nature sustainability

Article

https://doi.org/10.1038/s41893-026-01930-8

Global analysis of nitrogen inputs from irrigation water to cropland

Received: 24 July 2025

Accepted: 24 July 2026

Published online: 07 September 2026

Check for updates

J. Serra[1,2,3] ✉, L. Lassaletta[4], G. H. Ros[5], M. Quemada[4], F. Giannini-Kurina[1], E. Aguilera[6], M. Graversgaard[1,2], C. S. C. Marques-dos-Santos[3], M. R. Cameira[7], W. De Vries[5], A. Dobermann[8], X. Zhang[9], J. Rahimi[2,10], T. Dalgaard[1,2] & K. Butterbach-Bahl[2,10]

Irrigation unintentionally delivers reactive nitrogen to croplands via nitrate-rich water, yet this input is rarely quantified and remains largely absent from nitrogen budgets and fertilization policies. Here we compile over 1,300 field observations and upscale them using machine learning to quantify the nitrogen delivered through irrigation and map its contribution across irrigated croplands for 2010–2019. While the median input was 19 kg N ha^{-1} yr^{-1}, 10% of observations exceeded 100 kg N ha^{-1} yr^{-1}. Globally, we estimate that irrigation supplied 14 Tg N yr^{-1}, equivalent to 13% of synthetic fertilizers used on croplands. Important clusters appear in regions with intensive irrigation and high nitrogen inputs, indicating that irrigation represents a substantial but underused nitrogen source. Our findings expose an overlooked component of agricultural nitrogen budgets that can reduce fertilizer overuse, improve nitrogen-use efficiency and promote nitrogen circularity in irrigated croplands.

In irrigated agriculture, water is applied intentionally, but nitrogen (N) is delivered unintentionally along with it. Irrigation water drawn from groundwater and surface water sources often carries nitrate originating from leaching, runoff and other sources[1,2]. As a result, irrigation delivers not only water but also reactive N, primarily as nitrate and dissolved organic N (ref. 3). This 'pump and fertilize'[4] effect recycles legacy nitrate accumulated over decades of inorganic and organic fertilizer use back into cropland. Unlike fertigation, where fertilizers are deliberately injected into irrigation systems, N from irrigation water (N_{Irrig}) originates from pre-existing contamination in water sources, making it a hidden but potentially considerable input.

As irrigation volumes[5,6] and N pollution to water bodies[7] increase to meet rising food demands, there is an ongoing increase in the unintentional supply of N via irrigation water. The simultaneous increase in irrigation and N pollution is especially pronounced in intensively cultivated regions[8], such as the Indo-Gangetic basin, US High Plains or Southeast Asia, where N_{Irrig} plays an important role in how water and nutrients are co-managed.

Farmers who include N_{Irrig} in their management can better optimize N inputs, saving fertilizers and improving both productivity and profitability[9]. This practice also provides environmental benefits by preventing the overapplication of synthetic fertilizers or manure[10]. However, if unmanaged, this may deplete aquifers[11] or increase nitrate leaching to groundwater[12].

Despite its agricultural and environmental relevance, N_{Irrig} remains inconsistently considered in farm management. Some regional and

[1]Department of Agroecology, Aarhus University, Tjele, Denmark. [2]Center for Landscape Research in Sustainable Agricultural Futures (Land-CRAFT), Aarhus University, Aarhus, Denmark. [3]Forest Research Centre, Associate Laboratory TERRA, School of Agriculture, University of Lisbon, Lisbon, Portugal. [4]CEIGRAM/Dept. Agricultural Production/ETSIAAB, Universidad Politécnica de Madrid, Madrid, Spain. [5]Earth Systems and Global Change, Wageningen University and Research, Wageningen, the Netherlands. [6]Instituto de Economía, Geografía y Demografía, Consejo Superior de Investigaciones Científicas, Madrid, Spain. [7]LEAF-Linking Landscape, Environment, Agriculture and Food-Research Center, Associated Laboratory TERRA, Instituto Superior de Agronomia, Universidade de Lisboa, Tapada da Ajuda, Lisbon, Portugal. [8]International Fertiliser Association (IFA), Paris, France. [9]Appalachian Laboratory, University of Maryland Center for Environmental Science, Frostburg, MD, USA. [10]Institute of Meteorology and Climate Research, Atmospheric Environmental Research (IMK-IFU), Karlsruhe Institute of Technology (KIT), Garmisch-Partenkirchen, Germany. ✉e-mail: jserra@agro.au.dk

https://doi.org/10.1038/s41893-026-01930-8

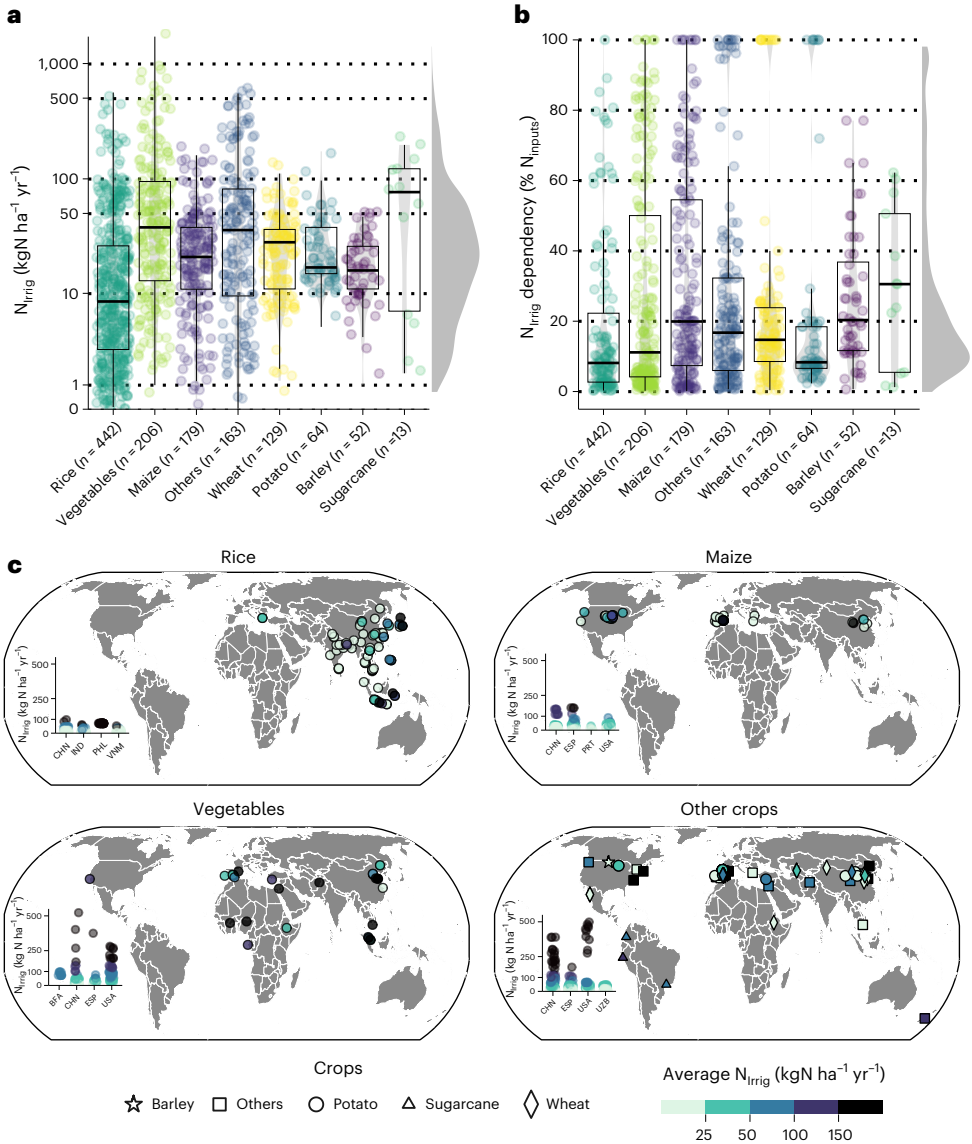


Fig. 1 | Field observations and spatial distribution of nitrogen inputs from irrigation water. a, Field experiment observations for the N input from irrigation water (logarithmic scaled). **b**, N_{Irrig} dependency (ratio of the N input from irrigation water to cropland N inputs). In **a** and **b**, boxplots show the distribution of field observations in each crop category. The centre line indicates the median, the lower and upper bounds of the box indicate the 25th and 75th percentiles, respectively, and the whiskers extend to the smallest and largest values no further than 1.5× IQR from the box bounds. Values beyond the whiskers are shown as individual points. If no values lie beyond 1.5× IQR, the whiskers correspond to the minimum and maximum values. For each crop category, *n* denotes the number of field observations, with each observation corresponding to a reported crop-specific N_{Irrig} estimate from the compiled literature. Grey shades on the right side of the different facets represent the distribution of all data. Point size represents the respective values. **c**, Spatial variation of the averaged N input from irrigation water available in the dataset disaggregated by crops. Inset maps correspond to the four countries according to their ISO3 code with the highest number of observations, showing intracountry variability. Scale for *y* axes of insets indicates the observed N_{Irrig} (kg N ha^{-1} yr^{-1}). Other crops include permanent (grass, apples, olive and citrus) and temporary (barley, sugarcane, sugar beet, wheat and tomato) crops. Tomato ($n = 45$), apple orchards ($n = 17$) and sugar beet ($n = 12$) were the most frequent crops in the 'Others' category. Country ISO3 codes are: BFA, Burkina Faso; BGR, Bulgaria; CHN, China; ESP, Spain; IND, India; ISR, Israel; JPN; Japan; PHL, Philippines; PRT, Portugal; USA, USA; UZB, Uzbekistan; and VNM, Vietnam. Basemap data in **c** from Natural Earth. Basemaps were transformed to Eckert IV projection and are shown without Antarctica.

local advisory systems have long urged farmers to reduce fertilizer rates in regions where irrigation nitrate concentrations are high[13–15]. Yet, these recommendations are not widespread, and many farmers remain unaware of N_{Irrig} as a readily available, low-cost and underused N source in irrigated croplands[16].

Although some national[17,18], regional[16,19] and global[20,21] estimates of N_{Irrig} exist, their reliability is limited because they are not comprehensive in coverage, outdated or not systematically validated against field observations. We address this gap by using a multiscale, data-driven approach to quantify N_{Irrig} and assess its implications for management and policy. We compiled 1,325 field observations of N_{Irrig} across 104 studies and trained a random forests model to predict crop-specific N_{Irrig} globally at 100 km^2 resolution for the period 2010–2019. Our predictions are used to update cropland N budgets, identify clusters where N_{Irrig} can strongly reduce farmers' fertilizer demand and support integration into agri-environmental frameworks.

Global variation in nitrogen inputs from irrigation water

In our global dataset, N_{Irrig} had a median of 19 kg N ha^{-1} yr^{-1} (interquartile range (IQR) 7–47, with IQR being between 25% and 75%), with 32% of observations below 10 and 10% exceeding 100 kg N ha^{-1} yr^{-1}. N_{Irrig}

contributed a median of 14% of total N inputs (IQR 5–33). Variation was driven by differences in irrigation rates (median of 607 mm yr^{-1}; IQR 267–1000) and nitrate concentrations in irrigation water (median of 17 mg NO_3^- l^{-1}; IQR 3–45). These patterns were consistent across crops, with both variables showing similarly skewed distributions (Extended Data Fig. 1).

There were also marked crop and regional differences in N_{Irrig} (Fig. 1) Rice from South and Southeast Asia, China (primarily), India and Vietnam had the most observations, with high irrigation volumes but modest N_{Irrig} (Extended Data Fig. 1 and Supplementary Figs. 1 and 2). Despite this, several regions showed much higher N_{Irrig}, such as Japan, where nearly 60% of the observations exceeded 100 kg N ha^{-1} yr^{-1}. High values also occurred in South Korea, Indonesia and Bangladesh, where N_{Irrig} contributed up to 64% of total N inputs.

Among crops with more than 50 observations, vegetables had both the broadest spatial coverage and the highest N_{Irrig} values (Extended Data Fig. 1). The median N_{Irrig} was 38 kg N ha^{-1} yr^{-1}, with 22% of the observations exceeding 100 kg N ha^{-1} yr^{-1} and occasional values above 500 kg N ha^{-1} yr^{-1}. However, N_{Irrig} accounted for a smaller fraction of total N inputs, as vegetable systems rely heavily on synthetic fertilizers. The highest N_{Irrig} values occurred in Central Asia, Sub-Saharan Africa and Southeast Asia. China (n = 83) and the USA (n = 48) had the largest coverage, with 14% and 31% surpassing 100 kg N ha^{-1} yr^{-1}, respectively.

Maize showed moderate N_{Irrig} values, with fewer extremes than rice or vegetables, but higher N_{Irrig} shares in total N inputs. Observations were mostly from the USA (n = 62), Spain and China. The US median N_{Irrig} was 19 kgN ha^{-1} yr^{-1}, roughly half the median reported for Spain.

Wheat and potatoes showed similar N_{Irrig} patterns to maize, with observations concentrated in Spain, the USA and China. Among less-represented crops, sugarcane and tomatoes had particularly high N_{Irrig} values in Latin America and China, respectively.

From field observations to global implications

Our gridded predictions of total N_{Irrig} showed a median of 46 kg N ha^{-1} yr^{-1} (IQR 35–71) across irrigated land, with 16% of the area exceeding 100 kg N ha^{-1} yr^{-1} (Fig. 2a). Although arbitrary, we use 100 kg N ha^{-1} yr^{-1} as a threshold to define potential management hotspots where irrigation may be agronomically substantial. We identify four multicrop clusters of hotspots (Fig. 2b) as regions of particular interest.

The most widespread cluster spanned from North Africa to South Asia (Fig. 2b), covering irrigated areas from the Nile Delta through Western and Central Asia to India (Extended Data Fig. 2). A second cluster was identified in rice paddies across most of Southeastern Asia. A third cluster covered Eastern China and Japan for rice, maize and vegetables. The fourth cluster included irrigated areas in the central and eastern US Great Plains region, primarily for crops such as maize, vegetables and wheat. Smaller clusters were also identified in Southern Europe (vegetables, maize and wheat), Southeast Brazil and Uruguay (sugarcane, maize and vegetables) and in parts of the Northern Andes (sugarcane in Colombia and Ecuador). Other crops, such as soybeans, cotton and potatoes, showed a similar spatial variation (Supplementary Figs. 3–7). The area of applicability, based on our training data, covered 95 ± 1% of irrigated crop areas (Extended Data Fig. 3).

We next assessed the global implications and regional importance by estimating the total N_{Irrig} for each crop as the product of irrigated areas in hectares and the N_{Irrig} per hectare (Fig. 3a). Globally, N_{Irrig} amounted to 13.8 Tg N yr^{-1} over 260 million ha of irrigated land. Together, rice (36%), wheat (23%) and maize (11%) accounted for 70% of the total contribution, each receiving about 50 kg N ha^{-1} yr^{-1}. Other crops had a much lower contribution, but with strong regional variations.

Regional totals varied markedly, with Eastern Asia (32%), Southern Asia (30%) and Southeastern Asia (10%) accounting for more than three-quarters of the global N_{Irrig}. Central Asia contributed 0.8 Tg N yr^{-1}, which is comparable to North America and Latin America and slightly more than North Africa (0.5 Tg N yr^{-1}). All remaining regions amounted to less than 8% of the global total.

Regional differences also extended to crop-specific N_{Irrig} patterns (Extended Data Fig. 4). Rice had the largest share of N_{Irrig} in Southeastern Asia (84% of N_{Irrig}) and the highest contribution of any crop in Eastern Asia (1.8 Tg N yr^{-1}). It also accounted for 28–55% of regional N_{Irrig} in Sub-Saharan Africa, Southern Asia and Latin America. Wheat contributed the most in Southern Asia (1.5 TgN yr^{-1}) and had the highest relative contribution in Central and Western Asia and North Africa. Maize was the main contributor in North America (35%) and in Southern and Western Europe. Other crops, such as sugarcane and cotton, were also important in Oceania and Africa and Central Asia, respectively.

At the national level (Fig. 3b), China totalled the highest N_{Irrig}, supplying twice as much as India and four times more than Pakistan (4.2 Tg N yr^{-1} versus 2.2 TgN yr^{-1} and 1.1 Tg N yr^{-1}, respectively). Aside from the USA (0.8 Tg N yr^{-1}), substantial contributions were mainly Egypt, Iran, Indonesia and Vietnam. Sub-Saharan African and European countries had very low total N_{Irrig} (0.004 ± 0.008 Tg N yr^{-1}), driven by smaller irrigated areas rather than low N_{Irrig} intensity (Fig. 3 and Supplementary Fig. 8). Countries in both regions had a median N_{Irrig} around 47 kg N ha^{-1} yr^{-1}.

Importance of irrigation in cropland nitrogen inputs

We estimate that irrigation water contributes nearly 14 Tg N yr^{-1} to global croplands, equivalent to 13% of global synthetic fertilizer usage (Fig. 4). This considerable amount of N must not be neglected in global representations of N flows at the agrofood system scale. This amount is similar to the total ammonia volatilized[22] and deposited onto cropland[23] and the N embodied in international trade[24]. Including N_{Irrig} in fertilizer recommendations would lower synthetic fertilizer requirements in many irrigated systems, improving N-use efficiency. The magnitude of the associated benefits would, however, differ regionally since this depends on local water quality, existing recommendation practices and the extent to which N_{Irrig} is already included.

We further assessed how N_{Irrig} affects the dependency on synthetic fertilizers using fertilizer dependency (FD), an indicator that measures the reliance on external N applied by farmers[25]. At the global scale, FD is presently estimated at 75%. When N_{Irrig} is considered a recovered N source and an equivalent portion of synthetic fertilizers is adjusted, global FD decreases to 67%. Reduction of fertilizers can represent less N_{Irrig} in the medium term and optimal fertilization will require re-estimation.

Our results confirm that this 'hidden' input is not only agriculturally relevant but also capable of reshaping N budgets. This directly affects fertilization strategies and agri-environmental policies because N_{Irrig} influences total N inputs, the risk of environmental losses and cycling processes[3].

When considered in the calculations of total N inputs to crops in irrigated systems (Fig. 1), N_{Irrig} exceeded synthetic fertilizers contributions in almost a quarter of all observations. Its magnitude varied by crops, reflecting differences in irrigation and N management. Although N_{Irrig} rises with both irrigation N inputs, it increases sharply once N inputs exceed around 250 kg N ha^{-1} yr^{-1} and irrigation surpasses 1,000 mm yr^{-1} (Supplementary Fig. 8). Total N inputs consistently had a stronger effect on N_{Irrig} than irrigation across all crops, particularly in rice and vegetables (Supplementary Figs. 9 and 10). Differences in irrigation technology may also influence irrigation volumes[26] and therefore N_{Irrig}, although these effects were not included in our approach. N_{Irrig} is highest in high-input irrigated systems, a field-level pattern that also emerges in the global predictions.

Our predictions show that N_{Irrig} clusters coincide with major agricultural production zones (Fig. 3) already recognized for high N surpluses[27]. However, the dominant drivers of N_{Irrig} vary regionally.

https://doi.org/10.1038/s41893-026-01930-8

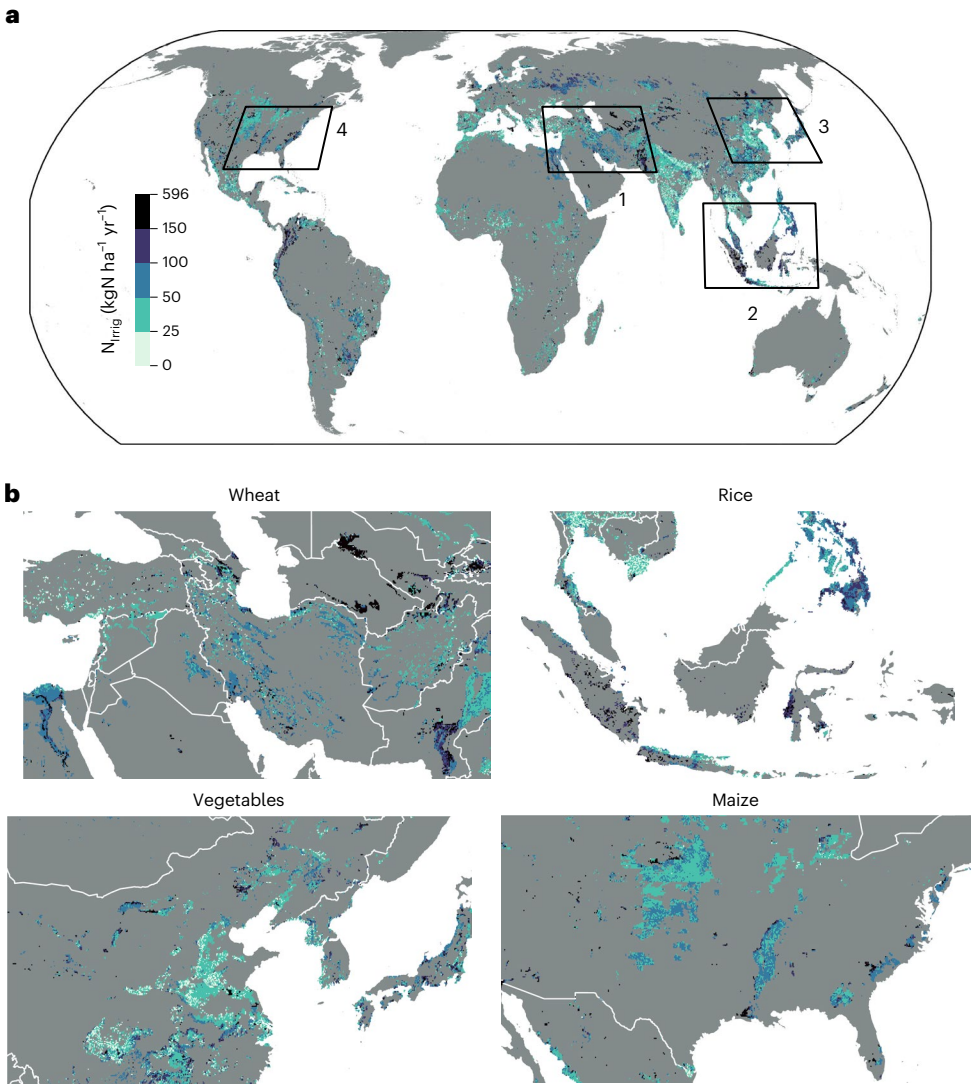


Fig. 2 | Nitrogen inputs from irrigation water are concentrated in global hotspots. a, Spatial variation of the total N_{Irrig} for the period 2010–2019 at 100 km^2 resolution, although the predictions shown were averaged to 400 km^2 for clearer visualization. Clusters marked 1–4 are shown in **b**. **b**, Zoomed regional clusters (regions of interest, where N_{Irrig} consistently exceeds 100 kg N ha^{-1} yr^{-1}) for the main irrigated crops at 100 km^2 resolution. All panels share the same colour scale. Grey areas indicate non-irrigated land in each geographical extent. Individual crop-specific N_{Irrig} are available in Supplementary Figs. 3–7. Basemap data in **b** from Natural Earth. Basemaps were transformed to Eckert IV projection and are shown without Antarctica.

In drier regions, such as Southern Europe and California, high N_{Irrig} contributions are primarily driven by irrigation rates. In temperate regions such as Western Europe, N_{Irrig} is more strongly influenced by N inputs. In other regions, such as the Nile delta and Pakistan, both high irrigation demand and N inputs drive N_{Irrig} (Extended Data Fig. 5).

These clusters do not automatically translate into large national contributions. This is because total N_{Irrig} is driven more by irrigated area than by per hectare N_{Irrig} intensity (Supplementary Figs. 11 and 12). This creates a scale discrepancy, where N_{Irrig} can be agronomically important in irrigated areas but remain negligible in national N budgets when irrigation covers only a small share of cropland. For example, in Sub-Saharan Africa, N_{Irrig} contributes little to national N budgets because only 5% of croplands are irrigated, while still showing local areas with high N_{Irrig} contributions (Fig. 2). This illustrates that small irrigated areas can still serve as meaningful management hotspots even if their national influence is small. Omitting N_{Irrig} can also bias national N indicators, leading to overestimation of cropland N-use efficiency in countries with high N_{Irrig} dependency (Extended Data Fig. 6).

Despite this spatial heterogeneity, our national-scale predictions of N_{Irrig} show strong agreement with external datasets[16,20] (Supplementary Figs. 13 and 14 and Supplementary Table 1). To support the integration of N_{Irrig} into N budgets at different scales, we propose a tiered estimation flowchart (Extended Data Fig. 7). This offers a practical methodology for estimating N_{Irrig} in both data-poor areas and areas with high-resolution monitoring. Our estimations offer a reasonable starting point for national to global N budgets.

Our findings imply that N_{Irrig} needs to be integrated N_{Irrig} into planetary boundary frameworks[28], thereby refining regional thresholds of critical N inputs. Where N_{Irrig} contributes substantially to total N supply, the critical thresholds for those inputs may be lower than previously estimated[29]. Irrigation also affects the risk of exceeding the acceptable N limits for ground and surface waters, particularly where runoff and leaching are amplified by inefficient irrigation practices and legacy nitrate. Addressing these challenges requires agronomic know-how with coordinated policy efforts that bridge nutrient and water governance.

Policy and management implications

Translating evidence on N_{Irrig} into practice remains challenging, even if its relevance is recognized. Some countries, such as Spain and Portugal[17], already include N_{Irrig} in fertilization guidelines, but

https://doi.org/10.1038/s41893-026-01930-8

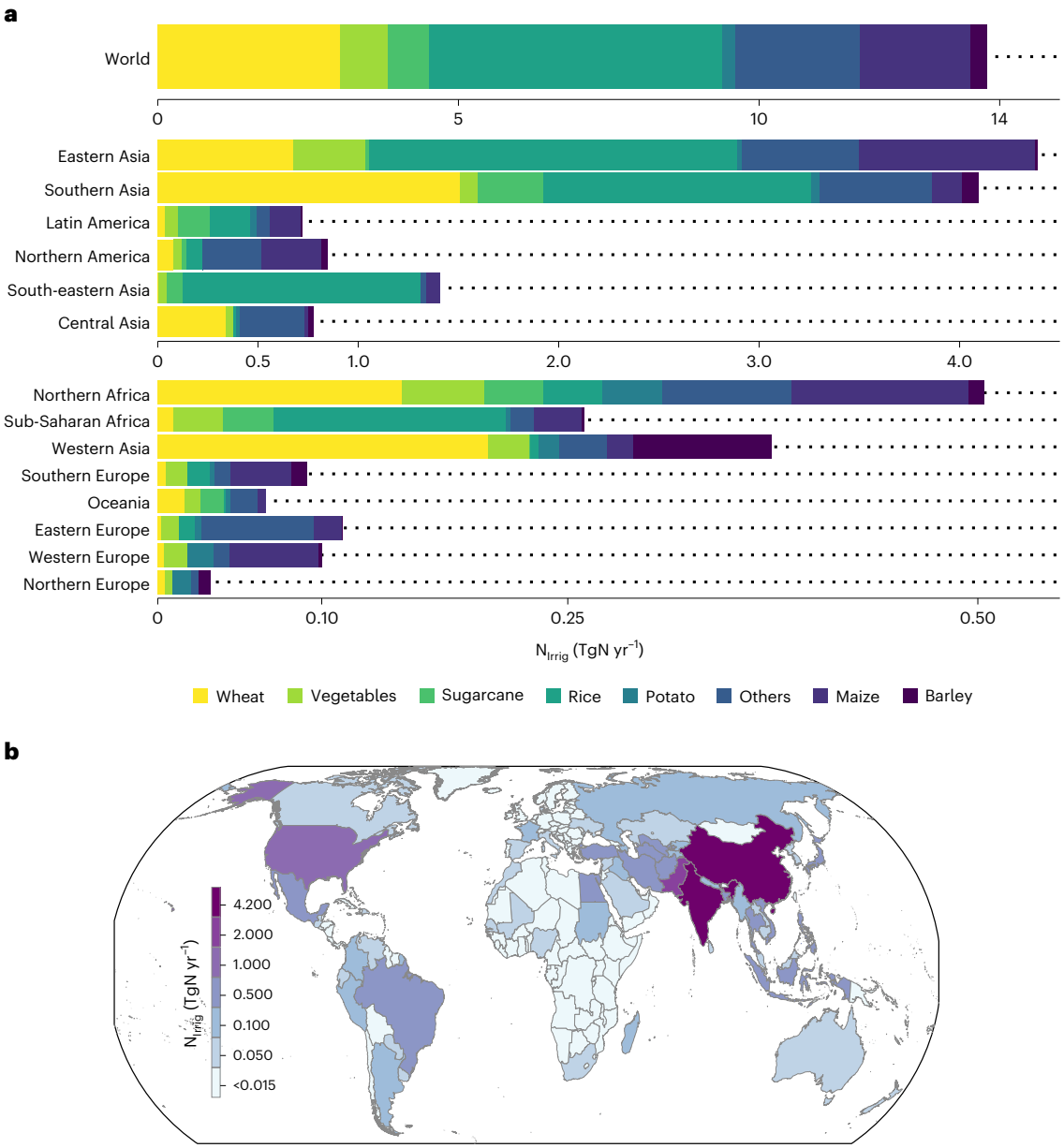


Fig. 3 | Nitrogen inputs from irrigation water strongly vary among regions and countries. a, Global and regional contributions of N_{Irrig} for all crops. **b**, Total N_{Irrig} contribution at the national level for the average conditions during 2010–2019. Global and regional totals include both cells inside and outside the area of applicability. Other crops refer to beans, soybeans, chickpeas, cotton, groundnuts, rapeseed, sugar beet and sunflower. In this group, cotton is the largest contributor globally (1.1 Tg N yr^{-1}), mainly from Eastern Asia (0.4), Central Asia (0.3), Southern Asia (0.3) and Northern America (0.10). Other regionally important contributions included soybeans in Northern America (0.2) and Eastern Asia (0.1), rapeseed in Southern Asia (0.1), groundnuts in Eastern Asia (0.1) and Northern Africa (0.03) and sugar beet in Northern Africa (0.02) and Western Europe (0.01). Regional aggregations follow the United Nations subregion classification, with Latin America including Central/South America and the Caribbean. Basemap data in **b** from Natural Earth. Basemaps were transformed to Eckert IV projection and are shown without Antarctica.

implementation remains inconsistent elsewhere. In India, for example, policy-makers have identified the lack of N concentration measurements[30] as a barrier to including N_{Irrig} in fertilization guidelines. Similar data gaps contribute to N_{Irrig} being largely absent from global and national N budgets, in which N_{Irrig} is often overshadowed by synthetic fertilizers and manure inputs[31].

Unlike synthetic fertilizers, which farmers apply in known amounts, N_{Irrig} is highly variable and more difficult to quantify. This variability makes it difficult to distinguish newly introduced N from legacy nitrate recirculated through irrigation after decades of fertilizer accumulation[27]. However, since current fertilization guidelines already account for uncertain inputs (for example, soil N supply), including N_{Irrig} would represent a similar adjustment rather than a fundamental change.

N_{Irrig} represents a new opportunity for improving N management without creating new policy structures. It fits well with existing regulations, such as the EU Farm to Fork strategy, which aims to reduce FD and promote nutrient circularity, and the US Clean Water Act, which promotes the re-use of treated effluents for irrigation[32]. N_{Irrig} also complements policy instruments that use N budgeting by improving estimates of total N inputs across scales[33], preventing the underestimation of N pollution and the overestimation of N-use efficiency[16].

Operationalizing N_{Irrig} in policy frameworks requires overcoming technical, social and institutional barriers. A primary challenge

https://doi.org/10.1038/s41893-026-01930-8

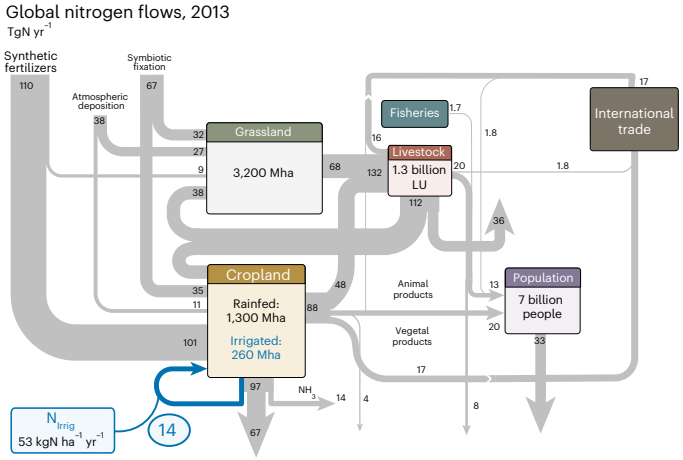


Fig. 4 | Irrigation water represents a considerable nitrogen flow in the global agrofood system. Global representation of the agrofood system (GRAFS) in 2013, expressed in N flows between main system compartments. LU, livestock unit.

is the limited awareness among farmers, particularly their risk perception and willingness to adopt new practices. This also extends to water managers and agricultural extension services, who may not fully acknowledge the dual role of irrigation as both a water and N input. The connection between N and water management in irrigated systems remains weak[34], even though irrigation can alter river flows and groundwater levels, impacting nitrate transport and affecting water quality[35]. Seasonal variation in nitrate concentrations further complicates management[9].

Social and financial barriers also limit adoption, particularly where irrigation infrastructure is underdeveloped and nitrate monitoring tools are lacking. This is of special importance not only to agriculture, but also to public health, because nitrate concentration in drinking water is linked to an increased cancer risk[36]. Investing in monitoring technologies may require upfront investment and regular maintenance costs, but over time these tools can be more cost-effective than relying on additional fertilizer inputs.

Addressing these barriers will require both incentives and regulatory mechanisms. Digital tools, such as satellite-based irrigation monitoring and farmer self-reporting platforms, could support policy compliance while minimizing administrative burdens. These platforms can facilitate the use of simple, low-cost tools to monitor nitrate concentrations in irrigation water. Their widespread adoption can generate valuable large-scale datasets, especially in regions with limited monitoring infrastructure. Public institutions could subsidize nitrate measurements and N_{Irrig} estimates, providing the data required to adjust fertilization rates (Supplementary Fig. 15). Funding of training programmes through extension services can build farmer capacity to measure, interpret and act according to nitrate data. Demonstration projects have already shown that N_{Irrig} can be used as efficiently as synthetic fertilizers[37], helping to shift farmers' perceptions and encourage a broader adoption.

Recognizing irrigation water as an N input reframes how water and N are co-managed in agriculture, supporting efforts to reduce FD and enhance nitrogen circularity.

Methods

Data collection

We developed a global dataset of N_{Irrig} by systematically reviewing the existing scientific literature from the Web of Science database, conforming to the PRISMA guidelines (Supplementary Fig. 16). Our bibliometric query targeted studies focused on N balances from irrigated agricultural systems using the keywords 'N' and ('balance' or 'budget') and ('irrigated' or 'irrigation'). We did not impose any time or crop restrictions to better assess the full extent of research focused on N_{Irrig}. Our requirements were that (1) N_{Irrig}, irrigation rates and total N inputs (N_{Inputs}) had to be reported and (2) publications focused only on field experiments or at the farm level.

The initial dataset contained over 1,700 publications, but only 102 (n = 802 observations) conformed to our requirements after manual inspection. Three external datasets were added to the data pool (n = 523): the first contained observations of several crops across Spain (n = 167), the second reported maize in Nebraska (n = 34) and the last one (n = 320) contained observations for rice across South Asia and Southeastern Asia. This totalled 1,325 observations from 105 individual sources. We populated the dataset with key information, such as coordinates, country, year and crop. We prioritized crop-specific studies, but we also collated data if the values were aggregated at crop-rotation level. Where available, we extracted data concerning nitrate concentration in irrigation water, irrigation water sources and irrigation systems. Those data were not used for the upscaling approach (see 'Upscaling the nitrogen inputs from irrigation water') since global gridded products are not available. All data were aggregated to yearly values if provided at daily or monthly timesteps according to growing season or irrigation period.

Upscaling the nitrogen inputs from irrigation water

We spatially upscaled crop-specific N_{Irrig} from field experiments to a gridded resolution of 100 km^2 for the average conditions during 2010–2019 using a random forests model. The primary crops, chosen according to their relevance in our dataset (Supplementary Fig. 1), but also in global food production, were maize, rice, vegetables, sugarcane, potato, wheat and barley[38]. The secondary crops, less covered in our dataset, were beans, chickpeas, cotton, groundnuts, rapeseed, soybeans, sugar beet and sunflower.

We compiled a georeferenced dataset with predictors that may drive N_{Irrig} from groundwater and surface waters (irrigation channels and rivers). No global high-resolution map of nitrate concentration in groundwater and surface water exists, so we used total cropland N inputs[39] as a proxy for both the potential losses to these water sources and management intensity. Note this concerns total cropland, and not its irrigated fraction, since those data are not available. We derived average crop-specific irrigation rates for the period 2010–2019[40], estimated at 100 km^2. Other covariates, such as population density and pedoclimatic conditions, are identified in Supplementary Table 2. We extracted information from the spatial covariates by averaging the values around a 5-km buffer within the coordinates of the observations.

The random forests model was trained and tuned on the basis of N_{Irrig} observations and geospatial covariates. Because the observations were highly clustered, we used different cross-validation strategies (Supplementary Methods and Supplementary Figs. 17–19) to balance performance and the maximization of the predictive geographical domain. The most pertinent strategy was the spatial stratification of the observations according to experimental sites. The cross-validated hyper-tuned model obtained a weighted performance with an R^2 of 0.38 and a root mean square error of 73 kgN ha^{-1} yr^{-1}. The performance was slightly better than spatial cross-validation and about half and a third of the performance achieved by random tenfold cross-validation and the typical partition into training (70%) and testing (30%) subsets, respectively. We provide a comparison across sampling strategies concerning the total area of applicability and N_{Irrig} (Supplementary Figs. 20 and 21), but also with different crop maps (Supplementary Figs. 22–26).

We addressed the constraints concerning spatial clustering in our dataset by using the concept of 'area of applicability'[41] (AOA). We calculated the AOA for each crop on the basis of the variable importance of the hyper-tuned model, along with a dissimilarity threshold defined by the training data[41]. The dissimilarity index, a measure of the distances to the training data in the multidimensional predictor variable space, was also computed. To enhance the transparency of regions not well

covered, we predicted the N_{Irrig} inside and outside the AOA. Predictions and AOA were masked according to crop irrigated areas (≥5 ha per grid cell) from MapSPAM for 2020[42].

Cropland nitrogen indicators

We contextualize the importance of N_{Irrig} by including it in one important performance indicator, the N_{Irrig} dependency or FD, depending on the focus. N_{Irrig} dependency ($\%N_{Inputs}$) was estimated as the ratio of N_{Irrig} and total N inputs, and FD ($\%N_{Inputs}$) as the ratio of synthetic and total N inputs. Apart from N_{Irrig}, the included inputs are synthetic fertilizers, manure application, biological N fixation from grain legumes and atmospheric deposition.

We analysed the impact of N_{Irrig} in both field observations and gridded predictions, but also at the national levels[43]. We independently estimated gridded cropland N inputs (Supplementary Information), whereas for regional scales we sourced those data from elsewhere[43]. For the field observations, the N inputs depended on the reported data and therefore varied on a crop basis and study basis.

Limitations

Our predictions share common limitations from global data-driven studies, affecting both model accuracy and generalizability. First, we acknowledge the biases towards regions with a larger emphasis on irrigation practices and environmental concern with N management that are sufficiently socioeconomically developed to enable the management of field trials. Regions such as Latin America, Sub-Saharan Africa and Southeastern Asia are under-represented (Fig. 1b). Since the predictions in these regions were performed beyond the training data, the errors were amplified as the dissimilarity index increased (Supplementary Fig. 27). Furthermore, the lack of generalization from the cross-validated dataset probably stems from not explicitly including individual crops in the model as a result of data limitations.

Second, our predictions are subject to both underestimations and overestimations. Underestimations probably result from the exclusion of irrigated permanent crops (for example, olives and citrus) because of data limitations, as these commonly receive more than 100 kg N ha^{-1} yr^{-1} via irrigation[16]. Overestimations may occur in the absence of well-defined system boundaries, because nitrate can be recirculated via irrigation, leading to a double accounting in N budgets, as is the case with atmospheric N deposition[44].

Third, the magnitude of N_{Irrig} in our gridded predictions depends on nitrate observations measured in the field experiments. We are unable to provide quality checks of the main irrigation source driving N_{Irrig} in the gridded maps because global maps of nitrate concentration in groundwater and surface water are not available. As a workaround, we used total N inputs in cropland as a proxy for water-quality contamination, but these are guesstimates. It is likely that the availability of spatially explicit nitrate concentrations in irrigation water sources would greatly improve the accuracy and applicability of our model. We nonetheless provide both a comparison with external data sources and a plausibility assessment of our estimates, particularly of the associated nitrate concentrations (Supplementary Results, Supplementary Figs. 28 and 29 and Supplementary Table 1).

Finally, there are other uncertainties related to the irrigated crop maps used to mask the predictions, because considerable differences exist with other crop maps (Supplementary Figs. 22–26) and crop irrigation water use. These uncertainties were propagated to the gridded maps because cropland N inputs and irrigation were the most important predictors (Supplementary Fig. 18), trained with measured data in the field experiments. Additionally, we also tested the effect of adding crop-specific N fertilizer rates[4] as a predictor, but this did not improve performance under the same site-level cross-validation strategy (Supplementary Table 3). Our modelling approach will bring benefit once new field measurement data are available, as well as more accurate spatial predictors.

Reporting summary

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

Data availability

The global gridded datasets of N_{Irrig} generated here, as well as national aggregations, are available via figshare at https://doi.org/10.6084/m9.figshare.29470148 (ref. 45). The underlying dataset, final machine learning model and training data are also available in the same repository. Source data are provided with this paper.

Code availability

The machine learning R pipeline and the scripts used to create Figs. 1–3 are available via figshare at https://doi.org/10.6084/m9.figshare.29470148 (ref. 45).

References

1. Van Puijenbroek, P. J. T. M., Beusen, A. H. W. & Bouwman, A. F. Global nitrogen and phosphorus in urban waste water based on the shared socio-economic pathways. *J. Environ. Manag.* **231**, 446–456 (2019).
2. Micella, I., Kroeze, C., Bak, M. P. & Strokal, M. Causes of coastal waters pollution with nutrients, chemicals and plastics worldwide. *Mar. Pollut. Bull.* **198**, 115902 (2024).
3. Zhang, B. et al. Leaching of dissolved organic nitrogen in long-term organic and conventional crop rotations in Denmark. *Eur. J. Agron.* **164**, 127482 (2025).
4. Harter, T. et al. *Report for the State Water Resources Control Board to the Legislature* (Center for Watershed Sciences, UC Davis, 2012).
5. Wu, B. et al. Quantifying global agricultural water appropriation with data derived from earth observations. *J. Clean. Prod.* **358**, 131891 (2022).
6. Haile, G. G. et al. Projected impacts of climate change on global irrigation water withdrawals. *Agric. Water Manag.* **305**, 109144 (2024).
7. Beusen, A. H. W. et al. Exploring river nitrogen and phosphorus loading and export to global coastal waters in the Shared Socio-economic pathways. *Glob. Environ. Change* **72**, 102426 (2022).
8. Mehta, P. et al. Half of twenty-first century global irrigation expansion has been in water-stressed regions. *Nat. Water* **2**, 254–261 (2024).
9. Campbell, T. A., Masarik, K. C., Heineman, E. M. & Kucharik, C. J. Quantifying the spatiotemporal variability of nitrate in irrigation water across the Wisconsin Central Sands. *J. Environ. Quality* **52**, 1102–1114 (2023).
10. Yin, Y. et al. Co-benefits for cropland yield, nitrogen emissions, and climate impact through multi-objective optimization agricultural manure solutions. *Nat. Commun.* **16**, 6415 (2025).
11. Orduña Alegría, M. E. et al. Unlocking aquifer sustainability through irrigator-driven groundwater conservation. *Nat. Sustain.* **7**, 1574–1583 (2024).
12. Quemada, M., Baranski, M., Nobel-de Lange, M. N. J., Vallejo, A. & Cooper, J. M. Meta-analysis of strategies to control nitrate leaching in irrigated agricultural systems and their effects on crop yield. *Agric. Ecosyst. Environ.* **174**, 1–10 (2013).
13. Cameira, M. R. et al. Spatial distribution and uncertainties of nitrogen budgets for agriculture in the Tagus river basin in Portugal—implications for effectiveness of mitigation measures. *Land Use Policy* **84**, 278–293 (2019).
14. Quemada, M. et al. Exploring nitrogen indicators of farm performance among farm types across several European case studies. *Agric. Syst.* **177**, 102689 (2020).

15. Meisinger, J. J., Calderón, F. J. & Jenkinson, D. S. In *Nitrogen in Agricultural Systems* (eds Schepers, J. S. & Raun, W. R.) 505–562 (John Wiley, 2008).
16. Serra, J. et al. Nitrogen inputs by irrigation is a missing link in the agricultural nitrogen cycle and related policies in Europe. *Sci. Total Environ.* **889**, 164249 (2023).
17. Serra, J. et al. Is irrigation water an overlooked source of nitrogen in agriculture?. *Agric. Water Manag.* **278**, 108147 (2023).
18. He, W. et al. Estimating soil nitrogen balance at regional scale in China's croplands from 1984 to 2014. *Agric. Syst.* **167**, 125–135 (2018).
19. Flint, E. M., Ascott, M. J., Gooddy, D. C., Stahl, M. O. & Surridge, B. W. J. Water supply processes are responsible for significant nitrogen fluxes across the United States. *Glob. Biogeochem. Cycles* **36**, e2022GB007340 (2022).
20. Gu, B. et al. Cost-effective mitigation of nitrogen pollution from global croplands. *Nature* **613**, 77–84 (2023).
21. Smil, V. Nitrogen in crop production: an account of global flows. *Glob. Biogeochem. Cycles* **13**, 647–662 (1999).
22. Zhan, X. et al. Improved estimates of ammonia emissions from global croplands. *Environ. Sci. Technol.* **55**, 1329–1338 (2021).
23. Vishwakarma, S., Zhang, X., Dobermann, A., Heffer, P. & Zhou, F. Global nitrogen deposition inputs to cropland at national scale from 1961 to 2020. *Sci. Data* **10**, 488 (2023).
24. Lassaletta, L. et al. Nitrogen use in the global food system: past trends and future trajectories of agronomic performance, pollution, trade, and dietary demand. *Environ. Res. Lett.* **11**, 095007 (2016).
25. Quemada, M. & Lassaletta, L. Fertilizer dependency: a new indicator for assessing the sustainability of agrosystems beyond nitrogen use efficiency. *Agron. Sustain. Dev.* **44**, 44 (2024).
26. Li, H. et al. Drip fertigation significantly increased crop yield, water productivity and nitrogen use efficiency with respect to traditional irrigation and fertilization practices: a meta-analysis in China. *Agric. Water Manag.* **244**, 106534 (2021).
27. Bouwman, A. F., Beusen, A. H. W., Doelman, J. C., Stehfest, E. & Westhoek, H. Impact of lifestyle, human diet and nutrient use efficiency in food production on eutrophication of global aquifers and surface waters. *Glob. Environ. Change* **87**, 102874 (2024).
28. Schulte-Uebbing, L. F., Beusen, A. H. W., Bouwman, A. F. & de Vries, W. From planetary to regional boundaries for agricultural nitrogen pollution. *Nature* **610**, 507–512 (2022).
29. Rockström, J. et al. Safe and just Earth system boundaries. *Nature* **619**, 102–111 (2023).
30. Subba Rao, A. et al. In *The Indian Nitrogen Assessment* (eds Abrol, Y. P. et al.) 59–76 (Elsevier, 2017).
31. Jordan-Meille, L. et al. Comparison of nitrogen fertilisation recommendations of West European countries. *Eur. J. Soil Sci.* **74**, e13436 (2023).
32. Mishra, S., Kumar, R. & Kumar, M. Use of treated sewage or wastewater as an irrigation water for agricultural purposes—environmental, health, and economic impacts. *Total Environ. Res. Themes* **6**, 100051 (2023).
33. Dalgaard, T. et al. Policies for agricultural nitrogen management—trends, challenges and prospects for improved efficiency in Denmark. *Environ. Res. Lett.* **9**, 115002 (2014).
34. Seijger, C. & Hellegers, P. How do societies reform their agricultural water management towards new priorities for water, agriculture, and the environment?. *Agric. Water Manag.* **277**, 108104 (2023).
35. Pinardi, M. et al. Agricultural practices regulate the seasonality of groundwater-river nitrogen exchanges. *Agric. Water Manag.* **273**, 107904 (2022).
36. Mendy, A. & Thorne, P. S. Long-term cancer and overall mortality associated with drinking water nitrate in the United States. *Public Health* **228**, 82–84 (2024).
37. Cahn, M., Smith, R., Murphy, L. & Hartz, T. Field trials show the fertilizer value of nitrogen in irrigation water. *Calif. Agric.* **71**, 62–67 (2017).
38. Smith, N. W., Fletcher, A. J., Millard, P., Hill, J. P. & McNabb, W. C. Estimating cropland requirements for global food system scenario modeling. *Front. Sustain. Food Syst.* **6**, 1063419 (2022).
39. Tian, H. et al. History of anthropogenic Nitrogen inputs (HaNi) to the terrestrial biosphere: a 5 arcmin resolution annual dataset from 1860 to 2019. *Earth Syst. Sci. Data* **14**, 4551–4568 (2022).
40. Mialyk, O. et al. Water footprints and crop water use of 175 individual crops for 1990–2019 simulated with a global crop model. *Sci. Data* **11**, 206 (2024).
41. Meyer, H. & Pebesma, E. Predicting into unknown space? Estimating the area of applicability of spatial prediction models. *Methods Ecol. Evol.* **12**, 1620–1633 (2021).
42. Global spatially-disaggregated crop production statistics data for 2020 version 2.0. *Harvard Dataverse* https://doi.org/10.7910/DVN/SWPENT (2026).
43. Ludemann, C. I. et al. A global FAOSTAT reference database of cropland nutrient budgets and nutrient use efficiency (1961–2020): nitrogen, phosphorus and potassium. *Earth Syst. Sci. Data* **16**, 525–541 (2024).
44. Leip, A. et al. Halving nitrogen waste in the European Union food systems requires both dietary shifts and farm level actions. *Glob. Food Secur.* **35**, 100648 (2022).
45. Serra, J. Global analysis of nitrogen inputs from irrigation water to cropland. *figshare* https://doi.org/10.6084/m9.figshare.29470148 (2025).

Acknowledgements

We thank R. Buresh and P. Grassini for sharing data in kind. We also thank the researchers whose published datasets enabled this study.

Author contributions

J.S. created the concept and design of the study, with support from all co-authors. L.L. calculated the global representation of food systems. J.S. collected and compiled the dataset, with support from M.Q. and A.D. J.S. built the machine learning model to predict N_{Irrig} and all subsequent analysis, with input from all authors. All authors wrote the paper.

Funding

J.S., J.R., K.B.-B., T.D. and M.G. disclose support for the research of this work from the Pioneer Center for Research in Sustainable Agricultural Futures (DNRF grant agreement no. P2). J.S., C.S.C.M.-d.-S. and M.R.C. disclose support for the research of this work from Fundação para a Ciência e a Tecnologia, I.P., through project references UID/00239/2025 (https://doi.org/10.54499/UID/00239/2025), UID/PRR/00239/2025 (https://doi.org/10.54499/UID/PRR/00239/2025) and LA/P/0092/2020 (https://doi.org/10.54499/LA/P/0092/2020). J.S., C.S.C.M.-d.-S. and M.R.C. also disclose support for the research of this work from the Path4Med project, 'Demonstrating Innovative Pathways Addressing Water and Soil Pollution in the Mediterranean Agro-Hydro-System', funded by the European Union under the Horizon Europe programme (grant agreement no. 101156867). L.L. and M.Q. disclose support for the research of this work from European Union under the Horizon Europe programme (RAINS project, grant agreement no. 101181890). L.L. and E.A. disclose support for the research of this work from AgrosceNa-NEXT, PID2023-152562OB-I00, funded by MCIU/AEI/10.13039/501100011033 and FEDER, UE.

F.G.-K., X.Z., A.D., W.D.V. and G.H.R. declare no relevant funding. Views and opinions expressed are those of the authors only and do not necessarily reflect those of the European Union or the granting authority. Neither the European Union nor the granting authority can be held responsible for them.

Competing interests
The authors declare no competing interests.

Additional information
Extended data is available for this paper at https://doi.org/10.1038/s41893-026-01930-8.

Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s41893-026-01930-8.

Correspondence and requests for materials should be addressed to J. Serra.

Peer review information *Nature Sustainability* thanks Tyler Hampton and the other, anonymous, reviewer(s) for their contribution to the peer review of this work. Peer reviewer reports are available.

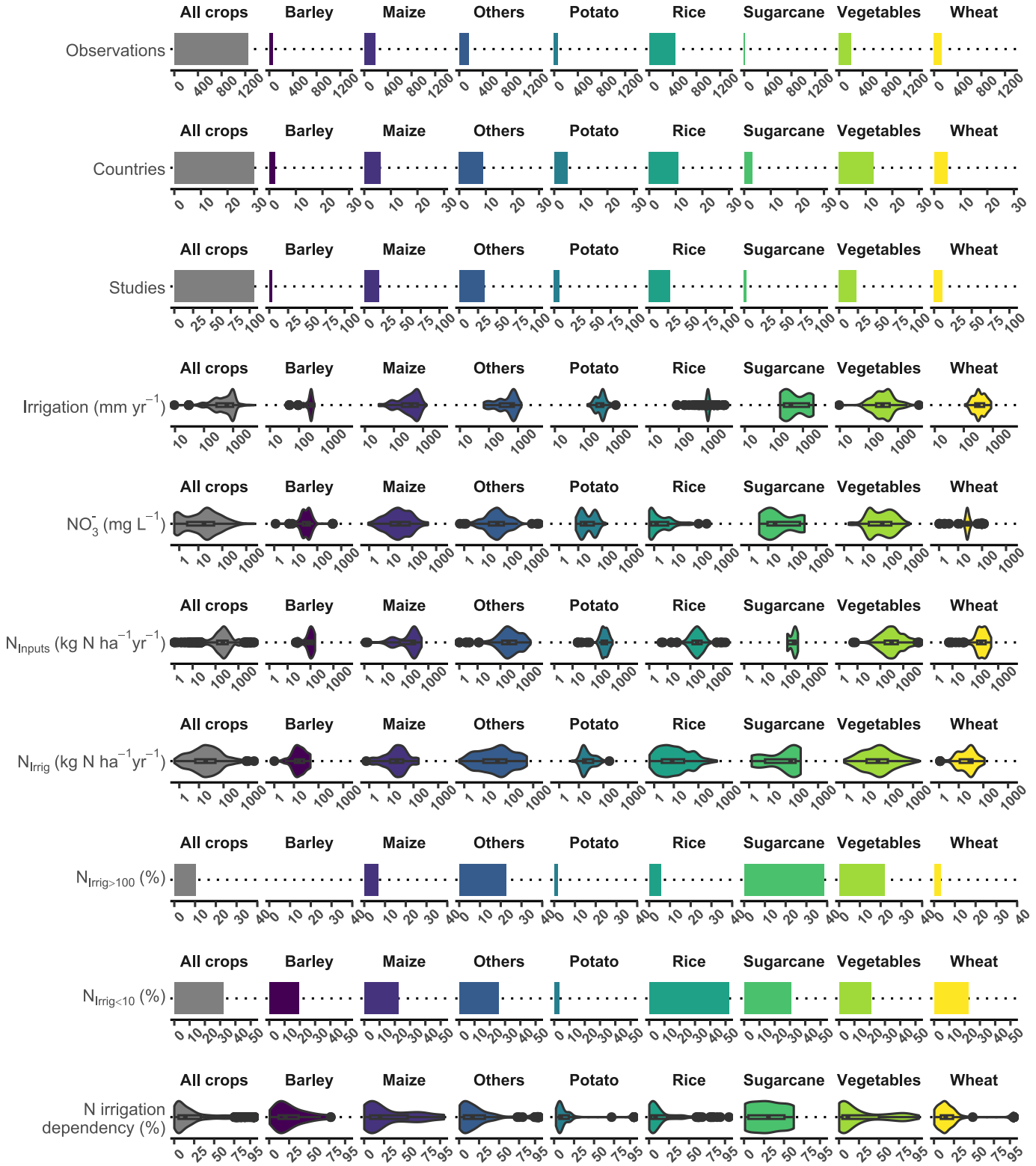
Reprints and permissions information is available at www.nature.com/reprints.

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Open Access This article is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License, which permits any non-commercial use, sharing, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if you modified the licensed material. You do not have permission under this licence to share adapted material derived from this article or parts of it. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by-nc-nd/4.0/.

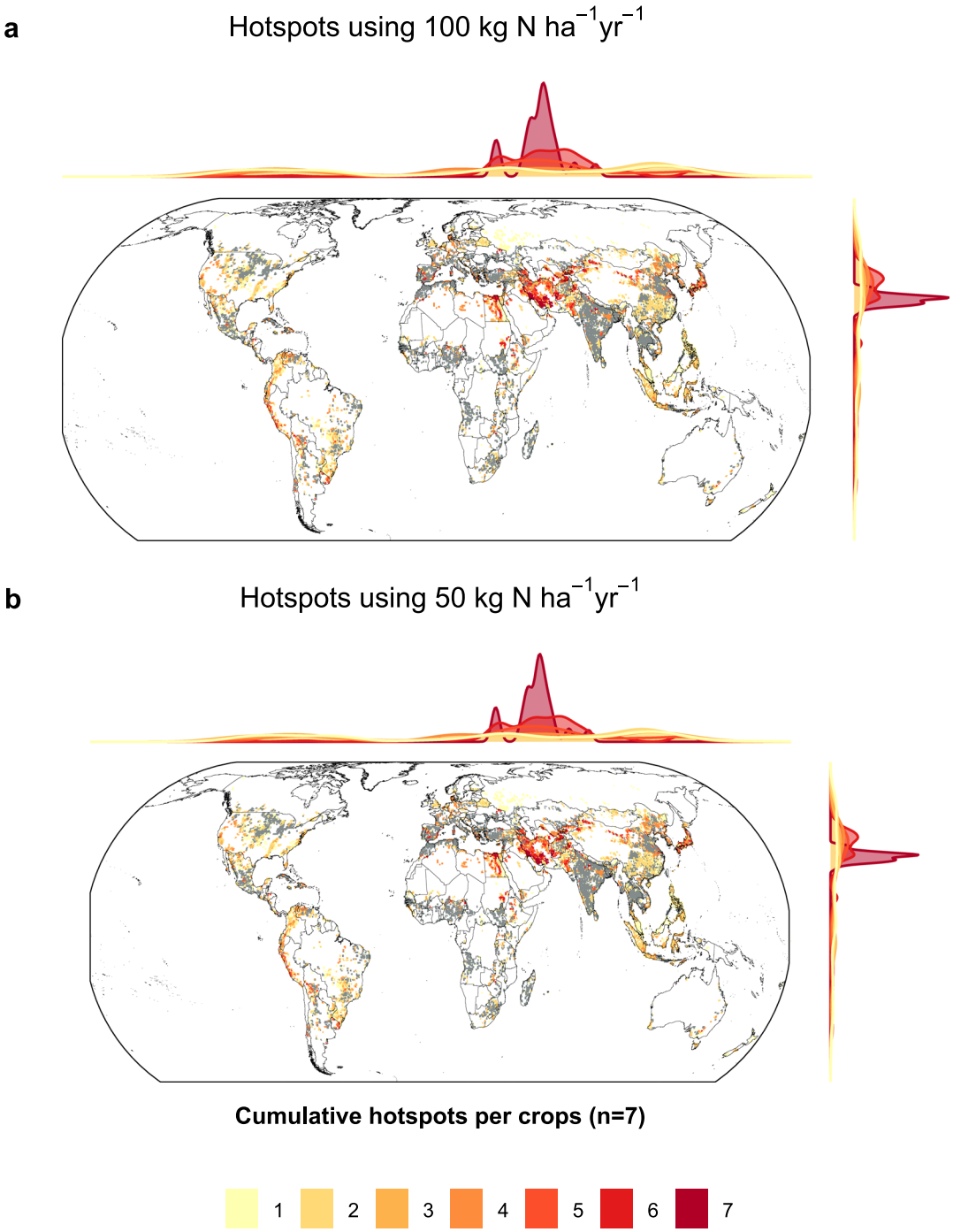
© The Author(s) 2026

https://doi.org/10.1038/s41893-026-01930-8



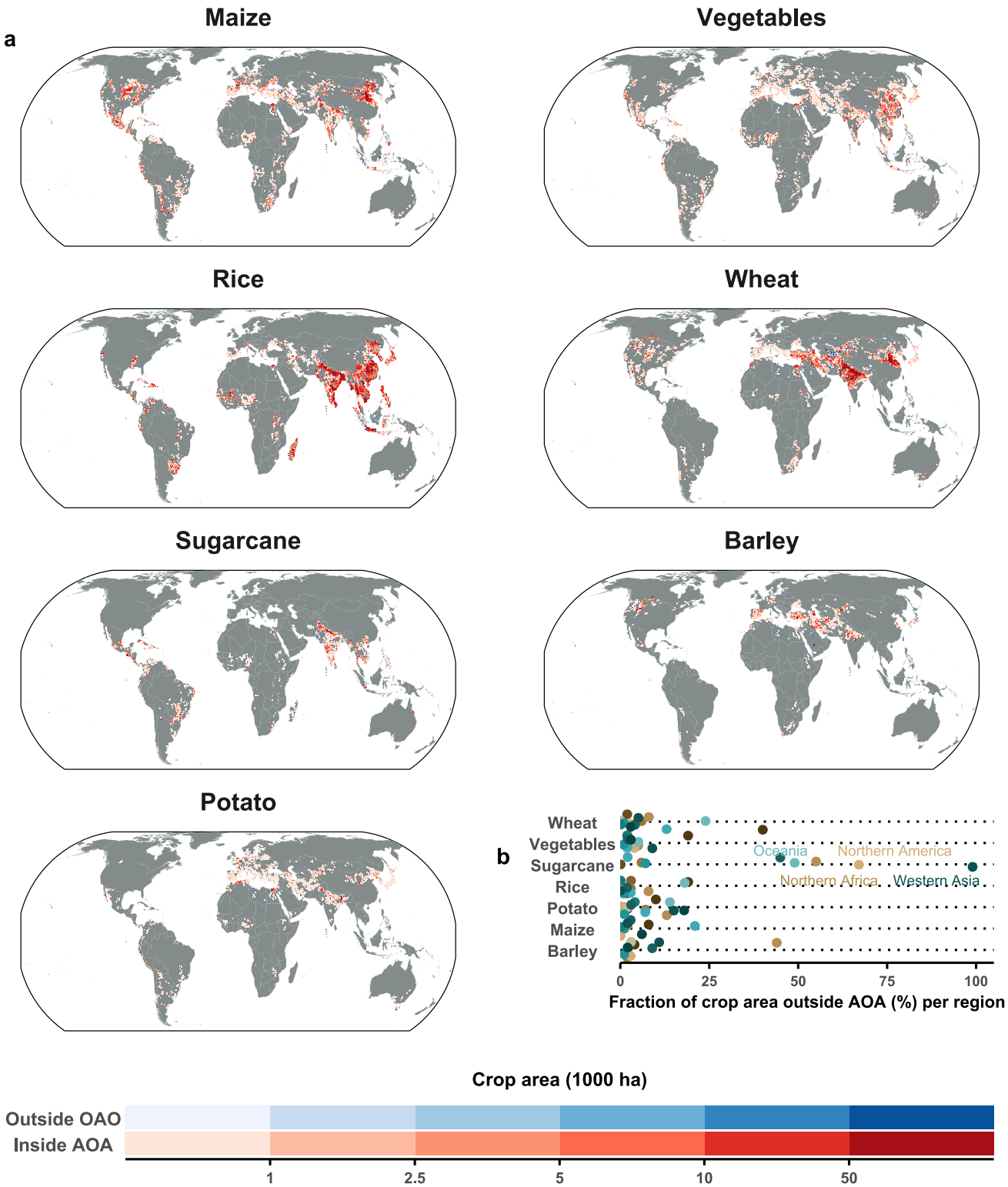
Extended Data Fig. 1 | Overview of the field observations of the compiled dataset across the major irrigated crops. Distribution of key variables compiled from more than 1300 observations, grouped by: number of observations, countries and studies; irrigation amounts, nitrate concentration in irrigated water, Total N inputs, N_{Irrig}, share of observations with a N_{Irrig} higher than 100 kg N ha^{-1} yr^{-1} and lower than 10 kg N ha^{-1} yr^{-1} and N_{Irrig} dependency.

https://doi.org/10.1038/s41893-026-01930-8



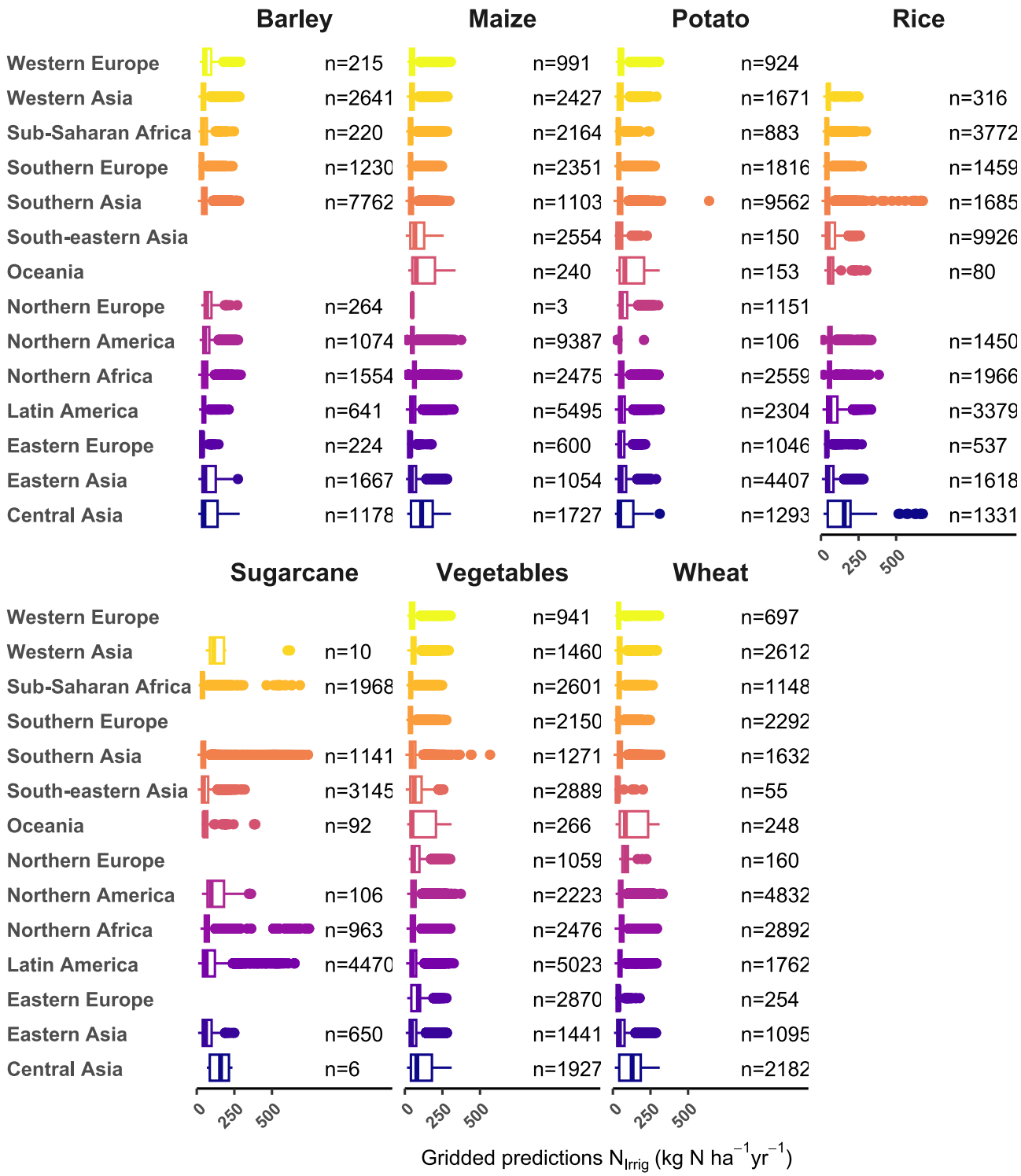
Extended Data Fig. 2 | Identification of hotspots for the predicted N_{Irrig} for 2010-2019 above a threshold of (a) 100 kg N ha^{-1} yr^{-1} (b) and 50 kg N ha^{-1} yr^{-1}. The longitudinal and latitudinal variation is also displayed for each cumulative hotspot count. Dark grey reflects non-hotspots cells. Only the main crops are here included (maize, rice, vegetables, wheat, barley, potato and sugarcane). Please note that the spatial distribution was aggregated to 50 km x 50 km, using the average, to enhance visualisation. Basemap data from Natural Earth. Basemaps were transformed to Eckert IV projection and are shown without Antarctica.

https://doi.org/10.1038/s41893-026-01930-8



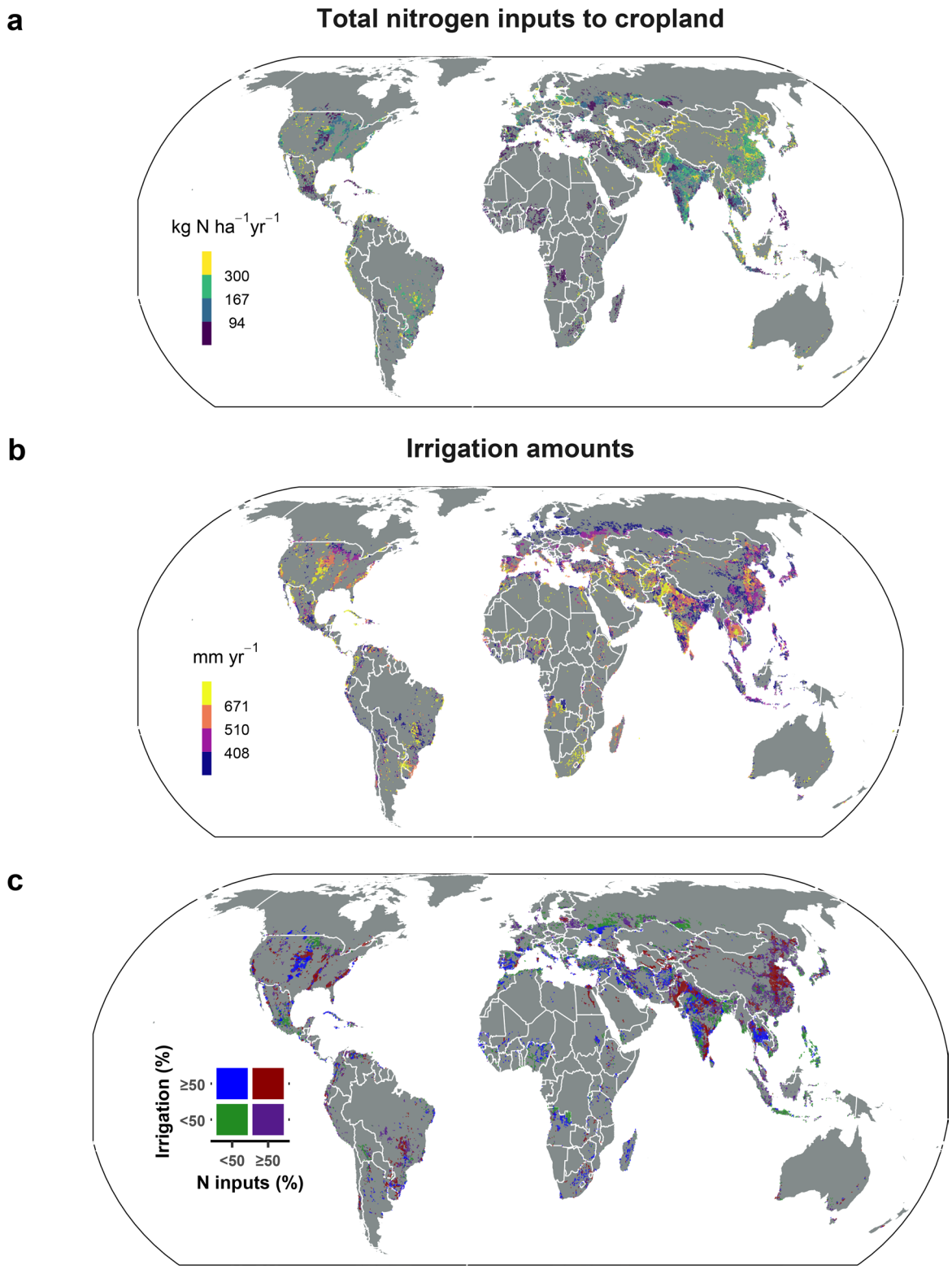
Extended Data Fig. 3 | Area of applicability of the gridded NIrrig predictions. (**a**) Crop-specific area distinguished by area of applicability (AOA) from the hyper-tuned random forest model: inside and outside AOA. Crop maps here were aggregated to 50 km x 50 km by summing all the areas at 10 km x 10 km, to enhance visibility. (**b**) Regional variation of the fraction of irrigated crop areas outside AOA. Only the main crops are here included (maize, rice, vegetables, wheat, barley, sugarcane and potato). Basemap data in **a** from Natural Earth. Basemaps were transformed to Eckert IV projection and are shown without Antarctica.

https://doi.org/10.1038/s41893-026-01930-8



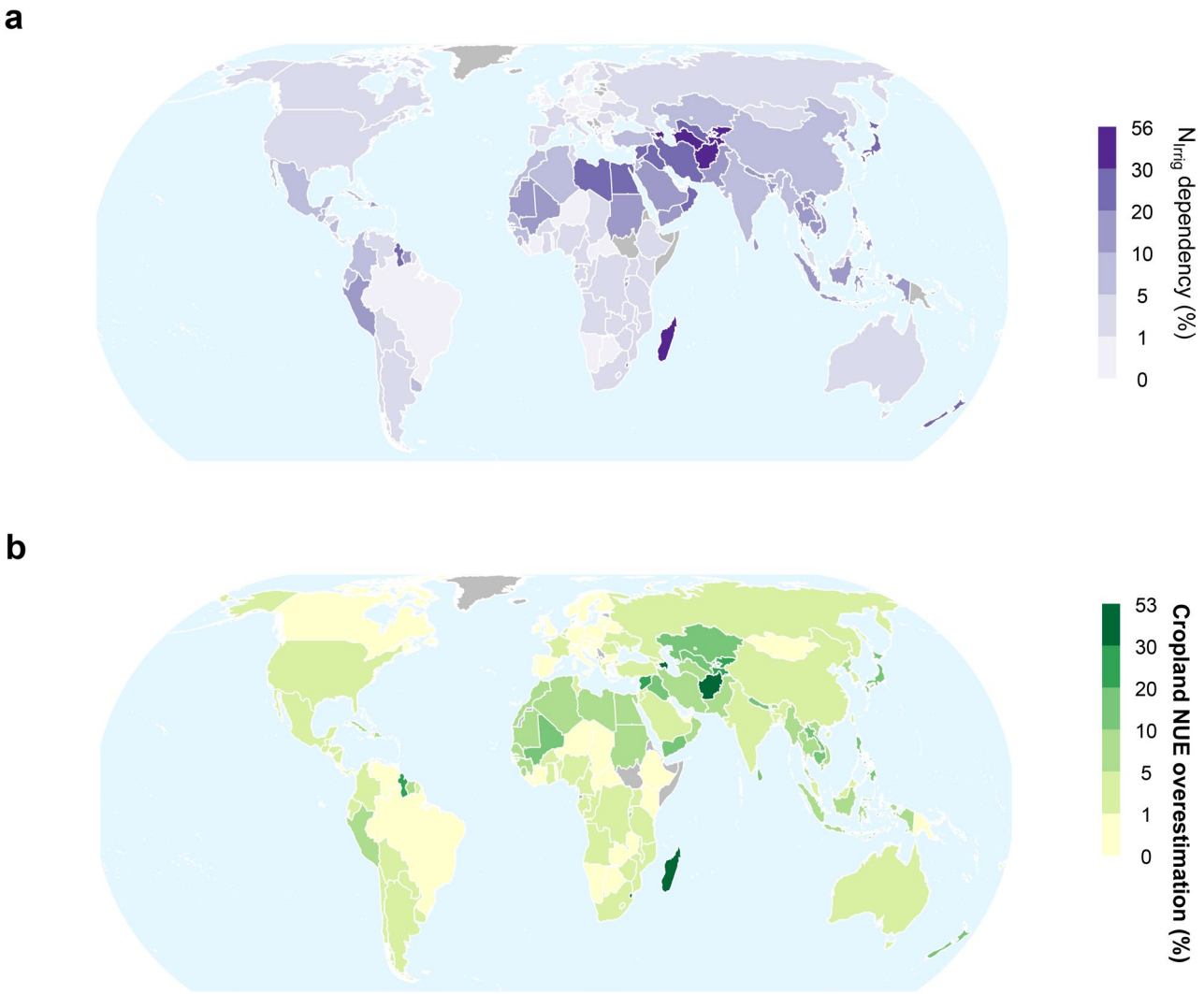
Extended Data Fig. 4 | Regional distributions of crop-specific gridded predictions of NIrrig. Boxplots show the distribution of crop-specific gridded predictions of NIrrig across grid cells within each region. The centre line indicates the median, the lower and upper bounds of the box indicate the 25th and 75th percentiles, respectively, and the whiskers extend to the smallest and largest values no further than 1.5 x the interquartile range from the box bounds. Values beyond the whiskers are shown as individual points. If no values lie be-yond 1.5 × the interquartile range, the whiskers correspond to the minimum and maximum values. For each boxplot, n denotes the number of crop-specific 100 km2 grid cells with irrigated harvested area used to derive the distribution. Regions follow the United Nations sub-region classification.

https://doi.org/10.1038/s41893-026-01930-8



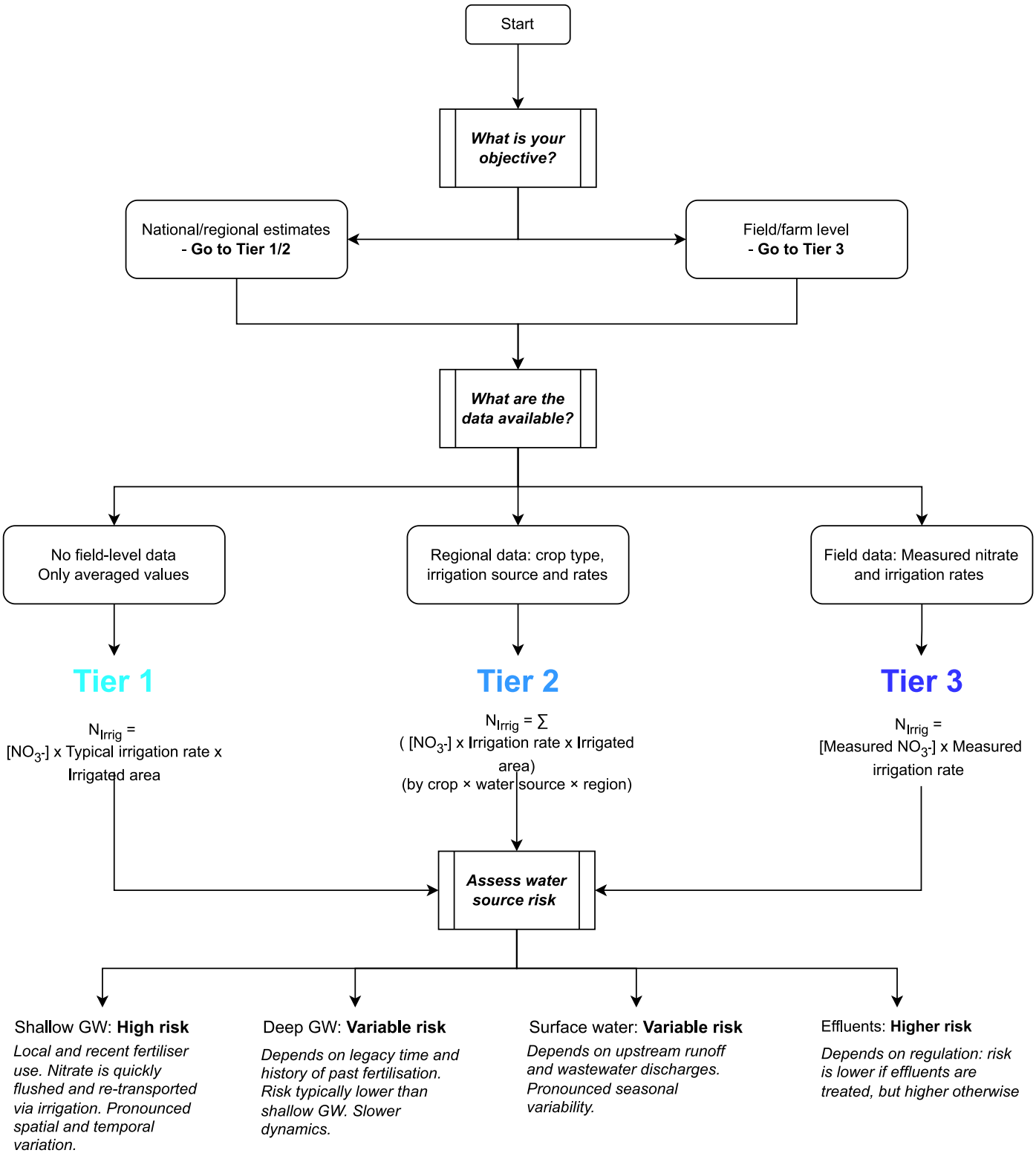
Extended Data Fig. 5 | Regional drivers of the predicted NIrrig. Spatial quantile maps for (**a**) total N inputs in cropland, (**b**) total irrigation rates for the averaged conditions during the period 2010-2019 at 100 km2. (**c**) Spatial variation of regions where both irrigation and N inputs are relative to their median (50th). Total inputs to cropland concern manure, synthetic fertilisers, biological fixation and atmospheric deposition. Total irrigation amounts were calculated by multiplying crop irrigation rates with irrigated areas for each crop, and their sum. Spatial maps resolution was aggregated from 100 km2 to 400 km2 to enhance visibility. Basemap data from Natural Earth. Basemaps were transformed to Eckert IV projection and are shown without Antarctica.

https://doi.org/10.1038/s41893-026-01930-8



Extended Data Fig. 6 | Effects of NIrrig on national indicators. (**a**) NIrrig dependency for cropland, defined as the ratio of NIrrig and total cropland N inputs. (**b**) Impact of including NIrrig on the cropland N Use Efficiency (NUE) as the difference of NUE with and without NIrrig. Both indicators were defined at the national level. Basemap data in **c**from Natural Earth. Basemaps were transformed to Eckert IV projection and are shown without Antarctica.

https://doi.org/10.1038/s41893-026-01930-8



Extended Data Fig. 7 | Decision tree to estimate the nitrogen input via irrigation water using a tiered approach. Additional information for the estimations of Tier 1 and 2 (for example, data sources) are provided in Data Availability.

nature portfolio

Corresponding author(s): João Serra, jserra@agro.au.dk

Last updated by author(s): 8/7/2026

Reporting Summary

Nature Portfolio wishes to improve the reproducibility of the work that we publish. This form provides structure for consistency and transparency in reporting. For further information on Nature Portfolio policies, see our Editorial Policies and the Editorial Policy Checklist.

Statistics

For all statistical analyses, confirm that the following items are present in the figure legend, table legend, main text, or Methods section.

n/a	Confirmed	
☐	☒	The exact sample size (*n*) for each experimental group/condition, given as a discrete number and unit of measurement
☐	☒	A statement on whether measurements were taken from distinct samples or whether the same sample was measured repeatedly
☒	☐	The statistical test(s) used AND whether they are one- or two-sided *Only common tests should be described solely by name; describe more complex techniques in the Methods section.*
☐	☒	A description of all covariates tested
☒	☐	A description of any assumptions or corrections, such as tests of normality and adjustment for multiple comparisons
☐	☒	A full description of the statistical parameters including central tendency (e.g. means) or other basic estimates (e.g. regression coefficient) AND variation (e.g. standard deviation) or associated estimates of uncertainty (e.g. confidence intervals)
☒	☐	For null hypothesis testing, the test statistic (e.g. *F*, *t*, *r*) with confidence intervals, effect sizes, degrees of freedom and *P* value noted *Give P values as exact values whenever suitable.*
☒	☐	For Bayesian analysis, information on the choice of priors and Markov chain Monte Carlo settings
☒	☐	For hierarchical and complex designs, identification of the appropriate level for tests and full reporting of outcomes
☒	☐	Estimates of effect sizes (e.g. Cohen's *d*, Pearson's *r*), indicating how they were calculated

Our web collection on statistics for biologists contains articles on many of the points above.

Software and code

Policy information about availability of computer code

Data collection	No software was used for data collection.
Data analysis	R (v4.5.0) packages for data processing, modeling and analysis: data.table v1.15.0, Tidyverse v2.0.0, doParallel v1.0.17, caret v7.0.1, terra v1.7-71, sf v.1.0-20, CAST v1.0.3, ranger 0.17.0, iml 0.11.4

For manuscripts utilizing custom algorithms or software that are central to the research but not yet described in published literature, software must be made available to editors and reviewers. We strongly encourage code deposition in a community repository (e.g. GitHub). See the Nature Portfolio guidelines for submitting code & software for further information.

Data

Policy information about availability of data

All manuscripts must include a data availability statement. This statement should provide the following information, where applicable:

- Accession codes, unique identifiers, or web links for publicly available datasets
- A description of any restrictions on data availability
- For clinical datasets or third party data, please ensure that the statement adheres to our policy

Data are archived on FigShare (https://figshare.com/articles/dataset/_b_Irrigation_is_a_considerable_nitrogen_input_in_global_cropland_b_/29470148), including: (i) full training dataset (except confidential data), (ii) cross-validated training data and final hypertuned model, (iii) gridded predictions per crop, (iv) estimations

aggregated at country level and (v) scripts used to generate the machine learning pipeline (incl. predictions) and plots 1-3 of the main text. Coordinates of farms with confidential data were removed.

Research involving human participants, their data, or biological material

Policy information about studies with human participants or human data. See also policy information about sex, gender (identity/presentation), and sexual orientation and race, ethnicity and racism.

Reporting on sex and gender	N/A
Reporting on race, ethnicity, or other socially relevant groupings	N/A
Population characteristics	N/A
Recruitment	N/A
Ethics oversight	N/A

Note that full information on the approval of the study protocol must also be provided in the manuscript.

Field-specific reporting

Please select the one below that is the best fit for your research. If you are not sure, read the appropriate sections before making your selection.

☐ Life sciences ☐ Behavioural & social sciences ☒ Ecological, evolutionary & environmental sciences

For a reference copy of the document with all sections, see nature.com/documents/nr-reporting-summary-flat.pdf

Ecological, evolutionary & environmental sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description	We systematically compiled field observations of nitrogen inputs from irrigation water (NIrrig) across global irrigated systems, recording associated management covariates such as irrigation volumes and fertiliser use when available. Using these empirical data, we trained a random forests model to upscale crop-specific NIrrig rates at 10 × 10 km resolution. The resulting maps were aggregated to national and global scales, providing the first data-driven quantification of NIrrig. Finally, we compared NIrrig with other major nitrogen flows to assess its relative contribution to agricultural nitrogen budgets and its implications for fertiliser management and sustainability assessments.
Research sample	The research sample consists of 1325 field observations of nitrogen inputs from irrigation water (NIrrig), compiled from 104 peer-reviewed studies spanning all major irrigated cropping systems and continents. Observations report nitrate or total dissolved nitrogen concentrations in irrigation water, paired with irrigation volumes, crop type, nitrogen input rates and irrigation systems.
Sampling strategy	No a priori statistical sample size calculation was performed because the study relied on published field measurements of NIrrig. Because our aim was comprehensive coverage rather than controlled sampling, the final sample size reflects the availability of published data rather than pre-determined statistical power.
Data collection	The dataset was compiled through a systematic literature review of peer-reviewed articles and selected report via Web of Science. The original measurements of nitrogen in irrigation water were collected and reported by independent research teams across the world, typically through field experiments or farm monitoring campaigns. These studies measured nitrate or total dissolved nitrogen concentrations in irrigation water and combined them with irrigation volumes to calculate NIrrig (kg N ha^{-1} yr^{-1}). We, the authors, did not conduct the field sampling ourselves but extracted values from the published literature following predefined screening and harmonization protocols. When studies reported values in non-standard units (e.g., mg L^{-1} nitrate concentration, irrigation water applied in mm), we converted them into annual nitrogen inputs per hectare. All entries were cross-checked by at least two authors for consistency and accuracy before being included in the database.
Timing and spatial scale	We did not restrict the compiled field observations by year or location to ensure a comprehensive global dataset. However, for the upscaling, georeferenced predictors were harmonised to represent average conditions for 2010–2019. Most predictors were static in time, with the exception of nitrogen inputs and irrigation, which were averaged over this period. All predictors were resampled to a standard resolution of 10 × 10 km, and model predictions were produced at this resolution to provide crop-specific NIrrig estimates representative of 2010–2019 conditions. Later, we aggregated our predictions at national scale.
Data exclusions	Field observations were excluded if they did not report both irrigation water nitrogen concentration and irrigation volume, or if insufficient information was available to convert values into annual nitrogen inputs per hectare. We also excluded observations reported for crop rotations, rather than single crops, as our objective was to quantify crop-specific Nirrig.
Reproducibility	The study is based on a reproducible pipeline from data compilation to model upscaling. All steps of data processing, model training, cross-validation, and uncertainty analysis were scripted in R using open-source libraries under the same pseudo-random generator

number (i.e., set.seed(123). The predictors used for upscaling were standardised geospatial datasets that are publicly available (soil, climate, irrigation, and fertiliser inputs). Field observations were harmonised using transparent inclusion criteria, and all exclusions were documented. We include our cross-validated dataset, including preditors as well as predictions, in the data repository.

Randomization: Randomization was not relevant to this study, samples retained their unique ID information for modeling and validation.

Blinding: Blinding was not relevant for this study, samples retained their unique ID information for modeling and validation.

Did the study involve field work? ☐ Yes ☒ No

Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

Materials & experimental systems

n/a	Involved in the study
☒	☐ Antibodies
☒	☐ Eukaryotic cell lines
☒	☐ Palaeontology and archaeology
☒	☐ Animals and other organisms
☒	☐ Clinical data
☒	☐ Dual use research of concern
☒	☐ Plants

Methods

n/a	Involved in the study
☒	☐ ChIP-seq
☒	☐ Flow cytometry
☒	☐ MRI-based neuroimaging

Plants

Seed stocks: N/A

Novel plant genotypes: N/A

Authentication: N/A