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Hotspots of irrigation-related US greenhouse gas emissions from multiple sources

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Irrigation effectively increases yields and buffers against intensifying climatic stressors to crop productivity but also produces greenhouse gas (GHG) emissions through several pathways including energy use for pumping (on farm and for interbasin water transfers), N_2O emissions from increased denitrification under elevated soil moisture, and degassing of groundwater supersaturated in CO_2. Despite irrigation's climate adaptation potential, associated GHG emissions remain unquantified. Here we conduct a comprehensive, county-level assessment of US GHG emissions from these irrigation-related pathways, estimating that irrigation produces 18.9 $MtCO_2e$ annually (95% confidence interval 15.2–23.5 Mt), with 12.6 Mt from on-farm pumping, 1.1 Mt from pumping for interbasin transfers, 2.9 Mt from elevated N_2O and 2.4 Mt from groundwater degassing. These emissions are highly spatially concentrated, revealing opportunities for geographically targeted and source-specific GHG mitigation actions. These findings enable strategic consideration of GHG emissions in decision-making associated with irrigation expansion for climate adaptation.

The area of irrigated agricultural land in the USA has expanded from approximately 16 million hectares to over 23 million hectares since 1970, and irrigated farms are now responsible for nearly 60% of crop market value production despite occupying only 17% of harvested cropland area[1]. Irrigation effectively buffers against drought and heat stress by both meeting crop water demand and reducing local temperatures through increased latent heat flux[2–4]. Thus, irrigated croplands on average have both higher yields and yield stability than comparable non-irrigated lands[5,6]. Although localized contractions in irrigated area have occurred in the western USA owing to water scarcity, there have been larger expansions in irrigated area in the central and eastern USA where water availability is less constrained. As climate change exacerbates precipitation variability and increases atmospheric water demand, irrigation is becoming increasingly valuable for reducing crop vulnerability to heat and drought stress[7–10], which are major drivers of crop losses historically[11–14].

Since irrigation is a key climate adaptation tool, a comprehensive understanding of irrigation-driven greenhouse gas (GHG) emissions is needed to identify the implications of irrigation expansion for meeting urgent agricultural-sector emissions reduction goals[15–18]. Potential feedbacks arise if climate change adaptation strategies increase GHG emissions and therefore compromise climate change mitigation goals. Existing research related to irrigation emissions at large spatial scales has predominantly focused on energy use for pumping[19–21], revealing that irrigation pumping represents a substantial proportion of agricultural energy use emissions[22]. However, this body of work captures emissions from only one of several pathways by which irrigation contributes to food system emissions[15,19,23,24].

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Groundwater supplies 48.5% of irrigation water in the USA[25], but it is supersaturated in CO_2 due to (1) passage through soil pore spaces with high CO_2 concentrations from microbial metabolism and (2) reactions with bedrock within the aquifer[26,27]. Upon extraction and application, groundwater CO_2 concentrations equilibrate with the atmosphere, releasing excess CO_2. Additionally, N_2O emissions are influenced by soil moisture levels, with peak emissions occurring at water-filled pore space levels exceeding roughly 70% due to denitrification of soil nitrate[28,29]. Temporarily saturated cropland soil depressions can produce N_2O at rates 80 times higher than adjacent, non-flooded land[30], and irrigation increases the likelihood of saturated conditions in croplands. However, field-scale studies of the impacts of irrigation on N_2O emissions have identified a very wide range of effects dependent on management practices, soil properties and crop type, ranging from non-significant changes to increases of up to 140% (ref. 31). Finally, interbasin transfers, or the non-natural transport water from one hydrologic basin to another, supply an estimated 19% of surface water for public supply and irrigation uses in the USA[32]. Some of these projects transport water long distances and have large elevation gains, leading to substantial pump energy demands[32,33].

Here, we comprehensively examine GHG emissions from agricultural irrigation across US counties due to groundwater degassing, elevated N_2O emissions and energy use for interbasin transfers circa 2020, opportunistically using available data primarily from 2015 to 2022 for each emissions source (dates for each data source are detailed in Supplementary Table 1). Emissions from groundwater degassing are calculated using measurements of pH, alkalinity and salinity of US well waters[34] and land surface temperature[35]. Nitrous oxide emissions are estimated using a statistical metamodel of site-level N_2O flux estimates that were developed with the DayCent biogeochemical model for the US GHG Inventory and are representative of all US agricultural production[36]. Finally, emissions from interbasin transfers are calculated using energy use data collected directly from the utility companies, irrigation districts and government agencies that operate transfers that supply irrigation water[32]. We couple these novel emissions datasets with existing data about on-farm energy use emissions to construct a comprehensive, county-level database[37] of irrigation-related GHG emissions in the USA (Supplementary Table 2). This publicly available database will facilitate improved life cycle assessment of irrigated crop products and enable the identification of locally relevant agricultural GHG mitigation opportunities.

Results and discussion

Total GHG emissions from irrigation

Irrigation produces an estimated 18.9 million metric tonnes (Mt) CO_2 equivalents (CO_2e) annually circa 2015–2022 in the USA (95% confidence interval (CI) 15.2–23.5 $MtCO_2e\ yr^{-1}$) (Fig. 1). On-farm energy use for pumping irrigation water accounts for 67% of the total emissions, or 12.6 $MtCO_2e\ yr^{-1}$ (95% CI 10.4–15.0 $MtCO_2e\ yr^{-1}$). Increased N_2O emissions from soils account for the second-largest proportion of total irrigation-related emissions (15%), producing 2.9 $MtCO_2e\ yr^{-1}$ (95% CI 2.7–3.0 $MtCO_2e\ yr^{-1}$). Degassing of CO_2 from groundwater produces 2.4 $MtCO_2\ yr^{-1}$ (95% CI 1.5–3.7 $MtCO_2\ yr^{-1}$), or 13% of the total emissions. Finally, off-farm energy use for interbasin transfers produces an additional 1.1 $MtCO_2e\ yr^{-1}$ (95% CI 0.6–1.8 $MtCO_2e\ yr^{-1}$), accounting for 6% of total irrigation-related emissions. State-level, source-specific CIs and relative uncertainty estimates are available in Supplementary Fig. 1, and county-level, source-specific CIs are available in Supplementary Table 2. Even though groundwater and surface water withdrawals for irrigation are of similar magnitude nationally (accounting for 49% and 51% of total withdrawals, respectively)[25], groundwater accounts for 79% of irrigation-related emissions (14.9 $MtCO_2e$) due to its higher energy requirements for on-farm pumping and the degassing flux, which, assuming eventual water–gas equilibration, does not apply to surface water. Only 21% of the total emissions (4.0 $MtCO_2e$) are attributable to surface water use, including all interbasin transfer emissions. However, this estimate does not include emissions from off-farm intrabasin pumping for conveyance of surface water owing to a lack of available data.

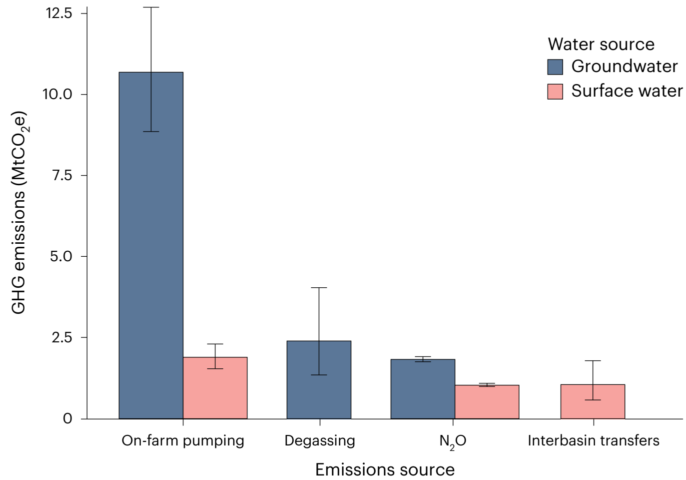

Fig. 1 | Total GHG emissions associated with irrigation in the USA by source. GHG emissions associated with irrigation in the USA by emissions source. The blue bars indicate emissions associated with groundwater use, and the red bars indicate emissions associated with surface water use. The error bars represent the 95% CIs for the emissions estimates, capturing quantifiable sources of uncertainty for each emissions source via a Monte Carlo bootstrapping approach (detailed in Methods; n = 10,000 bootstrap replications for on-farm energy use and interbasin transfers and n = 1,000 replications for N_2O and groundwater degassing).

Geographic hotspots of irrigation-related emissions have an outsized contribution to national totals, with the highest-emitting decile of counties (270 counties) producing over 76% of emissions (Fig. 2). Broadly, the identification of hotspots of environmental impacts can reveal the maximally impactful leverage points for intervention[38]. Gini coefficients (G) provide a measure of equality in the distribution of a variable, with a value of zero indicating that the variable is uniformly distributed (that is, all irrigated counties produce equal amounts of irrigation-related emissions) and a value of 1 indicating perfect inequality (that is, a single county produces all irrigation-related emissions)[39,40]. The Gini coefficient for total irrigation-related emissions indicates that the distribution of county-level emissions is highly skewed (G = 0.86). Moreover, G of emissions is larger than G of irrigated area (G = 0.82), indicating that the spatial concentration of emissions is greater than would be expected given the spatial concentration of irrigated area.

The spatially concentrated nature of the distribution of irrigation-related emissions clarifies geographic targets for GHG mitigation. Notable hotspots of irrigation-related emissions occur in the High Plains Aquifer region, the Mississippi Delta, California's Central and Imperial Valleys and Southern Arizona (Fig. 2a). Although county-level irrigation-related emissions are tightly correlated with irrigated area (Supplementary Fig. 2; r^2 = 0.77, P < 0.001), the area-based emissions intensity of irrigation also contributes to spatial variability in emissions. For instance, the highest-emitting decile of counties has an average emissions intensity of 1.0 $tCO_2e\ ha^{-1}$, while the remaining counties have an average emissions intensity of 0.50 $tCO_2e\ ha^{-1}$. High-emitting counties are often associated with higher per-hectare water use, higher aridity, higher groundwater reliance and the presence of an interbasin transfer (Supplementary Fig. 3).

Different emissions sources also exhibit different degrees of spatial concentration and different distributions (Figs. 2b and 3), suggesting that the most effective mitigation actions may vary depending on

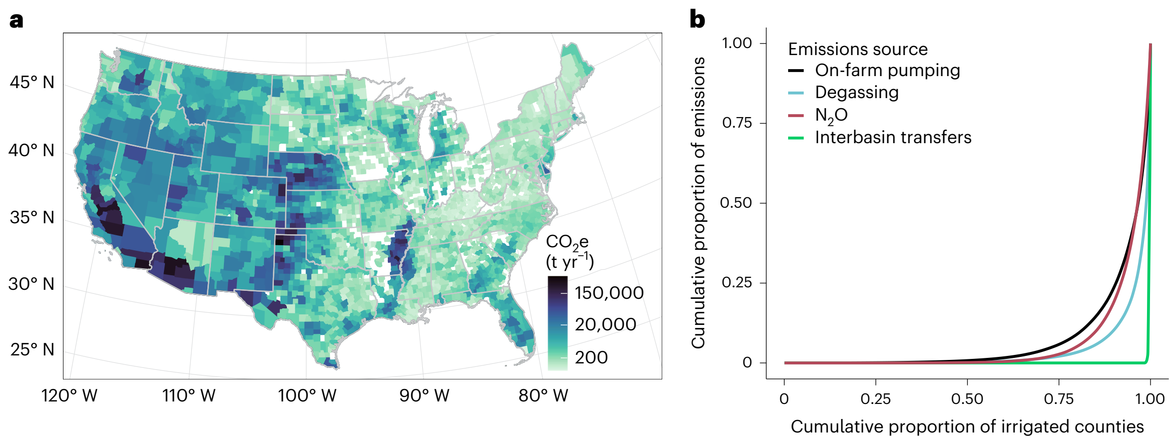

Fig. 2 | County-level distribution of total irrigation-related GHG emissions and spatial concentration by source. a, County-level map of total GHG emissions from irrigation. **b**, The cumulative proportion of emissions occurring within a given proportion of counties that contain irrigation. The colour scale in **a** is square-root transformed for improved visibility, and counties in white do not have any crop irrigation per the USGS 2015 water use dataset used in the analysis. The dashed black line in **b** represents a hypothetical uniform distribution of irrigation among counties, and the black, red, light-blue and green lines represent the observed distribution of irrigation-related emissions from on-farm pumping, nitrous oxide, groundwater degassing and energy use for interbasin transfers, respectively.

the locally dominant emissions source. Emissions due to interbasin transfers are the most spatially concentrated ($G = 0.99$), followed by CO_2 degassing from supersaturated groundwater ($G = 0.93$), on-farm pump energy use ($G = 0.91$) and elevated N_2O emissions ($G = 0.88$). On-farm energy use is the dominant source of irrigation-related emissions across 90% of irrigated counties, which contain 78.2% of irrigated land. Elevated N_2O emissions are the dominant source in 7% of counties (containing 9.6% of irrigated land), primarily in areas where pumping emissions and groundwater reliance are low. Groundwater degassing is the dominant emissions source in 55 counties (10.0% of irrigated land), including much of the Lower Mississippi River Valley region. Although energy use for interbasin transfers is the dominant emissions source in only 15 counties, the emissions impact is substantial in those locations.

Groundwater degassing

We estimated that CO_2 degassing from groundwater that is used for irrigation emits 2.4 $MtCO_2\ yr^{-1}$ (95% CI 1.5–3.7 $MtCO_2e$), at a national average volume-based rate of 30,866 $tCO_2\ km^{-3}$ of groundwater. These emissions are highly spatially heterogeneous (Fig. 3a,b) and are concentrated in the Mississippi River Valley region, which has experienced steady growth in irrigated area[41] and irrigation volumes[42] since the 1970s to support increasing corn and soybean production[43] in addition to rice and cotton. County-level degassing emissions are correlated with groundwater extraction volumes ($r = 0.68$), but emissions are also strongly influenced by the spatial variance in the partial pressure of CO_2 (pCO_2) in groundwater (Supplementary Fig. 4). For example, groundwater extractions from the 81 counties overlaying the Mississippi River Valley Alluvial Aquifer account for only 21% of total groundwater withdrawals nationally, but they produce 54% of the total degassing emissions with an average degassing emissions rate that is 250% of the national average due to a higher groundwater pCO_2. As a counterpoint, the 237 counties overlying the High Plains Aquifer produce only 15% of degassing emissions while accounting for 24% of groundwater withdrawals.

Localized reductions in groundwater withdrawals in areas with high pCO_2 values will be needed to reduce emissions from groundwater degassing. Increasing the water use efficiency of irrigation systems may reduce withdrawals of groundwater and, therefore, the emissions fluxes attributable to degassing and groundwater pumping, even if consumptive water use (that is, the volume leaving the system via evapotranspiration) is not substantially reduced by improved system efficiency[44,45]. For example, approximately 68% of irrigated area in the Mississippi River Valley utilizes highly inefficient flood or furrow irrigation systems[43], and nearly all rice is grown with continuous flooding[46]. Irrigation application rates for maize and soybean are approximately 49% and 51% lower, respectively, under pivot irrigation than furrow irrigation[42], and implementation of alternate wetting and drying systems can reduce water application rates for rice by 39% (ref. 46). CH_4 emissions can also be reduced via alternate wetting and drying, as discussed in the section on additional emissions sources below. Reductions in degassing emissions would be proportional to reductions in groundwater withdrawals, suggesting strong mitigation potential for this emissions flux via improved irrigation water use efficiency. However, switching to more efficient irrigation systems does not always reduce water withdrawals, as it can lead to an expansion in irrigated area and encourage planting of more water-intensive crop varieties[44]. Thus, policy efforts to regulate total groundwater withdrawals will be needed alongside improvements in system efficiency. Additionally, mitigation of degassing emissions via reduced groundwater withdrawals should be undertaken with consideration of crop yield impacts, as yield reductions may lead to increased GHG emissions through cropland intensification or expansion elsewhere.

Our estimate of CO_2 emissions from groundwater degassing falls within the range of another national-scale estimate developed using a national average value for groundwater bicarbonate concentration and an estimate of groundwater depletion (1.7 $MtCO_2\ yr^{-1}$; 95% CI 0.9–2.6 $MtCO_2\ yr^{-1}$)[26], though our mean estimate is 1.4 times higher. Two key methodological differences underly the difference between these two estimates. First, we derive spatially resolved pCO_2 estimates from groundwater pH, alkalinity and temperature, rather than relying on a national average value of bicarbonate concentrations. This spatial resolution allows for alignment of the large variability in both groundwater extractions and pCO_2. Second, we consider the gross flux from all groundwater extractions, rather than only groundwater depletion. Although there is a potential return flux of CO_2 to the aquifer via groundwater recharge, the timescale of this return, particularly for mineral-derived carbon, may be long enough that it is irrelevant for shorter-term GHG accounting and irrigation decision-making. Future work to assess potential return fluxes and their timelines, analyse degassing of dissolved N_2O from groundwater and evaluate interannual variability in groundwater extractions would further clarify the impact of groundwater degassing on agricultural GHG emissions.

Biogenic soil N_2O emissions

We estimate that irrigation contributes 2.9 $MtCO_2e$ annually (95% CI 2.7–3.0 $MtCO_2e$) through increased N_2O emissions on irrigated croplands (Fig. 3c,d). This direct contribution of irrigation represents approximately 9.9% of the total direct N_2O emissions (29.1 $MtCO_2e$) that are produced on the 21.5 Mha of irrigated cropland included in this analysis. Given that irrigation increases N_2O emissions by causing periods of elevated soil moisture that promote denitrification[30,47], avoidance of saturated conditions through improved irrigation scheduling may mitigate increased N_2O emissions. Additional reductions in irrigation-related direct N_2O emissions from cropland soils are potentially achievable through management practices such as the optimization of N application rates[48], use of controlled-release fertilizers[49] and use of nitrification inhibitors[50] (though inhibitors may increase indirect emissions[51]).

Total irrigation-related N_2O emissions and per-area rates of emissions are much higher in the western USA than the east. The five highest-emitting states (Nebraska, Texas, Idaho, Kansas and California) produced 68% of the total emissions attributed to irrigation despite containing only 46% of the irrigated cropland. These high-emitting states are characterized by both 49% higher average N use per hectare and 41% lower average ratios of precipitation to evapotranspiration than the remaining states, both of which are likely drivers of higher per-hectare irrigation-related N_2O emissions rates. In contrast to these high-emitting areas, the model indicates that irrigation reduces N_2O emissions in three eastern states on average (Maryland, Rhode Island and Connecticut). It is possible that irrigation in these areas either improves plant uptake of N or increases nitrate leaching to groundwater or runoff in surface water, thus reducing direct losses of N as N_2O from croplands. However, increased runoff and leaching of N may lead to increases in indirect N_2O emissions off-farm. Additionally, both the average area-based rate of decrease (−0.9 CO_2e ha^{-1}) and the total irrigated area in these states (54,657 ha) are very small, resulting in a negligible reduction of only 59 tCO_2e in total. Sharp gradients at state boundaries in the percentage of emissions contributed from each source (Fig. 3b,d,f,h), such as the high relative contribution of N_2O in Idaho, arise from reliance on some state-level input data and should be interpreted with caution.

To provide additional confidence in our estimate in light of model uncertainties, we performed a simplified Intergovernmental Panel on Climate Change (IPCC) Tier 1 calculation[52] using a global database of measured climate- and irrigation status-specific emissions factors[53] as a robustness check. Notably, these emissions factors were not from paired, co-located irrigated and rainfed systems, but rather included all cropland emissions factors in the database that contained information on irrigation status. Based on these emissions factors and the same dataset of N inputs that was used for the metamodel, we estimated that 5.8 $MtCO_2e$ (95% CI 2.4–10.2 $MtCO_2e$) were attributable to increased N_2O from irrigation in 2017 (Supplementary Fig. 5). This Tier 1 estimate of N_2O emissions is larger than the metamodel results and has a wider uncertainty band, though the CIs of the Tier 1 and DayCent-based estimates overlap.

The analytical approaches used for the estimation of irrigation-related N_2O emissions capture the variability in N_2O emissions attributed to irrigation but assume that no other model variables change, such as cropland area, crop types or N inputs. In reality, the elimination of irrigation would be accompanied by other management and land use changes such as retirement of croplands where production is not feasible without irrigation and reductions in N fertilizer application for systems that transition to rainfed production, further reducing N_2O emissions. On croplands that would be retired without irrigation, all N_2O emissions from applied N could be considered attributable to irrigation. This analysis does not capture hypothetical area or management changes and, thus, provides a lower-bound estimate for the contribution of irrigation to N_2O emissions, reflecting only emissions directly attributable to increased moisture inputs. Future work may consider irrigation-driven changes in cropland area and management to account for emissions impacts in areas where rainfed production is not possible and/or N application rates are higher under irrigation.

Field-scale studies have generally focused on measuring the effect of altered irrigation regimes, such as comparing N_2O emissions under sprinkler versus flood irrigation or different irrigation water volumes, rather than comparisons of adjacent irrigated and non-irrigated systems[54]. Additional in situ measurements of N_2O emissions from comparable, co-located irrigated and rainfed fields across a range of environmental conditions (where rainfed production is feasible) and management practices will be needed to reduce uncertainty in the impact of irrigation on N_2O emissions and facilitate scalability. Further improvements to N_2O emissions estimates may be achievable through the use of additional biogeochemical models, refinements in model representation of irrigation, and improvements in fertilizer use datasets.

Energy use for interbasin transfers

We evaluated energy use along 103 active interbasin transfer projects that supply irrigation water, which in total produce an estimated 1.1 $MtCO_2e$ yr^{-1} (95% CI 0.6–1.8 $MtCO_2e$) from the delivery of irrigation water (Fig. 3e,f). Interannual variability in pumping volumes and, thus, in energy requirements can be large; this variability underlies the relatively wide CI for this estimate. Many of interbasin transfers also supply water for municipal, domestic or industrial uses, so emissions for each transfer were scaled by the proportion of water delivered for irrigation. Some major projects supply very little water to agricultural users but have substantial total energy use and emissions, such as the Colorado River Aqueduct in California and the Coastal Water Authority Canals in Texas. Notably, 65% of the transfers (67 transfers) do not require any external energy inputs and instead rely primarily on gravity flow through canals and pipelines to transport water. This includes several very large transfers, such as the All American and Los Angeles Canals in California, the Fryingpan-Arkansas Project in Colorado and the Diamond Fork Project in Utah. Inverted siphons and, in some cases, hydraulic lift pumps enable uphill travel without energy inputs along these projects.

Among the 36 projects that do involve pump energy use, emissions are heavily dominated by two projects with large transfer volumes, substantial elevation gain and long conveyance distances. The Central Arizona Project (CAP; 379,484 tCO_2e yr^{-1}) and the California State Water Project (SWP; 519,347 tCO_2e yr^{-1}) produced 85.4% of the national total emissions associated with interbasin transfers of irrigation water. In contrast, 22 transfers had emissions footprints of less than 1,000 tCO_2e yr^{-1}, and the remaining 12 transfers produced between 1,030 and 65,469 tCO_2e yr^{-1}. All but one of the projects rely on electrical

Fig. 3 | Source-specific maps of GHG emissions and their relative contribution. a–**h**, County-level maps of total GHG emissions from irrigation (left; that is, **a**, **c**, **e** and **g**) and the percentage of irrigation-related GHG emissions within each county (right; that is, **b**, **d**, **f** and **h**) attributed to groundwater degassing (**a** and **b**), elevated N_2O (**c** and **d**), energy use for interbasin transfers (**e** and **f**) and on-farm energy use for pumping (**g** and **h**). In **e** and **f**, the red lines indicate interbasin transfer conveyance paths that require energy for pumping, and the black lines indicate interbasin transfer paths that do not require energy for pumping. The emissions associated with interbasin transfers are allocated equally to the counties containing each conveyance path, regardless of pump station locations. The colour bars for emissions estimates in **a**, **c**, **e** and **g** are square-root transformed to better illustrate the patterns. Counties in white are not associated with emissions for the source owing to not having any reported groundwater use for crop irrigation (**a** and **b**), ground or surface water use for irrigation (**c**, **d**, **g** and **h**) or interbasin transfers (**e** and **f**).

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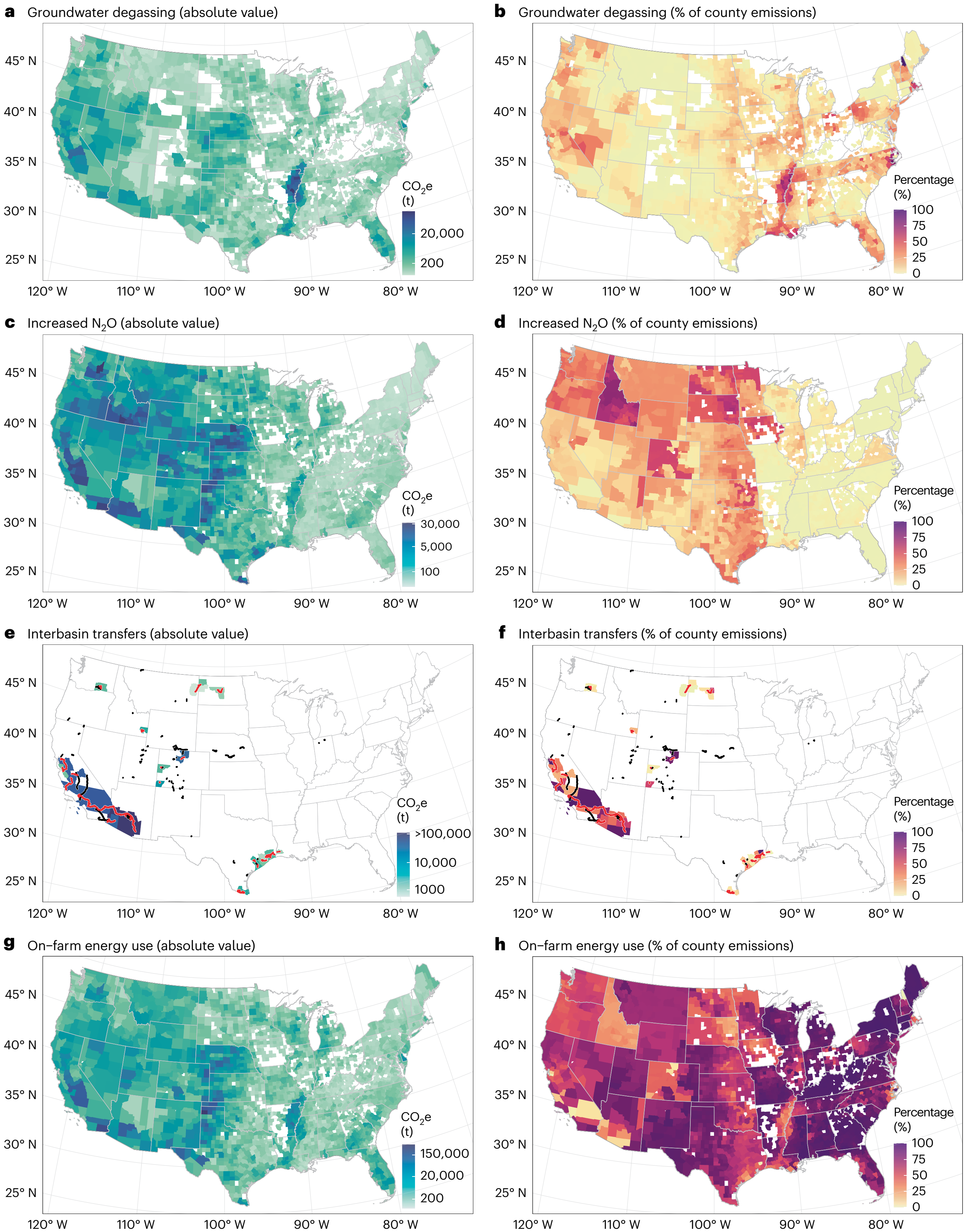

pumps (the exception being the Lower Neches Valley Authority Canals in Texas, which has one natural gas pump station).

Given heavy reliance on electricity, reductions in the emissions intensity of the electrical grid will serve to directly reduce emissions from interbasin transfers. Additionally, hydropower is produced along the paths of many of the major transfer projects, and some projects have invested in construction of renewable energy generation to meet pump energy demand. For example, approximately half of the power used for the SWP is produced at hydroelectric generating plants located along the project itself, which also deliver hydropower to the electrical grid. Since the 2019 closure of the coal-fired Navajo Generating Station, which supplied the majority of energy needed to power pumping along the CAP, the CAP has established long-term contracts to source 6% of its power from the Hoover Dam hydroelectric generating plant and 7% from new solar development.

Emissions associated with energy use for within-basin water conveyance by irrigation organizations were not estimated in this study owing to extremely large number of organizations involved in irrigation water delivery. Future efforts to develop a national inventory of within-basin water infrastructure would facilitate further analysis of the energy and emissions implications of intrabasin water conveyance.

Additional emissions sources

Two additional emissions sources that are influenced by irrigation include enhanced methane emissions from rice production systems and methane emissions from surface reservoirs that store irrigation water. The 2023 US GHG Inventory estimates that US rice production systems, all of which are irrigated, produced 16.8 $MtCO_2e$ of CH_4 in 2017 (ref. 36), although the 95% CI extended from 4.2 to 29.4 $MtCO_2e$ and estimates vary between Tier 1, Tier 2 and Tier 3 accounting strategies[55]. We excluded rice CH_4 emissions from the present analysis because there is no rainfed rice production in the USA to serve as a counterfactual to emissions from irrigated rice production and because several spatially explicit estimates of methane production from rice have already been generated. Although eliminating irrigation for rice production is not feasible in much of the rice-growing area in the USA, reducing irrigation intensity through practices such as alternate wetting and drying has potential to reduce CH_4 production by 39–83% (refs. 56,57). Surface water storage and delivery infrastructure, including reservoirs, canals and constructed ponds, were estimated to produce 20.1 $MtCO_2e$ of CH_4 in 2020. However, most reservoirs and similar infrastructure are multipurpose, with uses for power generation, flood control, recreation, habitat, navigation and public supply in addition to irrigation. Reservoir end uses are not comprehensively tracked, and thus, identifying the share of reservoir emissions attributable explicitly to water use for irrigation is non-trivial. Opting to include rice and reservoir methane production would substantially increase the estimated GHG emissions impact of irrigation.

Conclusions

We estimate that US irrigation produces 18.9 $MtCO_2e$ annually through pump energy use, groundwater degassing of CO_2 and increases in N_2O emissions circa 2020. Irrigation-related emissions are predominately attributable to energy use (72% of total emissions) and groundwater use (79% of total emissions). They are also highly spatially concentrated, leading to geographic hotspots of irrigation-related emissions in which emissions mitigation actions can be targeted towards the key sources. As energy use accounts for the majority of total emissions, pump electrification and grid decarbonization will be effective strategies for reducing irrigation-related emissions nationwide. Reductions in degassing emissions will require reductions in groundwater extractions, particularly from aquifers with high pCO_2, which will be achievable in part through increased irrigation system efficiency. Effective irrigation scheduling and improved efficiency may additionally help mitigate excess N_2O emissions by minimizing periods of very high soil moisture contents, particularly when coupled with interventions to reduce the excess reactive N load such as use of controlled-release fertilizers and optimized N application rates. Additional work to assess interannual variability in irrigation-related emissions and evaluate implications of hypothetical policy scenarios may be useful for further targeting mitigation efforts.

To our knowledge, this is the most comprehensive national-scale analysis of irrigation related emissions so far, and we believe that the resultant database has several important uses. First, the incorporation of irrigation-related emissions into life cycle assessment models will improve GHG accounting of products derived from irrigated crops. Second, the data provide insight into potential future changes in irrigation-related emissions due to changing environmental conditions, such as increased crop water demand, groundwater depletion and altered surface water availability, among others. Third, the data enable consideration of the GHG emissions impacts of irrigation policy decisions, such as incentives for irrigation expansion or improvements to system efficiency, which is particularly relevant for irrigation policy decisions motivated by climate change adaptation. In sum, these spatially resolved, source-specific estimates of GHG emissions from irrigation will enable more thorough evaluation of trade-offs between increased crop productivity, increased water scarcity and increased emissions in the context of continued irrigation expansion.

Methods

Groundwater degassing

Source data. We collected a suite of well water chemical species and parameters, including alkalinity, pH and salinity of the groundwater system in the contiguous USA from the US Geological Survey (USGS)[34]. Specifically, we selected 11 different parameter codes for alkalinity (00418, 00421, 29801, 29802, 29803, 39036, 39086, 39087, 99431, 00410 and 90410), three parameter codes for pH (00400, 00403 and 00408) and four parameter codes for salinity (that is, total dissolved solids) (70300, 70301, 70303 and 00515) according to the USGS parameter coding system[34]. For each of these parameters, we removed the samples that were not labelled as 'Groundwater'. We further calculated the average value of each of the parameters for the samples that have the same 'Activity Identifier' (an identifier for each measurement). Outlier data, defined as values lower than the 0.5th percentile and higher than the 99.5th percentile of each parameter, were removed. Sites with multiple measurements in a day were averaged on a daily basis for each parameter. To maintain a high-quality average annual signal, we removed the sites that lacked at least one data point for each season. We also removed data points from the winter season (December, January and February) to reflect the potential irrigation season in most of the USA. After data filtering, the average value of each parameter for each site was calculated by sequentially aggregating the samples by month, season and year. Note that, for pH values, we first converted original pH values from $-\log_{10}([H^+])$ scale to the $[H^+]$ concentration scale (mol l^{-1}) before data aggregation and then converted them back to $-\log_{10}([H^+])$ in the final step. This resulted in our final groundwater dataset (3,918 sites) with alkalinity, pH and salinity (Supplementary Fig. 6). The March to November average land surface temperatures for these groundwater sites (Supplementary Fig. 7) were extracted from the CHELSA dataset (Climatologies at High Resolution for the Earth's Land Surface Areas)[35].

Data analysis. The aqueous concentration of CO_2 ($[CO_2]_{aq}$) in groundwater was determined using compiled data on alkalinity, pH, salinity and surface temperature via the 'seacarb' R package[58]. Utilizing globally averaged atmospheric CO_2 concentrations from the National Oceanic and Atmospheric Administration Global Monitoring Laboratory[59] for 2015–2020 (excluding data from December, January and February), we calculated the equilibrium concentration of aqueous CO_2 ($[CO_2]_{aq\_eq}$) in groundwater, based on groundwater pH, salinity and surface temperature[58]. Subsequently, the difference between $[CO_2]_{aq}$ and $[CO_2]_{aq\_eq}$ ($[CO_2]_{aq} - [CO_2]_{aq\_eq}$) was computed for all sampling locations. To spatially extend these results, we employed inverse distance weighting to interpolate the calculated $[CO_2]_{aq} - [CO_2]_{aq\_eq}$ values across the contiguous USA at a 0.1° resolution. These interpolated values were then aggregated to the county-level average and integrated with the corresponding irrigation groundwater withdrawals for each county.

Assuming that all excess CO_2 in the groundwater would be degassed into the atmosphere, the CO_2 flux from irrigation to the Q8 atmosphere was calculated using equation (1):

$$f_{CO_2} = ([CO_2]_{aq} - [CO_2]_{aq\_eq}) \times V_{irrigation} \tag{1}$$

Here, f_{CO2} represents the carbon degassing flux resulting from irrigation, $[CO_2]_{aq}$ is the actual CO_2 concentration in the groundwater upon its extraction, $[CO_2]_{aq\_eq}$ is the equilibrium CO_2 concentration in the groundwater and $V_{irrigation}$ is the volume of groundwater withdrawn for irrigation. County-level irrigation groundwater use data were acquired from the USGS database 'Estimated Use of Water in the United States for 2015'[25] (the most recent year available at the county scale) and modified to account for golf course irrigation, as detailed in Supplementary Methods.

A 95% CI was constructed using a Monte Carlo approach. First, the standard errors of $[CO_2]_{aq}$ and $[CO_2]_{aq\_eq}$ were estimated using the default implementation of the 'errors' function in the 'seacarb' package[58], which propagates uncertainties associated with alkalinity, pH, salinity, temperature, atmospheric CO_2 concentration and seven key dissociation constants used in the calculation. We assumed a standard measurement error of 1% for pH and alkalinity, used the standard error of the monthly mean atmospheric CO_2 concentrations to incorporate uncertainty in the timing of pumping, and used the default standard uncertainty values for all remaining variables. The standard error of the difference of $[CO_2]_{aq\_eq}$ and $[CO_2]_{aq}$ for each measurement was calculated by taking the square root of the sum of squared errors. To incorporate uncertainty in the spatial interpolation step, we conducted 1,000 iterations of the interpolation of $[CO_2]_{aq\_eq} - [CO_2]_{aq}$ values. For each interpolation iteration, we first randomly sampled the sites to be included (with replacement). From each selected site, we then sampled from a distribution of potential $[CO_2]_{aq\_eq} - [CO_2]_{aq}$ values generated with the 'rnorm' function using the calculated mean and standard error of the estimate for each site. These sampled values were used as the input data for the interpolation, and the 2.5th and 97.5th percentile values from the bootstrapped iterations were used to calculate the CI for the national emissions estimate.

Biogenic emissions

Source data. The analysis of irrigation's contribution to N_2O emissions relied on an existing, point-level timeseries of agricultural GHG emissions and sinks that was developed for the US GHG Inventory[36]. Detailed descriptions of the database development and model inputs are available in section 5.4 of the 2023 US GHG Inventory Report[36]. Briefly, direct N_2O emissions for 22 major crops grown on mineral soils and most non-federal managed grasslands were estimated using DayCent, an ecosystem biogeochemical model with a daily timestep[60,61]. We utilized input and output data from the site-level DayCent model runs conducted at US Department of Agriculture (USDA) National Resource Inventory (NRI) survey locations on agricultural lands for 1990–2017. Each site was associated with an expansion factor, indicating the land area with similar physical and management characteristics, to allow for upscaling. Key land use and management input data included crop type and areas, irrigation, fertilization rates (from synthetic fertilizers and manure), cover crop management, tillage, and planting and harvest dates. Numerous data sources were leveraged for these underlying DayCent analyses reported in the US GHG Inventory, including the USDA NRI[62], USDA National Resource Conservation Service Conservation Effects and Assessment Project, the USDA Economic Research Service Agricultural Resource Management Surveys and the USDA Census of Agriculture, among others. Fertilizer application rates were harmonized with sales data from the USGS[63] and the Association of American Plant Food Control Officials reports, and manure input data were harmonized with estimates of the total manure available for land application. These nitrogen use data are somewhat uncertain and may present an opportunity for improving N_2O estimates, particularly with respect to the spatial distribution of nitrogen application. In addition to management data, the DayCent simulations utilized weather data from PRISM (Parameter-elevation Regressions on Independent Slopes Model)[64], soil physical properties from the Soil Survey Geographic Database[65] and MODIS Enhanced Vegetation Index data[66,67] to inform primary productivity.

Metamodel development. To isolate the effect of irrigation on N_2O emissions from US croplands and pastures, we fit a generalized linear mixed-effects model of DayCent predictions of N_2O-N ha^{-1}. The rate of N_2O emissions was modelled with a gamma distribution and log link function to avoid prediction of negative N_2O fluxes[68]. A random slope was included per site to account for non-independence of DayCent predictions across years. Twelve systematic predictors and two interaction terms were also included in the model (Supplementary Table 3). Specifically, binary predictors were included for irrigation status, previous-year fallow and a transition to cropland from grassland within the previous 3 years. Categorical predictors were included for crop type (16 categories) and tillage, including categories for conventional tillage, reduced tillage, no-till and 'not applicable' (for permanent pasture). Continuous predictors were included for total N application rate, precipitation minus evapotranspiration (P-ET), mean annual temperature, per cent sand, bulk density, soil pH and soil organic carbon. All continuous predictors were modelled as second-order orthogonal polynomials to allow for quadratic effects and reduce multicollinearity. Finally, interactions between irrigation and N application rate and irrigation and P-ET were also included as these variables may modulate the effect of irrigation on N_2O emissions.

The model was fit on a total of 6,651,156 observations, representing 258,832 unique cropland and pasture sites, using the 'lme4' package[69]. A total of 849,365 of the observations were irrigated. Variable inclusion in the full model was based on mechanistic drivers of N_2O emissions variability and data availability, and all predictors significantly influenced N_2O emissions ($\alpha = 0.05$). We calculated the average out-of-sample root mean square error by randomly resampling 80% of the sites in the database for training the model and using the remaining 20% of the sites for testing. The final metamodel effectively reproduced the DayCent emissions estimates (Supplementary Fig. 8; root mean square error 490 g N_2O-N ha^{-1}, $R^2 = 0.86$ at the site–year level).

Metamodel projections and uncertainty estimates. The metamodel was then used to generate predictions of the area-based rate of N_2O emissions on irrigated croplands under two scenarios: (1) the baseline scenario with full irrigation and (2) a hypothetical no-irrigation scenario with irrigation set to zero but otherwise identical input data. The difference between the baseline N_2O estimates and the no-irrigation scenario was used to approximate the additional N_2O emissions attributable to irrigation. Importantly, the no-irrigation scenario does not represent the cropland retirement or decreases in N application rates that would be expected in the absence of irrigation. This method therefore produces a conservative estimate of irrigation related N_2O emissions as it reflects only the increase attributable to changes in soil moisture.

We used a block bootstrapping approach to generate a 95% CI for N_2O emissions estimate. Individual sites were resampled with replacement, and all observations for the resampled sites were used to refit the metamodel, generate predictions under the baseline and the no-irrigation scenario, and calculate the total change in N_2O emissions.

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This procedure was repeated 1,000 times, and the CI was calculated as the 2.5th and 97.5th percentile estimates. The calculated CI for irrigation's contribution to N_2O emissions reflects only the uncertainty stemming from the metamodel itself, and not the uncertainty associated with the predicted site fluxes from the DayCent model, which are considerable. For example, the 95% CI for the US GHG Inventory estimate of total direct N_2O emissions from all croplands in 2015 ranges from 26% below to 31% above the central estimate, after incorporating uncertainty in input data, parameterization and structural uncertainty in the DayCent model. Moreover, uncertainty in N_2O emissions estimates is larger at smaller spatial scales[60] than at the national scale.

N_2O emissions mapping. The total CO_2e (E) associated with N_2O emissions attributed to irrigation for each state (s) was calculated according to equation (2). Here, R represents the rate of N_2O emissions in grams of N in N_2O per hectare associated with irrigation in each survey location (summed by state), M_{N2O} is the molar mass of N_2O (44.013 g mol^{-1}) and M_{N2} is the molar mass of N_2 (28.0134 g mol^{-1}). The ratio of molar masses is used to convert grams of N in N_2O to grams of N_2O before multiplying by G, the 100-year global warming potential of N_2O from the IPCC Sixth Assessment Report without feedbacks (273 g CO_2e per g N_2O), and A, the land area (hectares) in the state represented by the survey location according to the NRI.

$$E_{\mathrm{s}} = \sum R \times \frac{M_{\mathrm{N2O}}}{M_{\mathrm{N2}}} \times G \times A \tag{2}$$

The NRI expansion factors (A) for upscaling reflect the area that the survey location represents with respect to land cover, management, climate and soil characteristics and are based on a stratified sampling approach at the county and township levels. These area estimates contain larger uncertainty at smaller spatial scales (ex. counties) than
Q9 at larger spatial scales (ex. states). To account for trends in irrigated area over time, the average irrigated area for each land use type and county was taken from 2015–2017 for upscaling. We found that the total irrigated land area represented in the NRI data included in the analysis (21.5 Mha) was reasonably consistent with the USGS 2015 'Estimated Use of Water in the United States' database (23.4 Mha) but that the county-level distribution of irrigated area from the NRI data was not consistent with the USGS data (Supplementary Fig. 9) owing to uncertainty inherent in the NRI sampling approach. For consistency with other emissions sources, emissions estimates were summed to the state level and then allocated to the county level by multiplying the state-level total emissions by the proportion of statewide irrigation water use that occurs within that county. New Hampshire, Vermont, New York and Maine each contained zero or one irrigated observation each and, thus, were grouped for aggregation and downscaling. West Virginia contained no irrigated observations and was grouped with Virginia for aggregation and downscaling. County-level surface and groundwater irrigation water use data were acquired from the USGS[25] and modified to account for surface water conveyance losses[70] and golf course irrigation, as detailed in Supplementary Methods.

Comparison with Tier 1 methodology. In addition to the metamodel generated estimates, we produced a second, independent estimate of the contribution of irrigation to biogenic emissions using a Tier 1 approach and a database of experimentally derived emissions factors compiled by Hergoualc'h et al.[53]. This database contains 255 emissions factors that explicitly indicate irrigation status, which are further
Q10 broken down by IPCC climate type ('wet' versus 'dry' based on a P/P-ET threshold of 0.65). For this calculation, we took the average of emissions factors under each of the following conditions: irrigated in a wet climate (n = 20), irrigated in a dry climate (n = 106), non-irrigated in a wet climate (n = 85) and non-irrigated in a dry climate (n = 44). Consistent with IPCC guidelines[52], we calculated county-level aridity index as mean P/P-ET using 1988–2018 TerraClim data[71] and classified the counties as wet or dry accordingly, matching them with the relevant emissions factors. Using the same N input and land use data that were compiled for the US GHG Inventory and the metamodel analysis, we again calculated estimated emissions on irrigated croplands under irrigated and non-irrigated scenarios. The difference between these two estimates is indicative of the additional N_2O emissions due to irrigation. To construct a 95% CI for this estimate, emissions factors from each category were resampled with replacement to calculate a new average emissions factor for each climate–irrigation category. The emissions calculations were repeated 1,000 times, and the 2.5th and 97.5th percentile estimates from this bootstrapped distribution were taken as the 95% CI.

Energy use for interbasin transfers

Data collection. Interbasin water transfers that were currently active in the USA and had irrigation listed as at least one of the purposes of the project were identified from Siddik et al.[32]. Transfers that were part of a single interconnected project and managed by the same operator were then consolidated, producing a list of 136 unique systems for further investigation. Thirty of these projects were excluded from consideration after evaluating government records, satellite imagery and, when needed, contacting the operator. Exclusions were due to at least one of the following criteria: (1) the transfer did not supply any agricultural users, only municipal, domestic or industrial users, (2) the transfer was contained entirely within and operated exclusively for an individual ranch or (3) the transfer was no longer active. For transfers contained within an individual ranch, the energy use emissions are captured in our estimate of on-farm pumping emissions (see 'On-farm energy use for pumping' section). There were 106 projects Q11
included in the analysis.

The operator of each project was identified via web search and contacted via email (or phone, if email was unavailable) with a request for records from 2017–2022 related to (1) pump energy use along the transfer, (2) the proportion of water delivered to agricultural users and (3) static pump head, if available. Up to three follow-up emails were sent to non-responsive operators, as needed. Then, a formal public records request was submitted, consistent with state public records legislation. Finally, a minimum of two attempts were made to contact the operator via phone. Operators of 15 transfers remained non-responsive after these attempts. Energy requirements for these transfers were estimated on the basis of the best available information about pump head, pumping volumes and the average energy intensity of comparable projects. For three small transfer projects with evidence of pumping, insufficient information was available to estimate energy use and the transfers were excluded from the analysis. Detailed information about the estimation process for each transfer missing data and further information about the three excluded transfers are provided in Supplementary Methods.

If the operator was not immediately identifiable, county or city water districts, water conservancy organizations, researchers working in water conveyance, and state and/or regional water agencies in the surrounding area were contacted in an attempt to identify transfer operators. If the search for the operator failed, satellite imagery and all available documentation related to the transfer, such as historical reports, documentation from state engineering offices, and state water infrastructure databases were inspected for any indication of pumping. There was no evidence of pumping from data sources for 22 transfers, which were assumed to be gravity-fed. If there was an indication of pumping and the operator was not found, the data were treated as missing.

Calculation of GHG emissions. There were 67 transfers that did not rely on pumping plants and therefore were not associated with any emissions. For transfers that did involve pumping, data availability

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varied between projects, and the temporal coverage and type of data for each project are detailed in Supplementary Table 4. Energy use records were variably supplied as direct usage data, expenditures for electricity or the rate of energy use per volume of water coupled with pumping volumes. For projects that reported expenditure, energy use was calculated by dividing electricity expenditures by state-level annual average retail electricity prices for industrial users. Retail electricity prices for industrial users were accessed from the US Energy Information Administration. Electricity use data were then converted to emissions by multiplying by the annual average emissions factor for electricity consumption across all balancing authorities intersected by the path of the interbasin transfer, based on an hourly dataset of electrical grid emissions factors adjusted for the transfer of electricity across balancing authority boundaries[72]. One project reported natural gas usage in addition to electricity, which was converted to emissions using an emissions factor
Q12 of 53.608 kg per MMBtu, taken from the Environmental Protection Agency Greenhouse Gas Emissions Factor Hub. For mapping, emissions were allocated evenly among counties containing the path of the transfer, regardless of the location of the pump station or the site of electricity generation.

Uncertainty estimation. We used a bootstrapping approach to calculate 95% CIs for our estimate of GHG emissions from interbasin transfers by resampling with replacement 10,000 times from all available values used in the calculation. For projects with data supplied as an annual timeseries of electricity use, we randomly selected a year in each resampling and then a monthly emissions factor for the associated year to account for uncertainty in the timing of pumping. For projects with data supplied as an annual timeseries of energy expenditures, we followed the same procedure but additionally resampled from monthly energy prices. For projects with missing energy use data, we additionally resampled from the energy intensity, the pump head and/or the pumping volume, as applicable.

On-farm energy use for pumping

Emissions from on-farm energy use for irrigation pumping were calcu-
Q13 lated in Driscoll et al. (2024). Briefly, data on energy expenditures for irrigation pumps from the 2018 USDA Irrigation and Water Management Survey were coupled with concurrent energy prices from the Energy Information Administration and emissions factors from the Environmental Protection Agency to calculate emissions for each fuel and water source at the state level. Emissions were then downscaled to the county level on the basis of 2015 USGS irrigation water use data (adjusted for golf irrigation and conveyance losses), with groundwater pumping emissions scaled by groundwater depth. Emissions from on-farm electrical energy use for irrigation pumping reflect the site of irrigation, not necessarily the site of electricity generation.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

County-level emissions estimates and associated CIs, broken down by emissions source and water source, are available as Supplementary Table 2. The data required to reproduce the figures and analyses presented in this manuscript are available on Zenodo at https://doi.org/10.5281/zenodo.12552398 (ref. 37). The raw data used to calculate emissions estimates for groundwater degassing are available in the same repository. The raw data used to calculate emissions from individual interbasin transfer operators are available upon request to the corresponding author. The raw National Resource Inventory data underlying the N_2O emissions model are confidential, and data access is regulated by the USDA.

Code availability

The code used to produce the figures and analyses presented in this manuscript are available on Zenodo at https://doi.org/10.5281/zenodo.12552398 (ref. 37).

References

1. Hrozencik, R. A. & Aillery, M. Trends in U.S. irrigated agriculture: Increasing resilience under water supply scarcity. *U. S. Dep. Agric. Econ. Res. Serv*. (2021). Q15
2. Lobell, D. B., Bonfils, C. J., Kueppers, L. M. & Snyder, M. A. Irrigation cooling effect on temperature and heat index extremes. *Geophys. Res. Lett*. **35**, (2008). Q16
3. Siebert, S. & Döll, P. Quantifying blue and green virtual water contents in global crop production as well as potential production losses without irrigation. *J. Hydrol*. **384**, 198–217 (2010).
4. McDermid, S. et al. Irrigation in the Earth system. *Nat. Rev. Earth Environ*. https://doi.org/10.1038/s43017-023-00438-5 (2023).
5. Kukal, M. S. & Irmak, S. Impact of irrigation on interannual variability in United States agricultural productivity. *Agric. Water Manag*. **234**, 106141 (2020).
6. Kukal, M. S. & Irmak, S. Irrigation-limited yield gaps: trends and variability in the United States post-1950. *Environ. Res. Commun*. **1**, 061005 (2019).
7. Meza, I. et al. Global-scale drought risk assessment for agricultural systems. *Nat. Hazards Earth Syst. Sci*. **20**, 695–712 (2020).
8. Rosa, L. et al. Potential for sustainable irrigation expansion in a 3 °C warmer climate. *Proc. Natl Acad. Sci. USA* **117**, 29526–29534 (2020).
9. Lesk, C. et al. Compound heat and moisture extreme impacts on global crop yields under climate change. *Nat. Rev. Earth Environ*. **3**, 872–889 (2022).
10. Irmak, S., Sandhu, R. & Kukal, M. S. Multi-model projections of trade-offs between irrigated and rainfed maize yields under changing climate and future emission scenarios. *Agric. Water Manag*. **261**, 107344 (2022).
11. Lesk, C., Rowhani, P. & Ramankutty, N. Influence of extreme weather disasters on global crop production. *Nature* **529**, 84–87 (2016).
12. Luan, X., Bommarco, R., Scaini, A. & Vico, G. Combined heat and drought suppress rainfed maize and soybean yields and modify irrigation benefits in the USA. *Environ. Res. Lett*. **16**, 064023 (2021).
13. Zampieri, M., Ceglar, A., Dentener, F. & Toreti, A. Wheat yield loss attributable to heat waves, drought and water excess at the global, national and subnational scales. *Environ. Res. Lett*. **12**, 064008 (2017).
14. Choi, E., Rigden, A. J., Tangdamrongsub, N., Jasinski, M. F. & Mueller, N. D. US crop yield losses from hydroclimatic hazards. *Environ. Res. Lett*. **19**, 014005 (2023).
15. Yang, Y. et al. Sustainable irrigation and climate feedbacks. *Nat. Food* **4**, 654–663 (2023).
16. Clark, M. A. et al. Global food system emissions could preclude achieving the 1.5° and 2 °C climate change targets. *Science* **370**, 705–708 (2020).
17. Crippa, M. et al. Food systems are responsible for a third of global anthropogenic GHG emissions. *Nat. Food* **2**, 198–209 (2021).
18. Tubiello, F. N. et al. Greenhouse gas emissions from food systems: building the evidence base. *Environ. Res. Lett*. **16**, 065007 (2021).
19. Sowby, R. B. & Dicataldo, E. The energy footprint of U.S. irrigation: a first estimate from open data. *Energy Nexus* **6**, 100066 (2022).
20. Tidwell, V. C., Moreland, B. & Zemlick, K. Geographic footprint of electricity use for water services in the Western U.S. *Environ. Sci. Technol*. **48**, 8897–8904 (2014).

https://doi.org/10.1038/s44221-024-00283-w

21. Qin, J. et al. Global energy use and carbon emissions from irrigated agriculture. *Nat. Commun.* **15**, 3084 (2024).
22. Driscoll, A. W., Conant, R. T., Marston, L. T., Choi, E. & Mueller, N. D. Greenhouse gas emissions from US irrigation pumping and implications for climate-smart irrigation policy. *Nat. Commun.* **15**, 675 (2024).
23. McCarthy, B. et al. Trends in water use, energy consumption, and carbon emissions from irrigation: role of shifting technologies and energy sources. *Environ. Sci. Technol.* **54**, 15329–15337 (2020).
24. McGill, B. M., Hamilton, S. K., Millar, N. & Robertson, G. P. The greenhouse gas cost of agricultural intensification with groundwater irrigation in a Midwest U.S. row cropping system. *Glob. Change Biol.* **24**, 5948–5960 (2018).
25. Dieter, C. A. et al. Estimated use of water in the United States county-level data for 2015 (ver. 2.0). *US Geological Survey* https://doi.org/10.5066/F7TB15V5 (2018).
26. Wood, W. W. & Hyndman, D. W. Groundwater depletion: a significant unreported source of atmospheric carbon dioxide. *Earths Future* **5**, 1133–1135 (2017).
27. Macpherson, G. L. CO_2 distribution in groundwater and the impact of groundwater extraction on the global C cycle. *Chem. Geol.* **264**, 328–336 (2009).
28. Ruser, R. et al. Emission of N_2O, N_2 and CO_2 from soil fertilized with nitrate: effect of compaction, soil moisture and rewetting. *Soil Biol. Biochem.* **38**, 263–274 (2006).
29. Butterbach-Bahl, K., Baggs, E. M., Dannenmann, M., Kiese, R. & Zechmeister-Boltenstern, S. Nitrous oxide emissions from soils: how well do we understand the processes and their controls? *Philos. Trans. R. Soc. B* **368**, 20130122 (2013).
30. Elberling, B. B. et al. High nitrous oxide emissions from temporary flooded depressions within croplands. *Commun. Earth Environ.* **4**, 1–9 (2023).
31. Trost, B. et al. Irrigation, soil organic carbon and N_2O emissions. A review. *Agron. Sustain. Dev.* **33**, 733–749 (2013).
32. Siddik, M. A. B., Dickson, K. E., Rising, J., Ruddell, B. L. & Marston, L. T. Interbasin water transfers in the United States and Canada. *Sci. Data* **10**, 27 (2023).
33. Shumilova, O., Tockner, K., Thieme, M., Koska, A. & Zarfl, C. Global water transfer megaprojects: a potential solution for the water–food–energy nexus? *Front. Environ. Sci.* **6**, 150 (2018). Q17
34. National Water Information System (USGS water data for the nation). *US Geologic Survey* https://doi.org/10.5066/F7P55KJN (2016).
35. Karger, D. N. et al. Climatologies at high resolution for the Earth's land surface areas. *Sci. Data* **4**, 170122 (2017).
36. Inventory of U.S. greenhouse gas emissions and sinks: 1990–2021. *US EPA* https://www.epa.gov/ghgemissions/inventory-us-greenhouse-gas-emissions-and-sinks-1990-2021 (2023).
37. Driscoll, A. W. et al. US irrigation emissions from multiple sources. *Zenodo* https://doi.org/10.5281/zenodo.12552398 (2024).
38. West, P. C. et al. Leverage points for improving global food security and the environment. *Science* **345**, 325–328 (2014).
39. Sen, A. & Foster, J. *On Economic Inequality* (Oxford Univ. Press, 1973).
40. Weiner, J. & Solbrig, O. T. The meaning and measurement of size hierarchies in plant populations. *Oecologia* **61**, 334–336 (1984).
41. Yasarer, L. M. W., Taylor, J. M., Rigby, J. R. & Locke, M. A. Trends in land use, irrigation, and streamflow alteration in the Mississippi River alluvial plain. *Front. Environ. Sci.* **8**, (2020).
42. Massey, J. H. et al. Long-term measurements of agronomic crop irrigation made in the Mississippi delta portion of the lower Mississippi River Valley. *Irrig. Sci.* **35**, 297–313 (2017).
43. Lo, T. H. & Pringle, H. C. A quantitative review of irrigation development in the Yazoo–Mississippi Delta from 1991 to 2020. *Agronomy* **11**, 2548 (2021).
44. Grafton, R. Q. et al. The paradox of irrigation efficiency. *Science* **361**, 748–750 (2018).
45. Ward, F. A. & Pulido-Velazquez, M. Water conservation in irrigation can increase water use. *Proc. Natl Acad. Sci. USA* **105**, 18215–18220 (2008).
46. Atwill, R. L. et al. Alternate wetting and drying reduces aquifer withdrawal in Mississippi rice production systems. *Agron. J.* **112**, 5115–5124 (2020).
47. Harris, E. et al. Denitrifying pathways dominate nitrous oxide emissions from managed grassland during drought and rewetting. *Sci. Adv.* **7**, eabb7118 (2021).
48. Shcherbak, I., Millar, N. & Robertson, G. P. Global metaanalysis of the nonlinear response of soil nitrous oxide (N_2O) emissions to fertilizer nitrogen. *Proc. Natl Acad. Sci. USA* **111**, 9199–9204 (2014).
49. Halvorson, A. D., Snyder, C. S., Blaylock, A. D. & Del Grosso, S. J. Enhanced-efficiency nitrogen fertilizers: potential role in nitrous oxide emission mitigation. *Agron. J.* **106**, 715–722 (2014).
50. Qiao, C. et al. How inhibiting nitrification affects nitrogen cycle and reduces environmental impacts of anthropogenic nitrogen input. *Glob. Change Biol.* **21**, 1249–1257 (2015).
51. Lam, S. K., Suter, H., Mosier, A. R. & Chen, D. Using nitrification inhibitors to mitigate agricultural N_2O emission: a double-edged sword? *Glob. Change Biol.* **23**, 485–489 (2017).
52. Hergoualc'h, K. et al. in *Chapter 11: N2O Emissions from Managed Soils, and CO2 Emissions from Lime and Urea Application* Ch. 11 (2019). Q18
53. Hergoualc'h, K. et al. Improved accuracy and reduced uncertainty in greenhouse gas inventories by refining the IPCC emission factor for direct N_2O emissions from nitrogen inputs to managed soils. *Glob. Change Biol.* **27**, 6536–6550 (2021).
54. Sapkota, A., Haghverdi, A., Avila, C. C. E. & Ying, S. C. Irrigation and greenhouse gas emissions: a review of field-based studies. *Soil Syst.* **4**, 20 (2020).
55. Reavis, C. W., Reba, M. L., Shults, D. D. & Runkle, B. R. K. Assessing the methane mitigation potential of innovative management in US rice production. *Environ. Res. Lett.* **18**, 124020 (2023).
56. Linquist, B. A. et al. Greenhouse gas emissions and management practices that affect emissions in US rice systems. *J. Environ. Qual.* **47**, 395–409 (2018).
57. Balaine, N., Carrijo, D. R., Adviento-Borbe, M. A. & Linquist, B. Greenhouse gases from irrigated rice systems under varying severity of alternate-wetting and drying irrigation. *Soil Sci. Soc. Am. J.* **83**, 1533–1541 (2019).
58. Gattuso, J.-P. et al. seacarb: seawater carbonate chemistry. (2023). Q19
59. Lan, X., Tans, P. & Thoning, K. W. Trends in globally-averaged CO_2 determined from NOAA Global Monitoring Laboratory measurements. *Global Monitoring Laboratory* https://doi.org/10.15138/9N0H-ZH07 Q20
60. Del Grosso, S. J., Ogle, S. M., Parton, W. J. & Breidt, F. J. Estimating uncertainty in N_2O emissions from U.S. cropland soils. *Glob. Biogeochem. Cycles* **24**, (2010).
61. Parton, W. J., Hartman, M., Ojima, D. & Schimel, D. DAYCENT and its land surface submodel: description and testing. *Glob. Planet. Change* **19**, 35–48 (1998).
62. *National Resources Inventory* (UDSA Natural Resources Conservation Service, 2017).
63. Brakebill, J. W. & Gronberg, J. A. M. County-level estimates of nitrogen and phosphorus from commercial fertilizer for the conterminous United States, 1987–2012. *US Geological Survey* https://doi.org/10.5066/F7H41PKX (2017).
64. PRISM climate data. *PRISM Climate Group, Oregon State University* https://prism.oregonstate.edu/ Q21
65. 2014. Soil Survey Staff, Natural Resources Conservation Service. Soil Survey Geographic (SSURGO) Database. *USDA* https://gdg.sc.egov.usda.gov/ (2019). Q22

66. Didan, K. MOD13Q1 MODIS/Terra Vegetation Indices 16-Day L3 Global 250m SIN Grid V006. *NASA EOSDIS Land Processes Distributed Active Archive Center* https://doi.org/10.5067/MODIS/MOD13Q1.006 (2015).
67. Didan, K. MYD13Q1 MODIS/Aqua Vegetation Indices 16-Day L3 Global 250m SIN Grid V006. *NASA EOSDIS Land Processes Distributed Active Archive Center* https://doi.org/10.5067/MODIS/MYD13Q1.006 (2015).
68. Philibert, A., Loyce, C. & Makowski, D. Quantifying uncertainties in N_2O emission due to N fertilizer application in cultivated areas. *PLoS ONE* **7**, e50950 (2012).
69. Bates, D. et al. Lme4: linear mixed-effects models using 'Eigen' and S4. *J. Stat. Softw.* **67**, 1–48 (2019).
70. *Irrigation Organizations* (USDA National Agricultural Statistics
Q23 Service, 2020).
71. Abatzoglou, J., Dobrowski, S., Parks, S. & Hegewisch, K. TerraClimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958–2015. *Sci. Data* https://doi.org/10.1038/sdata.2017.191 (2018).
72. Siddik, M. A. B., Shehabi, A., Rao, P. & Marston, L. *Spatially and Temporally Detailed Water and Carbon Footprints of U.S. Electricity Generation and Use* (HydroShare, 2023).

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Author contributions
A.W.D. and N.D.M. conceived of the study and conducted the analysis, and A.W.D. led the writing of the initial draft. L.T.M. and M.A.B.S. contributed to conceptualization, data and analysis related to interbasin transfers, S.M.O. and S.S. contributed to conceptualization, data and analysis related to N_2O emissions and N.J.P. and S.Z. contributed to conceptualization, data and analysis related to groundwater degassing. All authors contributed to revising the manuscript for submission.

Competing interests
The authors declare no competing interests. Q14

Additional information
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Correspondence and requests for materials should be addressed to Avery W. Driscoll.

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Data collection	Existing data sources were leveraged for the majority of analyses in this manuscript. No code was used for the collection of interbasin transfer energy use, which were the only original data collected for this study. The code used for the production of on-farm energy use estimates is publicly available from a Zenodo repository associated with a prior publication. Access to the National Resource Inventory data and the DayCent output data used for the analysis of N2O emissions is regulated by the US Department of Agriculture. All source data using for the analysis of groundwater degassing were publicly available, and all code used for data processing and analysis of this emissions source are publicly available via Zenodo.
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County-level, source-specific emissions estimates are available as Supplementary Table 2 and are available in a Zenodo repository alongside the minimum data and code required to reproduce the figures and analyses presented in this manuscript. The source data and code used to calculate emissions estimates for groundwater degassing are provided via Zenodo. The primary data used to calculate emissions from individual interbasin transfer operators is available upon request to the corresponding author. The National Resource Inventory data underlying the N2O emissions estimates are confidential, and data access is regulated by the US Department of Agriculture.

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Randomization	were controlled OR if this is not relevant to your study, explain why.
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Ecological, evolutionary & environmental sciences study design

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Study description	This study analyzes greenhouse gas emissions associated with irrigation in the continental US due to energy use, groundwater degassing, and increased N2O emissions. It is an analytical study that primarily integrates existing data sets and is not experimental in nature.
Research sample	This study provides a comprehensive analysis of irrigation-related GHG emissions from all counties in the continental United States.
Sampling strategy	No sampling was conducted. The study uses all available data for each emissions source.
Data collection	Original data collection was only conducted for the interbasin transfer energy use analysis. Data were collected directly from IBT operators via email, phone, or public records requests. All data collection was done by the corresponding author.
Timing and spatial scale	The analysis includes comprehensive coverage of the continental US at the county scale. The exact timing of the data collection varied across datasets, but all estimates reflect recent conditions (2015-2022). Interbasin transfer energy use data were requested between March and November of 2023. Data from the past 5-10 years were requested, although the temporal coverage of available data varied as detailed in Table S1.
Data exclusions	A small number of outliers were excluded from the source data used for analysis of N2O and degassing emissions, as detailed in the methods.
Reproducibility	All analyses were conducted via reproducible code that will be made publicly available upon acceptance. Records of communications with interbasin transfer operators have also been archived.
Randomization	The study was not experimental in nature and no randomization was conducted.
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Did the study involve field work? ☐ Yes ☒ No

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Diffusion MRI ☐ Used ☐ Not used

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Statistic type for inference | *Specify voxel-wise or cluster-wise and report all relevant parameters for cluster-wise methods.*

(See Eklund et al. 2016)

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