The Impact of Water Quality on GDP Growth: Evidence from Around the World

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WATER GLOBAL PRACTICE • QUALITY UNKNOWN BACKGROUND PAPER

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WORLD BANK GROUP

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Abstract

Declining water quality can impact the economy in various ways. Impacts can be found in the health sector, where labor productivity can be affected, in agriculture, where the quality and quantity of food produced can be reduced, and in tourism, real estate, aquaculture/fisheries and other sectors which rely on environmental quality and ecosystem services. Despite these well-known impacts, finding economy-wide affects of water quality on economic activity can be elusive. In this paper we attempt to fill this gap by using a conventional empirical approach in contemporary environmental economics and new data on economic activity and water quality for 19 countries from 1990-2014. We find that when rivers become very heavily polluted, regions downstream see reductions in economic growth, losing between 0.8 and 2.0 percent of economic growth. These losses imply that in many places, the costs of environmental degradation are severely under-estimated and well above efficient levels.

Introduction

Economic growth and water pollution are intrinsically linked. Nearly all forms of production create pollution as a by-product. Because water is needed for life, health, and economic production, the impurities generated by upstream polluters may affect downstream users. With the understanding that eliminating all water pollution is too costly and infeasible, regulators and policy makers must make decisions about the appropriate level of water pollution. In strictly economic terms, this calls for weighing the benefits from the polluting activity against the costs of pollution.

In order to make these decisions, we must have accurate information on the true costs of water pollution, which can be elusive for several reasons. First, there are challenges with identification. Both benefits and costs derive from the same source—economic activity—thus making it difficult to isolate and quantify the macroeconomic impacts. A naïve approach that correlates water pollution to GDP will likely conflate the positive and negative impacts. Second, there is the curse of dimensionality. There are a multitude of water pollutants and parameters that may have harmful impacts on the economy, and these parameters are ever increasing. In the United States alone, the EPA receives manufacturing notices for more than 1,000 new chemicals each year (EPA 2019). A mere decade or two ago, the world was oblivious to concerns from pharmaceutical drugs and microplastics in water supplies. It is just waking up to these concerns, and nobody knows what contaminants may be uncovered in the future. Finally, there are enormous scientific uncertainties involved. There are uncertainties about the safe, or 'no impact' level of parameters, about the timing of impacts, and the types of impacts that be caused by poor water quality.

In this paper we attempt to overcome some of these challenges to estimate, globally, the economic cost of water pollution. We use recent global sub-national GDP data (Kummu, Taka and Guillaume 2018a) and show a significant impact of poor water quality on local GDP growth between 1990 and 2014. Following the recent climate-econometric literature (Dell, Jones and Olken, 2012; Burke, Hsiang and Miguel, 2015), we use fixed effects panel regressions to isolate the impact of water quality from time invariant factors or common time-varying factors that could be correlated with both water quality and GDP. To do so, we employ a reduced-form estimation strategy which aims to isolate the harmful impact of the water quality externality. This is done by using the direction of stream flow and a digital elevation model to separate regions which benefit from economic activity from the regions which are impacted by its externalities. Because water, and thus water pollution, flows downstream, whereas the economic benefits remain local, we can follow the pollution downstream where its impact on economic activity is both exogenous and measurable.

To overcome the curse of dimensionality, we rely on the water quality parameter biological oxygen demand (BOD) which is often considered an 'umbrella pollutant' due to its ability to proxy many different water quality parameters. BOD measures the amount of oxygen in water that would be required to break down present organic material (Barnes, Meyer, and Freeman 1998). It is highly correlated with other water quality indicators, such as dissolved oxygen and chemical oxygen demand, and is a good indicator of the amount of organic material in water. Thus, while BOD will not account for all types of water pollution, it will indicate the overall environmental health of a water body and is useful to obtain a lower bound estimate of the economic cost of water pollution.

Although no paper that we are aware of has attempted to estimate water quality impacts on GDP growth, large literatures exist which estimate sectoral impacts. Health impacts of consuming water contaminated with fecal bacteria (Prendergast and Kelly 2012; Christian et al. 2013; Padhi et al. 2015; Baker et al. 2018), nitrates (De Roos et al., 2003; Ward et al. 2010, 2018; Aschebrook-Kilfoy et al. 2012; Espejo-Herrera et al. 2016; Zaveri et al. 2019), salinity (Khan et al., 2014; Dasgupta, Huq, and Wheeler 2016; Naser et al. 2018; Akter, 2019), arsenic (Smith et al. 2000; Yu, Harvey, and Harvey 2003), to name just a few, are well-established. Likewise, it is well known that irrigation water quality is critical for determining agricultural yields (Warrence, Bauder, and Pearson 2002; Thompson 2004; Russ et al. 2019) and food quality (Sharma, Agrawal, and Marshall 2006; Khan et al. 2008; Mahmood and Malik 2014; Meng et al. 2016). Real estate is also a common sector for studying water pollution impacts, particularly because of its ability to proxy environmental amenity values (Keiser and Shapiro, 2018).

Data

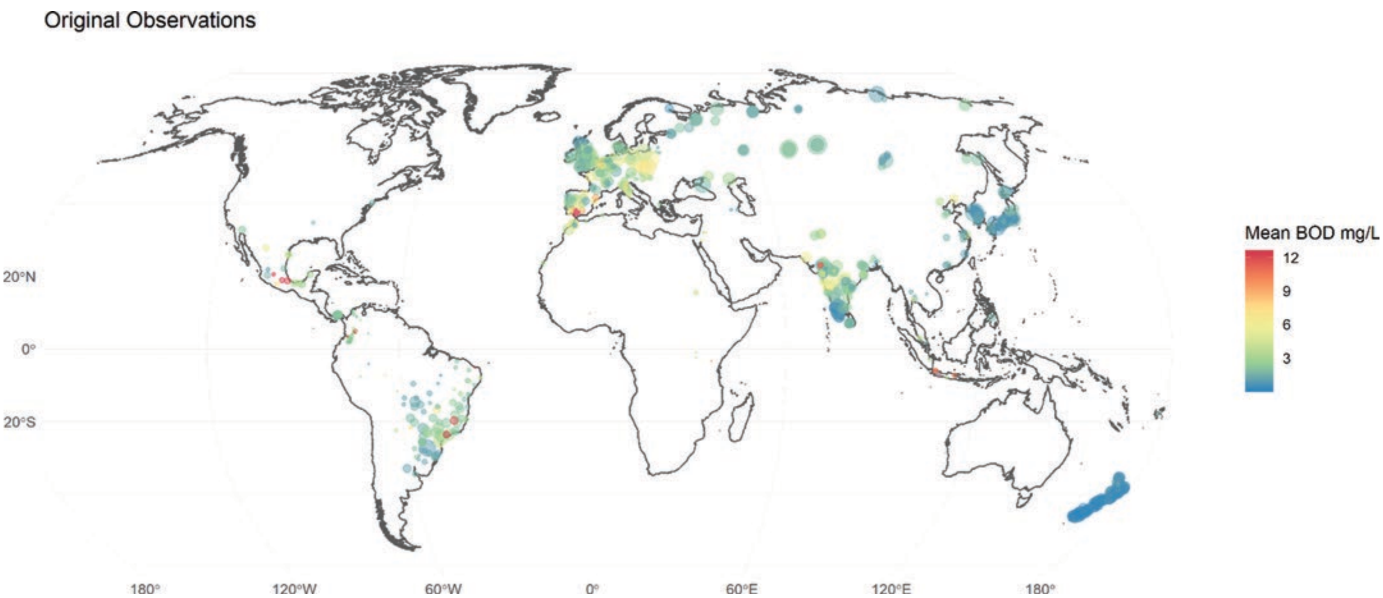
Several global datasets were combined to estimate the impact of poor water quality on economic growth. These datasets are described in this section.

Water Quality

Data on BOD come from the GEMStat, the only globally harmonized repository on water quality developed, hosted and maintained by UNEP-GEMS, the International Centre for Water Resources and Global Change and the Federal Institute of Hydrology in Koblenz.[1] For BOD, GEMStat records 93,127 observations, including 66,040 observations between 1990 and 2014. Observations come from 740 stations located in 19 countries (see figure 1).[2]

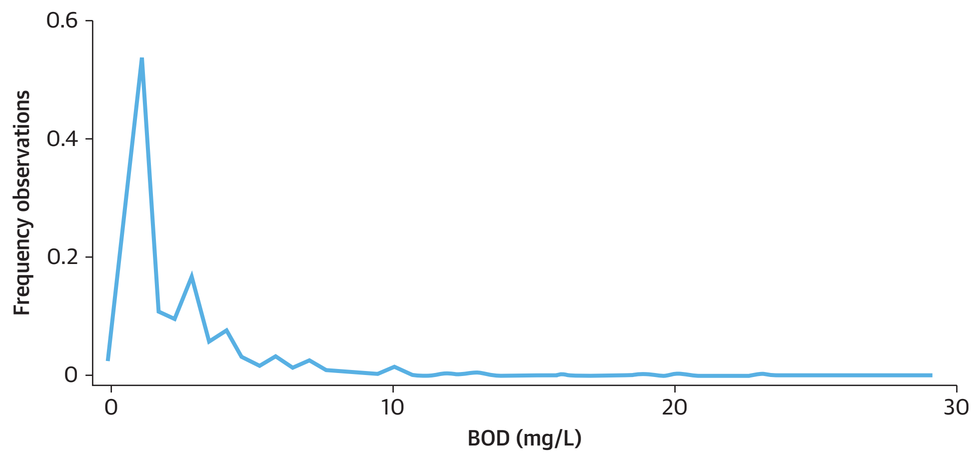
Following the scientific literature, rivers are considered as unpolluted when BOD is below 2mgL, moderately polluted when BOD is between 2 and 8 mgL and heavily polluted when BOD is larger than 8mgL. 60% of the observations in GEMStat have a BOD smaller or equal than 2mg/L and 5% of the observations have a value larger than 8mg/L (see figure 2).

FIGURE 1. **Mean BOD Across GEMStat Monitoring Stations, 1990–2014**



Notes: Mean value of BOD per station between 1990 and 2014. Size dots is a function of the number of observations per station with larger dots indicating stations with more observations.

FIGURE 2. **Distribution of BOD Observations, 1990–2014**



Notes: Figure shows a histogram of observations of BOD across all GEMStat monitoring stations from 1990–2014.

Economic Activity

Grid-level GDP data between 1990 and 2014 at a 0.5-degree resolution comes from Kummu, Taka and Guillaume (2018a). The data are primarily based on sub-national GDP per capita data constructed by Gennaioli, et al. (2013) and covers 82 countries, representing 85% of the global population and 92% of global total GDP (PPP) in 2015. For remaining countries, Kummu, Taka and Gillaume (2018a) used national level data from the World Bank and the CIA's World Factbook. Missing values were interpolated and extrapolated by the authors, using country specific thin plate splines and trends. The authors then disaggregated the filled-in data at a 0.5-degree spatial resolution.

As a robustness check, we also test our results using night-time lights (NTLs), a commonly used proxy for economic activity. Data on NTLs is from the Defense Meteorological Satellite Program- Operational Linescan System (DMSP-OLS) Nighttime Lights Time Series Version 4, from NOAA National Centers for Environmental Information, Earth Observation Group. The dataset used is the average visible, stable lights, and cloud free coverages product, which includes cloud-free image composites of average visible light for each year 1992-2013. NTL data is aggregated to the same 0.5-degree grid as the GDP data. Following Henderson, Storeygard, and Weil (2012) and Storeygard (2016), regions with frequent gas flares are removed using a mask provided by Elvidge et al. (2009), as are all water bodies using Esri's World Water Bodies shapefile.[3]

Additional Data

Weather data are taken from the *Terrestrial Air Temperature and Precipitation Version 4.01* compiled by the University of Delaware (Willmott and Matsuura 2012a and 2012b). This data set provides monthly precipitation and temperature at a 0.5 degree spatial resolution. Data are available for each month between 1901 and 2014.

Population data is from Gridded Population of the World (GPW) (CIESIN 2016), which contains population data at the same 0.5 degree gridcell level, at 5 year intervals between 1990 and 2015. For years between these 5 year intervals, linearly interpolated values are calculated and used. Given that gridcells are unchanging over time, population also represents population density.

Empirical Strategy

In order to estimate the impact of BOD on economic growth, we estimate a reduced-form growth equation. For each 0.5-degree grid cell and year between 1991 and 2014, the annual growth rate of the cell's gross domestic product (GDP) is computed adjusted for inflation (g). A fixed-effect panel regression is used to determine if g is impacted by poor water quality measured by biological oxygen demand (BOD). We estimate the following model:

$$\begin{aligned} g_{i,t,t-1} = {} & \beta_1 BOD^{up}_{i,t} + \beta_2 Rainfall_{i,t} + \beta_3 Rainfall^2_{i,t} + \beta_4 Temp_{i,t} + \beta_5 Temp^2_{i,t} + \beta_4 Log(Population)_{i,t} \\ & + \gamma_i + \phi^1_t + \phi^2_{m,t} + \phi^3_{m,t-1} + \mu_{c\times t} + \in_{i,t} \end{aligned} \tag{1}$$

Cells are indexed by *i* and year by *t*. Following the scientific literature, rivers are considered unpolluted when BOD is less than 2 mg/L, moderately polluted when BOD is between 2 and 8 mg/L, and heavily polluted when BOD is more than 8 mg/L. Accordingly, we construct a discrete variable for BOD with three levels: nonpolluted observations (BOD is less than 2 mg/L), moderately polluted observations (BOD is between 2 and 8 mg/L), and heavily polluted observations (BOD is more than 8 mg/L). Sixty percent of the observations have a BOD less than 2 mg/L, and 5 percent of the observations have a value larger than 8 mg/L. We control for rainfall and temperature because both are correlated with water quality and economic activity. For these two weather variables, we allow a quadratic relationship between them and GDP. Time invariant factors that affect cells' growth rates are controlled by grid cell fixed effects (γ_i). Global events are captured by year fixed effects (ϕ_t). There are a host of other factors that will affect BOD levels. These unobserved factors are controlled using a variety of fixed effects. Country changes are accounted for by country-specific time trends ($m_{c \times t}$). BOD is measured in each station and year in a different month of a year. To account for seasonal variations in BOD, we include fixed effects for the month during which BOD is measured in the current and the previous years. Standard errors are clustered at the cell level.

As discussed in the introduction, a setup that matches gridcells to nearby monitoring stations would suffer from endogeneity. Economic activity both generates and is impacted by water pollution. Thus, estimates would be biased and unreliable. Instead, we match gridcells to the nearest monitoring station which is a higher elevation than the gridcell, and is outside of the given gridcell, with a maximum distance of 200km. This ensures that water pollution can only flow from the monitoring station location, into the gridcell, and not the other way around. Thus, identification is predicated on the fact that BOD levels of exogenously determined, and likely to be randomly distributed and unexpected, and therefore orthogonal to any possible confounders. The rich set of fixed effects included in equation 1 isolates localized fluctuations in BOD, facilitating causal inference.

Results

Main Results

Our main results are presented in table 1. Column 1 displays the results of the baseline model in equation 1. We find that when pollution is moderate (i.e. BOD is between 2 and 8 mg/L), regions downstream see their growth fall by 1.4 percent. When BOD exceeds 8 mg/L, a level considered to be heavily polluted, growth falls by 2 percent. Columns 2 and 3 are subsample analyses for middle-income countries and high-income countries, respectively. Impacts are slightly larger in middle income countries than in the full sample, with moderate pollution leading to a fall in growth of 1.8 percent, and heavy pollution leading to a fall in growth of 2.5 percent. In the high income country sample, impacts disappear. The coefficient on moderate pollution is positive and statistically significant, but very small, indicating a precisely estimated null impact. In columns 4 through 6, we condense the “polluted” categories into a single bin containing all observations with a BOD larger than 8 mg/L, a threshold beyond which water is heavily polluted. The results remain qualitatively unchanged.

To further corroborate these results, several robustness checks are presented. In table 2, we use a continuous measure of BOD instead of bins. In column 1 we test for a linear relationship between GDP growth and BOD and in column 2 we allow a quadratic relationship. The estimates show a smaller impact than that estimated in table 1. This is evidence that the impact is non-linear, and consistent with impacts only occurring beyond a certain level of pollution. Thus, the semi-parametric specification in table 1 is likely the better fit.

In table 3, we test for a broad range of alternative specifications that are usual in the environmental econometrics literature. First, we drop month fixed effects to replicate classic models with only yearly data (column 2). Second, we include a country-specific quadratic time trend instead of a country-specific

TABLE 1. Impact of BOD on GDP Growth Rate

	1	2	3	4	5	6
Variables	**All countries**	**Middle-income**	**High-income**	**All countries**	**Middle-income**	**High-income**
Moderately polluted (vs. nonpolluted)	−1.438***	−1.759***	0.280***			
	(0.074)	(0.091)	(0.037)			
Heavily polluted (vs. nonpolluted)	−1.980***	−2.509***	−0.012			
	(0.100)	(0.138)	(0.086)			
Heavily polluted (vs. BOD < 8 mg/L)				−0.804***	−1.160***	−0.285***
				(0.086)	(0.124)	(0.078)
Rainfall	0.007***	0.009***	−0.001***	0.007***	0.009***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rainfall^2	−0.000***	−0.000***	−0.000+	−0.000***	−0.000***	−0.000+
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Temperature	−0.560***	5.274***	−1.557***	−0.663***	4.742***	−1.568***
	(0.109)	(0.288)	(0.118)	(0.109)	(0.280)	(0.118)
Temperature^2	−0.043***	−0.164***	0.040***	−0.041***	−0.154***	0.041***
	(0.006)	(0.008)	(0.006)	(0.006)	(0.007)	(0.006)
Log population	0.087	1.249***	−0.450***	0.060	1.152***	−0.451***
	(0.092)	(0.250)	(0.042)	(0.093)	(0.252)	(0.042)
Observations	**326,448**	**231,971**	**94,477**	**326,448**	**231,971**	**94,477**
R^2	**0.192**	**0.198**	**0.549**	**0.191**	**0.197**	**0.548**

Note: Dependent variable is change in gridcell log(GDP). Standard errors in parentheses are clustered at the gridcell level. Statistical significance is given by + p<0.1, * p<0.05, ** p<0.01, *** p<0.001. BOD = biological oxygen demand.

TABLE 2. Impact of BOD on GDP Growth Rate, Continuous BOD

	1	2
Variables	**Linear BOD**	**Quadratic BOD**
BOD	−0.011***	−0.031***
	(0.001)	(0.002)
BOD^2		0.000***
		(0.000)
Rainfall	0.007***	0.007***
	(0.000)	(0.000)
Rainfall^2	−0.000***	−0.000***
	(0.000)	(0.000)
Temperature	−0.663***	−0.653***
	(0.109)	(0.109)
Temperature^2	−0.041***	−0.041***
	(0.006)	(0.006)
Log population	0.064	0.061
	(0.093)	(0.093)
Observations	**326,448**	**326,448**
R^2	**0.191**	**0.191**

Note: Dependent variable is change in gridcell log(GDP). Standard errors in parentheses are clustered at the gridcell level. Statistical significance is given by + p<0.1, * p<0.05, ** p<0.01, *** p<0.001. BOD = biological oxygen demand

TABLE 3. Impact of BOD on GDP Growth Rate, Alternative Specifications

Variables	1 Base	2 No month	3 Quadratic time trend	4 Income category, year fixed effects	5 Income category, year fixed effects, no time trend	6 No year fixed effects	7 Lag GDP growth
Moderately polluted (vs. nonpolluted)	−1.438*** (0.074)	−1.433*** (0.079)	−1.270*** (0.072)	−1.094*** (0.074)	−1.478*** (0.075)	−1.094*** (0.074)	−1.147*** (0.077)
Heavily polluted (vs. nonpolluted)	−1.980*** (0.100)	−1.954*** (0.103)	−2.007*** (0.097)	−2.026*** (0.107)	−2.093*** (0.109)	−2.026*** (0.107)	−1.729*** (0.117)
Rainfall	0.007*** (0.000)	0.007*** (0.000)	0.007*** (0.000)	0.004*** (0.000)	0.005*** (0.000)	0.004*** (0.000)	0.007*** (0.000)
Rainfall^2	−0.000*** (0.000)	−0.000*** (0.000)	−0.000*** (0.000)	−0.000*** (0.000)	−0.000*** (0.000)	−0.000*** (0.000)	−0.000*** (0.000)
Temperature	−0.560*** (0.109)	−0.448*** (0.107)	−0.266* (0.111)	0.777*** (0.119)	2.168*** (0.118)	0.777*** (0.119)	0.332* (0.147)
Temperature^2	−0.043*** (0.006)	−0.042*** (0.006)	−0.047*** (0.006)	−0.088*** (0.006)	−0.120*** (0.006)	−0.088*** (0.006)	−0.074*** (0.008)
Log population	0.087 (0.092)	−0.048 (0.093)	0.299** (0.091)	0.175+ (0.091)	0.181+ (0.096)	0.175+ (0.091)	0.441*** (0.122)
Observations	**326,448**	**326,448**	**326,448**	**326,448**	**326,448**	**326,448**	**293,165**
***R*^{2}**	**0.192**	**0.188**	**0.198**	**0.223**	**0.217**	**0.223**	**0.205**

Note: Dependent variable is change in gridcell log(GDP). Standard errors in parentheses are clustered at the gridcell level. Statistical significance is given by + p<0.1, * p<0.05, ** p<0.01, *** p<0.001. BOD = biological oxygen demand.

linear time trend to allow for more complex dynamics (column 3). Third, we include an income category-year fixed effects in addition to (column 4) or instead of (column 5) year fixed effects. Fourth, we eliminate year fixed effects (column 6). Finally, we account for one lag GDP growth to model convergence as in a Solow growth model (column 7). Throughout these specifications, the coefficients on BOD vary very little. For moderately polluted areas, they range from a GDP loss of 1.09% to 1.4%. For heavily polluted, they range from a GDP loss of 1.7%–2.1%.

In table 4, we replicate the main results but replace the GDP growth rate with the GDP per capita growth rate. Here, results are qualitatively similar to the main results in table 1, though they are smaller by about a half. In table 5, we weight observations based on grid cell population to ensure that results are representative of the economy of the countries studied. Again, the results are qualitatively similar to the main results in table 1 though the magnitudes are lower. Lastly, in table 6, we validate our results by replacing the modeled GDP data with nighttime lights data, an independent measure of economic activity that is frequently used in the economics literature. Our results remain qualitatively unchanged, providing further confidence that the results are not an artifact of the GDP data that are used.

TABLE 4. Impact of BOD on GDP Per Capita Growth Rate

Variables	1 All countries	2 Middle-income	3 High-income	4 All countries	5 Middle-income	6 High-income
Moderately polluted(vs. nonpolluted)	−0.701***	−0.948***	−0.255**			
	(0.084)	(0.119)	(0.078)			
Heavily polluted(vs. nonpolluted)				−1.334***	−1.535***	0.312***
				(0.072)	(0.088)	(0.034)
Heavily polluted (vs. BOD < 8 mg/L)				−1.796***	−2.143***	0.049
				(0.098)	(0.133)	(0.085)
Rainfall	0.007***	0.009***	−0.001***	0.007***	0.010***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rainfall^2	−0.000***	−0.000***	0.000*	−0.000***	−0.000***	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Temperature	−0.711***	3.009***	−0.869***	−0.640***	3.262***	−0.854***
	(0.098)	(0.220)	(0.103)	(0.097)	(0.222)	(0.104)
Temperature^2	−0.038***	−0.109***	−0.014*	−0.039***	−0.114***	−0.014**
	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)
Observations	**358,816**	**252,237**	**106,579**	**358,816**	**252,237**	**106,579**
R^2	**0.178**	**0.185**	**0.524**	**0.179**	**0.186**	**0.524**

Note: Dependent variable is change in gridcell log(GDP). Standard errors in parentheses are clustered at the gridcell level. Statistical significance is given by + p<0.1, * p<0.05, ** p<0.01, *** p<0.001. BOD = biological oxygen demand.

TABLE 5. Impact of BOD on GDP Growth Rate, Weighted Regressions

Variables	1 All countries	2 Middle-income	3 High-income	4 All countries	5 Middle-income	6 High-income
Moderately polluted(vs. nonpolluted)	−0.772***	−0.923***	0.131*			
	(0.058)	(0.068)	(0.059)			
Heavily polluted(vs. nonpolluted)	−1.058***	−1.346***	−0.324**			
	(0.075)	(0.092)	(0.120)			
Heavily polluted(vs. BOD < 8 mg/L)				−0.441***	−0.626***	−0.443***
				(0.060)	(0.072)	(0.093)
Rainfall	0.003***	0.003***	−0.001***	0.003***	0.003***	−0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rainfall^2	−0.000***	−0.000***	0.000+	−0.000***	−0.000***	0.000+
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Temperature	−0.375*	2.666***	−1.144***	−0.436**	2.334***	−1.138***
	(0.151)	(0.517)	(0.180)	(0.154)	(0.506)	(0.180)
Temperature^2	−0.004	−0.066***	0.044***	−0.002	−0.058***	0.043***
	(0.004)	(0.010)	(0.008)	(0.004)	(0.009)	(0.008)
Log population	−2.434***	−3.032***	0.208	−2.499***	−3.086***	0.215
	(0.398)	(0.494)	(0.434)	(0.399)	(0.493)	(0.434)
Observations	**326,448**	**231,971**	**94,477**	**326,448**	**231,971**	**94,477**
R^2	**0.213**	**0.192**	**0.514**	**0.212**	**0.191**	**0.514**

Note: Dependent variable is change in gridcell log(GDP). Standard errors in parentheses are clustered at the gridcell level. Statistical significance is given by + p<0.1, * p<0.05, ** p<0.01, *** p<0.001. BOD = biological oxygen demand.

TABLE 6. Impact of BOD on Night-Time Light Growth Rate

Variables	1 All countries	2 Middle-income	3 High-income
Heavily polluted (vs. BOD < 8 mg/L)	−0.050*** (0.003)	−0.034*** (0.003)	−0.072*** (0.006)
Rainfall	−0.000*** (0.000)	−0.000*** (0.000)	−0.000*** (0.000)
Rainfall squared	0.000* (0.000)	0.000 (0.000)	0.000*** (0.000)
Temperature	−0.114*** (0.003)	−0.101*** (0.008)	−0.187*** (0.008)
Temperature squared	0.002*** (0.000)	0.002*** (0.000)	0.004*** (0.000)
Log population	−0.008 (0.007)	0.054*** (0.011)	−0.036** (0.011)
Observations	**309,519**	**218,596**	**90,923**
R^2	**0.353**	**0.427**	**0.298**

Note: Dependent variable is change in gridcell log(Night-Time Lights). Standard errors in parentheses are clustered at the gridcell level. Statistical significance is given by + p<0.1, * p<0.05, ** p<0.01, *** p<0.001. BOD = biological oxygen demand

Discussion and Concluding Remarks

This paper has provided the first reduced-form estimates of the impact of water pollution on economic growth. Here, we find that when rivers become moderately polluted, growth downstream is reduced by 1.4 percent, and when they become heavily polluted it is reduced by 2 percent. In middle income countries, growth impacts are higher, at 1.76 percent and 2.5 percent, respectively. Are these results qualitatively significant? Comparing the lost growth to average economic growth in the gridcells included in the study, over the time period of the data, 2.33 percent, we find that water pollution can wipe away over 33 percent of a region's growth, depending on specification and country income level.

These results are likely to be underestimates of the true impact. Examining downstream regions isolates the negative externalities of water pollution and partially excludes the benefits of the economic growth that generated them. However, all growth, particularly when it occurs within the same country, is intrinsically linked. It is therefore likely that downstream regions still see a spillover of economic benefits from upstream production, thus biasing our estimates toward zero. In addition, although BOD is an umbrella indicator of water pollution, it is not all encompassing. Many other pollutants and parameters may have economic impacts that would be not be captured by the BOD variable. In addition, many impacts may be slow moving and long-term, such as cancer-causing pollutants, and may take many years to show up in any aggregate economic statistics. The implication is that these results are likely an underestimate of the true impact.

Although these results provide summary evidence of the economic consequences of deteriorating water quality, several shortcomings of this analysis must be noted. First, the data on local GDP are novel and important, but also imperfect. Globally, data on economic activity are only available at the country level and, for some countries, at the province or state level. Data sets like the one employed collect as much subnational data as is available and then rely on algorithms to distribute these data into grid cells. Although the techniques for distributing these data are logical, they are imperfect. We test for robustness of these results by also using night-time lights as an indicator of economic activity, but since this too is a proxy, some caution should be warranted.

The use of BOD as a proxy for overall water quality also has its shortcomings. Although BOD is an important parameter for measuring the health of a water body, it does not provide information about the specific pollutant causing the changes in BOD or the source of the pollutant. In one region, for instance, industrial chemicals may be causing spikes in BOD, whereas in another region, bacterial contamination may be the source. These different types of pollutants will have different health, environmental, agricultural, and industrial impacts, which will translate into different overall economic impacts. These different impacts end up amalgamated into a single, overall average impact in the regression.

Data and methodological challenges have made research into the economic and societal impacts of water pollution difficult. However, in recent years, new data breakthroughs such as the use of remote-sensing to detect water quality (Odermatt et al. 2018), and more accurate models built using machine learning (Damania et al. 2019) offer opportunities to better study these impacts. While this paper offers a relatively general view into the economic impacts of declining water quality, there is a great need to dig into the mechanisms that individual pollutants have on different sectors.

Notes

1. www.gemstat.org
2. Countries include Argentina, Belgium, Brasil, Colombia, Fiji, Great-Britain, India, Japan, South Korea, Sri Lanka, Lituania, Morocco, New-Zeeland, Pakistan, Panama, Poland, Russia, Tanzania and USA
3. Available here: https://www.arcgis.com/home/item.html?id=e750071279bf450cbd510454a80f2e63

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