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Methane emissions from agricultural ponds are underestimated in national greenhouse gas inventories

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Agricultural ponds have some of the highest methane emissions per area among freshwater systems, and these anthropogenic emissions should be included in national greenhouse gas inventories. Here we deliver a continental-scale assessment of methane emissions from agricultural ponds in the United States and Australia. We source maps of agricultural ponds, compile a meta-analysis for their emissions and use published data to correct for temperature and the relative contributions of two methane fluxes (diffusion and ebullition). In the United States, 2.56 million agricultural ponds cover 420.9 kha and emit about 95.8 kt year^{-1} of methane. In Australia, 1.76 million agricultural ponds cover 291.2 kha and emit about 75.1 kt year^{-1} of methane. Despite large uncertainties, our findings suggest that small water bodies emit twice as much methane than is currently accounted for in national inventories. Managing these systems can reduce these emissions while benefiting productivity, ecosystem services, and biodiversity.

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Globally, aquatic systems contribute to half of total natural and anthropogenic emissions of methane (CH_4)[1], a powerful greenhouse gas (GHG) with much higher warming potential than carbon dioxide (CO_2)[2,3]. Small aquatic habitats (<0.1 ha in area) emit disproportionally more methane per unit area than larger lakes, contributing to ca. 37% of total lentic methane emissions, despite occupying <10% of the global freshwater surface area of lakes and ponds[4]. Many of these small systems are human-constructed to secure water for crops and livestock, and to support the ever-increasing demand for agricultural production[5–7]. This proliferation of agricultural water bodies is likely to affect global biogeochemical cycles significantly, but the evidence is lacking.

Agricultural ponds (also known as farm dams, impoundments, or dugouts) are small, constructed waterbodies (typically between 0.01 and 1 ha in surface area) with some of the highest methane emissions per area among freshwater ecosystems[8–10]. These recently discovered emissions are boosted by unusually high concentrations of fertiliser and manure runoffs, which increases organic matter and creates the ideal conditions for methane production[8,9]. Also, these systems are typically shallow and can warm up rapidly, boosting metabolic rates, bacterial build-up, and methanogenesis. For example, Ollivier et al.[9] estimated that farm ponds produce 3.43 times more CO_2-eq (methane + carbon dioxide) emissions per area than reservoirs.

Importantly, emissions from agricultural ponds are of anthropogenic nature and should therefore be included in national carbon inventories submitted to the United Nations Framework Convention on Climate Change (UNFCCC) under the Paris agreement[11]. The Intergovernmental Panel on Climate Change (IPCC) recently rectified their guidelines to encourage the inclusion of agricultural ponds as "*Other Constructed Waterbodies*" in National Greenhouse Gas Inventories[12]. Yet, there is little data on the abundance and distribution of agricultural ponds in most of the world[6], and this knowledge gap complicates their inclusion in national GHG inventories.

Here we deliver a first-order assessment of methane emissions from agricultural ponds in the United States and Australia (see Fig. S1 for the model diagram). We leveraged two mapping programs[6,13] to identify 4.17 million agricultural ponds in 1.75 million kha (17.5 million km^2) of land across both countries (Fig. 1a, b). We merged this dataset with annual temperatures (Fig. 1c, d), and we conducted a meta-analysis to quantify average methane emissions from agricultural ponds ($N = 286$, Fig. 2). Then, we used a published dataset[1] to calibrate the effects of temperature on methane emissions ($N = 257$, Fig. S2), and the relative contributions of ebullitive and diffusive methane fluxes ($N = 164$, Fig. S3). We calibrated a model to map temperature-adjusted methane emissions associated with agricultural ponds in the United States and Australia. Finally, we compared our results with the figures reported in the latest national GHG inventories reported to UNFCCC for 2020.

Results and discussion

Our meta-analysis showed that total temperature-adjusted methane emissions (diffusion + ebullition) from agricultural ponds are variable, with fluxes spanning from <1 to >10^3 kg CH_4 ha^{-1} $year^{-1}$ (Fig. 2). On average, we predict that agricultural ponds at 15 °C should emit 204 kg CH_4 ha^{-1} $year^{-1}$ (95% C.I.: 83–521; median: 157.7). Our estimate is within 12% of the relevant IPCC emission factor for "*freshwater and brackish ponds*" of 183 (95% C.I.: 118–228) kg CH_4 ha^{-1} $year^{-1}$ [12]. Yet, the proposed IPCC emission factor is temperature-independent and will underpredict emissions in warmer climates. For example, our model predicts that a farm dam at 30 °C should, on average, emit 405 (95% C.I.: 164–1037; median: 314.2) kg CH_4 ha^{-1} $year^{-1}$, which is twice as much as the IPCC emission factor.

In the United States, 2.56 million agricultural ponds cover 420.9 kha (Fig. 1a) and emit an estimated 95.8 kt CH_4 $year^{-1}$ (95% C.I.: 61–157; Fig. 3a). In Australia, 1.76 million agricultural ponds cover 291.2 kha (Fig. 1b) and emit 75.1 kt CH_4 $year^{-1}$ (95% C.I.: 47–123; Fig. 3b). Assuming a global warming potential of 28 times that of CO_2 over a 100-year time scale (following IPCC Fifth Assessment Report[3]), these methane emissions are equivalent to 4.79 Mt CO_2-eq $year^{-1}$ (95% C.I.: 3.01–7.86; see Fig. S4 for the hotspots of methane emissions from agricultural ponds in the United States and Australia).

After the 2019 Refinement of IPCC guidelines, states are recommended to include methane emissions from all constructed ponds smaller than 8 ha for agriculture, recreation, and aquaculture in UNFCCC GHG inventories (as "*Other Constructed Waterbodies*" under "*Land Use, Land Use Change, and Forestry*")[14]. For 2020, the United States reported 173.1 kha of pond area emitting 43.75 kt CH_4 (average emission factor of 252.78 kg CH4 ha^{-1} $year^{-1}$), and Australia reported 316.4 kha of pond area emitting 40.73 kt CH_4 [average emission factor of 128.75 kg CH4 ha^{-1} $year^{-1}$; see Table 4(II) of the Common Reporting Format by UNFCCC[15]]. Our analysis suggests that these emissions are underestimated by around half. Specifically, emissions reported to UNFCCC for all constructed waterbodies smaller than 8 ha in the United States (43.75 kt CH_4 $year^{-1}$) and Australia (40.73 kt CH_4 $year^{-1}$) are 46% and 54% lower than our estimates for methane emissions from agricultural ponds between 0.01 and 1 ha in the United States (95.8 kt CH_4 $year^{-1}$) and in Australia (75.1 kt CH_4 $year^{-1}$), respectively (Fig. 3c). Part of this discrepancy may be that guidelines for national GHG inventories allow separating methane emissions of agricultural ponds (under "*Other Constructed Waterbodies*") from those of animal manure contamination in agricultural ponds (under "Manure Management"). Unfortunately, national inventories lack details on the methods for accounting for manure in agricultural ponds.

Agriculture contributes to 36% and 47% of all methane emissions in the United States (10.04 Mt CH_4 $year^{-1}$) and Australia (2.08 Mt CH_4 $year^{-1}$), respectively—mainly through enteric fermentation and manure breakdown[16]. However, these calculations omit emissions from agricultural ponds associated with rearing livestock, which could be non-trivial. Thus, it will be important for future studies to quantify the relative contributions of agricultural ponds to the total carbon footprint of animal agriculture.

It is important to note that there are several sources of error in our calculations (Fig. S5). Of the parameters in our model, estimates for the average methane flux, temperature sensitivity, and the contribution of methane ebullition have the most significant uncertainties (CV between 20% and 28%), mainly because these estimates are based on relatively small sample sizes (Fig. S5). Therefore, future work should prioritise improving current estimates using on-the-ground measurements from agricultural ponds across different climates. Conversely, predictions for pond distribution (CV of 10%) were more accurate because of large-scale assessments using satellite data (Fig. S5).

There are other sources of relevant emissions from agricultural ponds that our model fails to capture. In particular, while methane is often the most prominent GHG associated with these ponds (e.g., 83-94% of CO_2-eq flux in Ollivier et al.[9]), our analysis ignored the contributions of other types of GHG—such as carbon dioxide (CO_2) and nitrous oxide (N_2O)[17,18]. Also, this model uses 10-year averages to account for temperature, and omits the seasonal variability in pond surface areas and temperatures on methane emissions. In this regard, the present work offers an initial assessment of methane emissions from agricultural ponds, but our results should only be taken as a first-order approximation.

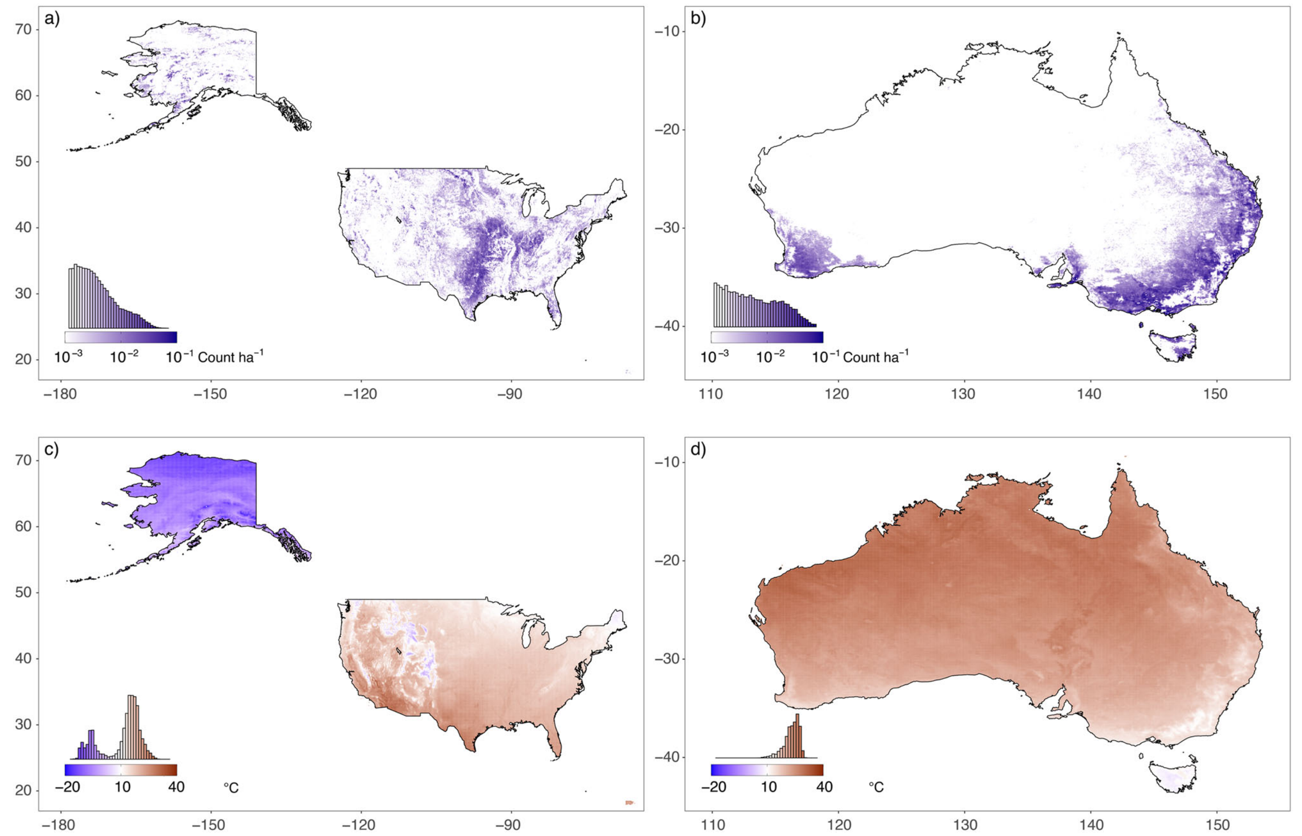

Fig. 1 Covariates (at 5 arcmin resolution) used to parametrise our model on methane emissions from agricultural ponds. **a** Densities of agricultural ponds in the United States (2.56 millions) from Moore et al.[13]. **b** Densities of agricultural ponds in Australia (1.76 millions) from AusDams in Malerba et al.[6]. **c** Annual median temperatures in the United States. **d** Annual median temperatures in Australia. All temperatures are calculated using 10 years of weekly data from MODIS Terra Land Surface in Wan et al.[32].

Conclusions and future directions

Agricultural ponds are often overlooked as GHG sources, particularly since it is often difficult to account for their anthropogenic carbon emissions. Our analysis suggests that these small water bodies emit more methane than is currently accounted for in national GHG inventories. Agricultural ponds are essential for water security, and their density will continue to grow with rising global food demand. Therefore, developing cost-effective management solutions is urgently needed to reduce their ecological and environmental impacts.

Methane emissions from agricultural ponds represent both a liability and an opportunity. Much of the nutrients in farming ponds originate from livestock manure and fertiliser runoffs[19,20] (Fig. 4). There is substantial evidence that higher nutrient concentrations in freshwater ponds promote GHG emissions[9,21,22]. There are several ways to reduce nutrient loads in agricultural ponds and their associated methane emissions. For example, Malerba et al.[22] showed that simple management interventions in agricultural ponds (such as using fences to exclude livestock from accessing the water) could increase water quality (32% less nitrogen, 39% less phosphorus, 22% more dissolved oxygen) and halve methane emissions (56% less methane). Improving water quality will also benefit livestock health, biodiversity, and ecosystem services in the long term[23,24]. Another way to reduce nutrient influx is establishing a vegetation buffer around ponds, a practice termed “phytoremediation”[25]. Such a strategy may also favour biodiversity and comes with well-documented direct and indirect environmental benefits, including higher pollination success, greater ecosystem functioning, better resilience to pests, and improved aesthetic value[24,26]. Yet, using plants to reduce nutrients in water bodies could come at the cost of reducing runoff to a dam, and increasing input of organic carbon (plant material) to fuel decomposition and GHG production[27,28]. More studies are required to understand the trade-offs of using phytoremediation for water security and GHG emissions. Importantly, agricultural ponds often represent an important wetland habitat for a wide range of wildlife, including threatened species[29]. In the future, governments could provide financial incentives such as carbon credits to subsidies management interventions (e.g., fencing, revegetation) to reduce methane emissions from ponds.

Methods

Spatial datasets. Refer to Fig. S1 for the diagram of our modelling approach. We sourced data on the distribution of agricultural ponds in Australia from AusDams.org ($N = 1.7$ million), which was developed by applying artificial intelligence to high-resolution satellite images, and it is estimated to contain around 90% of Australian farm ponds (scale from 1:25,000 to 1: 250,000)[6]. For agricultural ponds in the United States, we used the National Hydrography Dataset ($N = 7.8$ million), which was developed and verified by the US Geological Survey[13] (scale from 1:20,000 to 1:100,000). We retained all ponds between 0.01 and 1 ha (10^2–10^4 m^2) in surface area and we only considered ponds in crops, open forests, shrubs, herbaceous or bare land using the land use map at a 100 ha (1 km^2) resolution from Copernicus Global Land Service[29]. This approach produced a normally distributed population centred around 0.1 ha (10^3 m^2). Manual inspection using satellite images across land-use types confirmed that >95% of the waterbodies in our maps appeared artificial ponds related to agriculture. We followed IPCC guidance of assuming an overall uncertainty for remote sensing products of ±10%[30,31]. Finally, we created a global map of median annual daily temperatures using 10 years of weekly data (Jan 2010 to Jan 2020) recorded by MODIS Terra Land Surface Temperature (product MOD11A1.006) at a 100 ha (1 km^2) resolution using Google Earth Engine[32].

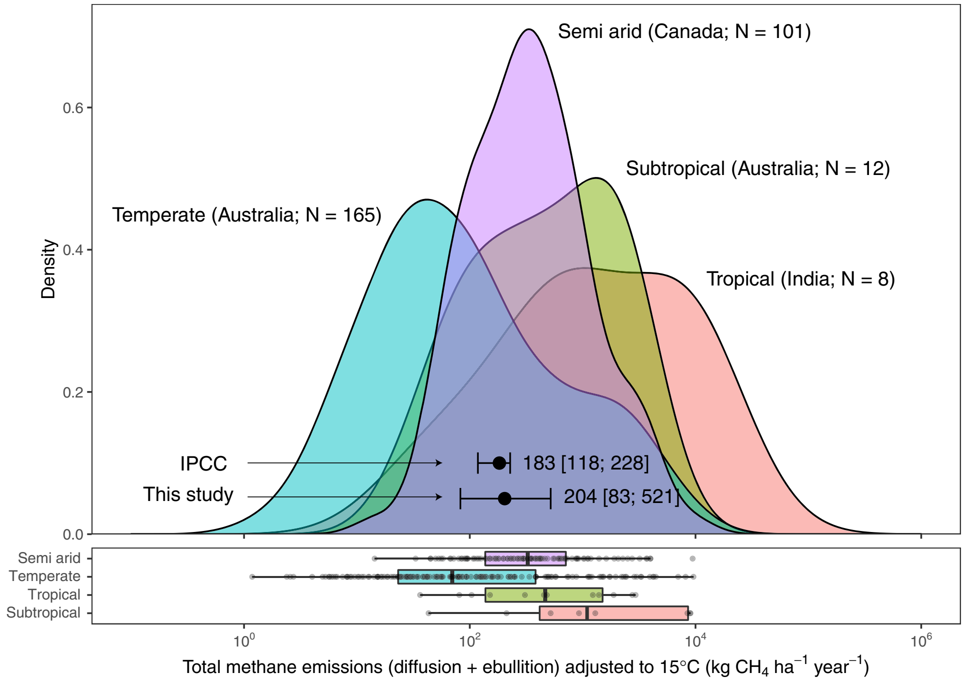

Fig. 2 Meta-analysis on total methane emissions (diffusion + ebullition) from agricultural ponds. We compiled values from the scientific literature, supplemented with new data from 11 sites in temperate Australia (see labels for sample size; *N*). We standardised all rates to 15 °C (using Eq. 1 and Fig. S2) and accounted for ebullition and diffusion (using Fig. S3). The colours of the density functions indicate the climate. Black points indicate either the IPCC emission factor recommended for constructed waterbodies across all climates (Table 7.12 in Lovelock et al.[14]), or the geometric mean calculated from all data compiled in this study—with error bars representing the 95% confidence intervals. Box-and-whiskers show the distribution of the compiled data divided by climate.

Methane emissions. The paucity of published studies worldwide on methane emissions from agricultural ponds complicates the estimation of average methane fluxes. On the 29th of April 2022, we used ISI Web of Science searching in all fields for: (methan*) AND (agricultural pond* OR farm dam* OR impoundment* OR dug out*; 503 results). We manually inspected each to identify seven datasets for agricultural ponds, with 12 subtropical records for Australia[8], 154 temperate records for Australia[9,22,33], 101 semi-arid records for Canada[10], and 8 tropical records for India[34]. We excluded two observations for Swedish cropland ponds in Peacock et al.[11] because there were too few data points to represent this region. We supplemented the available data with new measurements of 11 temperate agricultural ponds in Victoria (Australia) collected in April 2021 following the same protocols described in Malerba et al.[22]. We assumed that all studies used equivalent techniques to record methane emissions, either by recording gas emissions with floating chambers or by measuring gas concentrations dissolved in the water. However, Grinham et al.[8] used floating chambers to capture both diffusive and ebullitive methane fluxes using long continuous recordings (from 6–24 h). In contrast, all other measurements quantified only diffusive fluxes using multiple short recordings (ca. 5 min)[9,22] or the headspace extraction method[10]. Therefore, we used a dataset compiled by Rosentreter et al.[1] to quantify the average contribution of methane ebullition to the total methane flux of agricultural ponds. Given the lack of studies specific to agricultural ponds, we used data for lakes and reservoirs instead (Fig. S3). We also excluded water bodies in regions with sub-zero annual mean temperatures. Our analysis revealed that the ratio of methane diffusion to methane ebullition is temperature-dependent, with methane diffusion making up 72% of total methane emissions at 5 °C but only 12.5% at 30 °C. Importantly, the effect of temperature on ebullitive methane fluxes was nearly identical between lakes and reservoirs (Fig. S3). This finding suggests that the temperature-dependency of methane ebullition is similar among different freshwater systems (but see Deemer and Holgerson[35] for other drivers of methane emissions that differ between lakes and reservoirs).

Temperature standardisation. To compare estimates across sites and climates, we standardised daily rates of methane emissions at 15 °C, using the Boltzmann–Arrhenius relationship, as:

$$\ln[M_i(T_{15})] = \ln[M_i(T)] - E_M\left(\frac{1}{k_B T_{15}} - \frac{1}{k_B T_i}\right) \quad (1)$$

where $\ln[M_i(T)]$ is the $\log_e$-transformed rate of daily methane emissions (in units of mg CH_4 day^{-1} m^{-2}) recorded at site i (i = 1, 2, …, 286) with local air temperature T_i (in Kelvin), $\ln[M_i(T_{15})]$ is the equivalent rate standardised to 15 °C, T_{15} is the temperature used to standardise rates (where 15 °C is 288.15 K), E_M is the temperature sensitivity for methane emissions (in units of eV mg CH_4 day^{-1} m^{-2}), and k_B is the Boltzmann constant (8.617×10^{-5} eV K^{-1}). For the local temperature of each site (T_i), we used the 10-year median daily temperature recorded by MODIS Terra Land Surface Temperature (as described above). For the temperature sensitivity of methane emissions (E_M), we used the dataset published by Rosentreter et al.[1] for lakes and reservoirs (N = 313; Fig. S2). The effects of temperature on methane emission did not differ between lakes and reservoirs, suggesting that our estimate for E_M can represent different types of freshwater habitats. Finally, we used Eq. 1 to calculate total methane emissions (diffusion + ebullition) standardised at 15 °C (Fig. 2).

In summary, (1) we compiled data from the scientific literature and additional fieldwork on methane fluxes from 286 agricultural ponds in subtropical, temperate, semi-arid, and tropical climates, and we used the dataset published by Rosentreter et al.[1] to (2) standardise all emissions to 15 °C (Fig. S2) and to (3) estimate the contribution of methane ebullition (Fig. S3). Despite the low sample size and the uncertainty associated with the meta-analyses, the final dataset was normally distributed and consistent across climates and locations (Fig. 2), which suggests that our sample size may be a good representation of the whole population (albeit with wide confidence intervals).

Methane predictions. From the maps of agricultural ponds in the U.S. and Australia, we converted the density of pond surface area (pond ha ha^{-1}) into cumulative methane emissions (kg CH_4 year^{-1} ha^{-1}) after adjusting for local temperature. Specifically, we reorganised Eq. 1 to obtain the temperature-adjusted methane emissions for each pond ($M_i(T_i)$), as:

$$\ln[M_i(T_i)] = \ln[M_i(T_{15})] + E_M\left(\frac{1}{k_B T_{15}} - \frac{1}{k_B T_i}\right) \quad (2)$$

where $M_i(T_{15})$ is the methane flux from agricultural ponds standardised to 15 °C using records compiled from the scientific literature (Fig. 2), and T_i is the site-specific median annual temperature extracted from MODIS Terra Land Surface Temperature (see details above). All other coefficients remain the same as Eq. 1.

Sources of uncertainty. To quantify the overall uncertainty, we applied non-parametric bootstrapping to compound all sources of error using 1000 iterations where observations in Figs. 1, S2, and S3 were sampled with replacement[36]. At each iteration, we repeated all steps in our methods to estimate the distribution for each of our estimates. We compared the magnitude of each source of uncertainty using the coefficient of variation of the mean (i.e., the ratio between the standard error and the mean; Fig. S5).

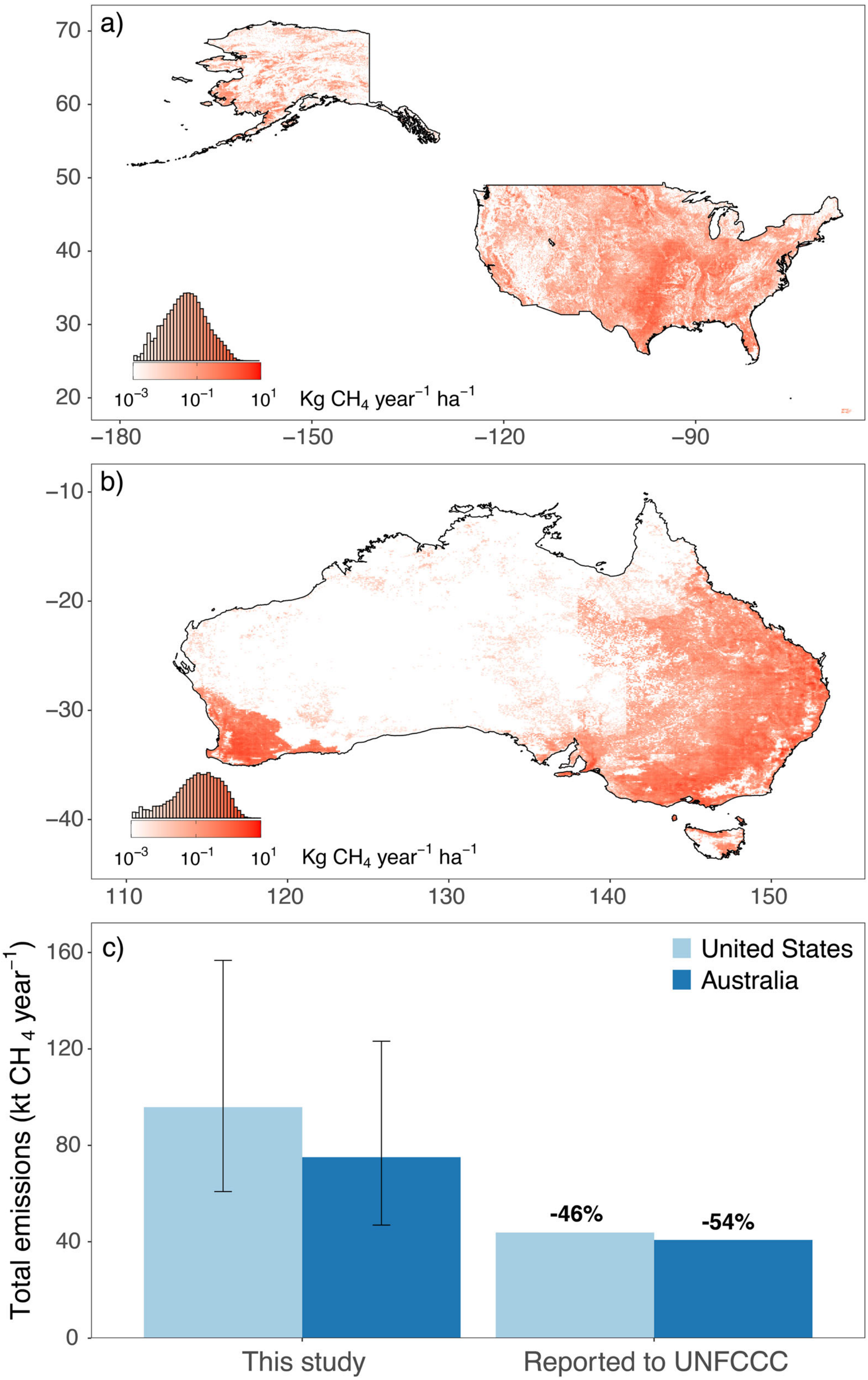

Fig. 3 Methane emissions from agricultural ponds in the United States and Australia. a Spatial model at five arcmin resolution for annual methane emissions for agricultural ponds in the United States (total of 96 kt CH_4 $year^{-1}$). **b** Spatial model at five arcmin resolution for annual methane emissions for agricultural ponds in Australia (total of 75 kt CH_4 $year^{-1}$). **c** Emissions from agricultural ponds calculated in this study (with error bars representing the 95% confidence intervals) compared against those from "*Other Constructed Waterbodies*" under "*Land Use, Land Use Change, and Forestry*" reported to UNFCCC[15] in 2020 for the United States and Australia. Percentages indicated above bars quantify the relative decrease from estimates in this study to those in UNFCCC reports. See Fig. S4 for the hotspots of methane emissions in the United States and Australia.

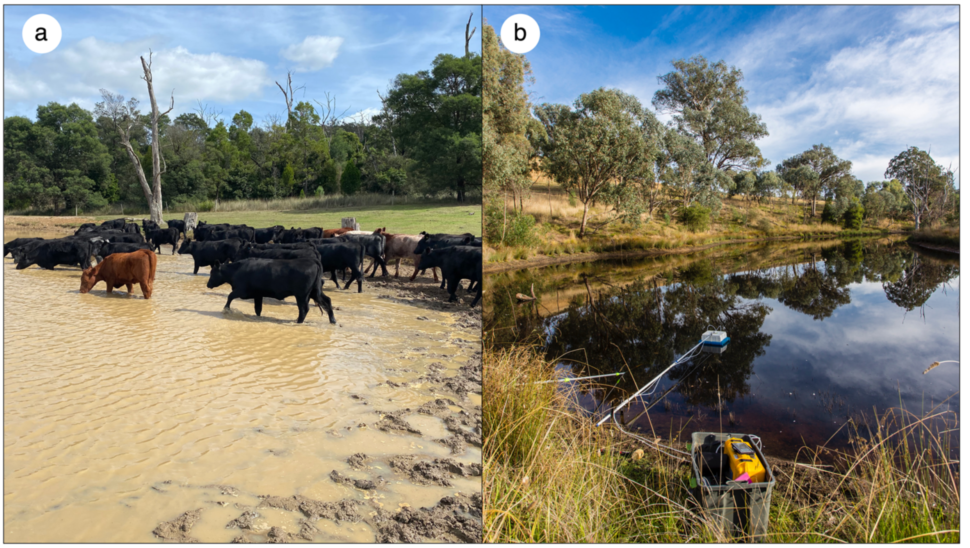

Fig. 4 Managing agricultural ponds to reduce their methane emissions. a Livestock manure and fertiliser often accumulate in agricultural ponds to create ideal conditions for methane production. Image credit: Martino E. Malerba **b** Simple management interventions, such as fencing to exclude livestock, are cost-effective solutions for reducing these emissions while providing additional environmental benefits (e.g., higher water quality, biodiversity, agricultural productivity, and aesthetic value)[22–24]. Image credit: I. Noyan Yilmaz.

Assumptions. Our approach makes several assumptions. First, agricultural ponds are between 0.01 ha (100 m^2) and 1 ha (10,000 m^2) in surface area[6,37]. Second, the effects of temperature on methane emissions from agricultural ponds follow a Boltzmann–Arrhenius relationship[38,39]. Third, the temperature sensitivity coefficient (parameter E_M in Eqs. 1 and 2; Fig. S2) and the temperature-dependency of ebullition to diffusive fluxes (Fig. S3) are comparable among lakes, reservoirs, and ponds (Figs. S2 and S3). Fourth, median annual temperatures represent long-term conditions and can be used to correct field observations taken at specific points of the year. Fifth, the densities and surface areas of agricultural ponds reported in the maps of the United States and Australia have an uncertainty of ±10%[30,31]. We used R version 4.2.2[40] for data compilation, analyses, statistics, mapping, and plotting, using R packages ggplot2[41], dplyr[42], tidyverse[43], raster[44], sf[45], and lme4[46], nlme[47]. All codes and data generated in this study are available in a public repository in Mendeley Data[48].

Data availability

All data, maps, and meta-analyses can be found in a public repository in Mendeley Data at https://data.mendeley.com/datasets/6j87tgp825, (https://doi.org/10.17632/6j87tgp825.2).

Code availability

All codes in R version 4.2.2 (2022-10-31) with analyses, plots, and maps can be found in a public repository in Mendeley Data at https://data.mendeley.com/datasets/6j87tgp825, (https://doi.org/10.17632/6j87tgp825.2).

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References

1. Rosentreter, J. A. et al. Half of global methane emissions come from highly variable aquatic ecosystem sources. *Nat. Geosci.* **14**, 225–230 (2021).
2. U.S. Environmental Protection Agency. Inventory of U.S. greenhouse gas emissions and sinks: 1990 – 2004 https://www.epa.gov/sites/default/files/2015-12/documents/06_complete_report.pdf (2006).
3. Myhre, G. et al. in *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (eds. Stocker, T. F. et al.) Ch. 8 (Cambridge University Press, 2013).
4. Holgerson, M. A. & Raymond, P. A. Large contribution to inland water CO_2 and CH_4 emissions from very small ponds. *Nat. Geosci.* **9**, 222–226 (2016).
5. Downing, J. A. Emerging global role of small lakes and ponds: little things mean a lot. *Limnetica* **29**, 0009–0024 (2010).
6. Malerba, M. E., Wright, N. & Macreadie, P. I. A continental-scale assessment of density, size, distribution and historical trends of farm dams using deep learning convolutional neural networks. *Remote Sens.* **13**, 319 (2021).
7. Swartz, T. M. & Miller, J. R. The American Pond Belt: an untold story of conservation challenges and opportunities. *Front. Ecol. Environ.* **19**, 501–509 (2021).
8. Grinham, A. et al. The importance of small artificial water bodies as sources of methane emissions in Queensland, Australia. *Hydrol. Earth Syst. Sci.* **22**, 5281–5298 (2018).
9. Ollivier, Q. R., Maher, D. T., Pitfield, C. & Macreadie, P. I. Punching above their weight: Large release of greenhouse gases from small agricultural dams. *Glob. Chang. Biol.* **25**, 721–732 (2018).
10. Webb, J. R. et al. Regulation of carbon dioxide and methane in small agricultural reservoirs: optimizing potential for greenhouse gas uptake. *Biogeosciences* **16**, 4211–4227 (2019).
11. Peacock, M. et al. Small artificial waterbodies are widespread and persistent emitters of methane and carbon dioxide. *Glob. Chang. Biol.* **27**, 5109–5123 (2021).
12. IPCC. 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. https://www.ipcc.ch/report/2019-refinement-to-the-2006-ipcc-guidelines-for-national-greenhouse-gas-inventories/ (2019).
13. Moore, R. B. et al. *User's Guide for the National Hydrography Dataset Plus (NHDPlus) High Resolution*. Report No. 2331-1258 (US Geological Survey, 2019).
14. Lovelock, C. E. et al. in *2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories*, Vol. 4 (eds. Zhu, Z. et al.) Ch. 7 (IPCC, 2019).
15. United Nations Framework Convention on Climate Change. National Inventory Submissions 2021. https://unfccc.int/ghg-inventories-annex-i-parties/2021 (2022).
16. Jackson, R. B. et al. Increasing anthropogenic methane emissions arise equally from agricultural and fossil fuel sources. *Environ. Res. Lett.* **15**, 071002 (2020).
17. Xiao, Q. et al. Surface nitrous oxide concentrations and fluxes from water bodies of the agricultural watershed in Eastern China. *Environ. Pollut.* **251**, 185–192 (2019).
18. Webb, J. R. et al. Widespread nitrous oxide undersaturation in farm waterbodies creates an unexpected greenhouse gas sink. *Proc. Natl Acad. Sci. USA* **116**, 9814–9819 (2019).
19. Blanchard, P. & Lerch, R. Watershed vulnerability to losses of agricultural chemicals: Interactions of chemistry, hydrology, and land-use. *Environ. Sci. Technol.* **34**, 3315–3322 (2000).
20. Brainwood, M. A., Burgin, S. & Maheshwari, B. Temporal variations in water quality of farm dams: impacts of land use and water sources. *Agric. Water Manag.* **70**, 151–175 (2004).
21. Grasset, C. et al. An empirical model to predict methane production in inland water sediment from particular organic matter supply and reactivity. *Limnol. Oceanogr.* **66**, 3643–3655 (2021).

22. Malerba, M. E. et al. Fencing farm dams to exclude livestock halves methane emissions and improves water quality. *Glob. Chang. Biol.* **28**, 4701–4712 (2022).
23. Dobes, L., Crane, M., Higgins, T., Van Dijk, A. & Lindenmayer, D. B. Increased livestock weight gain from improved water quality in farm dams: a cost-benefit analysis. *PLoS ONE* **16**, e0256089 (2021).
24. Westgate, M. J. et al. Improved management of farm dams increases vegetation cover, water quality, and macroinvertebrate biodiversity. *Ecol. Evol.* 12, e8636 (2022).
25. Pilon-Smits, E. Phytoremediation. *Annu. Rev. Plant Biol.* **56**, 15–39 (2005).
26. Hazell, D., Cunnningham, R., Lindenmayer, D., Mackey, B. & Osborne, W. Use of farm dams as frog habitat in an Australian agricultural landscape: factors affecting species richness and distribution. *Biol. Conserv.* **102**, 155–169 (2001).
27. Vroom, R. J. E., van den Berg, M., Pangala, S. R., van der Scheer, O. E. & Sorrell, B. K. Physiological processes affecting methane transport by wetland vegetation – a review. *Aquat. Bot.* **182**, 103547 (2022).
28. Bastviken, D. et al. The importance of plants for methane emission at the ecosystem scale. *Aquatic Botany* **184**, 103596 (2022).
29. Buchhorn, M. et al. Copernicus Global Land Service: Land Cover 100m: collection 3: epoch 2019: Globe 2020. https://doi.org/10.3390/rs12061044 (2020).
30. EPA. *Land Use, Land-Use Change, and Forestry* (U.S. Environmental Protection Agency, 2022).
31. IPCC. *Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (eds. Core Writing Team, R.K. Pachauri, R. K. & Meyer L.A.) (IPCC, 2014).
32. Wan, Z., Hook, S. & Hulley, G. MOD11A1 MODIS/Terra Land Surface Temperature/Emissivity Daily L3 Global 1km SIN Grid V006 [Data set]. NASA EOSDIS Land Processes DAAC. https://doi.org/10.5067/MODIS/MOD11A1.006 (2015).
33. Ollivier, Q. R., Maher, D. T., Pitfield, C. & Macreadie, P. I. Winter emissions of CO_2, CH_4, and N_2O from temperate agricultural dams: fluxes, sources, and processes. *Ecosphere* **10**, e02914 (2019).
34. Panneer Selvam, B., Natchimuthu, S., Arunachalam, L. & Bastviken, D. Methane and carbon dioxide emissions from inland waters in India - implications for large scale greenhouse gas balances. *Glob. Chang. Biol.* **20**, 3397–3407 (2014).
35. Deemer, B. R. & Holgerson, M. A. Drivers of methane flux differ between lakes and reservoirs, complicating global upscaling efforts. *J. Geophys. Res. Biogeosci.* **126**, e2019JG005600 (2021).
36. Efron, B. in *Breakthroughs in Statistics. Bootstrap Methods: Another Look at the Jackknife* (eds. Kotz, S. & Johnson, N. L.) 569–593 (Springer, 1992).
37. Chumchal, M., Drenner, R. & Adams, K. Abundance and size distribution of permanent and temporary farm ponds in the southeastern Great Plains. *Inland Waters* **6**, 258–264 (2016).
38. Yvon-Durocher, G. et al. Methane fluxes show consistent temperature dependence across microbial to ecosystem scales. *Nature* **507**, 488–491 (2014).
39. Zhu, Y. et al. Disproportionate increase in freshwater methane emissions induced by experimental warming. *Nat. Clim. Chang.* **10**, 685–690 (2020).
40. R Core Team. *R: A Language and Environment for Statistical Computing* (R Foundation for Statistical Computing, 2022).
41. Wickham, H. *ggplot2: Elegant Graphics for Data Analysis* (Springer-Verlag New York, 2009).
42. Wickham, H., François, R., Henry, L. & Müller, K. dplyr: A grammar of data manipulation. https://dplyr.tidyverse.org/reference/dplyr-package.html (2018).
43. Wickham, H. et al. Welcome to the tidyverse. *J. Open Source Softw.* **4**, 1686 (2019).
44. Hijmans, R. J. raster: Geographic data analysis and modeling. R package version 2.5-8. https://CRAN.R-project.org/package=raster (2016).
45. Pebesma, E. Simple features for R: standardized support for spatial vector data. *R J.* **10**, 439–446 (2018).
46. Bates, D., Maechler, M., Bolker, B. & Walker, S. Fitting linear mixed-effects models using lme4. *J. Stat. Softw.* **67**, 1–48 (2015).
47. Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D. & R Core Team. nlme: Linear and nonlinear mixed effects models. R package version 3.1-150 (R Core Team, 2020).
48. Malerba, M. E. Methane emissions from agricultural ponds are underestimated in national greenhouse gas inventories, Mendeley Data, V2. https://data.mendeley.com/datasets/6j87tgp825, (https://doi.org/10.17632/6j87tgp825.2) (2022).

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Author contributions

M.E.M., P.I.M., and T.d.K. designed the research, M.E.M., N.W., and L.S. collected the data, M.E.M. analysed the data, M.E.M. wrote the first draft, and all authors contributed to the final draft.

Competing interests

The authors declare no competing interests.

Additional information

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