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Journal Article

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Publication date:
2020-11-11

Permanent link:
https://doi.org/10.3929/ethz-b-000452561

Originally published in:
Nature Food 1, https://doi.org/10.1038/s43016-020-00185-6

Countries Influence the Trade-Off between Crop Yields and Nitrogen Pollution

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POSTPRINT to

Wuepper, D., Le Clech, S., Zilberman, D. et al. Countries influence the trade-off between crop yields and nitrogen pollution. Nat Food 1, 713–719 (2020).

https://doi.org/10.1038/s43016-020-00185-6

Abstract: 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 how much 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 neighbors only cause a 1 percent larger yield gap (the difference between attainable and attained yield). Explanations which countries cause the most pollution relative to their crop yields include economic development, population size, institutional quality, foreign financial flows to land resources, as well as countries' overall agricultural intensity and its 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.

Main

The global food system is at the epicenter of many of this century's greatest challenges[1-4]. To match growing demand, crop production will need to increase 25–70% from 2015 to 2050[4-7]. Because natural ecosystems must be simultaneously protected, increased production cannot mainly come 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, technologies and thus 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].

Because we now live on a “cultivated planet”[2], we can now often already see the impact of country-level factors on satellite images [17,23] (**Figure 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 why we see these border discontinuities is that the neighboring 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.

FIGURE 1 HERE

Fig.1. Revealing borders. Right at the political borders between (**a**) Kazakhstan and China and between (**b**) Turkey and Syria, the color of the agricultural fields changes discontinuously, revealing the impact of countries on agricultural production decisions. Greener colors indicate higher production intensity. Credit: (a) NASA Earth Observatory image by Robert Simmon, using Landsat data from the U.S. Geological Survey, (b) Copernicus Sentinel image, retrieved from Google Earth Engine

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 freshwater, 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 comparable to each other and they also do not have 100% influence on all 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 pre-dates the current countries[24-26]. Considering the examples from above **(Figure 1)**, Kazakhstan and China, and Turkey and Syria are very different in terms of e.g. their weather, soils, and other natural characteristics. It is only close to their borders where they become more and more comparable.

Our approach is to analyze 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 e.g. local or regional confounders[17,27,28]. This is a regression discontinuity design[29,30] which we estimate as a system of simultaneous regressions[31,32]. We describe and discuss this framework and all its assumptions in the **Materials and Methods**. We can visually illustrate the main mechanics, showing the spatial distribution of four outcomes, locally averaged in 200 bins of 300 meters length on each border side, as a function of border distance, for approximately all land-borders and countries around the world (**Figure 2)**. The outcomes are the nitrogen balance on croplands (**a**)[3], nitrogen pollution in freshwater (**b**)[14], average yield gaps (the difference between a location's attainable yield versus what is actually attained)(**c**)[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% (**d**)[33]. The observations are sorted the same way in all four plots (**a** – **d**), namely by each country's comparative water pollution (see **Materials and 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 neighboring countries. Then, the fitted linear trends (solid, black line on each side of the border) indicates the general spatial pattern (e.g. the yield gaps around a particular border might continuously change from west to east and north to south, because of continuously changing rainfall 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. It can be seen that globally, we see a sharp border discontinuity in cropland nitrogen balances (**a**), nitrogen water pollution (**b**), and yield gaps (**c**) - but not in the natural vegetation potential (**d**). 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 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 suggests 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. 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 analyzing individual borders further below.

FIGURE 2 HERE

Fig 2. Spatial distributions of nitrogen balances, water pollution, yield gaps and the natural vegetation potential around international borders. Border discontinuities were examined in (**a**) cropland nitrogen balances (n=151,232), (**b**) nitrogen in water pollution (n= 200,367), (**c**) yield gaps (n= 115,901), and (**d**) to test our main identifying assumption, natural vegetation potential (expressed as percentage of naturally occurring tree cover from 0 to 100%)(n= 200,367). Shown are all global data points that fall within a bandwidth of 60km to at least one of 289 land-borders all around the world, here averaged in 200 bins of 300m width. All outcomes are shown as standard deviations from their own mean. Border distances are shown in kilometers.

Global Estimates of Countries Influence on their Yield gaps and Nitrogen Pollution

We obtain three main results (**Figure 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, i.e. 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 sub-samples.

FIGURE 3 HERE

Fig 3. Estimated effect of countries on their yield gaps and nitrogen pollution. Circles show point estimates and bars show the 95% confidence interval. In general, the countries that achieve smaller yield gaps cause disproportionally more nitrogen pollution than their neighboring 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 one 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 chicken) 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 - 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 only little variation in our results across specifications.

The Spatial Distribution of Countries' Effect on their Yield Gaps and Nitrogen Pollution

Moving beyond global averages, **Figure 4** shows a global map of each country's estimated effect on its crop yields compared to its effect on nitrogen pollution (an aggregation of each country's estimated effect on nitrogen pollution minus its estimated effect on crop yields).

FIGURE 4 HERE

Fig.4. Countries' estimated effect on their yield gaps versus their nitrogen pollution. Quantification of how much nitrogen pollution countries are causing compared to how much they reduce their yield gaps, relative to directly neighboring countries. Darker colors reflect larger increases in nitrogen pollution compared to the closing of yield gaps, lighter colors reflect larger decreases in nitrogen pollution compared to widening yield gaps.

By far the highest value is estimated for China (170%, which can be interpreted as China is causing 170% more nitrogen pollution than it is reducing its crop yield gaps, both compared to all its neighboring countries). Other countries with less but still particularly high nitrogen pollution estimates compared to their neighboring 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 neighboring countries, so they are strictly relative. This means e.g. 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, e.g., are mostly attributable to the fact that they are being compared to China. It should also be noted that these relative values are an unweighted average of all discontinuities, i.e. a country might have a positive effect compared to one neighbor and a negative effect of a similar magnitude compared to another, and its final value then is close to zero. Finally, we have no results for the few countries worldwide that have no direct neighbors (e.g. 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 likely 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 (e.g. Sub-Saharan Africa, North America, etc.) and individual explanatory variables, which are shown together with their estimated coefficients below (**Figure 5**).

FIGURE 5 HERE

Fig.5. Explaining countries' estimated pollution versus yield gaps effect. This figure shows 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). To test a potential non-linear relationship with gdp and/or gdp growth, these variables where included linearly as well as squared.

Previous studies have found an asymmetric para-curve relationship between nitrogen pollution and economic development[13,34] (an Environmental Kuznets curve). Consistent with this, we find that middle income countries cause the most nitrogen pollution compared to the yields they achieve (e.g. China or Brazil) whereas several richer countries cause less nitrogen pollution compared to the yields they achieve (e.g. Germany or the US). Overall, however, we find an approximately linearly increasing relationship between countries' 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* (**2a** and **2b**). However, countries with larger populations cause more pollution compared to 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[35] (**5**). This suggests that globally, better 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 cautions to consider food security issues in this context.

Future research might moreover consider the influence of specific policies[19,22], national legislations[36], behavioral factors such as culture[26], and different farm sizes[21,37].

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[10,38]. Both are in large parts because nitrogen use is currently spatially inefficiently distributed[11,39,40]. We here 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. Importantly, 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 only achieve the pollution levels of their less polluting neighboring countries and even without any adjustments, this would only increase yield gaps by ~1%. Important to note, 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 to its production value[41,42]. There are also other possibilities for countries to support the adoption of new, more sustainable technologies and farming practices, e.g. 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, e.g. via input subsidies[43,44]. An increasingly important role might be played by precision farming and new plant breeding in the future, which require national government support and could vastly increase nitrogen use efficiency[45,46].

Materials and Methods

To understand countries' effect on yield gaps and nitrogen pollution, as well as their relationship, we analyze large, global datasets with a combination of a regression discontinuity design [17,30,47] and a seemingly unrelated regression framework [31,32].

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

Analytical Framework

Our analytical framework is a combination of a regression discontinuity design [17,30,47] and a seemingly unrelated regression framework [31,32]. 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. Often, political borders can be easily recognized in the landscape, even though natural environmental conditions are otherwise homogenous (see e.g. **Figure 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:

$$\log N\ Pollution_i = \beta_1 D_i^a + \beta_2 dist_i^A + \beta_3 dist_i^B + \beta_4 Vegetation_i + \epsilon_i \ \ if\ dist_i \leq \varphi^* \qquad (1)$$

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 arc-minute resolution, 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 $dist_i^B$ control for border-distance, separately in country A and B, $Vegetation$ controls for natural vegetation potential, expressed as naturally occurring tree cover in percentage from 0 to 100%, which summarizes a large number of environmental factors [33], ϵ_i is an error-term, and φ^* 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 20km on each side. We then estimate 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:

$$Yield\ Gap_i = \beta_1 D_i^a + \beta_2 dist_i^H + \beta_3 dist_i^L + \beta_4 location_i + \beta_5 \theta_i^a + \beta_6 \vartheta_j + \epsilon_i^a \ \ if\ dist_i \leq \varphi^* \qquad (2a)$$

$$\log N\ Pollution_i = \beta_7 D_i^b + \beta_8 dist_i^H + \beta_9 dist_i^L + \beta_{10} location_i + \beta_{11} \theta_i^b + \beta_{12} \vartheta_j + \epsilon_i^b \ \ if\ dist_i \leq \varphi^* \qquad (2b)$$

where $Yield\ Gap_i$ is the average yield gap[8] in percentage (the 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[33] 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, fit separately on both side of each border, and D_i^a quantifies the border discontinuity. Again, φ^* is the estimated optimal maximum border distance (the "bandwidth") that minimizes omitted variable bias with the largest sample possible. The error term of this first equation is assumed to be correlated with the error term of the second equation, as the observations are from the same place. For the second equation, which is simultaneously estimated with the first, the left side variable is $\log N\ Pollution_i$ which is alternatively the average nitrogen footprint[14] in the freshwater or the nitrogen balance on agricultural land[3] of pixel i on a gridded global map at 5 arc-minute resolution. Then, θ_i^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 auto-correlation. We also always transform the estimated effects so they are expressed as percentage changes (using the inverse of the logarithmic function).

Finally, we estimate individually at each border the effect 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 by non-agricultural sources, which is more likely when analyzing 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:

$$\text{pollution versus yield effect } = \beta_1 X_i + \beta_2 Region_i + \epsilon_i \qquad (3)$$

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 that we can distinguish between exogenous and endogenous borders (**a**), that we can learn something about countries from focusing on their border areas (**b**), that we have sufficient data near borders (**c**), and that systematic and random measurement error in our input data is not a first-order problem (**d**). We discuss each assumption and how we probe it below.

a. 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, also one side has one type of soil and the other side another, then we cannot interpret a border discontinuity as country-effect but it is possibly in part or in full the result of the difference in soil type. Thus, we must establish that international borders mostly divide naturally homogenous areas, i.e. that they are exogenous to differences in yields and nitrogen pollution.

In **Figure 2d** it is already shown that the countries that cause more nitrogen pollution than their neighboring 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, which are 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:

$$Indicator_i = \beta_1 D_i + \beta_2 dist_i^H + \beta_3 dist_i^L + \beta_4 \theta_i + \epsilon_i \ \ if \ dist_i \leq \varphi^+ \quad (4)$$

Where the $Indicator_i$ is alternatively altitude, temperature, and rainfall, D_i reveals whether there is a "jump" in the relevant indicator right at the border, $dist_i^H$ and $dist_i^L$ are linear polynomials of border distance, separately fitted on the two sides of each border, and θ_i are fixed effects for each border. 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 60km to one of 30km, the point estimates move closer to zero, consistent with the idea that we increase the environmental comparability of observations by excluding observations further away from the border. This is shown in **Supplementary Figure 1** in the Supplementary Materials.

At individual borders, we sometimes do 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.

b. Representative Borders

We achieve high internal validity - among others reasons - by only analyzing already quite comparable observations close to borders. This, however begs the question 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 Figure 2** shows that there is generally quite a high correlation, even though there are outliers in this pattern, and, as we discuss below, there is an in-built bias in the data towards this pattern. Overall, this is suggestive that we can learn something about the countries by only estimating what happens in their border areas.

c. 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, and 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. [33]. Finding a border discontinuity in the hypothetical natural vegetation comes either from an actual discontinuity in environmental characteristics right at the border, or alternatively, it comes from the fact that our observations at this particular border are actually not right at the border, but further 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 quite a general indicator. We estimate, similar to before:

$$Vegetation_i = \beta_1 D_i + \beta_2 dist_i^H + \beta_3 dist_i^L + \beta_4 \theta_i + \epsilon_i \;\; if \; dist_i \leq \varphi^* \quad (5)$$

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).

d. 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. Often, our data is based on multiple processing steps and it is unlikely that any one is error free. Second, due to data availability constraints, the global distribution of nitrogen pollution has a rather low resolution. It is not possible currently to model this at the same resolution like e.g. deforestation [52] or soil erosion [53]. For issues such as nutrient pollution [14] or greenhouse gas emissions [54], a 5-arc-minute resolution is currently the highest available resolution. This, however, means that a certain degree of measurement error it unavoidable.

It is also noteworthy 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] (e.g. via irrigation) and nitrogen in water also comes from non-cropland and non-agricultural sources[14,34,55,56].

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 our main variables are from datasets that have been created globally homogenously. However, there is a hidden source of systematic measurement error and that is low-resolution, statistical data that has 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 sub-national, but mineral N-fertilizer applications are only available at the country level [57-59] and for some countries also the yield data is 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 rather low resolution increasing random measurement error, this issue cannot be solved because for many countries in the world there exists no reliable data sub-national 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 especially nitrogen pollution, the estimated association between countries effect on pollution and yields can still be correctly estimated.

To take into account 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 including potential confounding factors, such as the population densities of humans and several animal species. This allows us to test how sensitive our estimates are e.g. to the influence of nitrogen pollution from domestic and industrial sources or 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 (see e.g.

Figure 2 above and **Supplementary Figure 3**). Moreover, Monfreda, et al. [60] provide data on the resolution of their utilized agricultural information, which is both used for the modelling of 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 (see **Figure 3** above and **Supplementary Figure 4** in the **Supplementary Materials**).

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. [33] for global data on the distribution of the natural environment without human impact (to evaluate our "border exogeneity" assumption). Moreover, we use environmental characteristics also provided by Bastin, et al. [33], and data on the human population density from SEDAC [49] and animal population densities from Gilbert, et al. [50]. We re-sampled all datasets at a 5-arc-minute resolution which is the resolution of the dataset of Mekonnen and Hoekstra [14] and dropped all observations further than 100 km away from any border.

To compute yield gaps, first attainable yields are needed. 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 is from Monfreda, et al. [60]. The yield gap of each place is then defined as the difference between attainable and actually attained yield. An important "proximate" (in contrast to "fundamental") explanation for the existence of yield gaps are 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, soy).

The nitrogen pollution is defined by Mekonnen and Hoekstra [14] as greywater "footprint", 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], 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 is 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 Dentener, et al. [74]. To then model nutrient removal, the nutrient density data of the USDA [75] was 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 border around the world are endogenously drawn, i.e. along environmental discontinuities, we use the data of Bastin, et al. [33]. 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. Then, they 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 [23], see also Gorelick, et al. [77]. We show the entire global distributions of all four datasets discussed above in **Supplementary Figure 5**. For a visual illustration how our initial sampling along international borders looks like, please see **Supplementary Figure 6** 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 Materials Section S2**.

Data availability

Data can be retrieved from Wuepper, et al. [78] and from the corresponding author upon reasonable request

Code availability

Code can be retrieved from Wuepper, et al. [78] and from the corresponding author upon reasonable request

Supplementary Materials for

Countries Influence the Trade-Off between Crop Yields and Nitrogen Pollution

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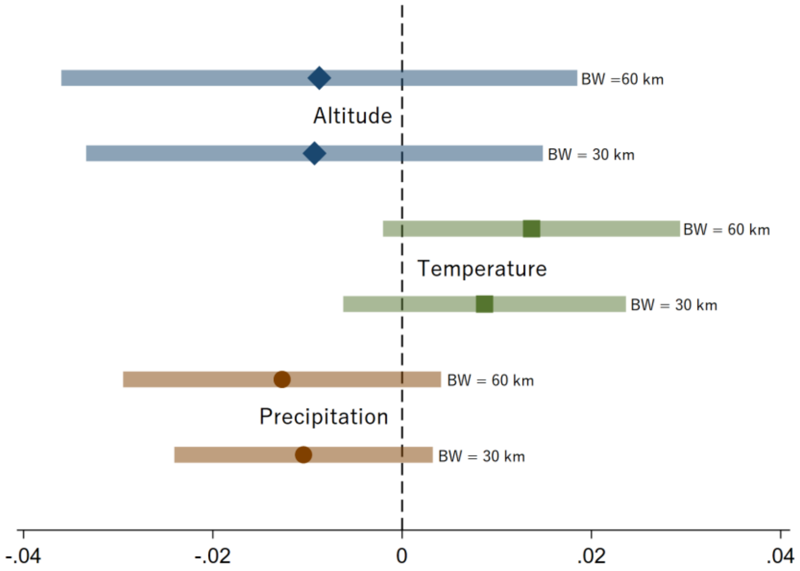
This PDF file includes:

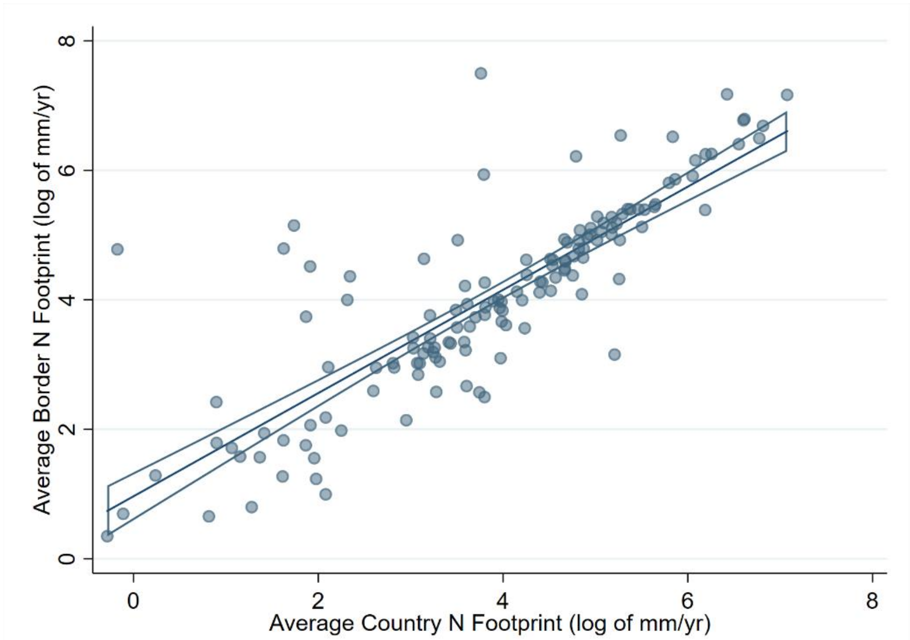
Fig. S1 to S6 and a discussion of our main explanatory variables and their data sources

Supplementary Materials for Wuepper, et al. [79]. All Data and Code can be retrieved from Wuepper, et al. [78] and from the corresponding author upon reasonable request

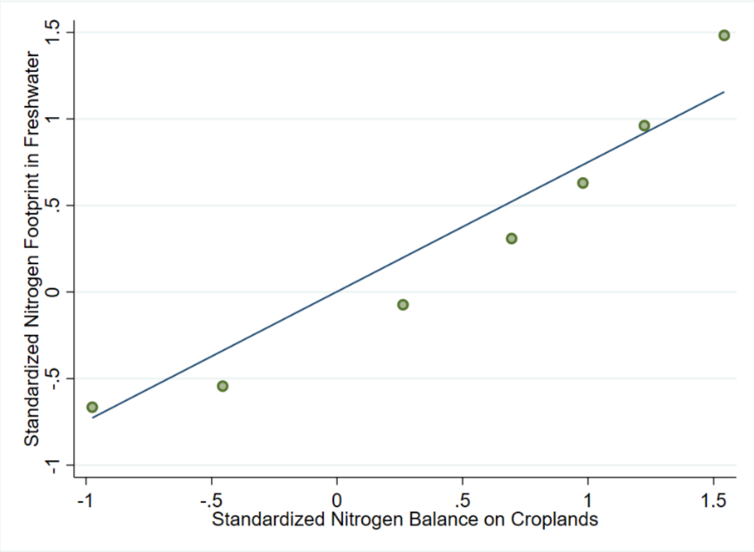
Section S1. Supplementary Figures



Supplementary Figure 1. Testing for Environmental Border Discontinuities. There are no statistically significant environmental border discontinuities, on average, between the countries. Diamonds, squares, and circles indicate the point estimates, the bars in blue, green, and brown show the 95 % confidence intervals, all of which range from positive upper bounds to negative lower bounds.

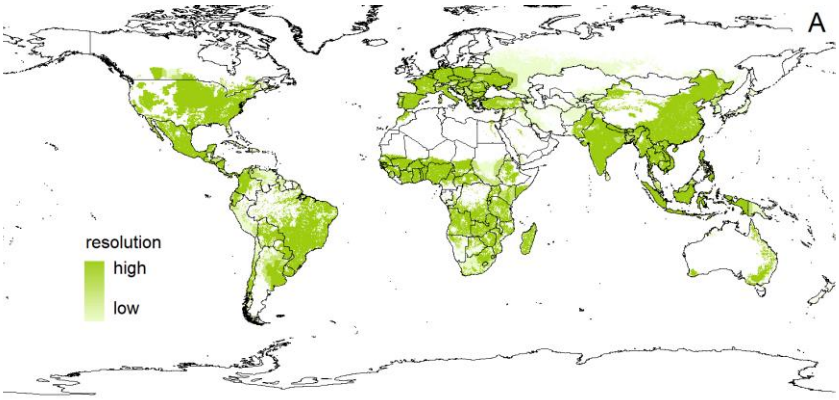


Supplementary Figure 2. Comparing Water Pollution in Border Areas and Country Averages. For our analysis, we focus exclusively on international border areas, because the areas just left and right of a border are more likely to be comparable environmentally and geographically than the areas further inland. Whether we can interpret our results as extrapolatable to the rest of the countries depends on how closely related are nitrogen water pollution in border areas and further inland. The graph above correlates country averages (x-axis) with border averages (y-axis). We see a strong positive relationship, suggesting that our findings in border areas are probably relevant beyond our sample.

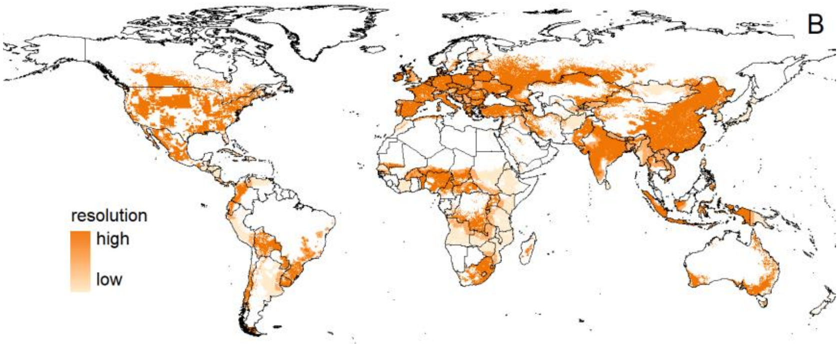


Supplementary Figure 3. Comparing Nitrogen Pollution in Water and Nitrogen Balances on Cropland. We are most concerned about nitrogen pollution in water, but not all nitrogen pollution in water comes from croplands. Here, however, we show that nitrogen pollution in freshwater (y-axis) and nitrogen balances on croplands (x-axis) are closely related. All observations are averaged in small bins (green) and their relationship is approximated with a linear regression line (blue).

The maps in **Supplementary Figure 4** below show two-resolutions of the yield data from Monfreda, et al. [60], once for maize (**a**), and once for potatoes (**b**), as examples. The yield data is used both for the modelling yield gaps and nitrogen pollution and, as can be seen below, the resolution of the data is distributed heterogeneously around the word. Above, we tested whether this influences our estimates and found that it does not. For these tests, we used the data shown in the maps below and that for all other crops that we used to compute local average yield gaps and once included this as a control variable in the baseline specification, and once excluded the countries with the lowest resolution (bottom 25%).



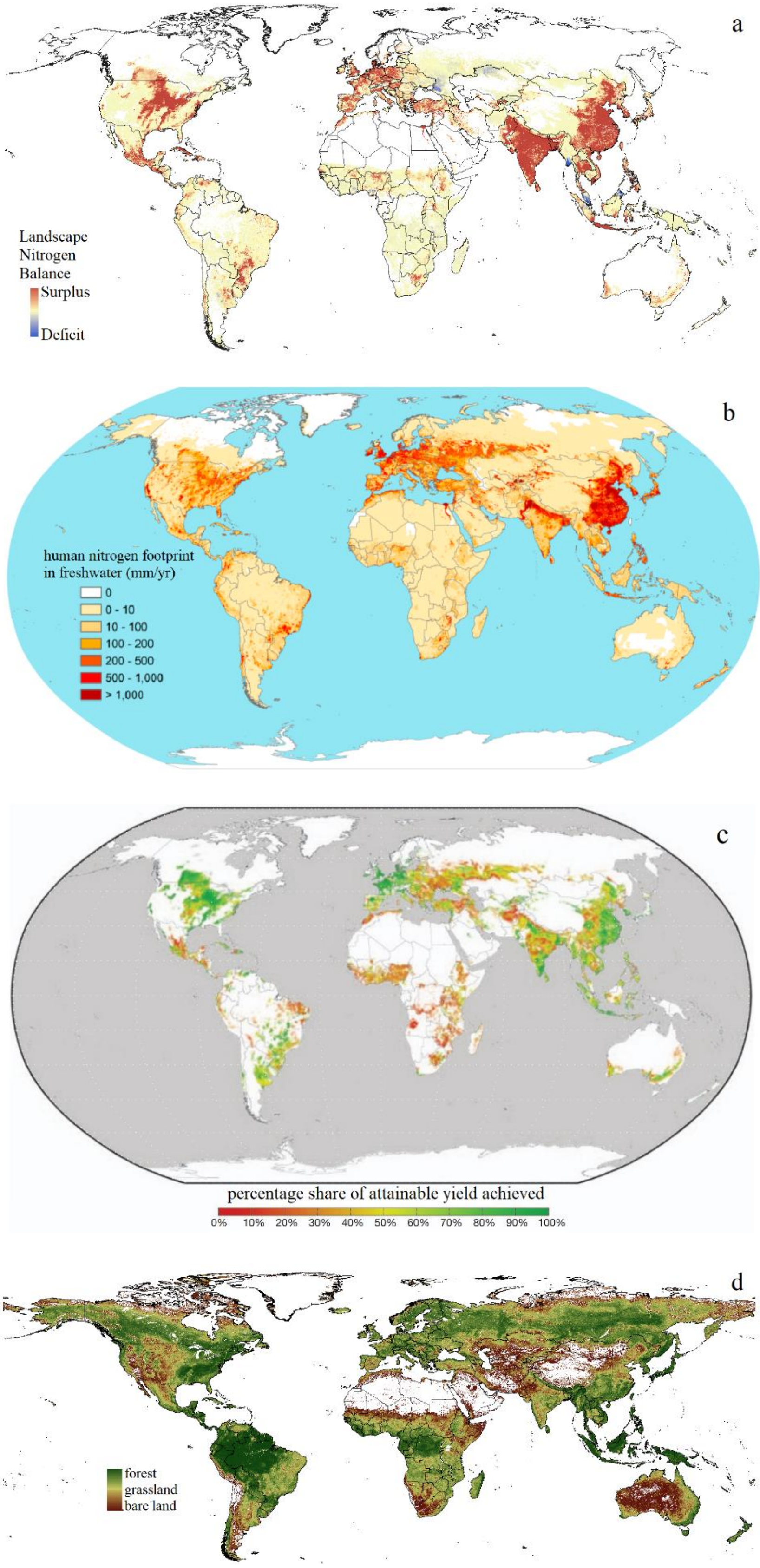
Maize



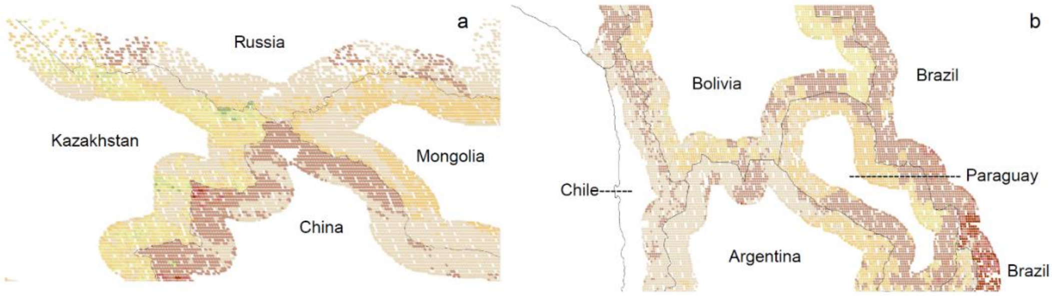
Potato

Supplementary Figure 4. Maps of Exemplary Yield Data Resolutions. Maize and Potatoes

The maps in **Supplementary Figure 5** show the global distributions of nitrogen balances on croplands[3] (**a**), water pollution[14] (**b**), attained yield as percentage of attainable[8] (**c**), and the predicted natural vegetation we would see without human impact[33] (**d**).



Supplementary Figure 5. Nitrogen Balances and Pollution, Crop Yields, and Hypothetical Natural Vegetation. The maps a to d show the global distributions of our main input data.



Supplementary Figure 6. By Analyzing Data Close to International Borders Only, We can Reduce the Impact of Environmental Influences. Shown here is the nitrogen balance on agricultural lands close to international borders in Asia and Latin America. Darker reds reflect larger nitrogen surpluses while darker greens reflect larger nitrogen deficits. The closer together the observations, the more similar are topography, weather, soils, and other confounders that are not caused by the countries. Still, comparing e.g. the land just in China with that just in Mongolia, or land just in Brazil with that just in Bolivia, there are apparent differences that reveal the influence of the countries.

Section S2. Data for the Exploration of Explanations

For our examination of what explains the global variation in countries' nitrogen pollution per yield, we require data on various country characteristics that relate directly or indirectly to farmers' incentives and constraints, what to grow where and how. First of all, we use data on countries gross domestic product, their value added in agriculture as percentage of gross domestic product, and their populations, all from the World Bank [80]. Previous studies have found that yield gaps close with increasing development[3,8] whereas nitrogen pollution first increases up to a point and then decreases[13,34]. However, most countries in the world are still on the increasing part of the curve and overall, richer countries cause more nitrogen pollution than poorer countries[13,34]. For population size and growth, the literature suggests lower yield gaps and more nitrogen pollution. From a policy point of view highly relevant, we also examine the role of institutional quality. The data comes from Kunčič [35]. The influence of institutional quality is ambiguous ex ante. Agricultural productivity is clearly positively associated with better institutions [81,82]. On the other hand, the effect on nitrogen pollution could be positive, if they mostly increase fertilizer use, or negative, if they also improve regulatory frameworks and environmental policies [16].

Then, we use data from the United Nations Food and Agriculture Organization - FAO [83] – on global development flows towards land resources. Previous studies have shown that financial flows can have large effects on agricultural and environmental outcomes[84]. However, again the sign is not clear again ex-ante, because less financial constraints are empirically associated both with more fertilizer input and higher yields[85]. We also use data on countries' agricultural intensity, as measured by fertilizer use, with data from FAO [83]. Higher agricultural intensity is both associated with higher yields and more pollution and overall, this should be strongly associated with more pollution per yield, given the prior literature and our own empirical evidence in this study.

Finally, two especially interesting and policy-relevant variables are countries' availability and affordability of food, provided by Chaudhary, et al. [86]. Thinking about the trade-off between yield gaps and nitrogen pollution as quantifying how much countries "buy" higher yields with environmental damage, a natural question is whether perhaps more available and affordable food for all is a benefit of lowering the costs of agricultural production by externalizing costs to the environment.

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