communications earth & environment

Article

https://doi.org/10.1038/s43247-024-01359-x

# The potential of carbon markets to accelerate green infrastructure based water quality trading

Check for updates

Braden J. Limb[1], Jason C. Quinn[1], Alex Johnson[2], Robert B. Sowby[3] & Evan Thomas[2]

Green infrastructure solutions can improve in-stream water quality in lieu of building electricity-consuming gray infrastructure. Permitted under the United States Clean Water Act, these programs allow regulated utilities to trade point-source water quality obligations with non-point source mitigation efforts in the watershed. Carbon financing can provide an incentive for water quality trading. Here we combine data on impaired waters, treatment technologies, and life cycle greenhouse gas emissions in the Contiguous United States, and compare traditional treatment technologies to alternative green infrastructure. We find green infrastructure could save $15.6 billion dollars, 21.2 terawatt-hours of electricity, and 29.8 million tonnes of carbon dioxide equivalent emissions per year while sequestering over 4.2 million tonnes CO2e per year over a 40 year time horizon. Green infrastructure solutions may have the potential to generate $679 million annually in carbon credit revenue (at $20 per credit), which represents a unique opportunity to help accelerate water quality trading.

Half of America's rivers are impaired and today do not meet Clean Water Act standards[1]. Point-source river discharges (i.e. Wastewater Treatment Facilities) are regulated by the United States Environmental Protection Agency (EPA) and state agencies under the Clean Water Act, while non-point sources are largely unregulated. These environmental and regulatory realities are subsequently putting increasing pressure on water and wastewater utilities to address riverine water quality. However, a substantial source of freshwater contamination in the United States is attributable to non-point source pollution from land-use change, agricultural and forestry practices, soil erosion, and urbanization as well as large-scale, short-and-medium term shocks associated with wildfires and other impacts of climate change. A dominant form of water quality impairment is fertilizer application and subsequent runoff to streams[2]. The most prominent water quality impacts of fertilizer are harmful algae blooms and subsequent anoxic zones either in lakes or in near-coastal environments[3].

Wastewater Treatment Facilities must construct gray infrastructure to reduce their pollutant loads under the National Pollutant Discharge Elimination System (NPDES). Wasteload allocations in an individual NPDES permit are often calculated in response to pollutant levels in a river via the establishment of Total Maximum Daily Loads. Given the success of the Clean Water Act since the 1970s, the percentage of instream pollutant loads directly attributable to NPDES permittees has become proportionately low in many watersheds[4,5].

Typically, water and wastewater utilities meet their NPDES water quality regulatory obligations by constructing gray infrastructure, such as secondary, tertiary and reverse osmosis treatment plants, requiring substantial capital and operational costs as well as embodied emissions from materials and indirect emissions from energy use throughout their operational lifetimes. Though point-source pollutant inputs from Wastewater Treatment Facilities are often proportionately low, a high overall level of a given pollutant in a river of concern often leads to substantially lower point-source wasteload allocations that may force a utility to the limits of existing wastewater treatment technology[4]. While there are other regulatory and nonregulatory pathways and attempts to improve instream water quality outside of Point Source permitting (such as conservation funding from the United States Department of Agriculture), none have had the levels of success over the last 50 years as the NPDES part of the Clean Water Act. While improving the quality of an NPDES permittee's discharge is not the only means to improve instream water quality, it has long been the dominant mechanism in the United States to drive public investments in regional water quality[6].

Water and wastewater treatment plants currently account for about 2% of energy use and 45 million tonnes of carbon dioxide equivalent (CO2e)

[1]Mechanical Engineering, Colorado State University, Fort Collins, CO, USA. [2]Mortenson Center in Global Engineering and Resilience, University of Colorado Boulder, Boulder, CO, USA. [3]Department of Civil and Construction Engineering, Brigham Young University, Provo, UT, USA. e-mail: ethomas@colorado.edu

emissions per year in the United States[7]. Further gray infrastructure technology upgrades would continue to increase overall energy demand and emissions. However, in many cases, further upgrades to gray infrastructure driven by current regulatory pressures and impaired riverine water quality could be substituted through regulator-approved water quality trading programs with green infrastructure including riparian, floodplain, and wetlands restoration; regenerative agricultural practices; improved forestry management; and other efforts to reduce non-point source contamination. Existing water quality trading (WQT) programs are governed by the EPA toward compliance with a NPDES permit. The EPA allows for what is known as Point Source to Non-Point Source water quality trading. This has been practiced in the United States for over three decades. These water quality trading programs enable point dischargers to meet regulated water quality obligations and in the process restore and sustain freshwater ecosystems[8]. These types of formal, market-based water quality trading programs were established and recently strengthened by the EPA[6,9] and several state-level regulators, but have not achieved large scale, despite often being much more cost effective[10–12].

Two recent studies have analyzed factors that contribute to the existence of water quality trading programs. In one study, a negative association between urban activity and the presence of WQT markets was observed, aligning with the historical context of WQT evolving as a tool to incentivize reductions in agricultural runoff. Further, this study identifies a substantial relationship between certain types of permit approaches taken by regulators and the likelihood of WQT market activity. Interestingly, the presence of impaired waterways does not consistently correlate with WQT markets, leading the authors to suggest a potential policy lag in addressing water quality issues[13]. In another recent analysis, insights on active and inactive WQT programs were drawn from 19 reviews. Eighty-four factors were identified in regulatory, institutional, environmental, economic, and social categories. Regulatory barriers, encompassing official rules set by government or regulatory agencies, were most frequently mentioned in 31% of cases. Economic, institutional, and environmental factors were considered relatively equally important in 19%, 19%, and 18% of cases, respectively. Specifically, the ability to directly monitor the success of WQT programs in addressing water quality was highlighted as a major institutional barrier[14]. Emerging technologies may support improved monitoring and management of green infrastructure water quality solutions (e.g. refs. 15–20). These studies emphasize the significance of regulatory support and utility technical capacity to enable WQT programs.

Paired with increase technical capacity and regulator interest, we propose that carbon markets may provide a private capital source to motivate utilities and regulators using green infrastructure to take pre-permit, early action. In this light, one way to view carbon market mechanisms is that they offer the potential to redirect climate-damaging capital toward water infrastructure and create a sustainable, performance-based funding stream to move away from fossil-fuel dependent infrastructure. For this to hold, the financing needs to occur in locations where the transition to renewables is slow and where existing efforts to switch from energy intensive infrastructure to nature based solutions is lacking. The Voluntary Carbon Market (VCM) facilitates the reduction of greenhouse gas emissions worldwide through economic incentives. A voluntary carbon credit is a financial commodity, currently worth about \$10 for many nature-based projects[21], and over \$1000 for some direct air capture projects[22], that represents the reduction or removal of one tonne of carbon dioxide. Many corporations are interested in buying carbon credits through the VCM to compensate for a proportion of their remaining emissions to achieve sustainability targets. The VCM is designed to financially incentivize voluntary action supporting climate change solutions. VCM projects include both nature-based solutions, such as improved forest management and reforestation, and technology-based solutions, such as renewable energy installations and improved cookstoves. While there is a growing, multi-billion dollar global market for carbon credits, water, as a local management challenge, has not typically been fungible in the same way. This local feature of water has made it challenging to create effective financing and trading mechanisms and has limited the value, transactability, and liquidity of various forms of so-called water credits, such as those developed to demonstrate compliance with the United States Clean Water Act[23] or the Gold Standard Water Benefit Certificates[24]. Alternatively, if the financial instrument is a carbon credit that motivates improved water quality, that credit accesses a liquid market and can be bought and sold and create revenue, incentivizing water security actions.

Market research conducted in 2022 projected a 20-fold increase in the demand for carbon credits by 2035, with prices rising to an estimated \$80–\$150 per tonne from the current \$25[25]. However, the VCM has recently faced several challenges, calling into question the additionality, permanence, and volume of credits issued, primarily those associated with REDD+ programs. Yet, there are also clear signals that the VCM may recover, including the strengthening of activities led by the Voluntary Carbon Markets Initiative and the Integrity Council for Voluntary Carbon Markets. Further, recent research suggested that corporations purchasing carbon credits decarbonize twice as fast as companies not participating in the VCM, belying suggestions that carbon credits enable greenwashing[26].

The VCM represents a fraction of overall climate finance, at about \$2 billion per year. In 2022, more than \$60 billion dollars in climate finance was provided by multilateral development banks to low- and middle-income economies, including loans (61 percent), policy-based financing (14 percent), and grants (10 percent). Of this, 15 percent of global climate adaptation finance, more than \$3.3 billion, was directed to the water and wastewater sector, preceded only by energy, transport, and other built environment and infrastructure (30 percent), and by cross-cutting operations (17 percent), suggesting large existing commitments[27]. Among high-income economies, the investment is even more substantial, with 29 percent of adaptation funds applied toward energy, transport, and other built environment and infrastructure, and 28 percent toward water and wastewater systems. In least-developed countries, 14 percent of adaptation funds are applied to the water and wastewater sector, ahead of crop and food production at 13 percent. Total climate adaptation finance allocations for water and wastewater in least-developed countries totaled nearly \$900 million in 2023, with nearly 89 percent allocated to Sub-Saharan Africa[27].

In this research, we evaluate the economic and environmental potential of water quality trading programs. The economic and life-cycle greenhouse gas (GHG) emissions savings by using green infrastructure methods in place of gray wastewater treatment methods is evaluated. The primary analysis evaluates the benefits seen by nutrient (nitrogen and phosphorus) reduction. The United States EPA defines five target effluent nutrient concentration levels for wastewater treatment technologies. Nutrient removal requirements vary state-by-state but have generally trended toward increased stringency, requiring water treatment plant technology upgrades and corresponding increases in energy demand[28–30]. Given this trend, we consider nutrient concentration limits ranging from Level 2 (removal of nitrogen to 8 mg $L^{-1}$ and phosphorus to 1 mg $L^{-1}$) to Level 5 (removal of nitrogen to 2 mg $L^{-1}$ and phosphorus to 0.02 mg $L^{-1}$)[28]. Geospatially resolved nutrient impaired water data is combined with the performance of various gray and green infrastructure alternatives to determine the total cost and environmental impact (GHG emissions) associated with various solutions to water quality targets. The discussion focuses on the potential impact of carbon markets (carbon credits) to support the development and deployment of green infrastructure.

## Results

The outcomes of the work are presented in three subsections: 1. nutrient treatment potential of green infrastructure, 2. global warming potential (GWP) of gray compared to green treatment technologies, and 3. total costs and carbon markets potential for gray and green treatment technologies. A summary table of key results from this analysis are shown in Table 1. All results are presented for the minimum cost technology for both green and gray technologies. The minimum costs gray technologies were Anaerobic/Anoxic/Oxic for Level 2, 4-Stage Bardenpho Membrane Bioreactor for

Levels 3 and 4, and 5-Stage Bardenpho Membrane Bioreactor with Side-stream Reverse Osmosis for Level 5 treatment scenarios.

### Nutrient remediation potential of green infrastructure

In total, we find that 31.7% (530,255 tonnes N $yr^{-1}$) and 20.8% (54,110 tonnes P $yr^{-1}$) of the desired nitrogen and phosphorus treatment could be achieved using green infrastructure, for the Level 5 scenario (Fig. 1). For the Level 2 scenario, Level 3 scenario, and Level 4 senario; results show that 36.8% (403,913 tonnes N $yr^{-1}$) and 22.5% (39,453 tonnes P $yr^{-1}$), 35.3% (447,888 tonnes N $yr^{-1}$) and 21.1% (50,147 tonnes P $yr^{-1}$), and 32.4% (505,953 tonnes N $yr^{-1}$) and 21.0% (52,457 tonnes P $yr^{-1}$) of the desired nitrogen and phosphorus treatment could be achieved using green infrastructure, respectively (Supplementary Discussion 1 and Supplementary Figs. 1–3). The primary reason why green treatment methods cannot achieve higher nutrient treatment loads is due to limited agricultural land in the waterbasins and limitations on geographic deployment. For example, saturated buffers and woodchip bioreactors can only be used in locations with tile drainage, but are also two of the treatment methods with the highest nutrient reduction effectiveness. These agricultural land limitations are seen in the desert southwest where limited agriculture land exists, in Missouri where high wastewater flow rates exist, and in the northeast where land availability is limited due to high population densities. While green treatment methods can only treat less than 40% of nitrogen and 25% of phosphorus needed in the United States, this would still represent a large decrease in infrastructure compared to the scenario where green treatment methods are not used. This is particularly true at the higher treatment levels where more advanced gray water treatment technologies are required. According to the EPA report, the only treatment technologies which can reach Level 5 concentration levels are those that use sidestream reverse osmosis filtration systems that suffer from issues of frequent fouling which both decreases treatment efficiency and increases operation expenses[28,31,32]. Therefore, reducing the need for any gray wastewater treatment infrastructure would be of benefit. Supplementary Fig. 4 illustrates the effectiveness of each of the green treatment methods (and combinations of methods) at meeting desired nutrient treatment goals.

**Table 1 | Aggregated results for the national deployment of gray or green technologies to meet regulated water quality obligations (Levels 2 thru 5 for gray infrastructure, compared to water quality trading based green infrastructure alternatives)**

| | Level 2 | Level 3 | Level 4 | Level 5 |
|---|---|---|---|---|
| Treatment Target mgN $L^{-1}$ | 8 | 6 | 3 | 2 |
| Treatment Target Limits mgP $L^{-1}$ | 1 | 0.2 | 0.1 | 0.02 |
| Gray Electricity Use (Tera Wh $Year^{-1}$) | 8.1 | 8.9 | 10.1 | 21.2 |
| Gray Emissions (MtCO2e $Year^{-1}$) | 11.9 | 17.4 | 18.5 | 29.8 |
| Gray Cost ($B $Year^{-1}$) | $14.9 | $18.3 | $19.5 | $28.5 |
| Green Emissions (MtCO2e $Year^{-1}$) | −3.4 | −3.8 | −3.9 | −4.2 |
| Green Cost ($B $Year^{-1}$) | $10.0 | $12.4 | $13.2 | $13.6 |
| Net Emissions (MtCO2e $Year^{-1}$) | 15.3 | 21.2 | 22.4 | 33.9 |
| Carbon Revenue | | | | |
| Total ($M $Year^{-1}$) | $307 | $424 | $449 | $679 |
| Green Net Savings w/ Carbon Revenue ($B $Year^{-1}$) | $5.2 | $6.3 | $6.8 | $15.6 |
| Mean Carbon Revenue vs Green Water-basin Costs | 5.4% | 6.0% | 5.8% | 8.6% |
| StDev of Carbon Revenue vs Green Waterbasin Costs | 5.7% | 6.8% | 6.7% | 10.5% |
| Max Carbon Revenue vs Green Water-basin Costs | 20.9% | 26.2% | 26.5% | 43.7% |

### Global warming potential of gray vs green infrastructure

Annually, we find that gray treatment technologies would emit 29.8 MtCO2e while green treatment technologies would sequester 4.2 MtCO2e for the Level 5 scenario (Fig. 2). This results in a annual carbon credit potential of 33.9 MtCO2e. Our results also show that green treatment technologies can reduce emissions compared to gray treatment technologies in every waterbasin.

Depending on the optimal green treatment technologies used (Supplementary Discussion 2 and Supplementary Fig. 5), waterbasin greenhouse gas emissions can be either positive or negative. When optimized for both minimum cost and maximum nutrient treatment, our results show that the primary green treatment technology to use in the Corn Belt is saturated buffers which has a positive GWP. Conversely, the primary treatment technologies to use in the western United States are constructed wetlands, nutrient rate reduction, and no-till farming which all have a negative GWP and therefore allow the waterbasin to also have negative nutrient treatment GWP compared to conventional practices. Similar results were observed for the Level 2 scenario, Level 3 scenario, and Level 4 scenario (Supplementary Discussion 3 and Supplementary Figs. 6, 7, and 8). In the Level 2 scenario,

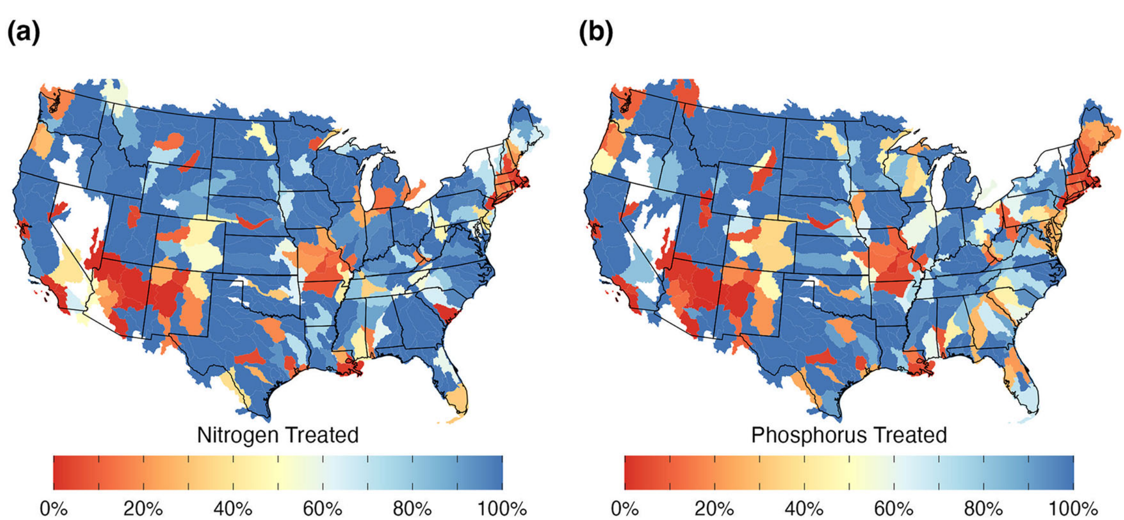


**Fig. 1 | Percent of nutrient treatment possible for green treatment technologies in each waterbasin for the Level 5 scenario of reducing mean nutrient concentrations to 2 mgN $L^{-1}$ and 0.02 mgP $L^{-1}$.** **a** Nitrogen treatment. **b** Phosphorus treatment. Red indicates no treatment, blue indicates full treatment. White space designates waterbasins which didn't have wastewater treatment facilities or didn't require nutrient treatment.

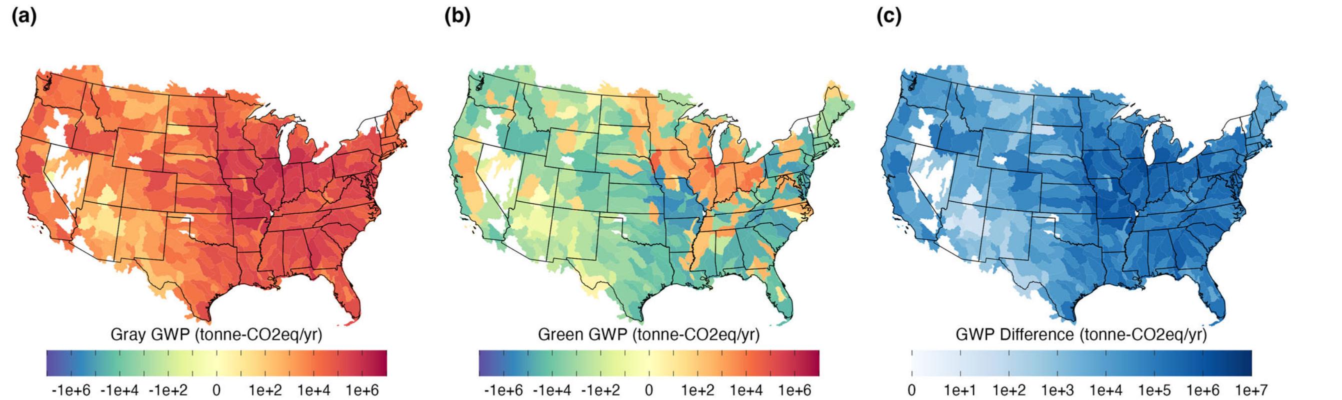


**Fig. 2 | Global warming potential (GWP) in tonnes of CO2 equivalent emissions per year for removal of removal of nitrogen (to 2 mg L$^{-1}$) and phosphorus (to 0.02 mg L$^{-1}$) for each treatment technology in the Contiguous United States.** **a** Nutrient removal using gray treatment technologies, blue indicates low and red high emissions per water basin (29.8 MtCO2e year$^{-1}$). **b** Nutrient removal using green treatment technologies, blue indicates low and red high emissions per water basin (−4.2 MtCO2e year$^{-1}$). **c** Net GWP representing potential carbon credit generation, increasingly dark blue indicates high generation per water basin (33.9 MtCO2e year$^{-1}$). White space designates waterbasins which didn't have wastewater treatment facilities or didn't require nutrient treatment.

gray treatment technologies emit 11.9 MtCO2e while green treatment technologies sequester 3.4 MtCO2e annually which results in a annual carbon credit potential of 15.3 MtCO2e. In the Level 3 scenario, gray treatment technologies emit 17.4 MtCO2e while green treatment technologies sequester 3.8 MtCO2e annually which results in a annual carbon credit potential of 21.2 MtCO2e. In the Level 4 scenario, gray treatment technologies emit 18.5 MtCO2e while green treatment technologies sequester 3.9 MtCO2e annually which results in a annual carbon credit potential of 22.4 MtCO2e. Overall, GWP values are reduced in the Level 2–4 scenarios compared to the Level 5 scenario due to the reduction in nutrient treatment required.

### Carbon financing potential of green infrastructure

Nutrient treatment costs for the Level 5 scenario were found to be $28.5B year$^{-1}$ and $13.6B year$^{-1}$ for gray and green technologies, respectively, when costs are normalized over the life of the technology. Additionally, we found the carbon financing potential is $679M year$^{-1}$ assuming a carbon credit price of $20 tonne-CO2eq$^{-1}$ which results in the total savings of green treatment technologies when compared to gray treatment and including carbon financing potential of $15.6B year$^{-1}$ (Fig. 3). Contrary to the GWP results, green treatment technologies are not cheaper than gray treatment technologies in all waterbasins. Of the 316 waterbasins in the Contiguous United States (CONUS) which required nutrient treatment, 222 (70%) had green treatment costs cheaper than the gray treatment technologies when excluding carbon financing revenues. If carbon financing revenue is added, 232 (73%) of waterbasins had green treatment costs cheaper than gray treatment technologies. However, when evaluated as a percent of total nutrients treated in the CONUS, 93.4% of nitrogen and 90.2% of phosphorus is treated in waterbasins where green treatment costs are cheaper than gray treatment technologies when carbon financing revenues are excluded. These values increase to 94.6% of nitrogen and 91.9% of phosphorus treated in the CONUS in waterbasins which green technologies are cheaper when carbon financing revenues are included. The primary driver for increased green treatment costs compared to gray technologies in some waterbasins is farmer incentive payments. These waterbasins are those where the optimum green treatment technology is land based (nutrient rate reduction, split nutrient application, cover crops, and no-till farming) which incurs annual farmer incentive payments, compared to the one-time farmer incentive payments for other green treatment methods. On a national level, farmer incentive payments make up 49% ($6.7B year$^{-1}$) of the total green treatment costs in the Level 5 scenario.

Nutrient treatment costs for the Level 2 scenario were found to be $14.9B year$^{-1}$ and $10.0B year$^{-1}$ for gray and green technologies, respectively, when costs are normalized over the life of the technology. Additionally, we found the carbon financing potential is $307M year$^{-1}$ assuming a carbon credit price of $20 tonne-CO2eq$^{-1}$ and a 40 year lifespan. This results in the total savings of green treatment technologies when compared to gray treatment and including carbon financing potential of $5.2B year$^{-1}$ (Supplementary Fig. 9). Of the 314 waterbasins in the CONUS which required nutrient treatment, 166 (53%) had green treatment costs cheaper than those of the gray treatment technologies when excluding carbon financing revenues. If carbon financing revenue is added, 172 (55%) of waterbasins had green treatment costs cheaper than gray treatment technologies. However, when evaluated as a percent of total nutrients treated in the CONUS, 80.9% of nitrogen and 66.2% of phosphorus is treated in waterbasins where green treatment costs are cheaper than gray treatment technologies when carbon financing revenues are excluded. These values increase to 85.6% of nitrogen and 72.0% of phosphorus treated in the CONUS in waterbasins which green technologies are cheaper when carbon financing revenues are included. Similar to the Level 5 scenario, green treatment costs were largely impacted by the farmer incentive payments. On a national level, farmer incentive payments make up 53% ($5.3B year$^{-1}$) of the total green treatment costs.

The nutrient treatment costs for both Level 3 and Level 4 scenario fall between those of the Level 2 and Level 5 scenarios. In the Level 3 scenario, treatment costs were found to be $18.3B year$^{-1}$ and $12.4B year$^{-1}$ for gray and green technologies, respectively, with a carbon financing potential of $424M year$^{-1}$ assuming a carbon credit price of $20 tonne-CO2eq$^{-1}$ and a 40 year lifespan. This results in the total savings of green treatment technologies when compared to gray treatment and including carbon financing potential of $6.3B year$^{-1}$ (Supplementary Fig. 10). In the Level 4 scenario, treatment costs were found to be $19.5B year$^{-1}$ and $13.2B year$^{-1}$ for gray and green technologies, respectively, with a carbon financing potential of $449M year$^{-1}$ assuming a carbon credit price of $20 tonne-CO2eq$^{-1}$ and a 40 year lifespan. This results in the total savings of green treatment technologies when compared to gray treatment and including carbon financing potential of $6.8B year$^{-1}$ (Supplementary Fig. 11). Additional information about the waterbasin-level economic feasibility of Level 3 and Level 4 scenarios is in the Supplementary Discussion 4 section in the Supplementary Information. A costs and emissions comparison between all green and gray treatment methods is discussed in Supplementary Discussion 5 and and shown in Supplementary Fig. 12.

## Discussion

River water quality improvements in the United States have been often delayed because of cost, complexity and litigation, with alternative compliance solutions, like nutrient trading, established but limited in scale. Meanwhile, carbon credits are designed to use market mechanisms to

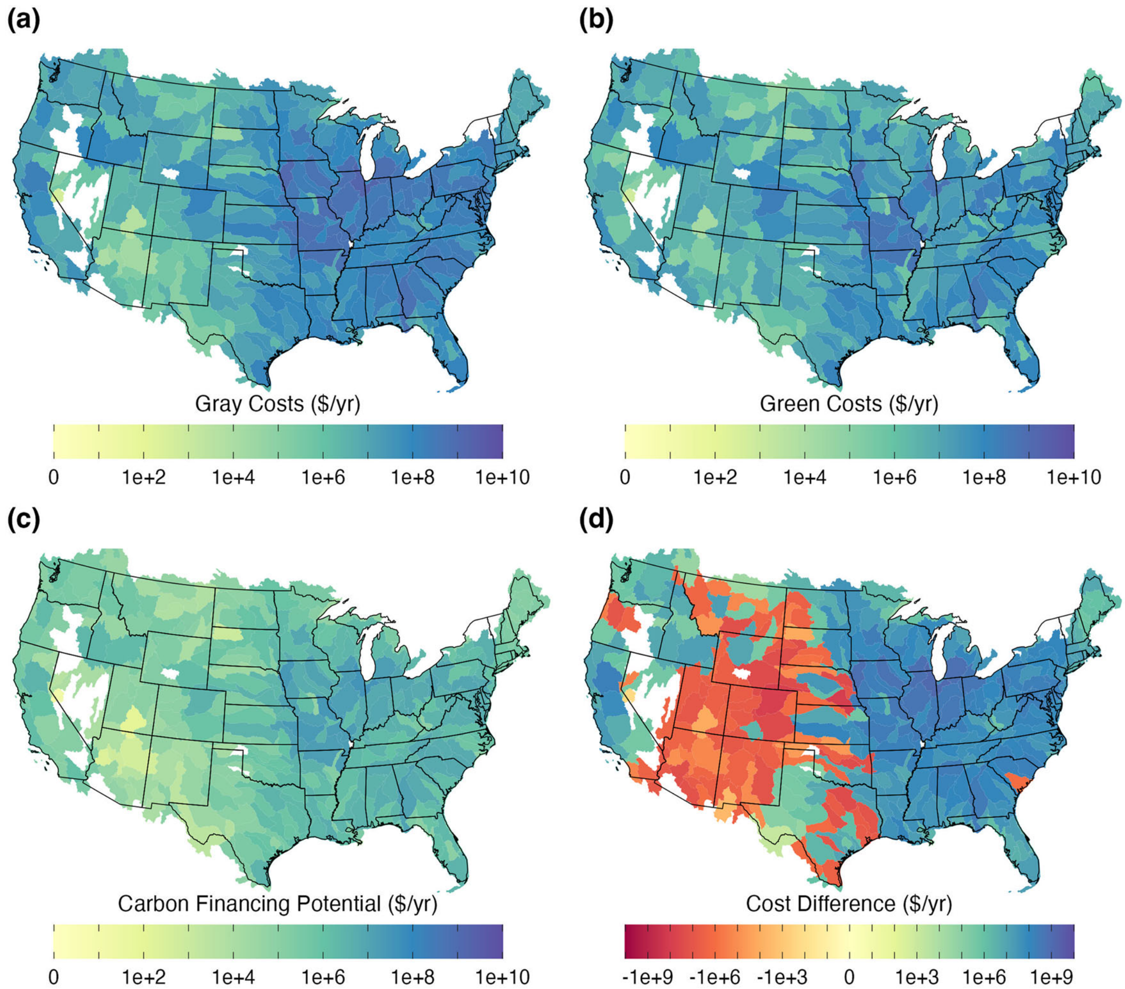


**Fig. 3 | Annual costs for removal of removal of nitrogen (to 2 mg $L^{-1}$) and phosphorus (to 0.02 mg $L^{-1}$) for each treatment technology in the Contiguous United States.** Dollar values ranging from low in yellow to high in blue for **a** Nutrient removal using gray treatment technologies (\$28.5B $year^{-1}$). **b** Nutrient removal using green treatment technologies (\$13.6B $year^{-1}$). **c** Potential carbon markets revenue (\$679M $year^{-1}$ at \$20 per credit). **d** Net cost difference ranging from negative in red to positive in blue between gray and green treatment technologies when including carbon financing revenue (\$15.6B $year^{-1}$). Negative cost differences show waterbasins where green technologies are more expensive than gray technologies. White space designates waterbasins which didn't have wastewater treatment facilities or didn't require nutrient treatment.

accelerate the energy transition. Combining this challenge and opportunity, there is a window of opportunity now to accelerate the improvement of America's rivers using these market mechanisms, as we transition to a renewable energy and restored watershed future.

Water and wastewater treatment in the United States already accounts for 2% of energy use and 45 million tonnes of CO2e emissions. We estimate these values could almost double over the coming years as utilities are obligated to increase treatment levels, even as states transition to renewable energy sources. Our results also indicate potential feasibility, effectiveness, and cost savings associated with green infrastructure alternatives to gray infrastructure to meet water quality goals and obligations. The EPA has recently re-vitalized their commitment to market-based water quality trading, emphasizing the role of the private sector in enabling improved river water quality in the United States, and encouraging regulators to embrace these opportunities and methodologies[6]. Yet, water quality trading programs in the United States have been limited in part by a reliance on regulator support, high transaction costs and a lack of pooled risk mitigation potential between programs. Fundamentally, local water problems have never benefited from a global, liquid economy. Carbon markets have been used extensively in the past fifteen years to deliver measurable clean drinking water services in low-income countries globally and could be applied in the United States to further motivate early, pre-permit green alternatives to meet water quality obligations[33].

International carbon credit markets are designed to financially incentivize early, voluntary action toward climate change mitigation, adaptation, and reduced emissions. Some estimates suggest that carbon credit markets can, "double climate ambition relative to current Paris pledges (NDCs) over 2020–2035, without increasing total costs,"[34]. In 2022, some market research estimates that the volume of carbon credits in demand will increase at least 20× by 2035, with credits increasing in value from around \$25 per tonne to a central estimate of \$80–\$150 per tonne by 2035[25]. Toward this opportunity, new methodologies are needed which enable the generation of carbon credits, salable for revenue, associated with replacing gray infrastructure with green infrastructure to improve watershed health and river water quality. In this approach, the GHG emissions envisioned are avoided, rather than sequestered or removed, through the avoided construction of electricity consuming infrastructure. These avoided emissions, when achieved early and voluntarily, can have substantial social benefits[35], while generating a potential \$679 million annually in carbon credit revenue (at \$20 per credit), representing an opportunity to further motivate green infrastructure solutions within water quality trading programs to meet regulated obligations in lieu of new gray infrastructure.

The results we've presented in this study are the best estimates possible with currently available data, but we acknowledge that some limitations exist with green nutrient technology research that should be addressed through future studies. Importantly the results and model presented here is not intended for top-down planning, it was developed to try and better understand the scope of the problem and opportunity. Any green infrastructure development must be done in a way that incorporates the local communities considerations, opportunities, values, and rights. Additionally, green infrastructure projects are notable for creating local jobs that do not require advanced degrees, and that are inherently 'local'. Disadvantaged communities are also disproportionately impacted by water rate increases, as well as emissions and the effects of accelerating climate change on watersheds and the resulting wildfire risks. In contrast to expensive, high-technology gray infrastructure construction, estimates suggest that approximately 20 jobs are created for every \$1M of public investment in green infrastructure, and investment in forest and watershed restoration is multiplied in local economic activity between 1.7 and 2.6 times[36].

Limited data exists on the current prevalence and effectiveness of green technologies across the United States which represents the largest uncertainty associated with this work. Existing research on these technologies is focused in the Midwestern United States (i.e. Corn Belt) and have found non-point source nutrient treatment methods to have a wide range of nutrient reduction efficiencies based on geographic location, agricultural techniques used, and local climate patterns. Studies need to be performed on each of the green treatment methods to evaluate their effectiveness in more geographically diverse regions across the United States. However, it should be noted that regions in the United States which are currently studying green treatment technologies correlate with those found in this study to have the largest economic incentive from implementing these technologies. Therefore, regions that we find to have receive the largest benefit from green treatment technologies are also those with the lowest uncertainties. Additionally, surveys need to be completed to provide better estimates of the current prevalence of these technologies throughout the United States to better estimate future potential. United States Department of Agriculture (USDA) census data is available for cover cropping and no-till farming across the United States, but limited data is available for saturated buffers, woodchip bioreactors, constructed wetlands, and smart fertilizer application strategies. Literature shows that green treatment methods can be used in combination with each other, but it is unknown how the benefits of these technologies compound. Research should be performed to evaluate the effectiveness of these technologies when used in combination with each other to ensure nutrient treatment isn't saturated and to maximize the nutrient reduction of the technologies being implemented. The LCA estimates made for green technologies in this study should also be evaluated in specific case studies to capture nuances of the local installations and performance data should be used to accurately determine the GHG emissions. Additionally, it is important to acknowledge the evolution of the grid in terms of carbon emissions will impact the carbon financing potential of green nutrient treatment technologies. As the grid evolves with less environmental impact, carbon credits generated by offsetting gray infrastructure with green infrastructure will be reduced, which meanS that the window of opportunity for leveraging carbon markets to incentivize a shift from gray to green infrastructure may be limited.

Extending this opportunity globally, there are many examples of watershed and water quality trading programs in Canada, Australia, New Zealand, the United Kingdom, the Netherlands, Honduras, India, China, and Kenya. Extending the findings of the United States study globally and assuming that an indicative 10 percent of irrigated croplands outside of the United States could be used to generate instream water quality benefits and thereby avoid facility-based treatment, the global potential for this approach could be close to 80 million tonnes of CO2e reduced or removed per year.

## Methods

This study evaluates the economics and emissions of water treatment technologies in the CONUS. The CONUS was divided into smaller sections as designated by the United States Geological Survey's Hydrological Unit Code (HUC) regions. To maximize geographic resolution of this analysis, HUC 12 sub-watersheds were used wherever possible. However, it was assumed that nutrient trading could take place at the HUC 6 waterbasin level and, therefore, all results were aggregated to the waterbasin level[37]. Geodatabase files for various HUC regions were downloaded from the United States Geological Survey's Watershed Boundary Dataset[38]. Data associated with HUC 12 sub-watersheds was aggregated from United States EPA's EnviroAtlas database[39]. EnviroAtlas provides national data layers at the HUC 12 sub-watershed level with many of these data layers being derived from data with a resolution of 30 m. Full details of which data was required is discussed in each subsection. It was assumed that nutrient trading could take place within each waterbasin (HUC 6), therefore stricter requirements placed on existing facilities could only be satisfied by gray or green treatment methods within the same waterbasin.

### Wastewater nutrient data

Geographically resolved nutrient loading data compared to water quality targets for point source dischargers in the CONUS motivates the water treatment trade study. Therefore, 2022 data from the Nutrient Model (Hypoxia Task Force Search) created by the EPA was used[40]. This data is provided through the EPA's Water Pollutant Loading Tool[41]. The Nutrient Model was created by EPA to provide access to aggregated nitrogen and phosphorus loads (including modeled loads) for facilities across the United States. As such, data is provided for wastewater treatment facilities with current EPA NPDES permits with facility information, total annual wastewater flow, total nutrient loads, and maximum allowable nutrient loads (if applicable). In total, 53,055 data entries were provided for 29,335 unique facilities. Data consists of both discharge monitoring report (28,318) and modeled (24,737) nutrient loads for both nitrogen (27,238) and phosphorus (25,817). Additionally, each data point was associated with a HUC 12 sub-watershed code so analysis could be evaluated on a geospatially resolved level. An overview of the input data including number of facilities, mean daily wastewater flow, mean nitrogen concentration, and mean phosphorus all aggregated to the waterbasin level can be viewed in Fig. 4. For analysis of all technologies in this study, a 40 year time horizon was assumed.

### Gray treatment methods

Gray nutrient treatment technologies outlined in the EPA's report title *Life Cycle and Cost Assessments of Nutrient Removal Technologies in Wastewater Treatment Plants* were used in this analysis[28]. The EPA report estimated the costs and GWP of 8 alternative wastewater treatment technologies to treat excess nitrogen and phosphorus in wastewater streams. Costs and GWP were also provided for a 9th 'baseline' technology, but it was excluded from this analysis because its primary design was not focused on nutrient removal and had low nutrient remediation potential. Details of the gray treatment methods can be seen in Table 2. Each gray nutrient treatment technology was assigned a treatment level in the EPA report. These levels range from Level 2 to Level 5 based on their ability to achieve target effluent nutrient concentrations. These concentration levels are 8 $mgN\,L^{-1}$ and 1 $mgP\,L^{-1}$ for Level 2, 6 $mgN\,L^{-1}$ and 0.2 $mgP\,L^{-1}$ for Level 3, 3 $mgN\,L^{-1}$ and 0.1 $mgP\,L^{-1}$ for Level 4, and 2 $mgN\,L^{-1}$ and 0.02 $mgP\,L^{-1}$ for Level 5. Level 1 designates that no effluent concentration is specified and has been excluded from this analysis accordingly.

To perform a geographically resolved analysis, costs and GWP of each gray treatment technology were adjusted based on the location of the facility being evaluated. For gray treatment technologies, only the electricity grid mix was assumed to vary geographically. Treatment costs and GWP presented in the EPA report assumed the 2010 United States average electrical grid mix was used for water treatment and all cost information was presented in 2014 dollars. We assumed a linear increase in energy demand between Level 2 and Level 5, which is likely conservative as some estimates suggest an exponential increase in energy use approaching Level 5[42]. Electricity prices were updated using the mean state electricity prices as reported by the United States Energy Information Administration's 2021 Annual

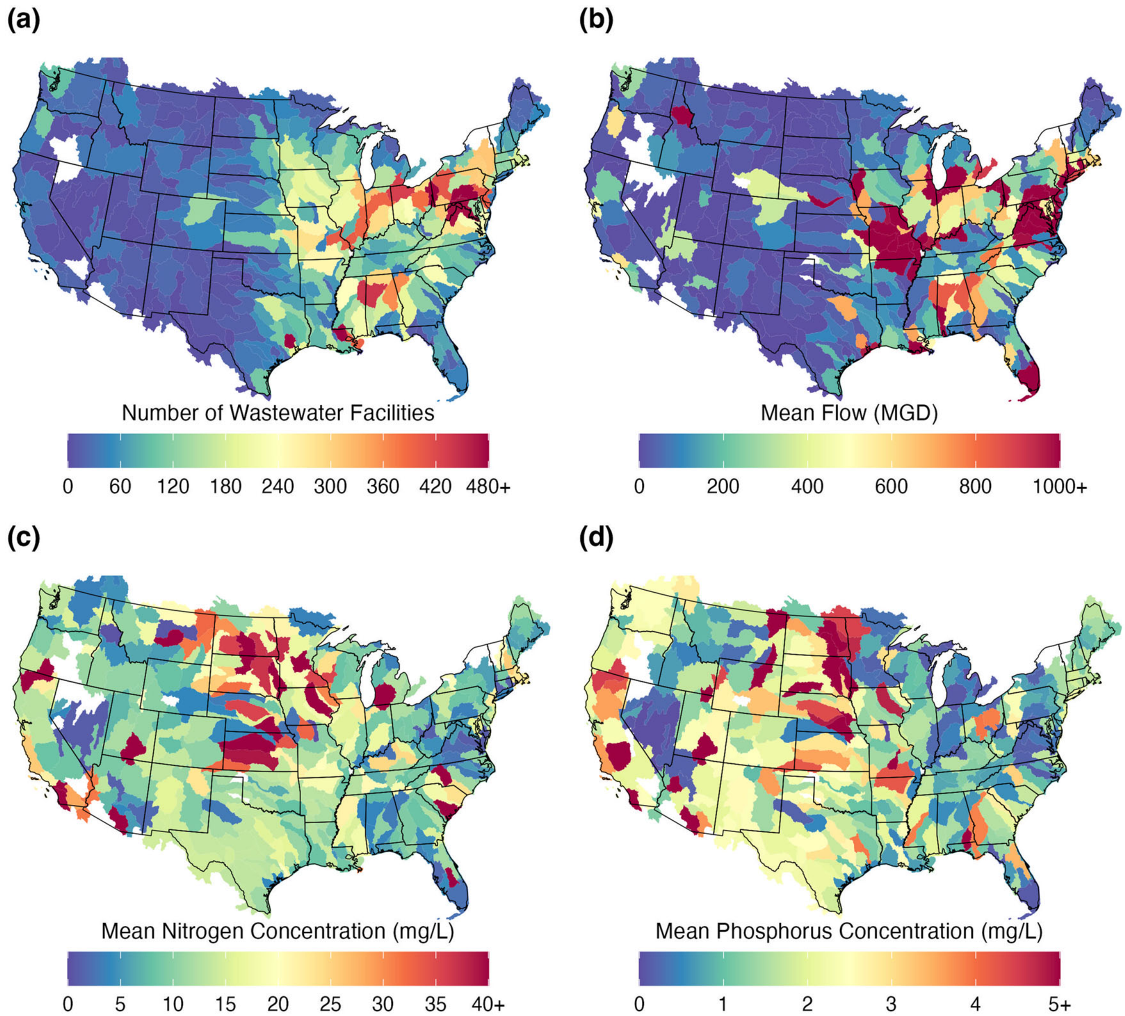


**Fig. 4 | Wastewater treatment facility data in the Contiguous United States.** **a** Number of wastewater facilities in each waterbasin. **b** Total mean flow in millions of gallons per day in each waterbasin. **c** Mean Nitrogen concentration of the wastewater (mg $L^{-1}$) in each waterbasin. **d** Mean Phosphorus concentration of the wastewater (mg $L^{-1}$) in each waterbasin.

**Table 2 | Costs and emissions of gray treatment methods**

| Name | Abbr. | Level | N Cost (2022$ $kgN^{-1}$) | P Cost (2022$ $kgP^{-1}$) | N GWP (kg-CO2eq $kgN^{-1}$) | P GWP (kg-CO2eq $kgP^{-1}$) | N Removal (mg $L^{-1}$) | P Removal (mg $L^{-1}$) |
|---|---|---|---|---|---|---|---|---|
| Anaerobic/Anoxic/Oxic | A2O | 2 | $ 28.59 | $ 194.64 | 24.06 | 163.83 | 32 | 4.7 |
| Activated Sludge, 3-Sludge System | AS3 | 2 | $ 46.36 | $ 370.86 | 28.75 | 230.00 | 32 | 4.0 |
| 5-Stage Bardenpho | B5 | 3 | $ 30.54 | $ 216.34 | 29.41 | 208.33 | 34 | 4.8 |
| Modified University of Cape Town Process | MUCT | 3 | $ 31.27 | $ 221.49 | 28.24 | 200.00 | 34 | 4.8 |
| 5-Stage Bardenpho with Denitrification Filter | B5/Denit | 4 | $ 31.41 | $ 237.15 | 29.73 | 224.49 | 37 | 4.9 |
| 4-Stage Bardenpho Membrane Bioreactor | MBR | 4 | $ 29.74 | $ 224.54 | 29.73 | 224.49 | 37 | 4.9 |
| 5-Stage Bardenpho with Sidestream Reverse Osmosis | B5/RO | 5 | $ 44.38 | $ 346.14 | 46.15 | 360.00 | 39 | 5.0 |
| 5-Stage Bardenpho Membrane Bioreactor with Sidestream Reverse Osmosis | MBR/RO | 5 | $ 42.29 | $ 321.41 | 47.37 | 360.00 | 38 | 5.0 |

Treatment "Level" refers to the EPA's target effluent nutrient concentration levels for wastewater treatment technologies.

Energy Outlook, which is the most recent annual outlook available[43]. To approximate the emissions associated with electricity use in various geographic regions in the United States, the United States EPA's Emissions & Generation Resource Integrated Database (eGRID) was used[44]. Since Energy Information Administration electricity prices and eGRID mixes are not aggregated to the sub-watershed level, the GeoPandas library in Python was used to compare the shapefiles for United States states and eGRID regions to HUC 12 sub-watersheds[45]. If two states or eGRID regions overlapped a sub-watershed region, the state or eGRID region which overlapped a larger area of the sub-watershed was assigned to the sub-watershed. All technology costs and electricity prices were converted to 2022 dollars using historical Consumer Price Index data provided by the United States Bureau of Labor Statistics using the mean annual Consumer Price Index values for all items and the United States city average was used[46,47]. The electricity prices and GWP was updated for each gray treatment method in each HUC region using the total electricity demand (kWh $m^{-3}$) presented in the EPA report and 2021 electricity values using Eq. (1):

$$X_{i,w} = X_{i,US} - ElectricDemand_i * Y_{US} + ElectricDemand_i * Y_w \quad (1)$$

where $X$ represents the technology's cost or GWP, $i$ represents the gray technology method, $w$ represents the waterbasin value, $US$ represents the United States mean value, *ElectricDemand* represents electricity demand of nutrient treatment for each gray technology, and $Y$ represents the geographic specific cost or GWP of electricity.

## Green treatment methods

Green non-point source nutrient treatment methods range from minimally invasive nutrient fertilizer reduction to land altering constructed wetlands[48,49]. For this analysis, 7 green treatment methods were considered, all of which are implemented on agricultural farmland (Table 3). These include 3 barrier treatment methods which are applied at the edge of the field (saturated buffers, woodchip bioreactors, and constructed wetlands) and 4 land treatment methods (nutrient rate reduction, split nutrient application, cover crops, and no-till farming). Some of these treatment methods treat both nitrogen and phosphorus, while others only treat one of the two nutrients considered. Mean nutrient removal percentages and treatment costs came from the 2016 *Illinois Nutrient Loss Reduction Strategy* report[49]. All values used within this analysis fall within the range of values reported in the literature[48,50–61].

One limitation to published values on green treatment methods is that they are presented in terms of the cost for the farmer to implement the technology, not the costs that would be incurred by a utility encouraging the adoption of these technologies to avoid new gray infrastructure upgrades. Therefore, some of the technology costs (i.e. applied nutrient reduction and no-till farming) are negative because they are cheaper than conventional farming practices. Since this analysis was performed from the utilities perspective, it was assumed that the utility would incur the costs of technology adoption, but would not claim the benefits of cost saving practices. Therefore, it was assumed that the technology costs of the negative cost technologies would be zero.

Additionally, it was assumed that farmers would need to be financially incentivized by the utility to implement green nutrient treatment methods. Therefore, it was assumed that the utility would pay farmers \$31 $acre^{-1}$ $year^{-1}$ for land treated with green treatment methods, which is the mean value reportedly paid to farmers in 2021 by the Soil and Water Outcomes Fund[62]. This incentive payment is in addition to the green technology costs paid for by the utility. Barrier treatment methods which only need to be installed once, were only assumed to pay incentive fees during the first year of operation. Land treatment methods are applied yearly and, as such, the incentive fees were paid out annually. Lastly, constructed wetlands require up to 6% of the treated farmland acres to be converted to a wetland[48]. As a conservative estimate, it was assumed that this land was productive farmland and the utility would need to rent the land from the farmer at the mean land rental prices as reported by the USDA's 2022 land cash rental prices in order to compensate farmers for reducing their farm size[63]. Farmland rental prices were reported at a state level and were applied to each waterbasin based on the states which the waterbasin resided in. If the waterbasin covered land in multiple states, the land rental prices were calculated using a weighted mean based on the number of agricultural acres in each state. Land rental prices were assumed to stay constant over the life of the project.

Similar to the costs of gray treatment technologies, the costs of green treatment technologies were received in 2016 dollars and were converted to 2022 dollars using historical Consumer Price Index data provided by the United States Bureau of Labor Statistics[46,47]. The GWP of each green treatment method were estimated using life-cycle inventory data from the EcoInvent 3.71 database, using cut-off analysis, accessed through the software openLCA 1.10.3 (https://openlca.org), and calculated using the Traci 2.1 impact assessment methodology[64,65]. The GWP estimate for constructed wetlands includes direct land use change effects which were calculated using IPCC methodology[66]. Details of LCA calculations for each treatment method are discussed in the Supplementary Methods 2 section in the Supplementary Information.

Since each green nutrient treatment method requires different topology, infrastructure, or climate in order to be implemented; not every green treatment method could be applied in every waterbasin. Therefore, land limitations were added to green infrastructure on a waterbasin basis. These land limitations included the availability of tile-drained soil (saturated buffers and woodchip bioreactors), the availability of riparian buffer between agricultural land and discharge waterways (saturated buffers), the soil and climate to support wetlands (constructed wetlands), and the requirement of supplemental fertilizer application (nutrient rate reduction and split nutrient application). It was assumed that if the requirements were met in one part of the waterbasin, the requirements could be implemented in the rest of the waterbasin and the nutrient reduction strategy could be applied. For example, if tile drains were used on agricultural land in one part of the waterbasin, it was assumed that they could be added to all agricultural land in the waterbasin. Data for tile drain locations was acquired from

**Table 3 | Costs and emissions of green treatment methods**

| Name | Abbr. | Type | N Cost (2022\$ $kgN^{-1}$) | P Cost (2022\$ $kgP^{-1}$) | N GWP (kg-CO2eq $kgN^{-1}$) | P GWP (kg-CO2eq $kgP^{-1}$) | N Removal (%) | P Removal (%) |
|---|---|---|---|---|---|---|---|---|
| Saturated Buffers | BU | Barrier | \$ 1.95 | \$ 14.63 | 0.10 | 3.98 | 90% | 50% |
| Woodchip Bioreactors | BR | Barrier | \$ 2.68 | \$ – | 0.70 | – | 25% | 0% |
| Constructed Wetland | W | Barrier | \$ 4.88 | \$ – | (3.90) | – | 50% | 0% |
| N Rate Reduction | NR | Land | \$ 0.00 | \$ 0.00 | (9.21) | (105.72) | 10% | 7% |
| Split N Application | NS | Land | \$ 7.56 | \$ – | 11.10 | – | 10% | 0% |
| Cover Crop | CC | Land | \$ 3.90 | \$ 158.52 | 0.55 | 8.10 | 30% | 30% |
| No-till | NT | Land | \$ – | \$ 0.00 | – | (91.35) | 0% | 50% |

Treatment "Type" designates if the green treatment method is applied at the edge of the field (Barrier) or applied across the entire farm (Land).

Nakagaki et al. based on analysis from Sugg and data for riparian buffers, wetlands, and fertilizer application were acquired from the EPA's EnvironAtlas[39,67,68]. Details of each green treatment method's requirements is provided in Supplementary Table 1 and maps of tile drainage, riparian buffers, wetlands, and fertilizer application availability in each waterbasin is presented in Supplementary Fig. 13.

One of the benefits of green nutrient treatment methods is that they can be used in combination with each other[48]. This analysis considered all combinations of the 7 treatment methods proposed. Since each of the barrier treatment methods are applied at the edge of the field before discharge to the waterway, it was assumed that only one barrier treatment method could be used at a time. Conversely, no limitations were placed on the land treatment methods. Therefore, 63 unique combinations of green treatment methods were evaluated to find the best performing treatment methods in each watershed. For combined green treatment methods, it was assumed that costs, GWP, and nutrient removal efficiency were compounded. For example, if saturated buffers were combined with cover crops, their nitrogen cost would be $\$1.95\ \mathrm{kgN^{-1}} + \$3.90\ \mathrm{kgN^{-1}} = \$5.85\ \mathrm{kgN^{-1}}$, nitrogen GWP would be $0.10\ \mathrm{kg-CO_{2eq}kgN^{-1}} + 0.55\ \mathrm{kg-CO_{2eq}kgN^{-1}} = 0.65\ \mathrm{kg-CO_{2eq}kgN^{-1}}$, and their nitrogen removal efficiency would be $90\% + 30\% * (100\% - 90\%) = 93\%$.

## Calculation methods and assumptions

In order to estimate the nutrient trading potential of green versus gray nutrient reduction technologies, multiple scenarios were assumed. The first scenario assumed that each of the wastewater treatment facilities evaluated were required to meet Level 2 nitrogen and phosphorus concentration limits of $8\ \mathrm{mgN\ L^{-1}}$ and $1\ \mathrm{mgP\ L^{-1}}$, respectively. These values were selected because they are the conservative limit that all gray treatment technologies can achieve based on their treatment level in the EPA report. The second scenario assumed that each of the wastewater treatment facilities evaluated were required to meet Level 5 nitrogen and phosphorus concentration limits of $2\ \mathrm{mgN\ L^{-1}}$ and $0.02\ \mathrm{mgP\ L^{-1}}$, respectively. These values were selected because they are the limit that the advanced reverse osmosis gray treatment technologies can achieve based on their treatment level in the EPA report. Two additional scenarios (Level 3 and Level 4) were also run to evaluate the sensitivity of results between the conservative Level 2 and advanced Level 5 scenarios. Concentration limits for nitrogen and phosphorus were $6\ \mathrm{mgN\ L^{-1}}$ and $0.2\ \mathrm{mgP\ L^{-1}}$ for the Level 3 scenario and $3\ \mathrm{mgN\ L^{-1}}$ and $0.1\ \mathrm{mgP\ L^{-1}}$ for the Level 4 scenario. Each scenario was evaluated independently of the other scenarios. For all treatment methods, analysis was performed on the facility level and nutrient trading was assumed to occur within each waterbasin.

For each scenario, all facilities where both nitrogen and phosphorus concentrations were lower than the specified limits were excluded from analysis. Additionally, each gray nutrient treatment technology had maximum concentration limits which they could decrease the effluent during treatment. It was assumed that the wastewater could be treated multiple times when the concentration was above this limit, but costs and GWP would increase by the multiple of the number of treatments required. To avoid the highest concentration scenarios which would exaggerate the gray treatment costs, facilities which required a mean nutrient concentration reduction greater than 5X the Level 2 treatable concentration limit were excluded from analysis. Facilities located outside CONUS (i.e. Alaska, Hawaii, Puerto Rico, Guam, United States Virgin Islands, and American Samoa) were also excluded due to their lack of HUC 12 sub-watershed data provided by the EPA's EnviroAtlas[39]. After data filtration to remove facilities residing outside the CONUS or with nutrient concentrations lower than treatable limits, 18,534 unique facilities remained for the Level 2 analysis (16,686 facilities treated for nitrogen, 14,444 facilities treated for phosphorus, and 12,633 facilities treated for both); 20,989 unique facilities remained for the Level 3 analysis (17,634 facilities treated for nitrogen, 19,369 facilities treated for phosphorus, and 16,045 facilities treated for both); 21,828 unique facilities remained for the Level 4 analysis (19,207 facilities treated for nitrogen, 20,110 facilities treated for phosphorus, and 17,514 facilities treated for both); and 22,386 unique facilities remained for the Level 5 analysis (19,769 facilities treated for nitrogen, 20,785 facilities treated for phosphorus, and 18,192 facilities treated for both).

In addition to gray treatment facility limitations, green treatment methods were limited by agricultural land availability within each waterbasin. Total area within each sub-watershed was calculated using the GeoPanda's area function in Python. The percentage of crop land and pasture land in each sub-watershed as reported by EnviroAtlas were used to approximate the total agricultural land in each sub-watershed[39]. Since nutrient trading was performed at the waterbasin level, sub-watershed values were aggregated to the waterbasin level to determine the maximum nutrient treatment of the waterbasin as a whole.

Additionally, some of the green treatment methods considered are already in use on farms throughout the CONUS, but limited information exists on their prevalence. The USDA's 2017 agricultural census provides state-level tillage and cover crop data, but geographically resolved data is unavailable for the other green treatment methods[69]. The most recent non-census data coverage data is provided by the Iowa Department of Agriculture and Land Stewardship in their *Iowa Nutrient Reduction Strategy 2018-19 Annual Progress Report*[58]. The report states that of the total 30,600,000 acres of farm land in Iowa, 8,200,000 acres (26.8%) were no-till farmed, 5,700,000 acres (18.6%) were treated with nutrient management strategies (nitrogen rate reduction and split nitrogen applications), 973,000 acres (3.2%) used cover cropping, 107,000 acres (0.35%) were treated with wetlands, and 2000 acres (0.35%) were treated with either saturated buffers or woodchip bioreactors[58,70]. To fill the gaps between the USDA census data and treatment methods considered, these values were applied to their respective green treatment methods across all waterbasins in the CONUS to provide a conservative estimate of land availability for additional green treatment applications. While accounting for land limitations, the maximum nutrient treatment potential of each green technology in each waterbasin was calculated using Eq. (2):

$$NT_{i,w} = A_w * (Pct_{crop,w} + Pct_{past,w}) * (1 - Pct_{tech,i}) * N_{mean-loss,w} * Pct_{N-removal,i} \tag{2}$$

where $NT_{i,w}$ represents the possible nutrient treatment for each green technology (subscript $i$) in each waterbasin (subscript $w$), $A_w$ represents the waterbasin total area, $Pct_{crop,w}$ represents the percent of waterbasin area which is crop land, $Pct_{pasture,w}$ represents the percent of waterbasin area which is pasture land, $Pct_{tech,i}$ represents the percent of agricultural land currently treated with each green treatment method, $N_{mean-loss}$ represents the mean nutrient loss per land area of agricultural land in the waterbasin, and $Pct_{N-removal,i}$ represents the percent of nutrient removal for each green technology. The state-level nutrient runoff values as predicted by the 2012 regional United States Geological Survey's Spatially Referenced Regression On Watershed attributes models were used to quantify nutrient loading from agricultural land in each waterbasin[71–76].

Analysis was performed first for all green treatment methods and combinations. The required nutrient treatment and the possible nutrient treatment were calculated on a waterbasin level as described in the previous paragraphs. If the available agricultural land in a waterbasin could not support the removal of the required nutrient load to meet the desired concentration limits, it was assumed that the maximum possible treatment would be applied based on the land available. The percentage of maximum nutrient treatment compared to the desired nutrient treatment was calculated and was used for nutrient treatment of all facilities within the waterbasin. Total land area required for nutrient remediation was also recorded to calculate farmer incentive payments. After the nutrient treatment loads were calculated for each wastewater facility, the new mean nutrient concentrations were calculated based on annual wastewater discharge. After final nutrient treatment loads were determined, the treatment costs (including farmer incentive and wetland costs) and GWP were calculated for both nutrients. Lastly, if both nitrogen and phosphorus were being treated, the total treatment costs and GWP of the facility were set by the nutrient which required more infrastructure. For example, if nitrogen required 500 ha of treatment to meet concentration limits and phosphorus required 1000 ha, the phosphorus treatment costs and GWP were assumed for treatment of both nutrients at the facility since both nutrients can be treated simultaneously for certain treatment methods. Comparison of the nutrient treatment levels for each green treatment method are presented in Supplementary Fig. 4.

After treatment costs and GWP were calculated for every wastewater treatment facility and each green treatment method (including combinations), an optimization was run to determine the maximum amount of nutrients that could be treated using green treatment methods in each waterbasin. In many waterbasins, multiple green treatment methods could treat the required nutrient load to reach the desired concentration limits. Therefore, a secondary optimization was performed to determine the minimum cost scenario and minimum GWP scenario when the maximum amount of nutrients were treated. Results for the minimum cost scenario are used for comparison to the gray treatment methods in the results section. The minimum GWP scenario was excluded from the primary results section because it has a breakeven carbon cost of $939 per tonne-CO2e when compared to the minimum cost scenario which is more expensive than direct air carbon capture technologies[77]. Detailed results for both optimization scenarios is discussed in the Supplementary Discussion 5 section in the Supplementary Information.

Once costs and GWP were determined for each green treatment method, costs and GWP were calculated for each of the gray treatment methods. In order to ensure green and gray treatments were compared evenly, the gray nutrient treatment levels were set equal to those of the green maximum treatment scenarios even though they are not limited by agricultural land constraints. If these limitations were not placed on gray treatment technologies, they would treat more nutrients than the green treatment methods which would increase their treatment costs and emissions and exaggerate the benefit of green treatment methods. Costs for all treatment methods were originally calculated at the wastewater facility level using sub-watershed characteristics. For analysis purposes, results were aggregated from the facility level to the waterbasin level. Supplementary Fig. 14 provides a diagram of the analysis process.

## Data availability

The primary data used in this study consisted of geographically resolved nutrient loading data a from the Nutrient Model (Hypoxia Task Force Search) created by the EPA[40] which was acquired through the EPA's Water Pollutant Loading Tool[41]. Using the data analysis techniques described in this paper and the Python code available in the Code Availability section, the results were generated for this study. All results data presented in this study is available on Zenodo[78]: https://doi.org/10.5281/zenodo.10456151.

## Code availability

All code used in this analysis is available on Zenodo[79]: https://doi.org/10.5281/zenodo.10790349. Any updates to the code will be publicly available on GitHub: https://github.com/bradenlimb/Green-Wastewater-Treatment.

Received: 14 September 2023; Accepted: 1 April 2024;
Published online: 15 April 2024

## References

1. Environmental Integrity Project. The Clean Water Act at 50. Technical Report. https://environmentalintegrity.org/wp-content/uploads/2022/03/CWA-report-3.23.22-FINAL.pdf (2022).
2. Cheng, F. Y., Van Meter, K. J., Byrnes, D. K. & Basu, N. B. Maximizing US nitrate removal through wetland protection and restoration. *Nature* **588**, 625–630 (2020).
3. Díaz, R. J. & Rosenberg, R. Introduction to environmental and economic consequences of hypoxia. *Int. J. Water Resour. Dev*. **27**, 71–82 (2011).
4. Tomczyk, N. et al. Nonpoint source pollution measures in the Clean Water Act have no detectable impact on decadal trends in nutrient concentrations in U.S. inland waters. *Ambio* **52** 1475–1487 (2023).
5. Murchison, K. M. Learning from More than Five-and-a-Half Decades of Federal Water Pollution Control Legislation: Twenty Lessons for the Future. *C. Envtl. Aff. L. Rev*. **32**, 527 (2005).
6. Ross, D. Updating the Environmental Protection Agency's Water Quality Trading Policy to Promote Market-Based Mechanisms for Improving Water Quality. Technical Report, USEPA, https://www.epa.gov/sites/default/files/2020-10/documents/trading-policy-memo-2019.pdf (2019).
7. EPA. Energy Efficiency for Water Utilities. https://www.epa.gov/sustainable-water-infrastructure/energy-efficiency-water-utilities (2016).
8. Chung, M. G., Frank, K. A., Pokhrel, Y., Dietz, T. & Liu, J. Natural infrastructure in sustaining global urban freshwater ecosystem services. *Nat. Sustain.* **4**, 1068–1075 (2021).
9. USEPA. Water Quality Trading Policy. Technical Report (USEPA, 2003). https://www.epa.gov/system/files/documents/2022-12/Water-Quality-Trading-Policy.pdf.
10. Liu, Y., Engel, B. A., Collingsworth, P. D. & Pijanowski, B. C. Optimal implementation of green infrastructure practices to minimize influences of land use change and climate change on hydrology and water quality: Case study in Spy Run Creek watershed, Indiana. *Sci. Total Environ.* **601-602**, 1400–1411 (2017).
11. Jaffe, M. Environmental Reviews & Case Studies: Reflections on Green Infrastructure Economics. *Environ. Pract.* **12**, 357–365 (2010).
12. Shakya, R. & Ahiablame, L. A synthesis of social and economic benefits linked to green infrastructure. *Water* **13**, 3651 (2021).
13. Liu, H. & Brouwer, R. What is the future of water quality trading? *Contemp. Econ. Policy* **41**, 194–217 (2023).
14. Bendor, T. K., Branham, J., Timmerman, D. & Madsen, B. Predicting the existence and prevalence of the us water quality trading markets. *Water* **13**, 185 (2021).
15. Bedell, E., Harmon, O., Fankhauser, K., Shivers, Z. & Thomas, E. A continuous, in-situ, near-time fluorescence sensor coupled with a machine learning model for detection of fecal contamination risk in drinking water: Design, characterization and field validation. *Water Res.* **220**, 118644 (2022).
16. Brown, C. J. et al. Tracing the influence of land-use change on water quality and coral reefs using a Bayesian model. *Sci. Rep.* **7**, 4740 (2017).
17. Ahearn, D. S. et al. Land use and land cover influence on water quality in the last free-flowing river draining the western Sierra Nevada, California. *J. Hydrol.* **313**, 234–247 (2005).
18. Hohner, A. K., Rhoades, C. C., Wilkerson, P. & Rosario-Ortiz, F. L. Wildfires Alter Forest Watersheds and Threaten Drinking Water Quality. *Accounts Chem. Res.* **52**, 1234–1244 (2019).
19. Basso, M., Vieira, D. C., Ramos, T. B. & Mateus, M. Assessing the adequacy of SWAT model to simulate postfire effects on the watershed hydrological regime and water quality. *Land Degrad. Dev.* **31**, 619–631 (2020).
20. Loiselle, D., Du, X., Alessi, D. S., Bladon, K. D. & Faramarzi, M. Projecting impacts of wildfire and climate change on streamflow, sediment, and organic carbon yields in a forested watershed. *J. Hydrol.* **590**, 125403 (2020).
21. Ecosystem Marketplace. Ecosystem Marketplace Insights Report: Paying for Quality. State of the Voluntary Carbon Markets. Technical Report. www.forest-trends.org (2023).
22. IEA. Unlocking the potential of direct air capture: Is scaling up through carbon markets possible? – Analysis - IEA. https://www.iea.org/commentaries/unlocking-the-potential-of-direct-air-capture-is-scaling-up-through-carbon-markets-possible (2023).

23. Johnson, A. H. & Whitworth, J. S. Enabling ecological restoration through quantification. In *Broken Pumps and Promises: Incentivizing Impact in Environmental Health* (Springer, 2016).
24. The Gold Standard. Gold Standard Water Benefit Certificates. https://www.goldstandard.org/articles/gold-standard-water-benefit-certificates (2022).
25. Ernst and Young. Essential, expensive and evolving: The outlook for carbon credits and offsets An EY Net Zero Centre report. Technical Report. https://assets.ey.com/content/dam/ey-sites/ey-com/en_au/topics/sustainability/ey-net-zero-centre-carbon-offset-publication-20220530.pdf (2022).
26. Ecosystem Marketplace. 2023 All in on Climate: The Role of Carbon Credits in Corporate Climate Strategies. Technical Report, https://www.ecosystemmarketplace.com/publications/2023-em-all-in-on-climate-report/ (2023).
27. European Investment Bank. 2022 Joint Report on Multilateral Development Banks' Climate Finance. https://www.afdb.org/sites/default/files/documents/publications/joint_mdb_climate_finance_report_2022.pdf (2023).
28. Cashman, S. et al. Life Cycle and Cost Assessments of Nutrient Removal Technologies in Wastewater Treatment Plants. Technical Report, EPA, Eastern Research Group. https://www.epa.gov/system/files/documents/2023-06/life-cycle-nutrient-removal.pdf. https://www.epa.gov/system/files/documents/2021-08/life-cycle-nutrient-removal.pdf (2021).
29. USEPA. Nutrient Reduction Progress Tracker. https://www.acwa-us.org/wp-content/uploads/2018/03/Nutrient-Reduction-Progress-Tracker-Version-1.0-2017-Report.pdf (2018).
30. Falk, M. W., Reardon, D. J., Neethling, J., Clark, D. L. & Pramanik, A. Striking the Balance between Nutrient Removal, Greenhouse Gas Emissions, Receiving Water Quality, and Costs. *Water Environ. Res.* **85**, 2307–2316 (2013).
31. Ghernaout, D. Short Communication: Requiring Reverse Osmosis Membranes Modifications – An Overview. *Am. J. Chem. Eng.* **5**, 81 (2017).
32. Tałałaj, I. A., Biedka, P. & Bartkowska, I. Treatment of landfill leachates with biological pretreatments and reverse osmosis. *Environ. Chem. Lett.* **17**, 1177–1193 (2019).
33. Thomas, E., Ntazinda, J. & Kathuni, S. Applying climate reparative finance toward water security. *Sci. Total Environ.* **875**, 162506 (2023).
34. Piris-Cabezas, P., Lubowski, R. N. & Leslie, G. Estimating the potential of international carbon markets to increase global climate ambition. *World Dev.* **167**, 106257 (2023).
35. Groom, B. & Venmans, F. The social value of offsets. *Nature* 1–6, https://www.nature.com/articles/s41586-023-06153-x (2023).
36. Nielsen-Pincus, M. & Moseley, C. The Economic and Employment Impacts of Forest and Watershed Restoration. *Restor. Ecol.* **21** 207–214 (2013).
37. United States Geological Survey. ydrologic Unit Codes (HUCs) Explained. https://nas.er.usgs.gov/hucs.aspx (2023).
38. United States Geological Survey. Watershed Boundary Dataset (WBD), https://datagateway.nrcs.usda.gov/catalog/productdescription/wbd.html (2022).
39. US EPA. EnviroAtlas Data Download, https://www.epa.gov/enviroatlas/forms/enviroatlas-data-download (2015).
40. US EPA. Nutrient Model (Hypoxia Task Force Search), https://echo.epa.gov/help/loading-tool/hypoxia-task-force-search-help/about-the-nutrient-model (2022).
41. US EPA. Water Pollutant Loading Tool - Data Downloads | ECHO | US EPA, https://echo.epa.gov/trends/loading-tool/get-data (2023).
42. Falk, M. W., Reardon, D. J., Neethling, J., Clark, D. L. & Pramanik, A. Striking the Balance between Nutrient Removal, Greenhouse Gas Emissions, Receiving Water Quality, and Costs. *Water Environ. Res.* **85** 2307–2316 (2013).
43. U.S. Energy Information Administration (EIA) Annual Energy Outlook, https://www.eia.gov/outlooks/aeo/ (2021).
44. US EPA. Emissions & Generation Resource Integrated Database (eGRID), https://origin-awswest-www.epa.gov/egrid (2020).
45. Bossche, J. V. d. et al. geopandas/geopandas: v0.13.2, https://doi.org/10.5281/zenodo.8009629 (2023).
46. US Bureau of Labor Statistics. Consumer Price Index (CPI), https://www.bls.gov/cpi/ (2023).
47. US Bureau of Labor Statistics. Bureau of Labor Statistics Data. https://data.bls.gov/pdq/SurveyOutputServlet (2023).
48. Christianson, L., Frankenberger, J., Hay, C., Helmers, M. & Sands, G. Ten Ways to Reduce Nitrogen Loads from Drained Cropland in the Midwest. http://draindrop.cropsci.illinois.edu/wp-content/uploads/2016/09/Ten-Ways-to-Reduce-Nitrate-Loads_IL-Extension-_2016.pdf. http://draindrop.cropsci.illinois.edu/wp-content/uploads/2016/09/ten-ways-factsheet-summary-FINAL.pdf (2016).
49. Illinois Water Resources Center. Nutrient loss reduction: Using science to find the right practices for your field. Technical Report, http://draindrop.cropsci.illinois.edu/wp-content/uploads/2016/10/IL-NLRS-Practice-Factsheet_2016.pdf (2016).
50. Christianson, L., Tyndall, J. & Helmers, M. Financial comparison of seven nitrate reduction strategies for Midwestern agricultural drainage. *Water Resour. Econ.* **2-3**, 30–56 (2013).
51. Christianson, L. Nitrogen Loss Reduction Practices: What Do They Cost? *farmdoc daily* **8**. https://farmdocdaily.illinois.edu/2018/11/nitrogen-loss-reduction-practices-what-do-they-cost.html (2018).
52. Christianson, L. E. Woodchip Bioreactor: A science-based option to reduce nitrate loss. http://draindrop.cropsci.illinois.edu/wp-content/uploads/2019/12/Christianson-et-al_2018_Woodchip-Bioreactor_2pg-Factsheet.pdf (2018).
53. Gu, B. et al. Cost-effective mitigation of nitrogen pollution from global croplands. *Nature* **613**, 77–84 (2023).
54. Zhou, Q., Sun, H., Jia, L., Wu, W. & Wang, J. Simultaneous biological removal of nitrogen and phosphorus from secondary effluent of wastewater treatment plants by advanced treatment: A review. *Chemosphere* **296**, 134054 (2022).
55. Jaynes, D. B. & Isenhart, T. M. Performance of Saturated Riparian Buffers in Iowa, USA. *J. Environ. Qual.* **48**, 289–296 (2019).
56. Jaynes, D. B. & Isenhart, T. M. Reconnecting Tile Drainage to Riparian Buffer Hydrology for Enhanced Nitrate Removal. *J. Environ. Qual.* **43**, 631–638 (2014).
57. Utt, N., Jaynes, D. & Albertsen, J. Demonstrate and Evaluate Saturated Buffers at Field Scale to Reduce Nitrates and Phosphorus from Subsurface Field Drainage Systems. Technical Report, https://www.fsa.usda.gov/Assets/USDA-FSA-Public/usdafiles/EPAS/natural-resouces-analysis/pdfs/admc_final_report.pdf (2015).
58. Iowa Department of Agriculture and Land Stewardship, Iowa Department of Natural Resources & Iowa State University. Iowa Nutrient Reduction Strategy 2018-19 Annual Progress Report. https://store.extension.iastate.edu/product/Iowa-Nutrient-Reduction-Strategy-2018-19-Annual-Progress-Report (2020).
59. Harrold, J. Indiana's State Nutrient Reduction Strategy. Indiana State Department of Agriculture Technical Report (2021). Accessed April 3, 2024. https://www.in.gov/isda/files/Indiana-State-Nutrient-Reduction-Strategy_final-Version-6_small.pdf.
60. Arkansas Department of Agriculture Natural Resources Division. *2022 Arkansas Nutrient Reduction Strategy*. Technical Report (Arkansas Department of Agriculture Natural Resources Division, 2022).
61. Iowa State University. Reducing Nutrient Loss: Science Shows What Works. https://www.cals.iastate.edu/files/misc/183758/reducing-nutrient-loss-science-shows-what-works.pdf (2017).
62. Soil and Water Outcomes Fund. Soil and Water Outcomes Fund Produces More Than Tenfold Increase in Environmental Outcomes in 2021. https://theoutcomesfund.com/news-release-2021-environmental-outcomes (2021).

63. United States Department of Agriculture. 2022 USDA/NASS QuickStats Land Rent Costs. https://quickstats.nass.usda.gov/results/58B27A06-F574-315B-A854-9BF568F17652#7878272B-A9F3-3BC2-960D-5F03B7DF4826 (2022).
64. Wernet, G. et al. The ecoinvent database version 3 (part I): overview and methodology. *Int. J. Life Cycle Assess.* **21**, 1218–1230 (2016).
65. Bare, J., Young, D., Qam, S., Hopton, M. & Chief, S. *Tool for the Reduction and Assessment of Chemical and other Environmental Impacts (TRACI)* (US Environmental Protection Agency, 2012).
66. IPCC. 2006 IPCC Guidelines for National Greenhouse Gas Inventories, https://www.ipcc-nggip.iges.or.jp/public/2006gl/index.html (2006).
67. Nakagaki, N., Wieczorek, M. & Qi, S. L. Estimates of Subsurface Tile Drainage Extent for the Conterminous United States, early 1990s, https://www.sciencebase.gov/catalog/item/get/56e86a60e4b0f59b85d71ff9 (2016).
68. Sugg, Z. Assessing U.S. Farm Drainage, https://www.wri.org/research/assessing-us-farm-drainage (2007).
69. United States Department of Agriculture. National Agricultural Statistics Service: Quick Stats. https://quickstats.nass.usda.gov/ (2022).
70. United States Department of Agriculture National Agricultural Statistics Service. Iowa Ag News - Farms and Land in Farms. Technical Report. https://www.nass.usda.gov/Statistics_by_State/Iowa/Publications/Other_Surveys/2021/IA-Farms-02-21.pdf (2021).
71. US EPA. Estimated Total Nitrogen and Total Phosphorus Loads and Yields Generated within States. https://www.epa.gov/nutrient-policy-data/estimated-total-nitrogen-and-total-phosphorus-loads-and-yields-generated (2023).
72. Ator, S. W. Spatially referenced models of streamflow and nitrogen, phosphorus, and suspended-sediment loads in streams of the northeastern United States. USGS Numbered Series 2019-5118, U.S. Geological Survey, Reston, VA. http://pubs.er.usgs.gov/publication/sir20195118 (2019).
73. Hoos, A. B. & Roland II, V. L. Spatially referenced models of streamflow and nitrogen, phosphorus, and suspended-sediment loads in the southeastern United States. USGS Numbered Series 2019-5135, U.S. Geological Survey, Reston, VA. http://pubs.er.usgs.gov/publication/sir20195135 (2019).
74. Robertson, D. M. & Saad, D. A. Spatially referenced models of streamflow and nitrogen, phosphorus, and suspended-sediment loads in streams of the midwestern United States. USGS Numbered Series 2019-5114, U.S. Geological Survey, Reston, VA. http://pubs.er.usgs.gov/publication/sir20195114 (2019).
75. Wise, D. R., Anning, D. W. & Miller, O. L. Spatially referenced models of streamflow and nitrogen, phosphorus, and suspended-sediment transport in streams of the southwestern United States. USGS Numbered Series 2019-5106, U.S. Geological Survey, Reston, VA, http://pubs.er.usgs.gov/publication/sir20195106 (2019).
76. Wise, D. R. Spatially referenced models of streamflow and nitrogen, phosphorus, and suspended-sediment loads in streams of the Pacific region of the United States. USGS Numbered Series 2019-5112, U.S. Geological Survey, Reston, VA, http://pubs.er.usgs.gov/publication/sir20195112 (2019).
77. Fasihi, M., Efimova, O. & Breyer, C. Techno-economic assessment of CO2 direct air capture plants. *J. Clean. Prod.* **224**, 957–980 (2019).
78. Limb, B. J., Quinn, J. C., Johnson, A., Sowby, R. B. & Thomas, E. Results Dataset for Greening America's Rivers: The Potential of Climate Financing for Nature-Based Water Quality Improvement, https://zenodo.org/records/10456151 (2024).
79. Limb, B. bradenlimb/Green-Wastewater-Treatment: Green Wastewater Treatment Code v1.0.0. *Zenodo*, https://zenodo.org/records/10790349 (2024).

## Acknowledgements
We acknowledge funding for this study from the Gordon and Betty Moore Foundation (PI Thomas: Mitigating Wildfire and Land-Use Impacts on Watersheds through Carbon Finance Supported Nature-Based Solutions), the National Science Foundation (PI Thomas: Measuring and Mitigating Land Management Impacts on In-Stream Water Quality with Sensor-Informed Data Fusion and Community-Led, Climate Financed Riparian Restoration [Award P23-000295]), and the United States Department of Energy (PI Quinn: Agent-based Modeling for the Multi-objective Optimization of Energy Production Pathways [DE-EE0008935]). We also thank Zia Mehrabi for his feedback on methodology and manuscript structure, the members of the Quinn Lab Group and Mortenson Center in Global Engineering for their insights, Kelli Morrill for her support and feedback, Owen Limb for reminding us to stay curious, and Rori Limb for reminding us of the importance of play.

## Author contributions
Braden J. Limb was responsible for conceptualization, data curation, formal analysis, methodology, and writing the original draft. Jason C. Quinn was responsible for conceptualization, data curation, formal analysis, funding acquisition, methodology, and reviewing/editing the writing. Alex Johnson was responsible for conceptualization, data curation, and reviewing/editing the writing. Robert B. Sowby was responsible for conceptualization and reviewing/editing the writing. Evan Thomas was responsible for conceptualization, formal analysis, funding acquisition, methodology, and writing the original draft.

## Competing interests
The authors declare the following competing interests: Authors Thomas, Quinn and Johnson are part time compensated employees of Virridy, a company specializing in areas related to the topic of this paper. None of the other authors declare any competing interests.

## Additional information
**Supplementary information** The online version contains supplementary material available at https://doi.org/10.1038/s43247-024-01359-x.

**Correspondence** and requests for materials should be addressed to Evan Thomas.