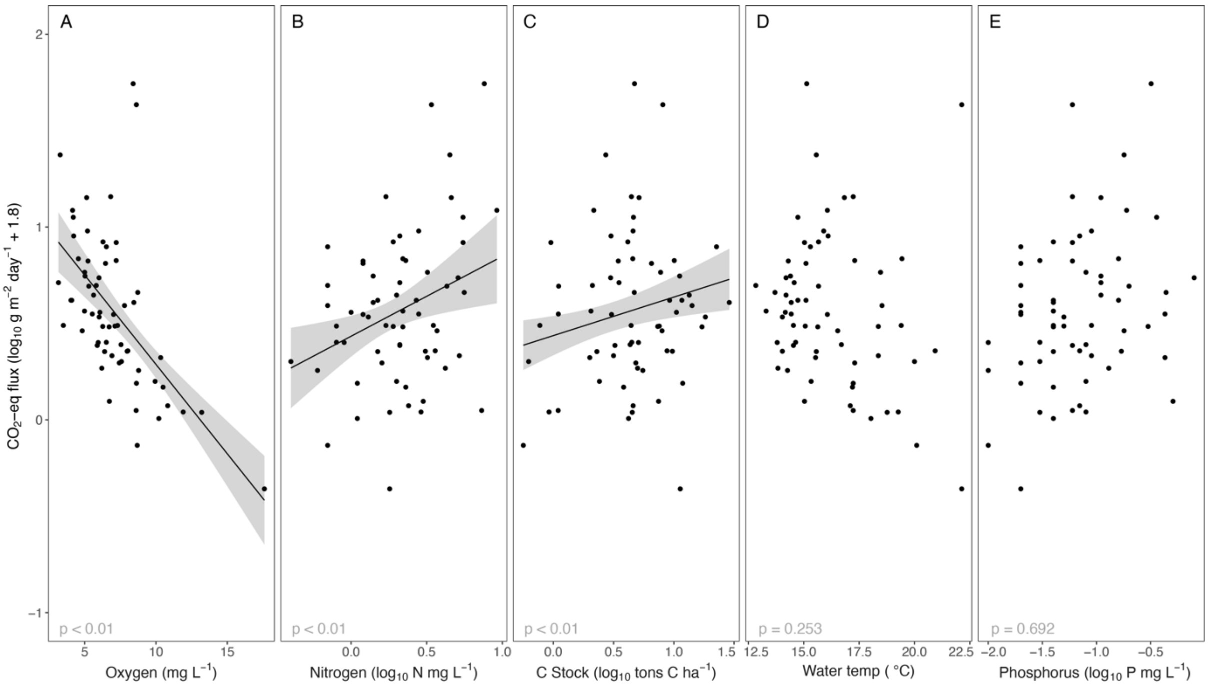

Fig S1. Effects of environmental parameters on the CO_2-eq. (methane + carbon dioxide) fluxes of farm dams on the same scale used for calibrating the best-fitting model. Each column represents a different explanatory variable in the model. See Fig 2 for the same model fits presented on an arithmetic scale.

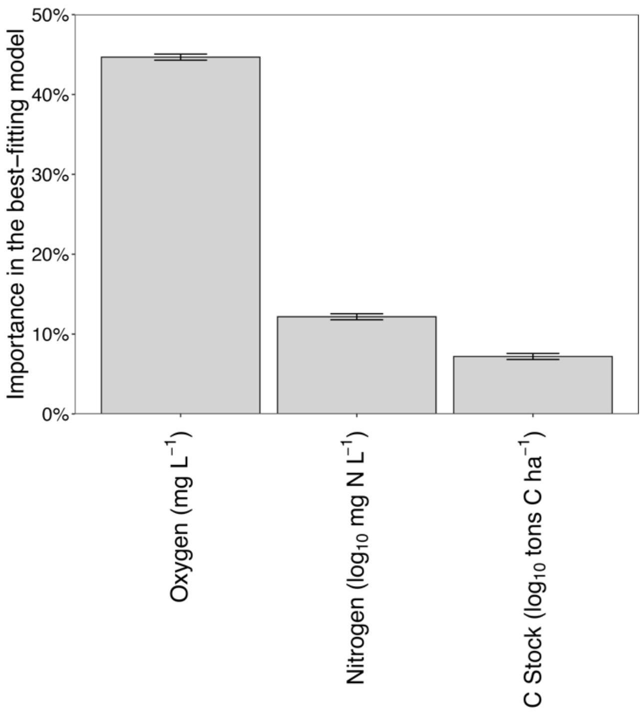

Fig S2. Sensitivity analysis for the best-fitting model explaining CO_2-eq (methane + carbon dioxide) fluxes as a function of environmental parameters. Each bar represents the contribution of a variable to the total explanatory power of the best-fitting model, calculated using eq. 2.

Explanatory Variable: Farm dam management (fenced vs unfenced)			
Dependent Variables	χ^2	df	P
A) Nitrogen (log_{10} mg N L^{-1})	7.399	1	**0.007**
B) Phosphorus (log_{10} mg P L^{-1})	6.589	1	**0.010**
C) Oxygen (mg L^{-1})	5.631	1	**0.018**
D) CH_4 diffusion (log_{10} mg m^{-2} d^{-1} + 2)	4.876	1	**0.027**
E) CO_2 diffusion (log_{10} mg m^{-2} d^{-1} + 1800)	1.65	1	0.19
F) Sediment organic carbon stock (log_{10} t C ha^{-1})	0.645	1	0.42

Table S1: Analysis of Deviance (Type II) for the best-fitting linear mixed models on the effects of fencing farm dams on water quality (A-C) and carbon dynamics (D-F). 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. Letters correspond to the effect plots in Fig. 1. All tests relied on a sample size of 64 farm dams across 17 properties. Statistically significant effects are indicated in bold.

Dependent Variable: CO_2-eq (CO_2+CH_4) fluxes ($\log_{10}$ g m^{-2} d^{-1} + 1.8)			
Explanatory Variables	χ^2	df	P
A) Oxygen (mg L^{-1})	55.229	1	**<0.001**
B) Nitrogen ($\log_{10}$ mg N L^{-1})	7.605	1	**0.006**
C) Carbon stock in soil ($\log_{10}$ t C ha^{-1})	7.807	1	**0.005**
D) Water temperature (°C)	1.308	1	0.253
E) Phosphorus ($\log_{10}$ mg P L^{-1})	0.157	1	0.692

Table S2: Analysis of Deviance (Type II) for the best-fitting linear mixed model on the drivers of farm dam emissions. Letters correspond to effect plots in Fig. 2. Each row reports the effects of each covariate on the CO_2-eq (CO_2+CH_4) 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 Fig. S1 for the explanatory powers of statistically significant terms). Akaike Information Criteria selected against including farm dam area, conductivity, and a 2-way interaction between dissolved nitrogen and dissolved phosphorus in the best-fitting model.

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