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Countries influence the trade-off between crop yields and nitrogen pollution

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National institutions and policies could provide powerful levers to steer the global food system towards higher agricultural production and lower environmental impact. However, causal evidence of countries' influence is scarce. Using global geospatial datasets and a regression discontinuity design, we provide causal quantifications of the way crop yield gaps, nitrogen pollution and nitrogen pollution per crop yield are influenced by country-level factors, such as institutions and policies. We find that countries influence nitrogen pollution much more than crop yields and there is only a small trade-off between reducing nitrogen pollution and increasing yields. Overall, countries that cause 35% less nitrogen pollution than their neighbours only show a 1% larger yield gap (the difference between attainable and attained yields). Explanations of which countries cause the most pollution relative to their crop yields include economic development, population size, institutional quality and foreign financial flows to land resources, as well as countries' overall agricultural intensity and share in the economy. Our findings suggest that many national governments have an impressive capacity to reduce global nitrogen pollution without having to sacrifice much agricultural production.

The global food system is at the epicentre of many of this century's greatest challenges[1–4]. To match growing demand, crop production will need to increase by 25–70% from 2015 to 2050[4–7]. Because natural ecosystems must simultaneously be protected, increased production cannot come predominantly from agricultural area expansion, but per-area production must increase[3,8,9]. Yet, increasing input intensity can negatively affect water and air quality, climate, biodiversity and human health[10–15].

The main solution to this food–water–environment nexus is to improve agricultural input use efficiency alongside the necessary increase in inputs[2,6,13]. However, the opportunities to increase yields while keeping environmental impacts low are context- and country-specific. Socio-economic circumstances, policies, institutions and regulations are a few examples of the country-level variables that affect crop mixes, input use and technologies, and thereby the resulting yields and environmental effects of crop production[13,16,17]. For example, for many years, nitrogen fertilizer was heavily subsidized in China[13,18]. More recently, China phased out these subsidies and started to fund improvements in nitrogen and manure management[19–22]. However, there are still policies in place that negatively affect nitrogen use efficiency[21,22]. Overall, China uses >30% of all global fertilizer on only 9% of global cropland, while achieving intermediate yields[22].

As we now live on a cultivated planet[2], we can often already see the impact of country-level factors on satellite images[17] (Fig. 1). The fields in China are visibly greener than the fields in Kazakhstan and the fields in Turkey are visibly greener than the fields in Syria and, importantly, the changes pop up right at the border. In both examples, greener fields generally indicate higher agricultural production intensity. The only reason we see these border discontinuities is that the neighbouring countries—as political entities—influence farmer decisions where and how to grow what and, as we establish below, there is no natural discontinuity of environmental conditions at these borders.

Here, we propose an approach to estimate countries' causal effect on their crop yields, expressed as yield gaps that account for differences in local attainable yields (for wheat, maize, rice, potato, soy, sorghum and cassava), their nitrogen balances on croplands and their nitrogen pollution in fresh water, as well the relationship between countries' effect on their yields and their pollution. Our approach is a formal econometric framework that is based on the logic of the examples shown above, applied at the global scale (examining 289 land borders around the world). Our analysis also allows us to investigate the driving forces behind the empirical patterns.

Results

In general, most countries are not easily comparable with each other and they also do not have 100% influence on all of the agricultural and environmental outcomes on their territories. For example, agricultural and environmental outcomes are strongly influenced by a range of natural factors that are mostly outside the influence of the countries. Moreover, in most countries around the world, there is at least some degree of cultural and institutional variation that also affects agricultural and environmental outcomes that predates the current countries[23–25]. Considering the examples from above (Fig. 1), Kazakhstan and China and Turkey and Syria are very different in terms of, for example, their weather, soils and other natural characteristics. It is only close to their borders that they become more and more comparable.

Our approach is to analyse only observations within a narrow band around political borders, where natural conditions tend to be more comparable, control for the general spatial distribution of yields and pollution, and estimate whether there are statistically significant discontinuities right at the countries' borders that can only be explained by country-level characteristics and actions, and not (for example) local or regional confounders[17,26,27]. This is

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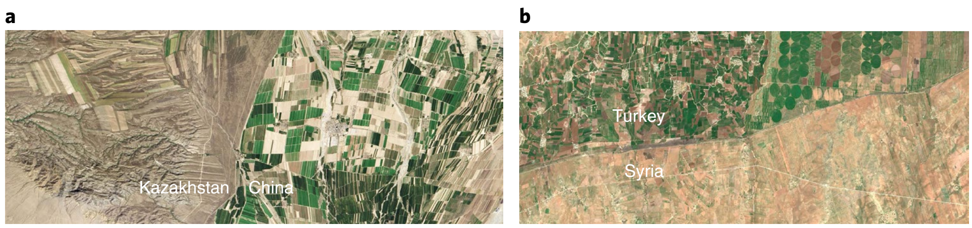

Fig. 1 | Revealing borders. a,**b**, Right at the political borders between Kazakhstan and China (**a**) and between Turkey and Syria (**b**), the colour of the agricultural fields changes discontinuously, revealing the impact of countries on agricultural production decisions. Greener colours indicate higher production intensity. Credit: NASA Earth Observatory image by Robert Simmon, using Landsat data from the US Geological Survey (**a**) and Copernicus Sentinel image, retrieved from Google Earth Engine (https://developers.google.com/earth-engine/datasets/catalog/sentinel) (**b**).

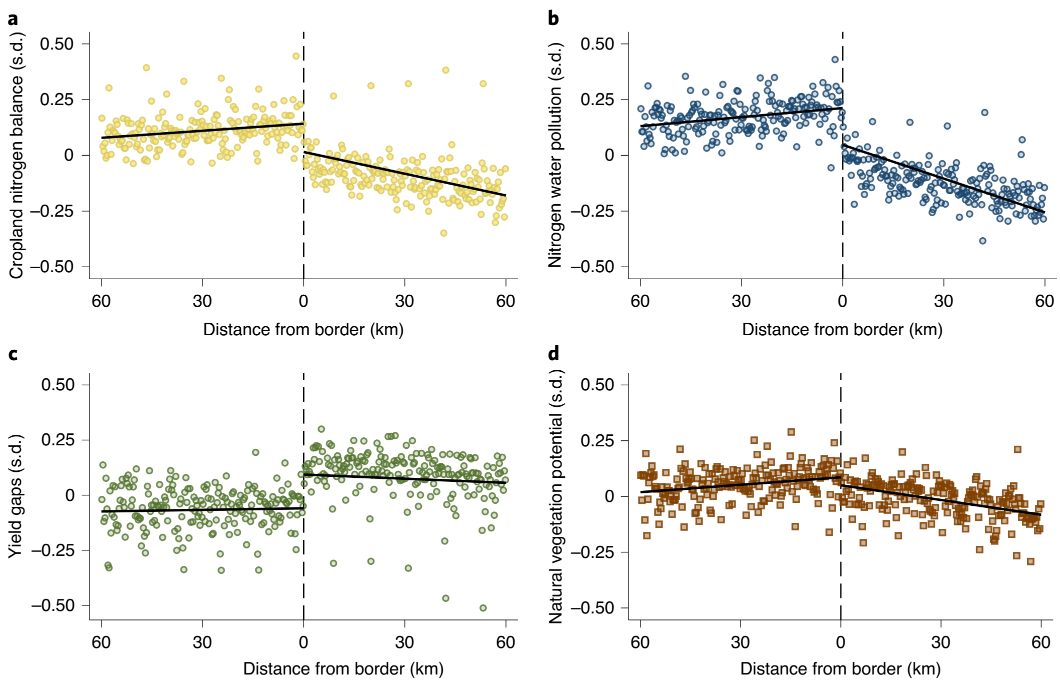

Fig. 2 | Spatial distributions of nitrogen balances, water pollution, yield gaps and the natural vegetation potential around international borders. **a**–**d**, Border discontinuities were examined in cropland nitrogen balances (**a**; $n = 151{,}232$), nitrogen in water pollution (**b**; $n = 200{,}367$), yield gaps (**c**; $n = 115{,}901$) and, to test our main identifying assumption, natural vegetation potential expressed as percentage of naturally occurring tree cover (**d**; $n = 200{,}367$). All global data points that fall within a bandwidth of 60 km of at least one of 289 land borders all around the world are shown, averaged in 200 bins of 300 m width. All outcomes are shown as standard deviations from their own mean.

a regression discontinuity design[28,29], which we estimate jointly for yields and pollution in a system of simultaneous regressions[30,31]. We describe and discuss this framework and all its assumptions in the Methods. We can illustrate the main mechanics by plotting the spatial distribution of four variables, locally averaged in 200 bins of 300 m length on each border side, as a function of border distance for most land borders and countries around the world (Fig. 2). The outcomes are the nitrogen balance on croplands (Fig. 2a)[3], nitrogen pollution in freshwater (Fig. 2b)[14], average yield gaps (the difference between a location's attainable yield versus what is actually attained) (Fig. 2c)[8], and the natural vegetation mixture that we would observe without human impact, which is a valuable summary indicator for overall environmental differences, expressed as percentage of naturally occurring tree cover from 0 to 100% (Fig. 2d)[32]. The observations are sorted the same way in all four plots; namely by each country's comparative water pollution (Methods). In each plot, the bins shown on the left of the border (vertical dashed line) are from countries that cause more nitrogen water pollution than their neighbouring countries. Then, the fitted linear trends (solid black lines on each side of the border) indicate the general spatial pattern (for example, the yield gaps around a particular border might continuously change from west to east and north to south, because of continuously changing precipitation and soil fertility). A discontinuity right at the border suggests an effect of the individual countries, whereas continuity right at the border would suggest no effect. Globally, we see a sharp border discontinuity in cropland nitrogen balances, nitrogen water pollution and yield gaps (Fig. 2a–c)—but not in the natural vegetation potential (Fig. 2d). The last finding is important for the interpretation of our other results. If the border areas of countries with more nitrogen pollution and smaller yield gaps were found to be naturally different from the border areas of countries with less nitrogen water pollution and larger yield gaps, this would compromise our identification strategy, because then border discontinuities could either be explained by the effect of the countries or the effect of their natural environment. Our data suggest that, in general, the border sides are naturally comparable, and countries' characteristics and actions (which we explore below) cause significant differences in nitrogen pollution and crop yields.

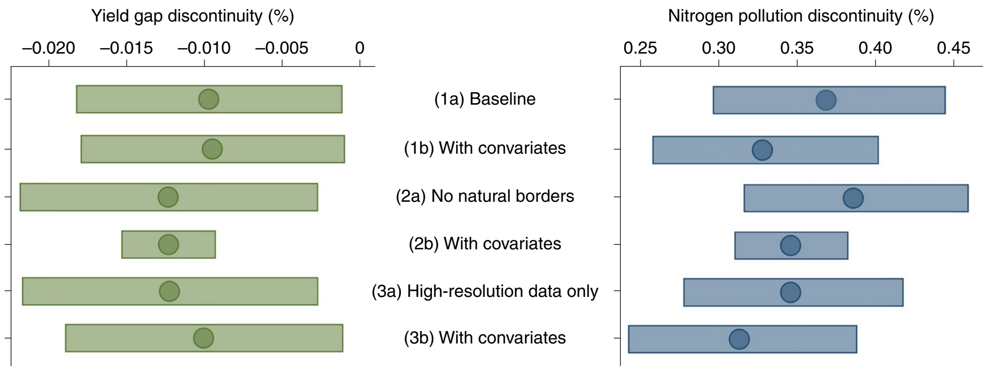

Fig. 3 | Estimated effect of countries on their yield gaps and nitrogen pollution. The circles show point estimates and the bars show the 95% confidence interval. In general, the countries that achieve smaller yield gaps cause disproportionally more nitrogen pollution than their neighbouring countries, and vice versa. In our baseline specification (1a, $n = 91,472$), we control for border distance (separately on each side of each border), fixed border effects and a linear polynomial of longitude and latitude. Standard errors are clustered by border. As a robustness check, we then add covariates regarding environmental characteristics (altitude, depth of bedrock, precipitation during wet and dry season, as well as overall precipitation, and soil organic carbon) in the yield gap equation and human and animal densities (pigs, cattle and chickens) in the nitrogen pollution equation (1b, $n = 91,472$). With this, we test whether it matters that sometimes the natural environment is different on one side of the border than it is on the other, even if this is not so on average, and whether potential discontinuities in human and animal population densities might confound our nitrogen pollution estimates. Next, we exclude borders at which we find any discontinuity in the natural environment, first without (2a, $n = 73,754$) and then with covariates (2b, $n = 73,754$). This is an alternative test for the influence of natural borders versus purely political borders, and—as we explain below in the Methods—also for the influence of data density around each border. Finally, we exclude borders with low-resolution input data (for some countries, important input data is only available at high aggregation), again without (3a, $n = 88,692$) and then with covariates (3b, $n = 88,692$). With this, we probe how measurement errors (both random and systematic) influence our estimates. We find little variation in our results across specifications.

However, we do find natural discontinuities at some borders and we carefully test whether these borders affect our results and control for these natural discontinuities when analysing individual borders further below.

Global estimates of countries influence on their yield gaps and nitrogen pollution. We obtain three main results (Fig. 3). First, we estimate that, on global average, countries cause a much larger discontinuity in the spatial distribution of nitrogen water pollution than in the spatial distribution of yield gaps. The discontinuity is around 35% for nitrogen pollution but only between 1 and 1.5% for yield gaps. Second, the two discontinuities are inversely related; that is, countries that achieve lower yield gaps (higher yields) tend to cause more nitrogen pollution. Third, the estimates are robust, only varying slightly in magnitude between different specifications and subsamples.

The spatial distribution of countries' effect on their yield gaps and nitrogen pollution. Moving beyond global averages, Fig. 4 shows a map of each country's estimated effect on its crop yields compared with its effect on nitrogen pollution (an aggregation of each country's estimated effect on nitrogen pollution minus its estimated effect on crop yields).

By far the highest value is estimated for China (170%, which can be interpreted as China causing 170% more nitrogen pollution than it is reducing its crop yield gaps, both compared with all its neighbouring countries). Other countries with less, but still particularly high, nitrogen pollution estimates compared with their neighbouring countries include Brazil, Mexico, Colombia, Israel, Thailand and Georgia, whereas countries such as the United States, Germany, France, South Korea and Austria achieve relatively high yields with comparably less nitrogen pollution. Important caveats are that all estimates are based completely on comparisons between neighbouring countries, so they are strictly relative. This means, for example, that the positive, comparative yield effect of South Korea can be as much attributed to its own high yields as it can be attributed to the particularly low yields in North Korea, and the comparative nitrogen pollution effects of Kazakhstan and Mongolia, for example, are mostly attributable to the fact that they are being compared with China. It should also be noted that these relative values are an unweighted average of all discontinuities; that is, a country might have a positive effect compared with one neighbour and a negative effect of a similar magnitude compared with another, and its final value then is close to zero. Finally, we have no results for the few countries that have no direct neighbours (such as Australia).

Explanations for countries' effect on their yield gaps and nitrogen pollution. Countries that produce a disproportionate amount of nitrogen pollution relative to their yield performance probably have potential to reduce pollution without large sacrifices in terms of yield. To learn what distinguishes the countries that cause more pollution per yield from those that cause less, we regress countries' estimated effect from above on regional fixed effects (for example, sub-Saharan Africa, North America and so on) and individual explanatory variables, which are shown together with their estimated coefficients in Fig. 5.

Previous studies have found an asymmetric para-curve relationship between nitrogen pollution and economic development[13,33] (an environmental Kuznets curve). Consistent with this, we find that middle-income countries cause the most nitrogen pollution compared with the yields they achieve (for example China or Brazil) whereas several richer countries cause less nitrogen pollution compared with the yields they achieve (such as Germany or the United States). Overall, however, we find an approximately linearly increasing relationship between countries' gross domestic product (GDP) and their pollution per yield (specifications 1a and 1b). Simply put, richer countries cause considerably more nitrogen pollution than poorer countries and this is not matched by commensurate yield advantages. In contrast, there is no associations with GDP growth (specifications 2a and 2b). However, countries with larger populations cause more pollution compared with their yield effect than countries with smaller populations (3). There is no association with population growth (4).

We also find a positive association with the quality of countries' economic institutions[34] (5). This suggests that, globally, better

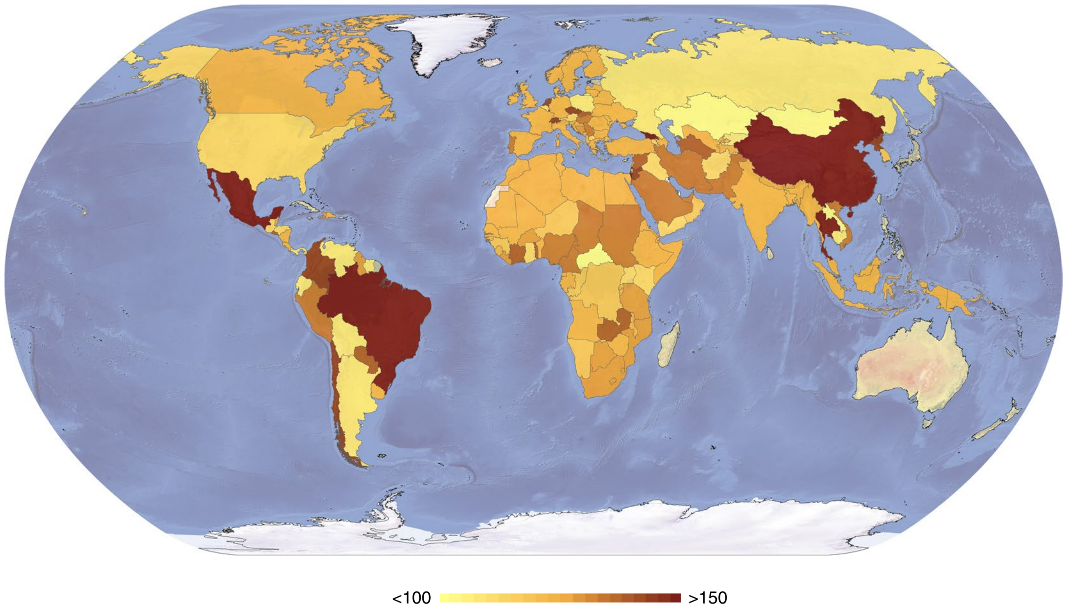

Fig. 4 | Countries' estimated effect on their yield gaps versus their nitrogen pollution. The map quantifies how much nitrogen pollution countries are causing compared with how much they reduce their yield gaps relative to directly neighbouring countries (colour scale, expressed as percentages). Darker colours reflect larger increases in nitrogen pollution compared with the closing of yield gaps, whereas lighter colours reflect larger decreases in nitrogen pollution compared with widening yield gaps.

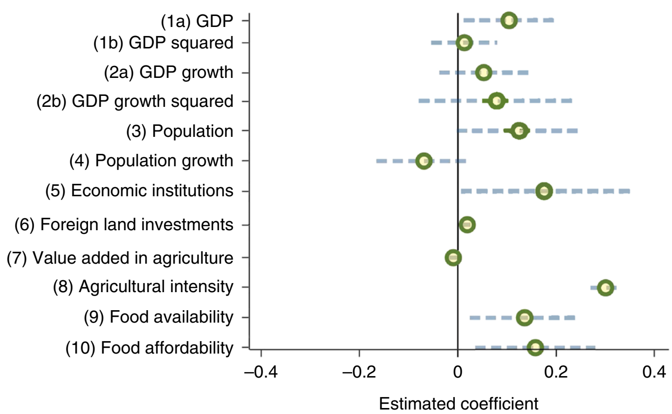

Fig. 5 | Explaining countries' estimated pollution versus yield gaps effects. The results from linear regressions of countries' estimated effect on their nitrogen pollution versus their effect on their crop yields (Fig. 4) on regional fixed effects, and a broad range of potential explanatory variables ($n = 143$), are shown. The green circles are the point estimates from the regressions and the dashed lines show the 95% confidence interval. To test a potential nonlinear relationship with GDP and/or GDP growth, these variables were included linearly as well as squared.

institutions are more tightly associated with heightened environmental impact than better environmental regulation.

A small, but statistically significant, positive association is found with foreign investments into countries' land resources (6). There is no association with countries' agricultural GDP share (7) but we find that more intensive farming systems are associated with more pollution per yield (8). At the same time, more pollution per yield is also associated with a significantly higher availability and affordability of food (9 and 10), which highlights the need to consider food security issues in this context.

Future research might also consider the influence of specific policies[19,22], national legislations[35], behavioural factors such as culture[25] and different farm sizes[21,36].

Discussion

Our global food system is more productive than ever before in human history. However, productivity growth may still be slightly below what we need to match projected future demand[4–6]. At the same time, environmental impacts, foremost nitrogen pollution, are far beyond any safe level[10,37]. Both are in large part because nitrogen use is inefficiently distributed spatially[11,38,39]. Here we have exploited a natural experiment created by spatial discontinuities at international borders to identify the role of countries. We find that they have a much larger effect on nitrogen pollution than they have on yield gaps, and many countries cause very high pollution for the yield that they actually achieve. It is important to note that closing yield gaps and mitigating nitrogen pollution is not a technically necessary trade-off. In particular, our empirical results suggest that nitrogen surpluses can be reduced by ~35% if the more polluting countries around the world cause only the pollution levels of their less-polluting neighbouring countries—even without any other adjustments, this would only increase yield gaps by ~1%. It is important to note that this 1% increase in yield gaps is not necessary, because countries can commonly adjust and even synergies exists. As we find, this is largely under the control of national governments.

An important lever for national governments is the ratio of fertilizer price to agricultural output price. Countries with nitrogen surpluses might re-allocate financial resources from agricultural subsidies that increase environmental impacts to those that incentivize a more environmentally friendly production. Another option is the introduction of taxation schemes that raise the relative price of nitrogen compared with its production value[40,41]. There are also other possibilities for countries to support the adoption of new, more sustainable technologies and farming practices, for example via improving extension systems and changing environmental and tenure regulations[13,16,19–22]. The opposite applies for countries with large yield gaps, where it is important to support (sustainable) intensification, for example via input subsidies[42,43]. An increasingly important role might be played by precision farming and new plant breeding in the future, which would require national government support and could vastly increase nitrogen use efficiency[44,45].

Methods

To understand countries' effects on yield gaps and nitrogen pollution, as well as their relationships, we analyse large, global datasets with a combination of a regression discontinuity design[17,29,47] and a seemingly unrelated regression framework[30,31].

We begin with a discussion of our analytical framework, its assumptions, and how we test them. Then we describe our four main datasets, and the data we use to explain our findings.

Analytical framework. Our analytical framework is a combination of a regression discontinuity design[17,29,47] and a seemingly unrelated regression framework[30,31]. The basic idea is that under a set of falsifiable assumptions, spatial discontinuities right at political borders reveal the influence of the countries that are separated there. Political borders can often be easily recognized in the landscape, even where natural environmental conditions are otherwise homogeneous (for example, Fig. 1). In a sense, the division of the world into different countries functions like a 'natural experiment' in many places around the globe.

Technically, we simultaneously estimate whether there is a statistically significant discontinuity at political borders in yield gaps and nitrogen pollution, while controlling for all continuously distributed confounders via linear polynomials of border distance and longitude and latitude, as well as covariates. For this, we first estimate at each border which country potentially causes more nitrogen pollution:

$$\log \text{N Pollution}_i = \beta_1 D_i^{\text{a}} + \beta_2 \text{dist}_i^{\text{A}} + \beta_3 \text{dist}_i^{\text{B}} + \beta_4 \text{Vegetation}_i + \epsilon_i \text{ if } \text{dist}_i \leq \varphi^\star \tag{1}$$

where log N Pollution$_i$ is the natural logarithm of nitrogen pollution in water[14] of pixel i on a gridded global map at 5 arcmin resolution, β_i are the coefficients to be estimated, D_i^{a} indicates which of the two countries A or B at every border might pollute its waters more with nitrogen[14], dist_i^{A} and $dist_i^{\text{B}}$ control for border distance, separately in country A and B, Vegetation controls for the natural vegetation potential, expressed as the percentage of naturally occurring tree cover, which summarizes a large number of environmental factors[32], $\in_i$ is an error term and $\varphi^\star$ is the estimated optimal bandwidth (the optimal maximum distance to each border, defining our sample), balancing bias and precision[48]. In our case, this is 20 km on each side. We then ran a global model, in which we simultaneously estimate whether there is a significant border discontinuity in the average yield gap between the countries with more nitrogen pollution and those with less, and whether there is a significant border discontinuity in nitrogen pollution between the same countries:

$$\begin{aligned}&\text{Yield Gap}_i \\ &\quad = \beta_1 D_i^{\text{a}} + \beta_2 \text{dist}_i^{\text{H}} + \beta_3 \text{dist}_i^{\text{L}} + \beta_4 \text{location}_i + \beta_5 \theta_i^{\text{a}} + \beta_6 \vartheta_j + \epsilon_i^{\text{a}} \text{ if } \text{dist}_i \leq \varphi^\star\end{aligned} \tag{2}$$

$$\begin{aligned}&\log \text{N Pollution}_i \\ &\quad = \beta_7 D_i^{\text{b}} + \beta_8 \text{dist}_i^{\text{H}} + \beta_9 \text{dist}_i^{\text{L}} + \beta_{10} \text{location}_i + \beta_{11} \theta_i^{\text{b}} + \beta_{12} \vartheta_j + \epsilon_i^{\text{b}} \text{ if } \text{dist}_i \leq \varphi^\star\end{aligned} \tag{3}$$

where Yield Gap$_i$ is the average yield gap[8] (the percentage difference between a place's achievable yield as a function of environmental constraints and the actually achieved yield). ϑ_j indicates to which pairwise border the observations belongs, θ_i^{a} is a vector of six environmental covariates[32] summarizing the influence 58 individual environmental characteristics, such as topography and bio-climate, location$_i$ is described by longitude, latitude and their interaction, dist_i^{H} and dist_i^{L} are linear polynomials of border distance, fitted separately on both sides of each border and D_i^{a} quantifies the border discontinuity. The superscripts H and L refer to the two border sides, H stands for higher nitrogen pollution and L stands for lower nitrogen pollution. Again, $\varphi^\star$ minimizes omitted variable bias with the largest sample possible. The error term of equation (2) is assumed to be correlated with the error term of equation (3), as the observations are from the same place. For equation (3), which is simultaneously estimated with equation (2), the left-side variable is log N Pollution$_i$, which is alternatively the average nitrogen footprint[14] in the fresh water or the nitrogen balance on agricultural land[3] of pixel i on a gridded global map at 5 arcmin resolution. $\theta_i^{\text{b}}$is a vector of four population densities (chicken, cattle, pigs and people)[49,50], D_i^{b} quantifies again the border discontinuity and all other variables are defined as above. Throughout, standard errors are clustered at the border, accounting for common unobservables and spatial autocorrelation. We also always transform the estimated effects so that they are expressed as percentage changes (using the inverse of the logarithmic function).

Finally, we estimate individually at each border the effects of the countries on their yield gaps and their nitrogen pollution to understand the trade-off between mitigating nitrogen pollution and closing yield gaps. Here, we use cropland N balances as our measure for nitrogen pollution[3], to avoid confounding with non-agricultural sources, which is more likely when analysing individual borders. We then aggregate all estimated effects by country (ignoring discontinuities from borders with natural discontinuities) and regress each country's pollution versus yield effect on regional fixed effects and hypothesized explanations:

$$\text{pollution versus yield effect} = \beta_1 X_i + \beta_2 \text{Region}_i + \epsilon_i \tag{4}$$

Where X_i are possible explanations, such as countries' gross domestic product, institutional quality and several others, and Region$_i$ are fixed effects for sub-Saharan Africa, the Middle East and North-Africa, Europe and Central Asia, South Asia, East Asia and the Pacific, and North and Latin America.

Assumptions and tests. Our main identifying assumptions are: (1) that we can distinguish between exogenous and endogenous borders; (2) that we can learn something about countries by focusing on their border areas; (3) that we have sufficient data near borders; and (4) that systematic and random measurement errors in our input data are not a first-order problem. We discuss each assumption and how we probe it below.

Exogenous borders. Our central assumption is that border discontinuities in nitrogen pollution and yield gaps reveal the causal influence of countries because there are no 'compound treatments'. The 'treatment' we are interested in is that one side of each border belongs to one country, and the other side belongs to another country. If, however, one side also has one type of soil and the other side another, we cannot then interpret a border discontinuity as country effect but must consider that it may be in part, or in full, the result of the difference in soil type. Thus, we must establish that international borders mostly divide naturally homogeneous areas—that is, that they are exogenous to differences in yields and nitrogen pollution.

In Fig. 2d it is shown that the countries that cause more nitrogen pollution than their neighbouring countries do not have systematically different environmental and geographical conditions close to their borders (summarized by their hypothetical natural vegetation). To test this statistically, we focus on three main determinants of the natural vegetation (altitude, temperature and precipitation) and estimate—similar to how we quantify the border discontinuities in yield gaps and nitrogen pollution—whether there is a border discontinuity in any of these indicators:

$$\text{Indicator}_i = \beta_1 D_i + \beta_2 \text{dist}_i^{\text{H}} + \beta_3 \text{dist}_i^{\text{L}} + \beta_4 \theta_i + \epsilon_i \text{ if } \text{dist}_i \leq \varphi^+ \tag{5}$$

where Indicator$_i$ is altitude, temperature or precipitation, D_i reveals whether there is a 'jump' in the relevant indicator right at the border, θ_i are fixed effects for each border, and φ^+ is optimal. As before, standard errors are clustered at the border. Neither altitude, temperature, nor precipitation exhibit any discontinuity at the average border that we use for our analysis. Moreover, moving from a maximum border distance of 60 km to one of 30 km, the point estimates move closer to zero, consistent with the idea that we increase the environmental comparability of observations by excluding observations farther away from the border. This is shown in Supplementary Fig. 1.

At individual borders, we do sometimes find natural discontinuities, so these borders are less reliable for our analysis and we investigate this issue further below. First, we examine our second assumption, which is that we can estimate the causal effect of countries in border areas.

Representative borders. We achieve high internal validity by—among other factors—only analysing already fairly comparable observations close to borders. This, however, begs the question of how representative international border areas are for countries' interiors[51]. We examine this with a simple correlational analysis of the nitrogen pollution found in border areas and the nitrogen pollution of the entire countries. Supplementary Fig. 2 shows that there is generally a high correlation, even though there are outliers in this pattern, and, as we discuss below, there is a built-in bias in the data towards this pattern. Overall, this suggests that we can learn something about the countries by only estimating what happens in their border areas.

Sufficient data density. Our third assumption is that we have sufficiently high densities of croplands left and right of the border. This is important because we use observations just left and right of the border as counterfactuals, and if there are not many observations, our sample is small and our estimator imprecise; if we compare observations far away from the border, we risk increasing omitted variable bias. We test this assumption together with our first assumption that natural discontinuities at international borders are small and seldom. For this, we individually estimate at each border whether we find a discontinuity in the hypothetical natural vegetation, as predicted by Bastin et al.[32]. A border discontinuity in the hypothetical natural vegetation would come either from an actual discontinuity in environmental characteristics right at the border or, alternatively, from the fact that our observations at this particular border are actually not right at the border, but farther apart. It should be noted that the natural vegetation depends on many environmental and geographic characteristics that also affect yield and nitrogen pollution potentials, so it is a general indicator. We estimate, similar to before:

$$\text{Vegetation}_i = \beta_1 D_i + \beta_2 \text{dist}_i^{\text{H}} + \beta_3 \text{dist}_i^{\text{L}} + \beta_4 \theta_i + \epsilon_i \text{ if } \text{dist}_i \leq \varphi^\star \tag{6}$$

Where Vegetation$_i$ is the vegetation we would see all around the world if there was no human impact. All other variables are defined as above.

We mark all borders at which we find a statistically significant border discontinuity as less reliable (19% of all borders) and all others as more reliable (81% of all borders).

Measurement error. All else equal, modelled data is often less precise than remote sensing data because it involves at least one more processing step. Thus, there is at least one more source of measurement error. Our data are often based on multiple processing steps and it is unlikely that any step is error free. Second, due to data availability constraints, the global distribution of nitrogen pollution has a low resolution. It is not yet possible to model this at the same resolution as, for example, deforestation[52] or soil erosion[53]. For issues such as nutrient pollution[14] or greenhouse gas emissions[54], a 5 arcmin resolution is the highest available resolution. This means, however, that a certain degree of measurement error is unavoidable.

It is also worth noting that both yields and water pollution by nitrogen are related to each other but also caused by third variables. For example, yields are strongly affected by water availability[3,5,8] (via irrigation, for example) and nitrogen in water also comes from non-cropland and non-agricultural sources[14,33,55,56].

Whereas random measurement error might lead to a bias towards statistically insignificant and/or smaller border discontinuities, our data could also contain systematic measurement error with the opposite effect. At first, one would not expect any systematic measurement error in our data because all of our main variables are from datasets that have been created as globally homogeneous. However, there is a hidden source of systematic measurement error and that is low-resolution statistical data that have been used as input data. For example, in the N pollution data of Mekonnen and Hoekstra[14], the distribution of cropland and production systems, manure input and N output are all subnational, but mineral N fertilizer applications are only available at the country level[57–59] and for some countries the yield data is also only available at this level[60]. The cropland nitrogen balance data[3] incorporate some subnational fertilizer application rate data from Mueller et al.[8], but only for a subset of countries. The resolution of our source datasets could bias estimated border discontinuities. Similar to the low resolution increasing random measurement error, this issue cannot be solved because for many countries in the world there exist no reliable data on subnational fertilizer application rates. However, even if the ratio of random to systematic measurement error is such that we over- or underestimate the average border discontinuity in yield gaps and/or nitrogen pollution, the estimated association between countries effect on pollution and yields can still be correctly estimated.

To take into account the fact that yield gaps and nitrogen water pollution are caused by other sources than each other, we estimate all our specifications once without covariates and then include potential confounding factors, such as the population densities of humans and several animal species. This allows us to test how sensitive our estimates are to the influence of nitrogen pollution from domestic and industrial sources, for example, or to yield differences caused by rainfall patterns. Specifically for nitrogen pollution in water[14], we also examine cropland nitrogen balances[3], which are the intermediate channel (for example, Fig. 2 and Supplementary Fig. 3). Moreover, Monfreda et al.[60] provide data on the resolution of their utilized agricultural information, which is used for the modelling of both yield gaps and nitrogen pollution. Thus, we are able to test the robustness of our estimates by excluding observations at the bottom end of the quality spectrum (Fig. 3 and Supplementary Fig. 4).

Main data. Our main data sources are Mueller et al.[8] for the global distribution of yield gaps, Mekonnen and Hoekstra[14] for the global distribution of nitrogen pollution, West et al.[3] for the global distribution of nitrogen balances on croplands (the direct connection between closing yield gaps and increasing nitrogen pollution in freshwater) and Bastin et al.[32] for global data on the distribution of the natural environment without human impact (to evaluate our border exogeneity assumption). We also use environmental characteristics provided by Bastin et al.[32] and data on the human population density from SEDAC[49] and animal population densities from Gilbert et al.[50]. We resampled all datasets at a 5 arcmin resolution, which is the resolution of the dataset of Mekonnen and Hoekstra[14], and dropped all observations farther than 100 km away from any border.

To compute yield gaps, we first needed attainable yields. For this, Mueller et al.[8] created 100 zones of similar annual precipitation[61] and growing degree-day characteristics[62]. Then, they defined attainable yield as the area-weighted 95th percentile observed yield within each bin. The yield data are from Monfreda et al.[60]. The yield gap of each place is then defined as the difference between the attainable and actually attained yields. An important 'proximate' (in contrast to 'fundamental') explanation for the existence of yield gaps is differences in nitrogen fertilizer applications[8]. The main advantage of working with yield gaps in this study—and not simply with yields—is that the yield gaps already incorporate an estimate of the yield potential of each observation; working with yields directly would be subject to the confounding influence of changes in yield potential due to agro-ecological differences.

For this study, we computed the average yield gap by aggregating the individual yield gaps of the six major crops (maize, wheat, potato, cassava, sorghum and soy).

The nitrogen pollution is defined by Mekonnen and Hoekstra[14] as greywater 'footprints', which are all anthropogenic N emissions divided by the difference between the ambient water quality standard for N and the natural concentration of N in the receiving water body. This approximates how much pristine water is necessary to assimilate the entire nitrogen pollution. To compute N inputs, they combined data on the global distribution of croplands from Monfreda et al.[60], which also provides information on N fixation by legumes, then fertilizer and manure applications[57–59,63], atmospheric N deposition[64] and the N content of irrigation water[65], as well as a large number of point emission sources. To compute N removal, harvests[60], soil erosion[66], ammonia[67], N_2O and NO emissions[68] are considered. Data on soil parameters comes from Batjes[69], the rooting depths of individual crops is from Allen et al.[70] and precipitation data are from Mitchell and Jones[71].

To model nitrogen balances at the landscape level, West et al.[3] first modelled nitrogen input by adding crop-specific nitrogen fertilizer applications[8] and their own estimate of manure applications based on the distribution livestock density and crop- and pasture land, similar to the approach of Foley et al.[2] and Potter et al.[72]. Then, nitrogen fixation by legumes was added using the data of Smil[73], and atmospheric nitrogen deposition using the data of Dentene, et al.[74]. To then model nutrient removal, the nutrient density data of the USDA[75] were combined with the harvest data from Monfreda et al.[60]. The difference between input and removal is then the estimated nitrogen balance.

Finally, to evaluate which borders around the world are endogenously drawn (that is, along environmental discontinuities), we use the data of Bastin et al.[32]. The most sophisticated indicator for environmental border discontinuities is their globally mapped natural vegetation distribution. For this, they let a random forest algorithm[76] learn how differences in natural environmental characteristics predict differences in natural vegetation. For this, they trained the algorithm with photo-interpretations from protected areas all around the world, under the assumption that protected areas are the best available demonstration for the natural vegetation in each region. They then used global data on summary measures of 58 environmental characteristics to predict the natural vegetation all around the world. For our analysis, we both use their natural vegetation map and their predictor variables, all available via Google Earth Engine (https://earthengine.google.com); see also Gorelick et al.[77]. We show the entire global distributions of all four datasets discussed above in Supplementary Fig. 5. Supplementary Fig. 6 shows a visual illustration of our initial sampling along international borders for the example of landscape nitrogen balances in Asia and Latin America.

For a description of our data to explain the estimated global patterns, see Supplementary Section 2.

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

Data availability

Data can be retrieved from Wuepper et al.[46] and from the corresponding author upon reasonable request

Code availability

Code can be retrieved from Wuepper et al.[46] and from the corresponding author upon reasonable request

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Author contributions

D.W. conceived the project, prepared some of the data, and carried out the analysis. S.L.C. prepared most of the data. All authors contributed to the analysis and writing the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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Software and code

Policy information about availability of computer code

Data collection	All first data processing was done in Esri Arcmaps 10.7. Final data processing was done in Stata 16.
Data analysis	All analyses were performed in Stata 16

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Study description	The data is global, cross-sectional, and quantitative. It covers the global distributions of yield gaps, nitrogen pollution, and covariates.
Research sample	We use secondary geo-spatial datasets - all peer-reviewed and publicly available
Sampling strategy	From the available datasets, we selected all observations closer than 100 kilometers to international borders, as our econometric approach only requires observations close to borders (for causal inference). Then, it was statistically determined how many of these observations to use for the actual analysis (there is a statistical optimum from a variance-bias trade-off).
Data collection	All used data is openly available. We downloaded it, processed it, and merged it into one dataset.
Timing	Does not apply.
Data exclusions	We excluded data from places further away than 100 kilometers to an international border. This is because our method is effectively based on comparing observations close to international borders, to mitigate unobserved heterogeneity.
Non-participation	There are no participants in this study. The unit of observation are grid-cells / pixels
Randomization	We exploit a "natural experiment". Many international borders have the effect of "randomly asigning" places into different countries. we use this instead of our own randomization (which would clearly not be possible).

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☒	☐	ChIP-seq
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