Is urban wastewater treatment effective in India? Evidence from water quality and infant mortality

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Abstract

In developing countries, untreated sewage exposes people to alarming water pollution levels, yet there is limited knowledge about the effectiveness of wastewater treatment investments. I evaluate the effect of wastewater treatment on water quality and infant mortality in India, exploiting the staggered introduction of urban sewage treatment plants over the period 2010-2020. I match granular data on sewage treatment plants, river water quality, as well as child births and deaths using the hydrological network. I show that after starting wastewater treatment, levels of fecal coliforms – a commonly used measure of fecal contamination in water – decreased by 50%. Mortality under the age of six months declined by 20% downstream of the plants, with larger effects for boys and children from the bottom wealth quintiles. The results are consistent across several estimators robust to heterogeneous treatment effects, are not driven by selective migration, and are only found downstream of the plants, which rules out confounding effects from other local policies. A back-of-the-envelope calculation suggests that starting wastewater treatment earlier – from 2010 – in urban areas later selected into treatment – after 2020 – would have prevented over 40,000 child deaths in downstream sub-basins.

JEL Codes : C31, D78, H70, O13, 018, 053, Q25

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1 Introduction

In developing countries, the lack of sanitation infrastructure and water facilities exposes the population to alarming inland water pollution levels. Globally, 80% of wastewater flows back into the ecosystem without being treated or reused [UN Water, 2017], contributing to a situation where around 1.8 billion people use a source of drinking water contaminated with faeces, putting them at risk of contracting diseases such as cholera, dysentery, typhoid and polio [WHO/UNICEF, 2015]. Although access to clean water is vital, the literature on the impacts of major sanitation infrastructure investments on downstream ambient water quality in developing countries is generally thin and mixed [Olmstead and Zheng, 2021]. Implementation and operational challenges – arising from energy demand, the need for skilled workers, and capital requirements – make the efficacy of wastewater treatment facilities uncertain. Moreover, due to our limited understanding of exposure to untreated sewage, the health benefits of mitigating river water pollution via wastewater treatment remain ambiguous. Assessing the benefits of wastewater treatment investments in developing countries is important, particularly because the public funds used for sanitation projects could be invested in other infrastructure needed for human development.

This paper examines the effect of urban sewage treatment on water quality and downstream infant mortality in India using granular data of the hydrological network. My identification strategy relies on a difference-in-difference (DiD) approach and event-study specifications, exploiting the staggered introduction of sewage treatment plants between 2010 and 2020. Specifically, I compare urban areas that started wastewater treatment from 2010 onwards to those with only planned or under-construction plants as of 2020. Fecal coliform levels serve as my primary indicator of water pollution due to their widespread use as a measure of fecal contamination. I focus on mortality under the age of six months, a critical period when infants' digestive systems are still developing, consequently heightening the risk of gastrointestinal infections.

The Indian context is particularly relevant for three reasons. First, India is one of the most polluted countries in the world, where untreated sewage remains the main source of water pollution. This pollution has direct implications for public health, as waterborne diseases linked to fecal pathogens are major contributors to mortality rates, especially among infants. Second, a lot of public investments have recently been directed toward building sewage treatment plants (STPs).[1] According to the governement, around 30% of urban wastewater is treated in 2020. Yet, many plants do not function at maximum capacity and others do not meet the prescribed environmental standards. The unreliability of access to electricity (due to frequent power shortages), the lack of qualified labor, and the lack of funding in maintenance and operation activities raise concerns about the functioning of current plants [CPCB, 2007]. Third, while wastewater treatment is initially planned for and by urban areas, assessing its effects on downstream areas, where most of the population is marginalized, offers insight into the potential mitigation of social inequalities regarding pollution.

I compile one of the most comprehensive database on wastewater treatment and water quality in India at the urban level. I use the national inventory of sewage treatment plants conducted in 2020-21 and attribute plants to nearby urban areas. In this dataset, 273 urban areas started wastewater treatment from 2010 onwards whereas 185 urban areas had a wastewater treatment plant still at the project stage or under construction in 2020. Combining different data sources on water quality, I build a panel of 313 monitoring stations located on river segments within and downstream up to 100km of these urban areas over the period 1991-2020. Using an Indian representative birth history panel, I geolocalize around 90,000 children born over the period 1991-2019 in sub-basins encompassing river segments within 100km downstream of river segments crossing the urban areas.

The study has two primary results. First, I find that treating wastewater in an urban area decreased average fecal coliform levels within and downstream of this area by 50%. This result is consistent across several estimators robust to heterogeneous effects when treatment varies over time, namely Gardner [2022] estimator, Sun and Abraham [2021]'s estimator and the stacked regression approachs. Event-study regressions suggest that the decrease in the levels of fecal coliforms intensifies over time, which may be explained by the opening of new treatment plants or increased compliance with environmental standards. Wastewater treatment also decreases water pollution as measured by two other organic pollution measures, biological oxygen demand (BOD) and dissolved oxygen (DO).

Second, I find that wastewater treatment decreased the mortality under the age of six months in downstream sub-basins. Mortality decreases by 8.1 children per 1000

[1] Sewage treatment plants are designed to intercept and treat sewage through piping infrastructure and treatment plants before its discharge into lakes, rivers, and streams.

after operating sewerage treatment according to the Gardner [2022]'s estimator, which corresponds to a 20% decrease with respect to the average mortality under six months over the period 1991-2019. These results control for child-, mother-, household- and weather-level determinants of health, as well as place of birth and year fixed effects. Findings are robust to the use of other staggered treatment estimators and to a specification including mother fixed effects, controlling for unobserved family characteristics that could be correlated with both water quality and infant mortality. Heterogeneity analysis shows that boys and children in the lowest wealth quintiles benefited the most from wastewater treatment, especially those born in households practicing open defecation.

Finally, robustness tests support these findings, ruling out alternative explanations such as selective migration of mothers into treated sub-basins or differences in household behaviors related to water treatment, open defecation or exclusive breastfeeding practices. I further show that mortality decreased downstream but not upstream of the urban areas treating wastewater, which supports the assumption that no other policy has taken place locally at the same time. Falsification tests on air pollution provides supportive evidence that other environmental policies are not systematic confounders of wastewater treatment and that health impacts found in this study are attributable to water pollution.

Applying my results to a back-of-the-envelope calculation, over 40 000 deaths would have been prevented if wastewater treatment had been implemented since 2010 in urban areas where the treatment was still not operational in 2020. The cost per life saved is INR 6 million ($93,000 in 2015). The cost per disability-adjusted life year (DALY) averted is INR 73,308 ($1,145 in 2015), which is lower than the GDP per capita in India.

The paper contributes to three strands of the literature. First, to the best of my knowledge, this study provides the first national estimates of how sewerage treatment plants affect ambient water pollution concentrations in a developing country. In the USA, Keiser and Shapiro [2019] find that grants distributed to municipal wastewater treatment plants from the 1972 Clean Water Act (CWA) reduced most water pollution types and Flynn and Marcus [2021] observe that these reductions occured only downstream from facilities required to upgrade their technology. While recent literature evaluates industrial water pollution control in China [Zhang et al., 2019, He et al., 2020] and in India [Do et al., 2018, Duflo et al., 2018, Joshi and Shambaugh, 2018], assessment of domestic pollution control remains scarce in low- and middle-income countries. In India, Greenstone and Hanna

[2014] find that water regulations, over the period 1986-2005, had on average no effect on water pollution in cities covered by the National River Conservation Plan (NRCP) because of low public demand for ambient water quality improvements and weak institutional support for water policies. I make progress by studying wastewater treatment investments based on the national inventory of sewage treatment plants conducted by the Indian government in 2020 instead of using a binary indicator for exposure to the NRCP, which does not reflect the actual implementation of wastewater treatment. My findings show that recent sewage treatment plants have significantly improved water quality in India, with the effects intensifying over time. The study suggests that there is a strong potential for wastewater treatment in developing countries, which face much higher levels of pollution than developed countries.

While I am unaware of any study assessing public policies to control water pollution at the city-level in India since the analysis of Greenstone and Hanna [2014], two recent papers examine the effect of public policies on surface water quality and infant mortality at the district level. Motohashi [2023] explores the effect of toilet construction on river pollution and diarrheal mortality, using an instrumental variable approach and a difference-in-differences design with baseline latrine coverage as a continuous treatment. I differ from this study in the type of data measuring mortality – I use a representative birth history panel instead of aggregated indicators calculated using survey data. More importantly, my identification strategy at the urban area level allows me to compare treated outcomes to not-yet treated outcomes in a staggered difference-in-differences design, with many estimators robust to heterogeneous effects when treatment varies over time. Bhupatiraju et al. [2023] investigate the impacts of judicial policies on surface water toxicity and infant mortality, based on an instrumental approach relying on judges' random assignment and writing styles. Unlike my paper focused on domestic pollution control, most court cases analysed in their paper involve firms and industrial pollution.

To the best of my knowledge, this paper also provides the first estimate of how urban wastewater treatment affects health outcomes in India. In Peru, Bancalari [2020] estimates that unfinished sewerage infrastructure increased early-life mortality. Recent evidence suggests that sewerage infrastructures highly contributed to the decline of mortality in the advanced economies during the late nineteenth century [Kesztenbaum and Rosenthal, 2017, Alsan and Goldin, 2019, Chapman, 2019, Harris and Helgertz, 2019, Gallardo-Albarrán, 2020].[2] My paper differs from these studies by investigating health effects in areas downstream of sewage treatment plants, thus isolating wastewater treatment from other covariates like sewage disposal access. This study is closely related to the study by Flynn and Marcus [2021] on the impact of the Clean Water Act on birth weight in the USA. In a context where water pollution is much lower,[3] and clean water and healthcare provision are much higher than in India, Flynn and Marcus [2021] show that CWA grants to municipal wastewater treatment plants increased average birth weight by 8 grams in counties downstream of the plants. By examining urban sewage treatment in India, my empirical findings highlight the considerable benefits of treating wastewater in developing countries, many of which experiencing high mortality damages from pollution exposure [Landrigan et al., 2018].

Finally, this study builds on the literature emphasizing the health costs of ambient microbiological water pollution. In Indonesia, Garg et al. [2018] estimate that the use of upstream rivers for bathing and sanitation practices accounts for up to 7.5% of all diarrhoea-related deaths downstream each year. In Bangladesh, Buchmann et al. [2022] estimate that households, who suddenly abandonned water infrastructure contaminated by arsenic, saw 28% greater child mortality driven by diarrheal disease. In South Asia, diseases related to ambient microbiological water pollution represent a significant cause of child mortality. The findings of my study advocate for targeted investments in wastewater treatment to improve public health. These benefits are close to those obtained by local chlorination campaigns, as the recent Kremer et al. [2023]'s meta-analysis estimates the effect of water treatment on child mortality to be a reduction of about 30% in the odds of all-cause under-5 mortality in low- or middle-income countries. The cost per DALY averted estimated in the context of sewage treatment in India is, however, lower, with the caveat that wastewater treatment not only affects human health but also ecosystems and related activities.

The paper proceeds as follows. Section 2 documents the mechanisms through which untreated sewage affects health as well as the Indian context regarding water pollution regulation and sewerage infrastructures. Section 3 describes the data. Section 4 presents the empirical approach and the identification strategy. Section 5 shows the main results

[2] However, Anderson et al. [2022] find little evidence that sewage treatment explains the decline in infant and diarrheal mortality observed during the period 1900–1940 in 25 major American cities.

[3] Figure A1 compares the levels of fecal coliforms over the period 1985-2001 in India versus in the USA. On average, pollution in India is more than 10 times higher than in the United States.

relating to the impact of wastewater treatment on water pollution and downstream infant health. Section 6 presents robustness checks. Section 7 discusses the implications of the effects on infant mortality, and section 8 concludes.

2 Background and institutional context

2.1 Effects of domestic wastewater pollution on health outcomes

The discharge of untreated sewage in rivers poses significant public health concerns as it contaminates water supplies and recreational areas.

Fecal pathogens (bacteria, parasites or viruses) present in wastewater are directly harmful to human health. Pathogens transmission from water to humans can occur through different channels: drinking contaminated water or eating unsafe food,[4] contact with polluted water when bathing or recreational use, and transmission by insects that breed in the water.

Contamination by fecal microorganisms is responsible for the high disease burden in children, particularly acute diarrheal mortality [Liu et al., 2016],[5] morbidity [Wolf et al., 2018] and chronic stunting [Guerrant et al., 2013]. Because of this high disease burden and these risks, the World Health Organization (WHO) recommends and sets regulatory guidelines at 0 per 100 mL for fecal coliforms in drinking water [WHO, 2017]. Though not generally pathogenic, fecal coliforms – bacteria found in the intestines of warm-blooded animals – serve globally as an indicator of potential fecal contamination in water.

Given these concerns about water quality, the dietary choices for infants, such as breasfeeding, play a crucial role for infant health. For this reason, the WHO recommends six months of exclusive breastfeeding partly because children who are exclusively breastfed have a lower risk for gastrointestinal infections and mortality. Before six months, infants' digestive systems are still developing and there is an increased risk of gastrointestinal infections if solids or other non-breastmilk foods are introduced. Around six months, many babies' digestive systems are developed enough to process solid foods, including

[4] Unsafe food is food mixed or washed with contaminated water or food from the river that is not cooked such as shellfish – for example mussels or oysters – which concentrate the microorganisms in their flesh.

[5] Diarrhea is the second leading cause of death in children 1-59 months of age [Liu et al., 2016].

potential allergens. However, while the importance of breastfeeding in low-income and middle-income countries is well recognised, only 37% of children younger than six months of age are exclusively breastfed in these countries [Victora et al., 2016].

In India, millions of people lack access to clean water, meaning that they use either an unimproved water source or an improved source that is contaminated with fecal matter (World Health Organization).[6] Even where piped water systems are available, they frequently do not meet WHO's recommended standards [Rayasam et al., 2019], and water supply is intermittent [Amrose et al., 2015]. While water purifiers have become popular in urban households with recent technological advances and increased affordability, many rural areas still face challenges in accessing disinfected water.

Despite the high risk of fecal pathogen infection through drinking water, the practice of exclusive breastfeeding has not been fully adopted across India. Data from the National Family Health Survey (NFHS-IV, 2015–2016) show that 55% of Indian mothers exclusively breastfeed their infant under age six months. Many children in that age group consume other liquids, such as plain water, in addition to breastmilk. Indian infants under six months of age, a period crucial for digestive system development, face an increased risk of infections from contaminated water if they are not exclusively breastfed.

2.2 Water pollution regulations and monitoring

Indian environmental regulations on water quality have been implemented since 1974 by the Water (Prevention and Control of Pollution) Act. The Indian government has created central and state agencies of the Ministry of Environment, Forest and Climate Change (MoEFCC) to prevent, control and abate environmental pollution. These agencies, the Central Pollution Control Board (CPCB) and the State Pollution Control Boards (SPCBs), are responsible for developing the India National Water Plan.

The CPCB establishes water usage criteria across five categories (Figure D1). The first three categories correspond to drinking water and outdoor bathing, and they depend on four water quality indicators: total coliform count, pH level, Biological Oxygen Demand (BOD), and Dissolved Oxygen (DO) content. Total coliform count encompasses

[6] According to the WHO, unimproved water sources include unprotected wells, unprotected springs, surface water (e.g. river, dam or lake), vendor-provided water, bottled water (unless water for other uses is available from an improved source) and tanker truck-provided water. Improved water sources include household connections, public standpipes, boreholes, protected dug wells, protected springs and rainwater collection. See https://www.who.int/news-room/fact-sheets/detail/drinking-water.

fecal coliform numbers. Fecal coliforms are specifically monitored to indicate fecal contamination in water. Both BOD and DO gauge organic pollution levels. BOD measures the quantity of oxygen required by the decomposition of organic waste in water. High values (mg/L) are indicative of heavy pollution. DO is similar to BOD except that it is inversely proportional to pollution. These indicators are consistently monitored within India's water quality monitoring network to detect public health risks for those exposed to surface waters.

Overall, Indian rivers are heavily polluted due to the discharge of untreated sewage, industrial effluents, and agricultural runoff. While human activities are the main sources of water pollution, weather can also play a role in the concentration of pollutants. Precipitation can decrease pollution by diluting the concentration of pollutants or increase water pollution by bringing new pollutants into the river, especially in the case of flooding. Temperature also plays an important role because of its influence on water chemistry, as the rate of chemical reactions generally increases at higher temperatures. In 2015, 70% of rivers monitored (275 out of 390) were identified as polluted by the CPCB based on assessment of BOD monitored during the years 2009-2012. The report identifies the discharge of untreated domestic wastewater from the urban centres as the main source of pollution.

The CPCB sets the wastewater discharge standards for the entire country.[7] At the state level, SPCBs are responsible for monitoring the performance of all wastewater discharging entities (buildings, industries, large and small-scale sanitation systems). However, there are not in charge of the construction and operation of wastewater treatment facilities.

2.3 Sewage treatment plants in India

In the Constitution of India, the responsibility of large-scale sanitation is delegated to the states, under purview of the Ministry of Housing and Urban Affairs (MoHUA - formerly Ministry of Urban Development) [Reymond et al., 2020]. MoHUA is the largest funder of the sanitation sector [Wankhade, 2015]. Urban Local Bodies (ULBs) and Water Supply and Sewerage Boards (WSSBs) are given the responsibility of devising and implementing

[7]BOD below 30 mg/l without dilution is the standard for discharge of treated sewage from sewage treatment plants and general standard for effluent discharge from effluent treatment plants to rivers/streams.

sanitation strategies at the city level. Figure D2 summarizes the responsibilities in the large-scale sanitation sector.

To improve standards of living, a running water-supply has been established in most of the cities, towns and even in some villages over the past four decades in India. This has, in turn, led to flush-latrines and much larger use of water in homes for bathing, washing of clothes and utensils etc, generating significant amount of wastewater. Due to the lack of resources, sewerage did not get much attention and has lagged far behind water supply until the turn of the century.

In 2007, India had 234 Sewage Treatment Plants (STPs), of which 84 were inspected by the Central Pollution Control Board team [CPCB, 2007]. During this period, the efficacy of the water treatment process raised some concerns. Many of these STPs were not functioning adequately, primarily due to operational and maintenance shortcomings. Out of the inspected plants, only 8 received a 'good' performance rating, while 30 were rated 'satisfactory.' Capacity utilization was often inadequate, many plants lacked an alternative power source, and underqualified labor compromised the performance of the plants. The CPCB report emphasizes the urgent need to prioritize wastewater treatment to reduce pollution and preserve water resources.

For over 15 years, ULBs have gradually worked on setting up sewage treatment plants to address the pollution and public health challenges posed by untreated sewage. Various international agencies and the central government have provided financial and technical assistance to ULBs for constructing and upgrading STPs. In addition, the National Green Tribunal (NGT), established in 2010 under the National Green Tribunal Act, has played a pivotal role in pushing for environmental conservation and sustainable development in India, including in the domain of wastewater management and sewage treatment.

Since 2007, the number of sewage treatment plants has more than quadrupled. From 522 operational STPs in 2015, the count rose to 1,093 by 2020. However, the installed capacity of municipal wastewater treatment plants represents less than 30% of the estimated urban wastewater generated in 2020 and many plants do not function at maximum capacity or do not meet the prescribed effluent water quality standards. In the context of rapid urbanization and population growth, water treatment will become an increasingly important challenge in India competing with meeting other basic needs. Evaluating the effectiveness of current treatment plants is an opportunity to optimally plan its development. Furthermore, while wastewater treatment is initially planned for and by urban areas, assessing its effects on downstream areas, where most of the population is marginalized, offers insight into the potential mitigation of social inequalities regarding pollution.

3 Data

3.1 National inventory of sewage treatment plants

I use the national inventory of sewage treatment plants (STPs) released in March 2021 by the Central Pollution Control Board (CPCB). This inventory was carried out during 2020-21 by the State Pollution Control Boards and the Pollution Control Committees. This inventory focuses on urban sewage treatment plants that are built under the decision of Urban Local Bodies (ULBs) and Water Supply and Sewerage Boards (WSSBs). The inventory lists 1,631 STPs all over India.[8]

Since the plants are not geocoded, I manually match each of them according to the administrative descriptors provided in the CPCB inventory (state, town and an accompanying string description of location) to a 2001 town or village polygon [Meiyappan et al., 2018]. I then merge neighboring polygons, that forms a unique urban area (See Appendix D). This indicates that many urban areas invested (or plan to invest) in one or several water treatment plants. Current work consists in providing exact plant geolocation based on Google Maps identification (Figure 1). So far, I have identified 564 of the 1631 plants that are correctly located in the urban areas.

3.2 Water quality

I use water pollution readings from four data repositories: the Global Environment Monitoring System for Freshwater database, the India-Water Resource Information System platform, the published database from Greenstone and Hanna [2014] and the public database from the Central Pollution Control Board (CPCB). Appendix D.2 describes details and steps taken to clean these data.

[8] Of 1,631 STPs listed in the inventory, 1,093 STPs are operational, 102 are non-operational, 274 are under construction and 162 STPs are proposed for construction.

The resulting geolocalized water quality dataset covers 2,505 monitoring stations on rivers (2,110 stations), lakes (331 stations) and canals (64 stations) over the period 1978-2020. The monitoring is done on a monthly or quarterly basis in surface waters, however the most recent database (provided by the CPCB for the post-2015 period) is available only at the annual scale and provides the maximum and minimum pollution measurements for the year. Consequently, I aggregate all measurements are at the annual level.

In the analysis, the main indicator of water pollution is the level of fecal coliforms, which is consistenly measured to monitor the level of fecal contamination in water and the presence of pathogens harmful to human health (see Section 2). I also examine two additional indicators of water pollution by organic matter: biochemical oxygen demand (BOD) and dissolved oxygen (DO) levels. High values of fecal coliforms and BOD are indicative of heavy pollution, while DO levels are inversely proportional to pollution. As observed in the USA by Keiser and Shapiro [2019], dissolved oxygen levels follow a roughly normal distribution, while fecal coliforms and biological oxygen demand are more skewed (Figure A2).

Over the period 1990-2020, no major change in average pollution is observed for any of the three organic indicators across the oldest river water monitoring stations. Figure A3 extends the trends of these pollutants studied up to 2005 by Greenstone and Hanna [2014]. Over the full period, water pollution measured by fecal coliforms and biological oxygen demand levels are on average above the thresholds used by the Indian government to define water fit for bathing. The health of the population exposed to the high pollution levels is particularly at risk.

Figure A4 represents the annual means of average fecal coliform level over the full sample of monitoring stations, according to their location within urban areas reported in the STP inventory (N=518), downstream up to 100km of an urban area reported in the STP inventory (N=469) and other monitoring stations (N=1518). India's rivers flowing through urban areas – as reported in the sewage treatment plants inventory – and their downstream couterparts are the most heavily polluted surface water across India.

3.3 Health measures

I use the two latest rounds of the National Family Health Survey (NFHS-4 and NFHS-5), conducted respectively in 2015-16 and in 2019-21.[9] The NFHS is a large, nationally representative survey that collects data of women aged 15 to 49. Respondents report birth histories, including deaths and stillbirths. NFHS also includes information on household assets and provides the geo-coordinates of groupings of households that participated in the survey, known as NFHS clusters.

The main outcome variable is mortality within the first six months of life. The rationale is that children aged 0 to 6 months are particularly vulnerable to gastrointestinal infections since their digestive system is not yet fully developed (See Section 2). According to the information collected on food consumption among the children under two years old in the NFHS-4 and NFHS-5 surveys, more than half of the children aged 4 to 6 months are not exclusively breastfed and received plain water during the day and night before the survey (Figure 3). This implies that most children, before reaching six months of age, are at a high risk of infections from drinking water if it is contaminated with fecal pathogens. In the sensitivity analysis, I explore several alternative variables related to mortality temporality.

For each birth history panel of NFHS-4 and NFHS-5, I create a binary indicator based on whether child i born in year y died within the first six months of life.[10] Children born during the COVID-19 pandemic in 2020 and 2021 are excluded from the analysis. For readability, I scale mortality variables per 1,000 live births.

Health determinants included in the analysis are at the child level, mother level, and household level. Child determinants include indicators for the child being a female, being part of a multiple birth, being the first born, being the fourth child or more. Determinants at the mother level include indicators for the mother being either under 18 years old or over 35 years old at the time of the child's birth, educational attainment (primary, secondary education or higher education), religious affiliation (being Muslim, neither Hindu nor Muslim), and caste affiliation (scheduled caste, scheduled tribe, or other backward caste). Household-level determinants include indicators related to wealth quintiles.

[9] The National Family Health Survey is India's version of the Demographic and Health Survey (DHS).
[10] I exclude all children born within 6 months of the interview date.

3.4 Hydrological network HydroSHEDS

I matched each urban area polygon, which contains at least one sewage treatment plant, to both the river network and hydrological sub-basins boundaries from HydroSHEDS [Linke et al., 2019]. First, I identify water quality monitoring stations located on river segments crossing urban areas and located up to 100km downstream.[11] Second, I identify NFHS cluster coordinates located inside sub-basins polygons containing river segments downstream urban areas. In the following sections, I use the expression "main basin" to identify the entire river basin to which a river segment or a sub-basin belongs to (see Figure 2). Appendix E provides details of the matching process.

3.5 Other data

3.5.1 Weather data

I use gridded weather datasets from the Indian Meteorological Department (IMD) that provides high resolution daily rainfall and temperature (minimum and maximum) datasets spanning 1951-2020. First, I add up the amount of precipitation that falls within a 20 km radius of each monitoring station and NFHS cluster in a year. Second, I compute the daily average temperature within a 20 km radius of each site, and then calculate the annual mean of this average temperature for each monitoring station and NFHS cluster.

3.5.2 Demographic growth

To measure population, I use WorldPop gridded population estimates [WorldPop and Center for International Earth Science Information Network (CIESIN), 2018]. The dataset offers an estimated total number of people per grid-cell at a resolution of 3 arc (approximately 100m at the equator) for the years 2000, 2005, 2010, 2015, 2020. I then compute total population per urban area polygon for each of the available datasets and linearly interpolate between years.

[11] The length of the area affected by microbiological water pollution depends on the river's discharge and the disappearance rate of fecal bacteria, the latter resulting from combined actions of various biological and physico-chemical parameters (e.g. nutrients depletion, sunlight intensity, and temperature decrease) and from possible deposition to sediments [Servais et al., 2007].

3.5.3 Air pollution

To quantify air pollution levels, I use annual estimates of ground-level fine particulate matter (PM 2.5) proposed by Van Donkelaar et al. [2021] and aggregated at the town and village level by Asher et al. [2021]. The dataset includes minimum, maximum and mean PM 2.5 concentrations within each village and town polygon, as part of the Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG). I calculate the minimum, maximum and mean PM 2.5 concentrations per urban area polygon based on the intersection with SHRUG towns and villages polygons.

4 Empirical strategy

The empirical strategy first tests for a decrease in water pollution within and downstream of urban areas that initiated wastewater treatment from 2010 onwards. Second, it assesses the subsequent impact on infant health in downstream sub-basins.

4.1 Selection of urban areas

To estimate the causal effect of wastewater treatment on water quality and health outcomes, I exploit variation from the treatment timing across urban areas. The foundation of my approach is to compare changes in outcomes downstream urban areas where wastewater treatment started from 2010 onwards relative to changes in outcomes downstream urban areas where wastewater treatment is planned or under construction in 2020 (the end of the study period).

I exclude from the sample the urban areas that have started wastewater treatment before 2010 because they are much bigger than the other both in terms of surface and population (Table A3). Urban areas that started wastewater treatment from 2010 onwards are also a bit bigger than the ones where wastewater treatment is under construction in 2020 but Figure A5 illustrates the similarity in annual population density (both mean and median) between the two groups of urban areas. As generated wastewater is proportional to the population, it suggests that domestic water pollution trends and downstream water-related infant mortality trends should respectively be parallel in both groups of urban areas.[12] The parallel trend assumption is further validated by compar-

[12]The largest urban areas, such as Delhi, Bangalore, Chennai, Hyderabad, and Pune, began wastewater

ing the annual mean of the main outcomes and examining event-study specifications in subsequent analyses.

I have identified 273 urban areas that began wastewater treatment from 2010 onwards (Figure 4) and 185 urban areas where wastewater treatment is in project in 2020. In the following sections, "treated" observations will refer to pollution and health outcomes related to urban areas that have started wastewater treatment from 2010 onward, and "control" observations will refer to pollution and health outcomes related to urban areas where wastewater treatment is in project in 2020. For infant mortality outcomes, it is crucial that the child was born and spent its initial months in the NFHS cluster where the mother was interviewed. I then exclude all children who are born from visiting mothers or who are born at a time when the mother did not live in the residence corresponding to the NFHS cluster. Table A1 and Table A2 provide descriptive statistics for respectively water pollution and infant mortality panels.

Both the water pollution and infant mortality panels are unbalanced and do not precisely overlap in their coverage of urban areas. Some monitoring stations are in urban areas without a corresponding downstream NFHS cluster, such as when the urban area is near the sea, and some of the births occurred downstream urban areas where water quality is not monitored. To enhance the accuracy of the treatment effect estimate and mitigate selection bias,[13] I apply two restrictions to the full sample before analysis: (i) if there is an outcome data (water pollution measure or birth) from a monitoring station or NFHS cluster related to an urban area after it has started wastewater treatment, then that monitoring station or NFHS cluster is only included if it has at least one data point before the urban area starting wastewater treatment; (ii) if the urban area does not treat wastewater in 2020, then the monitoring station or the NFHS cluster is only included if it has at least two outcome data points. A monitoring station or a NFHS cluster is only included in the subsequent regressions if it has outcome data for the specific dependent variable of that given regression. Table 1 summarizes the number of urban areas, monitoring stations, NFHS clusters and births of the regression samples by year. The water regressions sample covers 67 treated urban areas (135 operational sewage treatment plants) and 75 control urban areas. The infant mortality regressions

treatment before 2010. I assume that the trends in outcomes downstream of these areas differ from those downstream of urban areas where treatment is still under construction or proposed as of 2020.

[13]For instance, there might be a selection bias if urban areas begin monitoring water quality only after initiating wastewater treatment.

sample covers 134 treated urban areas (214 operational sewage treatment plants) and 138 control urban areas. Appendix F maps state by state all the urban areas, monitoring stations and NFHS clusters included in the main regressions.

The difference-in-differences methodology relies on the assumption of parallel trends between the treatment and control groups. A simple comparison of the evolution of the annual mean of the two main outcomes variables, the logarithmic transformation of fecal coliforms levels and the mortality under six months, between the treatment and control groups already encouragingly shows signs of parallel pre-trends (Figure A6 and Figure A7).

4.2 Water pollution specifications

Difference-in-differences

Recent literature has shown that standard two-way fixed effect regression estimates are subject to bias when effects are heterogeneous across units and time. Such estimates can be severely biased – and may even be incorrectly signed – when treatment effects change over time within treated units [De Chaisemartin and d'Haultfoeuille, 2020, Goodman-Bacon, 2021].

To solve this issue, I use the estimator proposed by Gardner [2022] that is robust to heterogeneous effects in the case of a staggered difference-in-differences design where treatment effects vary over time. The estimator is determined by fitting a regression of the outcome on group and time fixed effects in the sample of untreated observations. This regression then predicts the counterfactual outcome for treated observations. Provided there is common support for group and period fixed effects, implying the existence of treatment and comparison units in each group and period, we can identify fixed effects using solely the untreated groups and periods. The treatment effect estimates are then simply derived by subtracting the counterfactual from the actual outcome of those observations. This approach is equivalent to the one proposed by Borusyak et al. [2021] methodology. This estimator offers flexibility for specifications allowing for group-specific linear trends [De Chaisemartin and D'Haultfoeuille, 2022].

I estimate the regressions:[14]

[14] I use the R package from Butts and Gardner [2021]

$$
\begin{aligned}
\textit{Not (yet) treated:} \quad & ln(Fcoli)_{iaby} = X_{iy}\gamma + \delta_i + \eta_{by} + \epsilon_{iaby} \\
\textit{Full sample:} \quad & ln(Fcoli)_{iaby} - \widehat{\delta_i} - \widehat{\eta_{by}} = \beta T_{ay} + X_{iy}\gamma + \mu_{iaby}
\end{aligned} \tag{1}
$$

where $ln(Fcoli)_{iaby}$ is the log of fecal coliforms at monitoring station i located within or downstream urban area a in main basin b and year y. T_{ay} is a binary indicator variable that switches on and stays on for all subsequent years when sewerage treatment started in the urban area a.[15] X_{iy} includes the logarithmic transformation of the sum of precipitation that fell within a 20 km radius of the monitoring station i in year y. Monitoring station fixed effects (δ_i) control for time-invariant characteristics of each monitoring station and the surrounding location. To account for any time-varying trends in water quality across years, which may vary across main river basins (b), I include main basin-year fixed effects η_{by}. Lastly, standard errors are clustered at the urban area level.

Event-study

The underlying assumption for Equation 1 to be causal is the parallel trends assumption. To empirically test the parallel trends assumption and explore dynamic effects, I conduct an event-study analysis in which I replace the treatment indicator in Equation 1 with yearly lead and lag treatment indicators. Sun and Abraham [2021] show that, in settings with variation in treatment timing across units, the coefficient on a given lead or lag can be contaminated by effects from other periods, and apparent pretrends can arise solely from treatment effects heterogeneity. As for the static difference-in-differences specification, I use the Gardner [2022] estimator to estimate the regression:

$$
\begin{aligned}
\textit{Not (yet) treated:} \quad & ln(Fcoli)_{iaby} = X_{iy}\gamma + \delta_i + \eta_{by} + \epsilon_{iaby} \\
\textit{Full sample:} \quad ln(Fcoli)_{iaby} - \widehat{\delta_i} - \widehat{\eta_{by}} = & \sum_{\substack{-10 \leq \tau \leq 6 \\ \tau \neq -1}} \beta_\tau 1[T_{a,y-\tau} = 1] + X_{iy}\gamma + \mu_{iaby}
\end{aligned} \tag{2}
$$

Here τ indexes years since urban area a started sewerage treatment. I use a window of 10 years before and six years after starting treatment and bin all other observations

[15] Year of starting treatment in urban area a corresponds to the first year in which a sewage treatment plant is commissioned in a.

outside the event-study window into the window endpoints. The year before treatment ($\tau = -1$) is the reference year. For $\tau \geq 0$, β_τ estimates the cumulative effect of $\tau + 1$ years within or downstream an urban area that started sewerage treatment. For $\tau < 0$, β_τ is a placebo relative to period prior sewerage treatment.

4.3 Infant Health specifications

Difference-in-differences

To assess the effect of upstream wastewater treatment on infant mortality, I employ the same wastewater treatment timing as mentioned above. This specification, however, emphasizes downstream outcomes, aiming to separate the health effects of wastewater treatment from other factors like sewage disposal access. I employ a difference-in-differences methodology, drawing upon the Gardner [2022]'s estimator, as described in the following specification:

$$\begin{aligned} \textit{Not (yet) treated:} \quad & Mortality_{icamy} = X_{iy}\gamma + \delta_c + \eta_y + \theta_m + \epsilon_{icamy} \\ \textit{Full sample:} \quad & Mortality_{icamy} - \widehat{\delta_c} - \widehat{\eta_y} - \widehat{\theta_m} = \beta T_{ay} + X_{iy}\gamma + \mu_{icamy} \end{aligned} \tag{3}$$

$Mortality_{icamy}$ is a binary indicator set to one if child i, born in month m of year y, and whose mother participated in the NFHS cluster c survey within 100km downstream of urban area a, died within the first six months of life. T_{ay} is a binary indicator variable that switches on and stays on for all subsequent years when sewerage treatment started in the urban area a. X_{iy} includes controls for child-level, mother-level, household-level and weather determinants of health. Child controls include indicators for the child being a female, being part of a multiple birth, being the first born, being the fourth child or more. Controls at the mother level include indicators for the mother being either under 18 years old or over 35 years old at the time of the child's birth, educational attainment (primary, secondary education or higher education), religious affiliation (being Muslim, neither Hindu nor Muslim), and caste affiliation (scheduled caste, scheduled tribe, or other backward caste). Household controls include indicators for first, second, fourth and fifth wealth quintiles. Weather controls include the logarithmic transformation of the sum of precipitation that fell in the year within a 20km radius of the cluster coordinates and the daily mean temperature over the year within a 20km radius of the cluster coordinates. δ_c controls for all NFHS cluster time-invariant characteristics while θ_m and ζ_y capture respectively birth month and birth year fixed effects. Standards errors are clustered at the urban area level.

Event-study

Mirroring the water pollution approach, I empirically test the parallel trends assumption and explore dynamic effects using the subsequent event-study specification :

$$\begin{aligned} \textit{Not (yet) treated:} \quad Mortality_{icamy} &= X_{iy}\gamma + \delta_c + \eta_y + \theta_m + \epsilon_{icamy} \\ Mortality_{icamy} - \widehat{\delta_c} - \widehat{\eta_y} - \widehat{\theta_m} &= \sum_{\substack{-6\leq\tau\leq 6 \\ \tau\neq -1}} \beta_\tau 1[T_{a,y-\tau} = 1] + X_{iy}\gamma + \mu_{icamy} \end{aligned} \tag{4}$$

4.4 Robustness specifications

For robustness checks, I use the estimator proposed by and Sun and Abraham [2021], as well as the stacked regression approach. Both methods are robust to heterogeneous treatment effects in cases where treatment is binary and staggered.

According to the methodology of Sun and Abraham [2021], groups are aggregated into cohorts that start receiving the treatment at the same period. I use the never-treated groups as controls.

With the stacked regression approach, each treated unit is matched to "clean" (i.e. not-yet-treated) controls and there are separate fixed effects for each set of treated units and its control, as in Cengiz et al. [2019] among others. Gardner [2022] shows that this approach estimates a convex weighted average of the average treatment effect on the treated (ATT) under parallel trends and no anticipation, although the weights are determined by the number of treated units and variance of treatment within each stacked event, rather than by economic considerations [Roth et al., 2023].

5 Results

5.1 Wastewater treatment and Water Pollution

I find large decline in most pollutants after operation of wastewater treatment.

5.1.1 Fecal coliforms

The first analysis examines the relationship between wastewater treatment and average fecal coliforms levels.[16]

Main results Table 2 presents results on average fecal coliforms levels for a variety of specifications and the estimators by Gardner [2022], Sun and Abraham [2021], and classic TWFE estimator. Column 1 compares measures of fecal coliforms in monitoring stations within or downstream agglomerations that started wastewater treatment from 2010 onwards to urban areas where wastewater treatment was proposed or under construction in 2020 by estimating Equation 1. Column 2 adds weather controls to this specification. The log-transformed results imply that operating sewage treatment plants decreased fecal coliforms levels within and downstream urban areas by around 53%, a result that is significant at the 5% level.

The results are robust to regressions using urban area fixed effects. Columns 3 and 4 of Table 2 present results from estimating the specification using urban area fixed effects while controlling for the distance along the river network between the monitoring station and the urban area. The Stacked Difference-in-Differences (Stacked DD) methodology estimates are on a similar order of magnitude (Table B1). The estimate of Column 2 implies a decrease by 50% significant at the 10% level.

Figure 5 summarizes the results across all the specifications and estimators. The estimators robust to heterogeneous treatment effects when treatment varies over time provide consistent results. Only the classic TWFE estimate is of a slightly smaller order of magnitude and non-significant at the 10% level. Negative weights may be part of the reason for the difference as Figure B2 shows that 7% of treated observations receive negative weights in the TWFE regression reported in Column (2) of Table 2. Across all robust

[16] I use the average of the minimum and the maximum of the fecal coliforms measures. Since 2015, the CPCB doesn't provide annual mean measurements (only the minima and maxima are available). The correlation between mean values and average values of fecal coliform up to 2014 (up to 0.9914) suggests that average values are good proxies of mean values.

estimators and specifications using monitoring station fixed effects or urban area fixed effects, the decrease of fecal coliforms levels after wastewater treatment is as high as 50%.

Dynamic specification Figure 6 presents dynamic effects of wastewater treatment on ambient water pollution according to the Gardner [2022] methodology. The event study, as described in Equation 4 aids in diagnosing potential endogeneity in the timing of the rollout by examining pre-existing trends in water pollution. Prior to the commencement of sewage treatment in an urban area, there appears to be no discernible trend in pollution, supporting the parallel trends assumption. In the post-treatment period, the coefficients are negative and decrease over time which suggests that the decrease in fecal coliforms levels intensifies over time. The opening of new treatment stations or increased compliance with environmental standards could explain this finding.

Alternative estimators based on the Sun and Abraham [2021] methodology and the simple two-way fixed effects provide similar results (Figure B1).

5.1.2 Other measures of organic water pollution

I examine here the other two water pollutants, biochemical oxygen demand (BOD) and dissolved oxygen (DO), which indicate organic matter pollution and are consistently reported by the Indian water agencies. Contrary to fecal coliforms and BOD levels, DO levels are inversely proportional to pollution. Maximum measures of fecal coliforms and BOD levels, as well as minimum measures of DO levels, indicate the highest organic water pollution exposure over the year, while minimum of fecal coliforms and BOD levels and maximum of DO levels correspond to the lowest organic water pollution exposure.

Table 3 presents results using Equation 1 for each minimum and maximum measure of the three organic pollutants over the year. Columns (1) and (2) show that maximum fecal coliforms and maximum BOD levels decreased significantly after the operation of wastewater treatment and Column (3) that minimum DO level increased. According to the Gardner [2022] estimate, the maximum of BOD decreased by 23% and the minimum of DO increased by 0.35mg/L, which represents around 6% of the mean over the period. Since sewage is not the only source of BOD and DO pollution, the presence of other sources of pollution near urban areas, which are untreated by wastewater treatment plants, might account for the less pronounced decrease in these pollutants compared to fecal coliforms. Another possible explanation for the disparity in reduction magnitudes is that wastewater treatment plants are more effective in reducing fecal coliform levels than the other pollutants.

Moreover, while the operation of wastewater treatment significantly affected the maximum organic pollution levels, it seemingly had no impact on the minimum pollution levels throughout the year, as shown in Columns 4 to 6. This suggests that water quality during periods of minimal pollution might already be at a threshold where any further improvement from wastewater treatment would be minor or negligible.

5.2 Wastewater treatment and Infant Health

5.2.1 Mortality Results

Main results Table 4 displays the effects on mortality for children under six months of age, with results robust across various specifications. Column 1 compares children born in NFHS clusters located downstream urban areas that started wastewater treatment from 2010 onwards to children born in NFHS clusters located downstream of urban areas where wastewater treatment was proposed or under construction in 2020 by estimating Equation 3. Column 2 adds child, mother, household and weather controls to this specification.

Based on Gardner [2022]'s estimate in Column 2, mortality decreases by 8.1 children per 1000 following the initiation of upstream wastewater treatment, which corresponds to a decrease by 20% with respect to the mortality over the period 1991-2019.

Columns 3 and 4 of Table 4 present results from estimating the specification using urban area fixed effects while controlling for the distance along the river network between the NFHS cluster and the urban area. The estimates are consistent with the results of the baseline specification.

Table B2 presents consistent results with the Stacked Difference-in-Differences (Stacked DD) estimator.

Figure 7 summarizes the results across the specifications with NFHS clusters or urban area fixed effects and the four estimators.

Table B3 presents results that employ mother fixed effects, controlling for unobserved family characteristics that could be correlated with both water quality and infant mortality. In each regression, the sample is restricted to mothers downstream treated urban areas who gave birth at least to one child before treatment and one child post-treatment and mothers downstream control urban areas who gave birth to at least two children. Overall the coefficients are less precise, partly reflecting a reduction in statistical power as a result of the fewer observations, however the magnitude of the estimates do not change in comparison with Table 4.

Dynamic specification Figure 8 presents the dynamic effects of wastewater treatment on mortality. I observe no significant pre-trends in the pre-treatment period. Alternative estimators based on the Sun and Abraham [2021] methodology and the simple two-way fixed effects provide similar results (Figure B3).

Heterogeneity I continue the mortality analysis by examining subgroup responses. I repeatedly split the sample into two using respectively child sex and the wealth quintile distribution of households, wherein I study children into the first two quintiles and the last three quintiles separately. Table A4 presents heterogeneity results according to child gender and household wealth for Equation 3. The decrease in mortality is larger among boys and children from low wealth (first and second) quintiles. The higher reduction for boys is consistent with the medical observation that boys, on average, are more vulnerable to infections than girls. Since children from low wealth quintiles have lower access to clean water sources, the effect on lower wealth quintiles suggests that wastewater treatment is effective in mitigating social inequalities regarding water pollution exposure.

Given the cross-sectional nature of NFHS interviews, the information related to water treatment, main source of drinking water, and toilet access is recorded based on behavior at the date of the interview and not at the child's birth date. Knowing that this information may have changed over time, I split the sample into two according to whether the household reports treating water before drinking, whether the main source of drinking water at the household level is groundwater or another source, and whether the household practices open defecation. Table A4 presents heterogeneity results according to drinking water and sanitation variables. Since only 30% of children are born into households that treat water before drinking it and 33% of children are born into households that practice open defecation at the time of interview, the sample sizes according to these variables are not comparable. Nevertheless, we observe a mortality decreases of 8.5 children per 1,000 in the sample of children born in households that do not treat water. This estimate is higher in magnitude than the estimate for the entire sample and supports the sewage treatment plants effect. Furthermore, the estimate on mortality in households practicing open defecation is significantly high, corresponding to 43% of the mortality in the subsample (21.6 children per 1,000). In India, open defecation is frequently practiced near water bodies such as lakes, rivers, and streams. Consequently, wastewater treatment may provide greater benefits to these households. Heterogeneity in effects according to the main source of water suggests that the effect for children born in households drinking sources other than groundwater is slightly higher than for those drinking groundwater.

Finally, Figure B4 compares the estimates of equation 3 for mortality rates from neonatal mortality (child died before one month) to infant mortality (child died before one year) at the monthly level. While results are consistent for the different variables, mortality under four and six months are most significantly affected. This result is likely due to children aged 4 to 6 months being more susceptible to gastrointestinal infections, given their still-developing digestive systems (See Section 2). Additionally, from 4 months onwards, many mothers no longer exclusively breastfeed and introduce complementary foods to their children, which increases the risk of contamination (Figure 3).

5.2.2 Other health outcomes

During each NFHS interview, anthropometric measurements, blood tests, and information on the health of children under 5 years are collected, either performed by the NFHS interviewer or reported by the mother. However, as NFHS surveys are cross-sectional, few health variables, apart from mortality, can be studied in a panel at the NFHS cluster level. Using NFHS cluster fixed effects is important because it controls for unobserved birthplace characteristics such as access to healthcare services, road infrastructure, and the neighborhood. Variables related to other health outcomes do not permit the detailed study of the effect of wastewater treatment on health with the same precision as mortality variables (See Appendix C).

6 Robustness checks

Certain factors could challenge the benefits of wastewater treatment on mortality in children under six months, especially when questioning the independence of the treatment's timing. Plausible confounders must affect downstream sub-basins differently only after the urban area starts wastewater treatment.

6.1 Composition and Births

There may be concerns that the composition of mothers somehow changes. In other words, it is possible that the mothers giving birth after wastewater treatment begins in upstream urban areas possess different characteristics in ways that could explain some of the variation in health outcomes. To test if individuals sort into treated communities, I explore how demographic and maternal characteristics evolve after that wastewater treatment starts upstream the treated sub-basins.

I investigate how wastewater treatment impacts the controls used in the mortality regressions. Tables B4, B5 and B6 estimate Equation 3 on respectively child, mother and household controls.

The only variable influenced by wastewater treatment is the one indicating that the mother has received a higher education. This result suggests a potential migration of mothers with higher education levels to the treatment areas, a logical outcome if the reduction in pollution becomes noticeable or known. To verify that this migration is not the reason why mortality decreases after wastewater treatment, I run the regression following Equation 3 by excluding from the main sample all children born to mothers with the highest education levels. Table B7 presents the results excluding children born from mothers with higher education with the Gardner [2022], the Sun and Abraham [2021] and the classical TWFE methodologies, as well as Table B8 with the stacked regression approach. Figure B5 summarizes the results. The magnitude of the estimates does not change. The Gardner [2022]'s estimate suggests a decrease of 7.4 children per 1000. The mortality decrease in downstream sub-basins after wastewater treatment begins in urban areas is not attributable to the potential migration of highly-educated mothers.

These tests provide supporting evidence that the mortality results are unlikely to be explained by sorting pattern of mothers into treated sub-basins.

6.2 Effect on upstream areas

Another potential concern is that other local policies coincide with wastewater treatment. From 2014 to 2019, the Government of India initiated the Schachh Bharat Mission (SBM) or Clean India Mission at the country-level to achieve an "open-defecation free" India through construction of toilets. If toilet construction coincided with sewage treatment, improved sanitation could be a potential confounder in the observed decrease in mortality.

Table B9 replicates the regressions from Table 4, focusing on mortality in sub-basins upstream of urban areas. The estimates are non-significant (and positive), suggesting that the reduction in mortality occurred only downstream of the urban areas. These findings suggest that the reduction in infant mortality can be attributed to improvements in water quality in the sub-basins downstream urban areas that started wastewater treatment.

Figure B6 summarizes the results across the specifications with NFHS clusters or urban area fixed effects and the four estimators.

6.3 Comparison of upstream versus downstream mortality

The results are robust to the comparison of treated downstream outcomes to upstream outcomes with urban area fixed effects (Table B10). In this analysis, statistical power is lower because the restriction to years when treated urban areas that have both downstream and upstream births outcomes halves the sample of treated child births to around 3,700, whereas there are 7,700 in the main specification. It is also a bit less precise because without birth place fixed effect, we don't account for local factors such as healthcare provision or road access.

6.4 Parental behavior

The potential transmission of fecal pathogens is significantly influenced by drinking water treatment, hygienic practices like open defecation, and exclusive breastfeeding. Fecal coliforms, like other bacteria, can typically be inhibited in growth by boiling water, treating with chlorine, or using UV disinfection. The World Health Organization recommends exclusively breastfeeding infants up to the age of 6 months to protect them from potential infections (See Section 2).

Given the cross-sectional nature of NFHS interviews, which are used to construct the birth history panel, there is no control over various parental behaviors related to water treatment, toilet use, or liquids given during childbirth for the entire panel. These variables are recorded based only on behavior at the date of the interview.

Table B11 presents summary statistics of water treatment, open defecation practices, toilet sharing, and liquids given to children under the age of 6 months at the interview date. Panel A pertains to children born in 2015-2016 (NFHS-4) and Panel B to those born in 2019 (NFHS-5). Observations are available for approximately 600 children in both the control and treatment (200 pre-treatment and 400 post-treatment) groups respectively according to NFHS-4, and for about 360 children in each group per NFHS-5. Due to low statistical power, no major differences are found between the two groups regarding parental behavior towards water treatment, open defecation, or exclusive breastfeeding.

These comparisons suggest that the mortality results are not driven by differences in parental behavior.

6.5 Falsification test on air pollution

As falsification test, I estimate the effect of starting wastewater treatment on air pollution measured by the minimum, mean and maximum PM 2.5 annually from 1998-2020. I use urban area and year fixed effects, while clustering standard errors at the state level.

Table B12 shows that air pollution, measured by minimum, mean and maximum PM 2.5 over the year, did not respond to wastewater treatment within urban areas.

This is supportive evidence that other environmental policies related to air quality are not systematic confounders of wastewater treatment and that health impacts are attributable to water pollution and not to a change in air quality.

7 Discussion

7.1 Mortality burden of late treatment

I can calculate the total number of child deaths that could have been prevented if wastewater treatment was implemented since 2010 in control urban areas. From 2010 to 2019, approximately 5.3 million births took place in control sub-basins.[17] Using the Gardner [2022]'s estimate of 8.1 prevented deaths per 1,000 births in treated sub-basins (Table 4), a back-of-the-envelope calculation implies that over 40,000 deaths could have been prevented if wastewater treatment was implemented earlier.[18]

7.2 Cost-Effectiveness over the period 2010-2019

To compare the cost-effectiveness of the construction and operation of sewage treatment plants with other interventions, I use the commonly used measure of overall disease burden: the Disability-Adjusted Life Year (DALY). The DALY expresses years of life lost to premature death and years lived with a disability of specified severity and duration. One DALY is thus one lost year of healthy life. To calculate DALYs for a given condition in a population, years of life lost (YLLs) and years lived with disability of known severity and duration (YLDs) for that condition must each be estimated, and then the total summed [Murray and Lopez, 1996]. The Commission on Macroeconomics and Health of the World Health Organization defines very cost-effective interventions as those which avert each additional DALY at a cost less than GDP per capita, and cost-effective interventions as those where each DALY averted costs between one and three times GDP per capita [Organization, 2002].

My estimates suggest that reductions in pollution lead to an 8.1 children per 1000 decrease in average mortality under-six months in sub-basins downstream from urban areas that started wastewater treatment from 2010 onwards. I use this information to quantify the DALYs loss averted over the period 2010-2019. This estimation is conservative because I assume that mortality benefits only accrue to infants, and that there are no other morbidity benefits. In addition, the mortality benefits focus on places located downstream of urban areas that treat wastewater, without considering benefits within the urban areas themselves.

I calculate the total number of child births that took place in the sub-basins downstream from the 134 treated urban areas included in the mortality regressions. From 2010

[17] I estimate the number of live births per year in each downstream sub-basin by computing the WordlPop total population in each sub-basin and using the Indian crude birth rate (per 1,000 people) provided by the World Bank (https://genderdata.worldbank.org/indicators/sp-dyn-cbrt-in/?geos=IND&view=trend)

[18] $5,263,387 \times 10^6 \times 8.1/1000 \sim 42,633$

to 2019, approximately 5.6 million births took place in treated sub-basins.[19] Using the estimate of 8.1 prevented deaths per 1,000 births (Table 4), a back-of-the-envelope calculation implies that over 45,342 deaths have been prevented through wastewater treatment over the period 2010-2019.[20]

In the 134 treated urban areas included in the analysis, 214 sewage treatment plants are operational, accounting in total for 3,000 megaliters treated per day (MLD). Costs associated with implementation, operation, and maintenance differ significantly based on the treatment technology used. Specific requirements — including land area, energy consumption, chemical needs, and skilled labor levels — vary depending on the technology. I use the upper bound of the expenditure for both capital cost, and operation and maintenance cost to estimate the total expense of treating 1 MLD.

I assume that the capital cost for treating 1 MLD averages INR 40 million using Indian government infrastructure data.[21] It encompasses expenses related to sewage collection, treatment, and disposal systems and exceeds any capital cost detailed for specific technologies in the CPCB [2013]'s report.

For annual operation and maintenance costs, I rely on the upper-limit values from the CPCB [2013]'s report. These costs break down to INR 0.5 million/MLD for power, INR 0.2 million/MLD for repairs, INR 0.9 million/MLD for chemicals, and INR 3.4 million/MLD for manpower, totaling approximately INR 5 million/MLD in overall annual operation and maintenance expenses. Over 10 years, the total operation and maintenance cost then equals to around INR 50 million/MLD.

The total cost of constructing and operating the 214 sewage treatment plants from 2010 to 2019 reaches an upper bound of INR 270 billion.[22] This yields to a cost per life saved of INR 6 million ($93,000 in 2015).[23] Following WHO guidelines and assuming that infant deaths result in the loss of 81.25 disability-adjusted life years (DALYs), it yields a

[19] I estimate the number of live births per year in each downstream sub-basin by computing the WordlPop total population in each sub-basin and using the Indian crude birth rate (per 1,000 people) provided by the World Bank (https://genderdata.worldbank.org/indicators/sp-dyn-cbrt-in/?geos=IND&view=trend)

[20] $5,597,793 \times 8.1/1000 \sim 45,342$

[21] I gathered data about infrastructure projects implemented by the Government, either through traditional procurement or Public Private Partnership (PPP), by webscraping the Department of Economic Affairs website in June 2021: https://www.pppinindia.gov.in/iipdf_projects. I compute the mean implementation costs of 25 sewage treatment plants funded between 2009-2017.

[22] $3,000 \times (40 + 50) \times 10^6 \sim 270$ billion

[23] $270 \times 10^9/45,342 \sim 6 \times 10^6$
According to the OECD, the exchange rate in 2015 is $1 = INR 64 (https://data.oecd.org/conversion/exchange-rates.htm)

cost per DALY loss averted of INR 73,308 ($1,145 in 2015).

The cost per DALY averted is lower than GDP per capita in India (constant 2015 US$1,590 in 2015),[24] the threshold long used by the WHO to identify highly cost-effective interventions. While wastewater treatment is less cost-effective than water treatment with chlorine tablets in Kenya [Kremer et al., 2023], it can have broader benefits on ecosystems and related activities, such as fish farming, that are not represented in the analysis.

8 Conclusion

This paper examines the role of wastewater treatment in improving water quality and mitigating the negative health impacts of downstream pollution. I focus on the recent operations of sewage treatment plants in India. Using detailed river water quality datasets, along with geo-localized data on child births and deaths, the analysis shows that recent wastewater treatment installations have been cost-effective. Fecal coliform levels within and downstream urban areas that started sewage treatment from 2010 onwards decreased by 50%. Mortality under the age of six months decreased by 20% in sub-basins downstream urban areas that started wastewater treatment compared to those located downstream urban areas where plants were not operational as of 2020. The estimates suggest that the cost per life saved through the construction and operation of sewage treatment plants over the period 2010-2019 is INR 6 million ($93,000 in 2015). The cost per disability-adjusted life year (DALY) averted is INR 73,308 ($1,145 in 2015), which is lower than the GDP per capita in India, rendering wastewater treatment cost-effective.

Surprisingly, these benefits have occured despite many sewage treatment plants not operating at maximum capacity and others failing to meet stringent environmental standards. It suggests that the effects of fully functional and compliant plants could exceed the current estimates, potentially offering higher health improvements. Thus, the observed reductions in fecal coliforms and infant mortality may represent a conservative baseline from which to evaluate the full potential of wastewater treatment enhancements.

From a policy standpoint, India still holds potential to realize health benefits through enhanced wastewater treatment. As of 2020, the capacity of municipal sewage treatment plants covered less than 30% of the total urban wastewater estimate.

[24] https://data.worldbank.org/indicator/NY.GDP.PCAP.KD?end=2015&locations=IN-US&name_desc=false&start=2015

Given that water pollution is not monitored either within nor downstream each urban area, this paper advocates for the enforcement of water quality monitoring as a means to better control water pollution. To ensure global access to safe and affordable drinking water, better information is needed. This can be achieved through enhanced risk-based monitoring by national agencies and water service providers [Charles and Greggio, 2021]. There is especially an urgent need for reducing widespread exposure to fecal contamination through drinking water services in low- and middle-income countries [Bain et al., 2021]. To provide a better risk management to reduce fecal contamination, cross-sectional water quality data can also be collected in household surveys and can be used to examine risk factors for contamination.

India's experience offers valuable insights for other developing countries that are facing alarming inland water pollution levels. In many low-income countries, the infrastructure for wastewater treatment is often inadequate or does not exist. Additionally, those most vulnerable to pollution often lack the resources to engage in avoidance behaviors. Operating sewage treatment plants is a cost-effective tool to help households mitigate health damages from water pollution. Furthermore, in regions where water scarcity is a pressing issue, properly treated wastewater can serve as an alternative water source for a variety of uses. The implementation of effective wastewater treatment infrastructure, therefore, not only reduces the direct health impacts of water pollution but can also address water scarcity by augmenting the available water resources. The potential for water reuse can be a key factor in choosing technologies for the treatment and disposal of sludge and residues [Patel et al., 2021, Minier et al., 2023].

References

M. Alsan and C. Goldin. Watersheds in child mortality: The role of effective water and sewerage infrastructure, 1880–1920. *Journal of Political Economy*, 127(2):586–638, 2019.

S. Amrose, Z. Burt, and I. Ray. Safe drinking water for low-income regions. *Annual Review of Environment and Resources*, 40:203–231, 2015.

D. M. Anderson, K. K. Charles, and D. I. Rees. Reexamining the contribution of public health efforts to the decline in urban mortality. *American Economic Journal: Applied Economics*, 14(2):126–57, 2022.

S. Asher, T. Lunt, R. Matsuura, and P. Novosad. Development research at high geographic resolution: an analysis of night-lights, firms, and poverty in india using the shrug open data platform. *The World Bank Economic Review*, 35(4), 2021.

R. Bain, R. Johnston, S. Khan, A. Hancioglu, and T. Slaymaker. Monitoring drinking water quality in nationally representative household surveys in low-and middle-income countries: cross-sectional analysis of 27 multiple indicator cluster surveys 2014–2020. *Environmental health perspectives*, 129(9):097010, 2021.

A. Bancalari. Can white elephants kill? unintended consequences of infrastructure development in peru. Technical report, IFS Working Paper, 2020.

S. Bhupatiraju, D. L. Chen, S. Joshi, P. Neis, and S. Singh. Environmental justice? activist judges, water quality and infant mortality in india. 2023.

R. E. Black, C. G. Victora, S. P. Walker, Z. A. Bhutta, P. Christian, M. De Onis, M. Ezzati, S. Grantham-McGregor, J. Katz, R. Martorell, et al. Maternal and child undernutrition and overweight in low-income and middle-income countries. *The lancet*, 382(9890):427–451, 2013.

K. Borusyak, X. Jaravel, and J. Spiess. Revisiting event study designs: Robust and efficient estimation. *arXiv preprint arXiv:2108.12419*, 2021.

N. Buchmann, E. Field, R. Glennerster, and R. Hussam. The lifesaving benefits of convenient infrastructure: Quantifying the mortality impact of abandoning shallow tubewells contaminated by arsenic in bangladesh. Technical report, Working Paper, 2022.

K. Butts and J. Gardner. did2s: Two-stage difference-in-differences. *arXiv preprint arXiv:2109.05913*, 2021.

D. Cengiz, A. Dube, A. Lindner, and B. Zipperer. The effect of minimum wages on low-wage jobs. *The Quarterly Journal of Economics*, 134(3):1405–1454, 2019.

J. Chapman. The contribution of infrastructure investment to britain's urban mortality decline, 1861–1900. *The Economic History Review*, 72(1):233–259, 2019.

K. J. Charles and E. Greggio. Invited perspective: beyond national water quality surveys: improving water quality surveillance to achieve safe drinking water for all (sustainable development goal 6.1). *Environmental Health Perspectives*, 129(9):091301, 2021.

D. Coffey and D. Spears. Neonatal death in india: birth order in a context of maternal undernutrition. *The Economic Journal*, 131(638):2478–2507, 2021.

CPCB. Evaluation of operation and maintenance of sewage treatment plants in india 2007, control of urban pollution series: Cups/68/2007, 2007.

CPCB. Performance evaluation of sewage treatment plants under nrcd, 2013.

C. De Chaisemartin and X. d'Haultfoeuille. Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, 110(9):2964–96, 2020.

C. De Chaisemartin and X. D'Haultfoeuille. Two-way fixed effects and differences-in-differences with heterogeneous treatment effects: A survey. Technical report, National Bureau of Economic Research, 2022.

Q.-T. Do, S. Joshi, and S. Stolper. Can environmental policy reduce infant mortality? evidence from the ganga pollution cases. *Journal of Development Economics*, 133: 306–325, 2018.

E. Duflo, M. Greenstone, R. Pande, and N. Ryan. The value of regulatory discretion: Estimates from environmental inspections in india. *Econometrica*, 86(6):2123–2160, 2018.

W. E. Federation, A. Association, et al. Standard methods for the examination of water and wastewater. *American Public Health Association (APHA): Washington, DC, USA*, 2005.

P. Flynn and M. M. Marcus. A watershed moment: The clean water act and infant health. Technical report, National Bureau of Economic Research, 2021.

D. Gallardo-Albarrán. Sanitary infrastructures and the decline of mortality in germany, 1877–1913. *The Economic History Review*, 73(3):730–757, 2020.

J. Gardner. Two-stage differences in differences. *arXiv preprint arXiv:2207.05943*, 2022.

T. Garg, S. E. Hamilton, J. P. Hochard, E. P. Kresch, and J. Talbot. (not so) gently down the stream: River pollution and health in indonesia. *Journal of Environmental Economics and Management*, 92:35–53, 2018.

M. Geruso and D. Spears. Neighborhood sanitation and infant mortality. *American Economic Journal: Applied Economics*, 10(2):125–62, 2018.

A. Goodman-Bacon. Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2):254–277, 2021.

M. Greenstone and R. Hanna. Environmental regulations, air and water pollution, and infant mortality in india. *American Economic Review*, 104(10):3038–72, 2014.

R. L. Guerrant, M. D. DeBoer, S. R. Moore, R. J. Scharf, and A. A. Lima. The impoverished gut—a triple burden of diarrhoea, stunting and chronic disease. *Nature reviews Gastroenterology & hepatology*, 10(4):220–229, 2013.

B. Harris and J. Helgertz. Urban sanitation and the decline of mortality, 2019.

G. He, S. Wang, and B. Zhang. Watering down environmental regulation in china. *The Quarterly Journal of Economics*, 135(4):2135–2185, 2020.

S. Joshi and G. Shambaugh. Oversized solutions to big problems: The political economy of partnerships and environmental cleanup in india. *Environmental development*, 28: 3–18, 2018.

D. A. Keiser and J. S. Shapiro. Consequences of the clean water act and the demand for water quality. *The Quarterly Journal of Economics*, 134(1):349–396, 2019.

L. Kesztenbaum and J.-L. Rosenthal. Sewers' diffusion and the decline of mortality: The case of paris, 1880–1914. *Journal of Urban Economics*, 98:174–186, 2017.

M. Kremer, S. P. Luby, R. Maertens, B. Tan, and W. Więcek. Water treatment and child mortality: A meta-analysis and cost-effectiveness analysis. Technical report, National Bureau of Economic Research, 2023.

P. J. Landrigan, R. Fuller, N. J. Acosta, O. Adeyi, R. Arnold, A. B. Baldé, R. Bertollini, S. Bose-O'Reilly, J. I. Boufford, P. N. Breysse, et al. The lancet commission on pollution and health. *The lancet*, 391(10119):462–512, 2018.

S. Linke, B. Lehner, C. O. Dallaire, J. Ariwi, G. Grill, M. Anand, P. Beames, V. Burchard-Levine, S. Maxwell, H. Moidu, et al. Global hydro-environmental sub-basin and river reach characteristics at high spatial resolution. *Scientific data*, 6(1):1–15, 2019.

L. Liu, S. Oza, D. Hogan, Y. Chu, J. Perin, J. Zhu, J. E. Lawn, S. Cousens, C. Mathers, and R. E. Black. Global, regional, and national causes of under-5 mortality in 2000–15: an updated systematic analysis with implications for the sustainable development goals. *The Lancet*, 388(10063):3027–3035, 2016.

R. B. McCleskey, D. K. Nordstrom, and J. N. Ryan. Electrical conductivity method for natural waters. *Applied Geochemistry*, 26:S227–S229, 2011.

P. Meiyappan, R. P.S., A. Soliman, T. Li, P. Mondal, S. Wang, and J. A. K. India village-level geospatial socio-economic data set: 1991, 2001. *Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC)*, 2018.

P. Minier, F. Esculier, B. Tassin, and K. Chatzis. Can sewerage be considered safe management of human feces? *City and Environment Interactions*, 19:100107, 2023.

K. Motohashi. Unintended consequences of sanitation investment: Negative externalities of water quality and health in india. 2023.

C. J. L. Murray and A. D. Lopez. The global burden of disease : a comprehensive assessment of mortality and disability from diseases, injuries, and risk factors in 1990 and projected to 2020. *Published by the Harvard School of Public Health on behalf of the World Health Organization and the World Bank*, Global burden of disease and injury series, volume 1, 1996.

S. Olmstead and J. Zheng. Water pollution control in developing countries: Policy instruments and empirical evidence. *Review of Environmental Economics and Policy*, 15 (2):261–280, 2021.

W. H. Organization. *The world health report 2002: reducing risks, promoting healthy life.* World Health Organization, 2002.

A. Patel, A. Arkatkar, S. Singh, A. Rabbani, J. D. S. Medina, E. S. Ong, M. M. Habashy, D. A. Jadhav, E. R. Rene, A. A. Mungray, et al. Physico-chemical and biological treatment strategies for converting municipal wastewater and its residue to resources. *Chemosphere*, 282:130881, 2021.

A. J. Prendergast, S. Rukobo, B. Chasekwa, K. Mutasa, R. Ntozini, M. N. Mbuya, A. Jones, L. H. Moulton, R. J. Stoltzfus, and J. H. Humphrey. Stunting is characterized by chronic inflammation in zimbabwean infants. *PloS one*, 9(2):e86928, 2014.

S. D. Rayasam, I. Ray, K. R. Smith, and L. W. Riley. Extraintestinal pathogenic escherichia coli and antimicrobial drug resistance in a maharashtrian drinking water system. *The American journal of tropical medicine and hygiene*, 100(5):1101, 2019.

P. Reymond, R. Chandragiri, and L. Ulrich. Governance arrangements for the scaling up of small-scale wastewater treatment and reuse systems–lessons from india. *Frontiers in Environmental Science*, page 72, 2020.

J. Roth, P. H. Sant'Anna, A. Bilinski, and J. Poe. What's trending in difference-in-differences? a synthesis of the recent econometrics literature. *Journal of Econometrics*, 2023.

P. Servais, T. Garcia-Armisen, I. George, and G. Billen. Fecal bacteria in the rivers of the seine drainage network (france): sources, fate and modelling. *Science of the Total Environment*, 375(1-3):152–167, 2007.

D. Spears. Exposure to open defecation can account for the indian enigma of child height. *Journal of Development Economics*, 146:102277, 2020.

L. Sun and S. Abraham. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2):175–199, 2021.

UN Water. Wastewater: The untapped resource. *The United Nations World Water Development Report*, 2017.

A. Van Donkelaar, M. S. Hammer, L. Bindle, M. Brauer, J. R. Brook, M. J. Garay, N. C. Hsu, O. V. Kalashnikova, R. A. Kahn, C. Lee, et al. Monthly global estimates of fine particulate matter and their uncertainty. *Environmental Science & Technology*, 55(22): 15287–15300, 2021.

C. G. Victora, R. Bahl, A. J. Barros, G. V. França, S. Horton, J. Krasevec, S. Murch, M. J. Sankar, N. Walker, and N. C. Rollins. Breastfeeding in the 21st century: epidemiology, mechanisms, and lifelong effect. *The lancet*, 387(10017):475–490, 2016.

K. Wankhade. Urban sanitation in india: key shifts in the national policy frame. *Environment and Urbanization*, 27(2):555–572, 2015.

WHO. Guidelines for drinking-water quality: first addendum to the fourth edition. Technical report, Geneva: World Health Organization, 2017.

WHO/UNICEF. *Progress on sanitation and drinking water: 2015 update and MDG assessment*. World Health Organization, 2015.

J. Wolf, P. R. Hunter, M. C. Freeman, O. Cumming, T. Clasen, J. Bartram, J. P. Higgins, R. Johnston, K. Medlicott, S. Boisson, et al. Impact of drinking water, sanitation and handwashing with soap on childhood diarrhoeal disease: updated meta-analysis and meta-regression. *Tropical medicine & international health*, 23(5):508–525, 2018.

WorldPop and Center for International Earth Science Information Network (CIESIN). Global high resolution population denominators project, 2018.

Q. Zhang, Z. Yu, and D. Kong. The real effect of legal institutions: Environmental courts and firm environmental protection expenditure. *Journal of Environmental Economics and Management*, 98:102254, 2019.

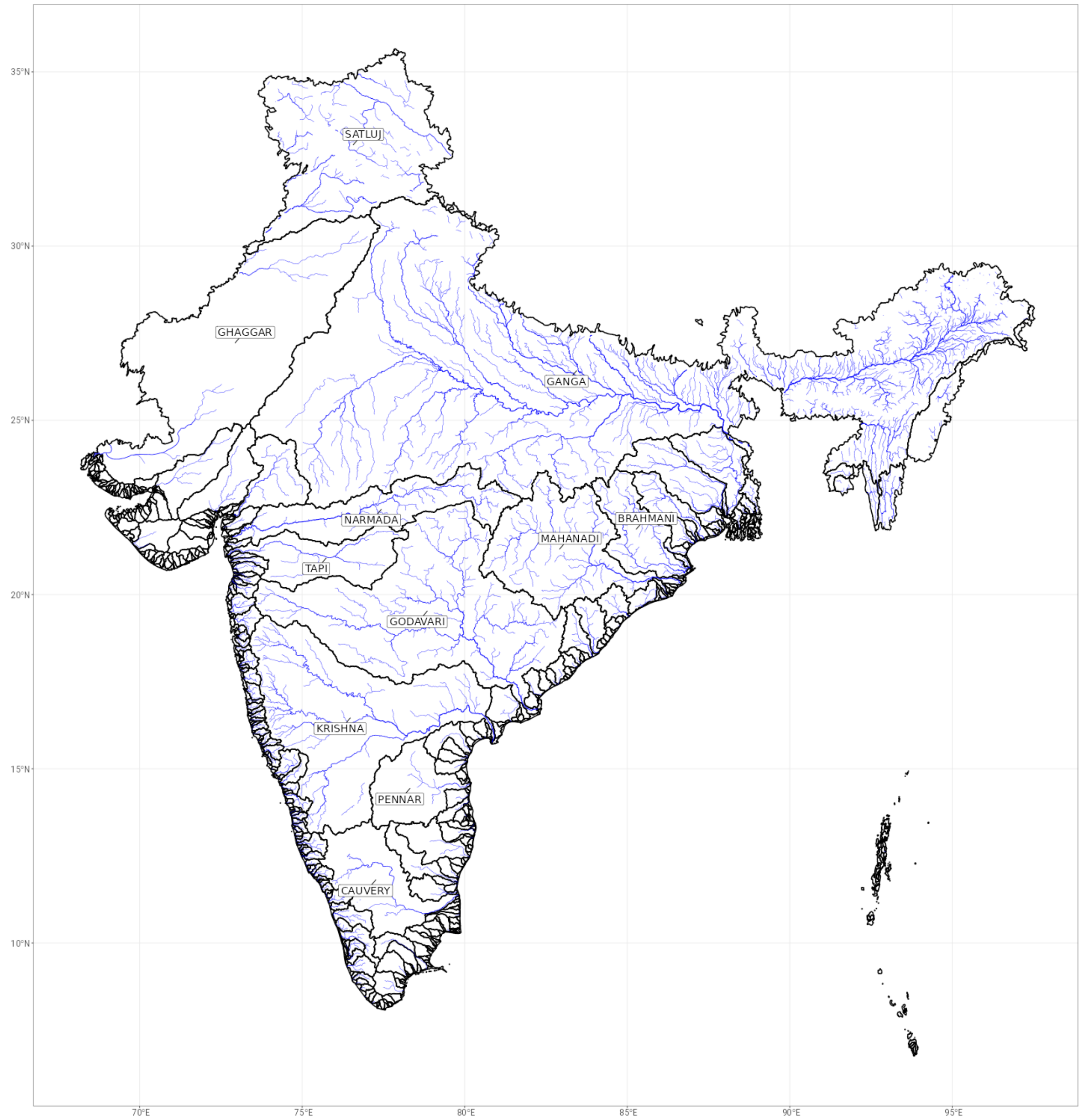
9 Figures

Figure 1: Example of geolocation of sewage treatment plants on Google Maps

UASB technology in Lucknow

SBR technology in Dehradun

Figure 2: Map of main basins according to the HydroSHED basins at Pfafstetter level 12



Notes: In HydroSHED, the main basin is defined by the most downstream sink, i.e. the outlet of the main river basin. The name of the basin matches the name of the river that has the highest number of monitoring stations in the water quality dataset.

Figure 3: Liquids consumed by children in the day or night preceding the NFHS interview

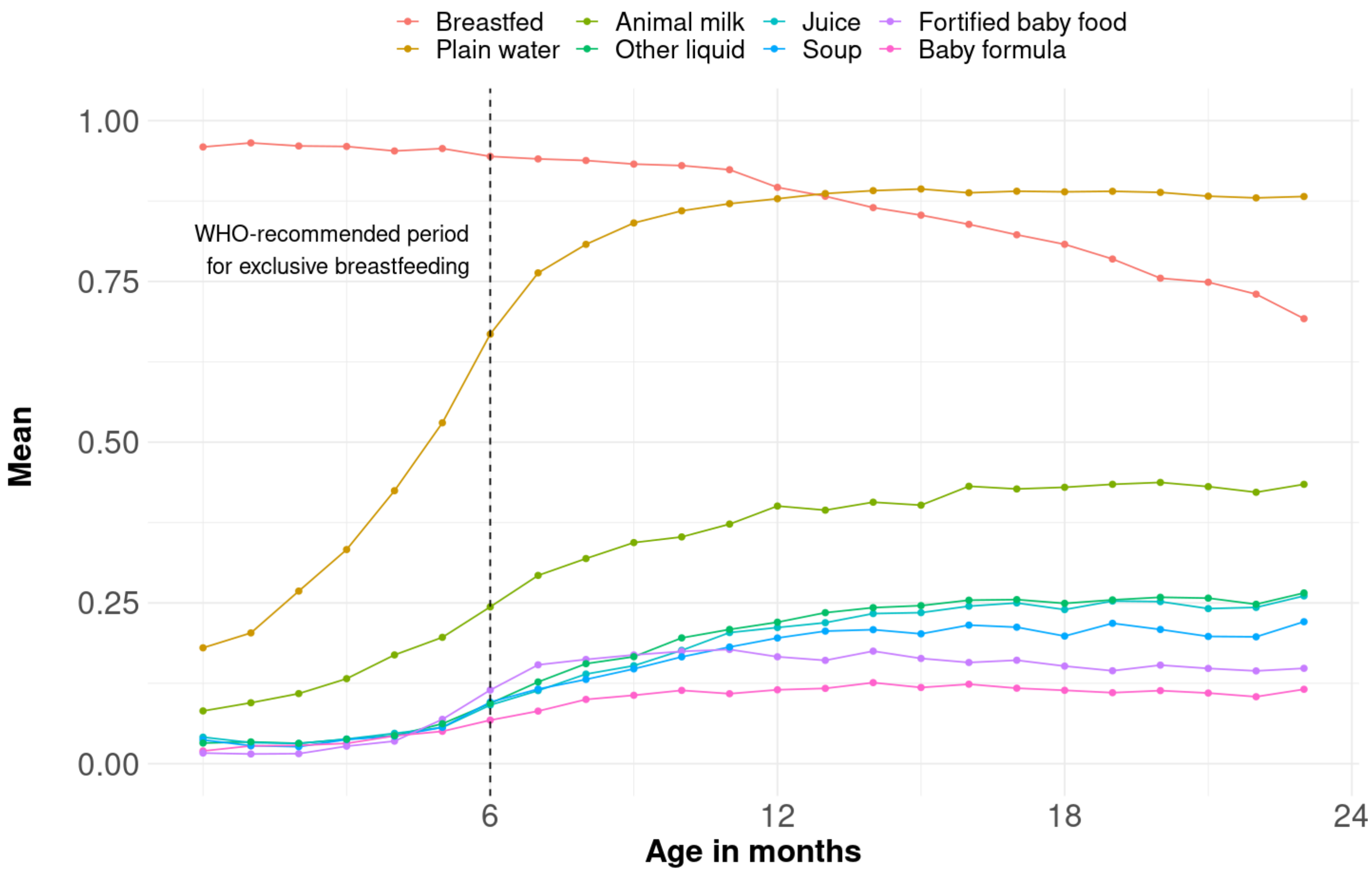


Figure 4: Histogram of the first year in which urban areas started operating sewage treatment plants

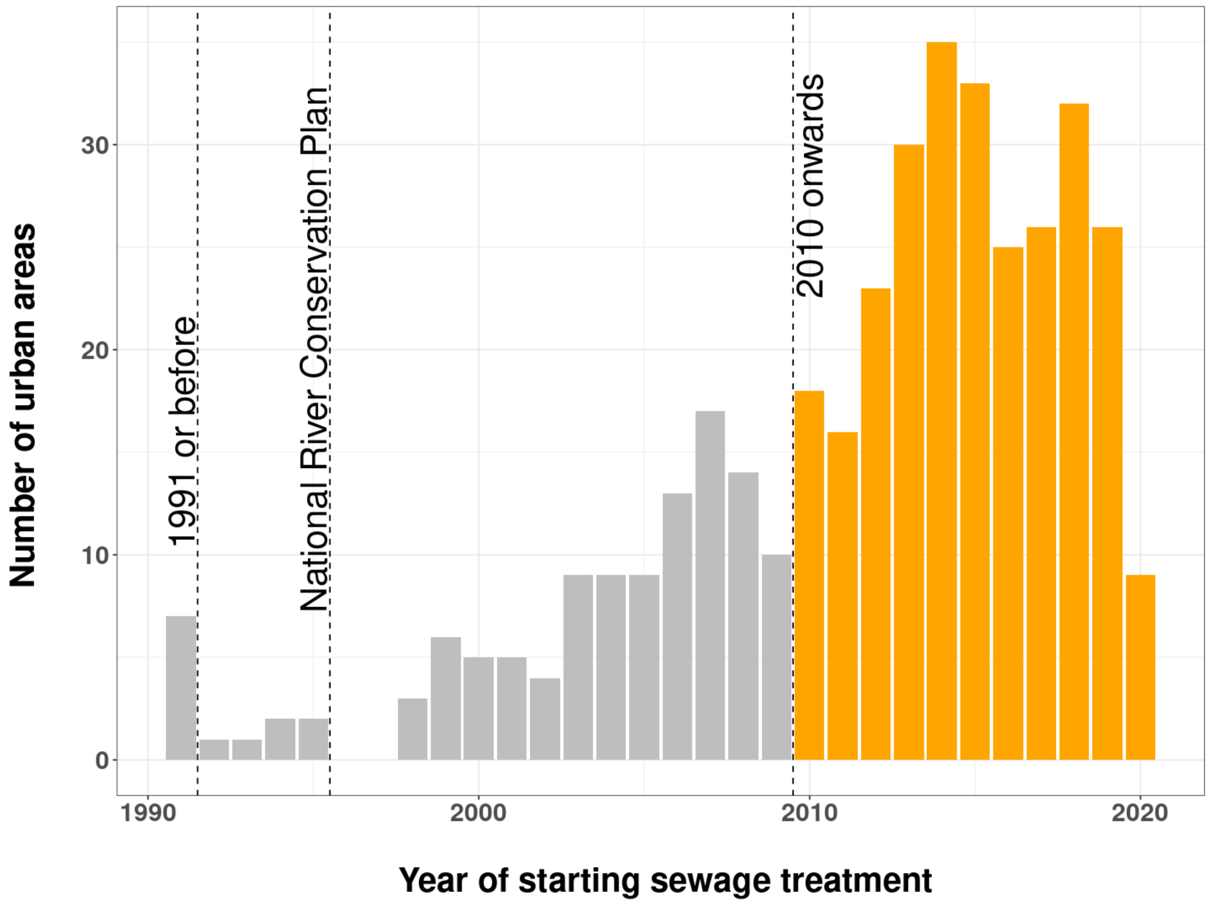
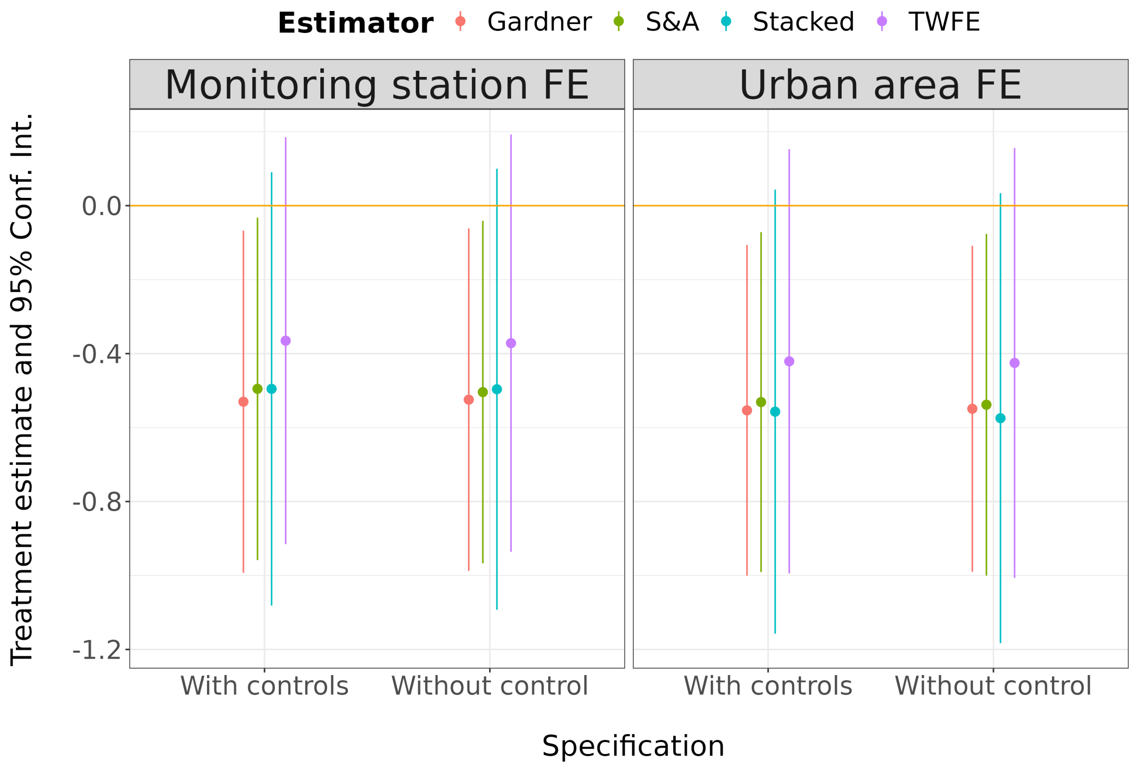
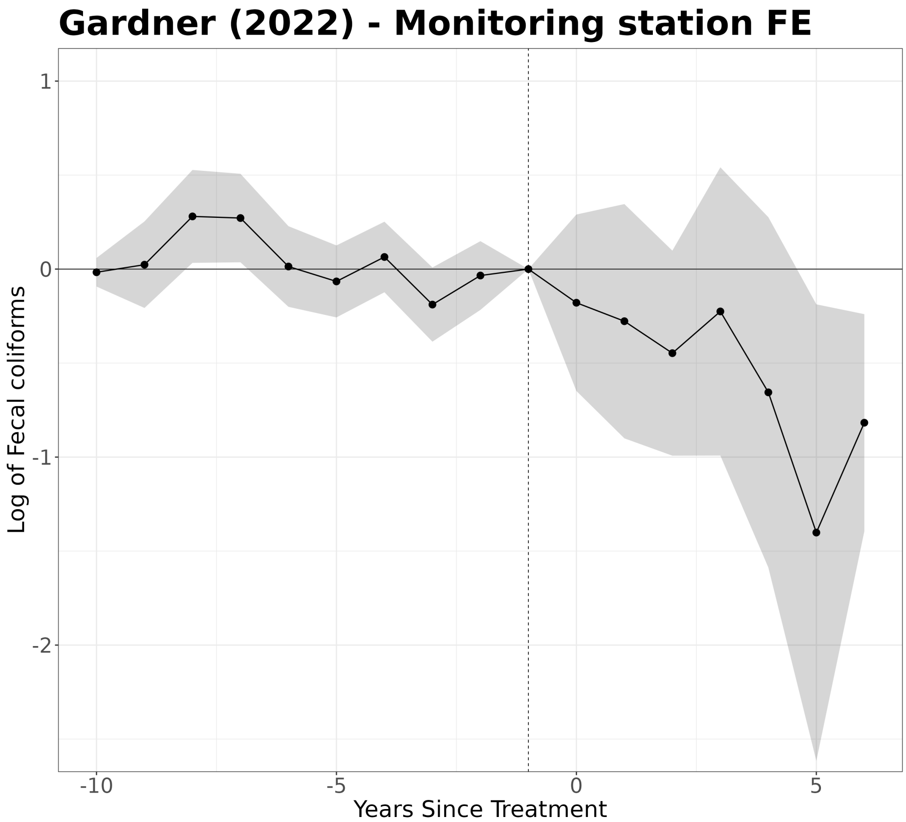


Figure 5: DiD water pollution results summary



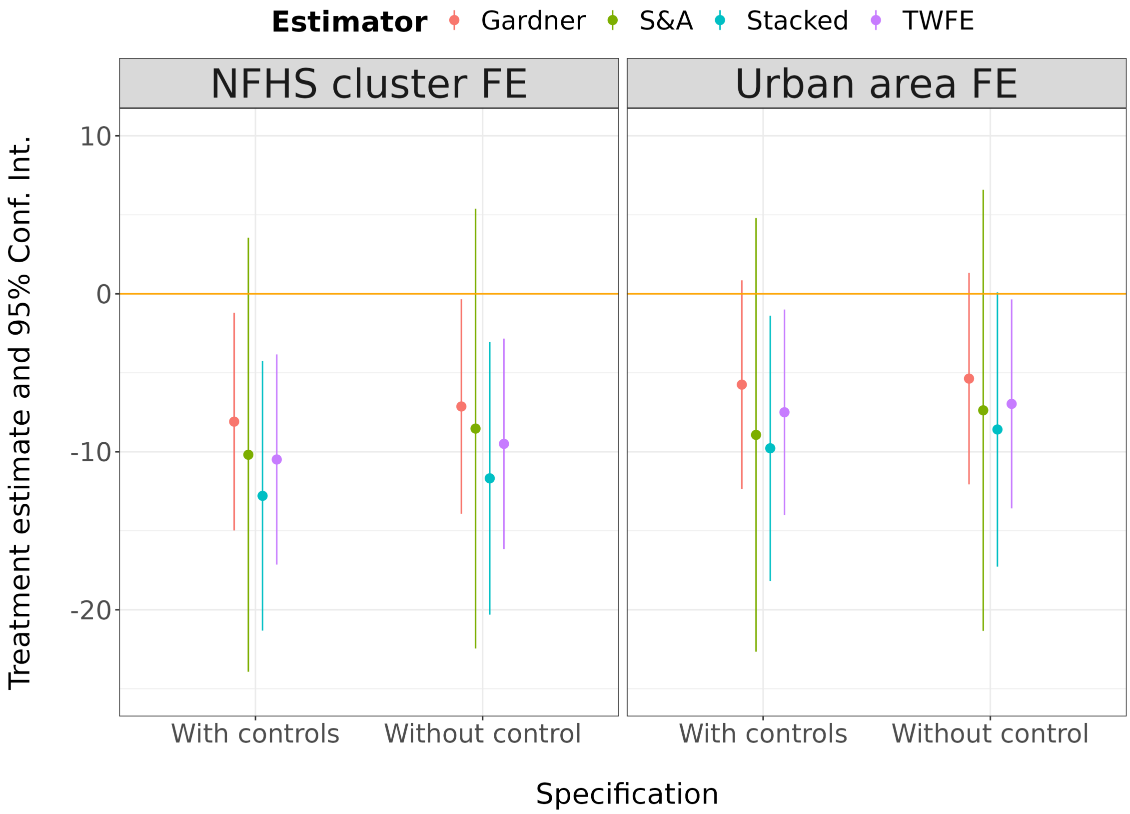
Notes: Figures plot coefficient estimates and 95% confidence intervals for the difference-in-differences on the logarithm of fecal coliforms based on different estimators: Gardner [2022], Sun and Abraham [2021], stacked regression and classic TWFE with and without controls, as well as with monitoring station fixed effect or urban area fixed effects.

Figure 6: Pollution Event Study



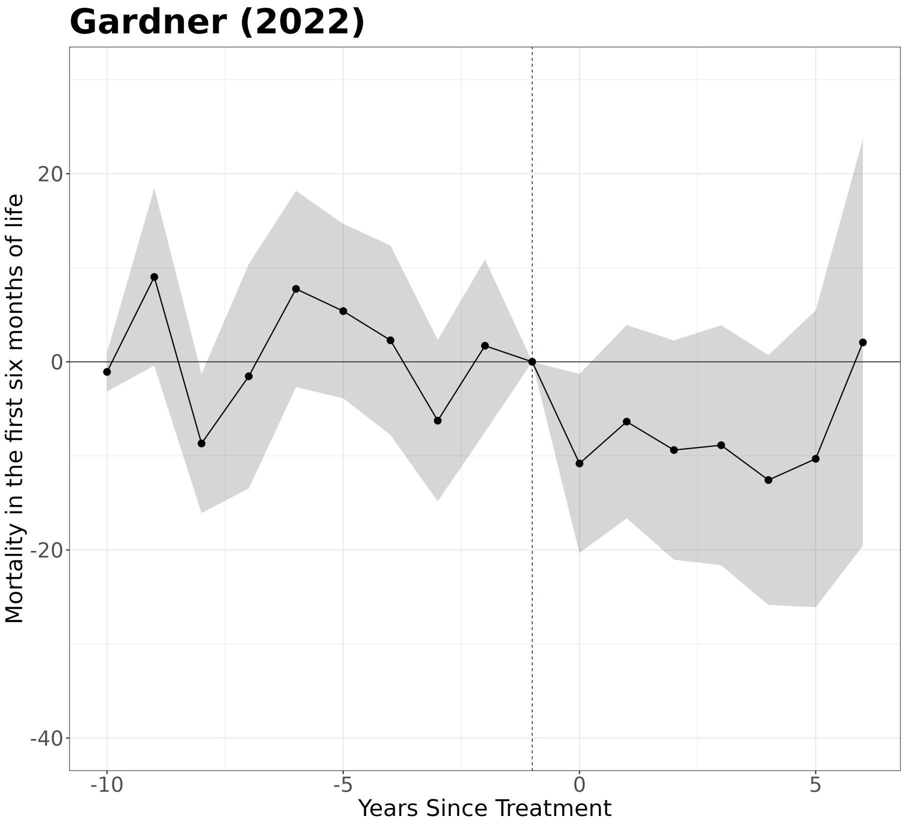
Notes: This figure shows the coefficients of the estimators according to the Gardner [2022] methodology. The 95% confidence intervals bands are shown. Data include years 1991-2020. The model includes monitoring station fixed effects and main basin-by-year fixed effects, as well as controls for precipitation and temperature. Standard errors are clustered at the urban area level. All observations more than 10 years before treatment are set at 10 years before treatment and all observations more than 6 years after treatment are set at 6 years after treatment.

Figure 7: DiD mortality results summary



Notes: Figures plot coefficient estimates and 95% confidence intervals for the difference-in-differences on the mortality under six months based on different estimators: Gardner [2022], Sun and Abraham [2021], stacked regression and classic TWFE with and without controls, as well as with NFHS cluster fixed effect or urban area fixed effects.

Figure 8: Mortality Event Study



Notes: This figure shows the coefficients of the estimators according to the Gardner [2022] methodology. The dependent variable is an indicator for death in the first six months of life × 1,000. The 95% confidence intervals bands are shown. Data include years 1991-2019. The model includes cluster fixed effects and year fixed effects, as well as controls for child-level, mother-level, household-level and weather determinants of health. Child controls include indicators for the child being a female, being a multiple birth, being the first born, being the fourth or more born. Controls at the mother level include indicators for the mother being either under 18 years old or over 35 years old at the time of the child's birth, educational attainment (primary, secondary education or higher education), religious affiliation (being Muslim, neither Hindu nor Muslim), and caste affiliation (scheduled caste, scheduled tribe, or other backward caste). Household controls include indicators for first, second, fourth and fifth wealth quintiles. Weather controls include the logarithmic transformation of the sum of precipitation felt in one year within a 20km radius of the cluster coordinates and the daily mean temperature over the year within a 20km radius of the cluster coordinates. Standard errors are clustered by urban area. All observations more than 10 years before treatment are set at 10 years before treatment and all observations more than 6 years after treatment are set at 6 years after treatment.

10 Tables

Table 1: Presentation of the main regression samples

	Fecal coliforms levels				Infant mortality					
Year	All urban areas (1A)	All monitoring stations (1B)	Treated urban areas (1C)	Treated monitoring stations (1D)	All urban areas (2A)	All NFHS clusters (2B)	All births (2C)	Treated urban areas (2D)	Treated NFHS clusters (2E)	Treated births (2F)
1991	42	56	0	0	215	878	1250	0	0	0
1992	38	52	0	0	229	1101	1662	0	0	0
1993	49	66	0	0	242	1212	1827	0	0	0
1994	46	62	0	0	244	1335	2112	0	0	0
1995	55	75	0	0	258	1509	2549	0	0	0
1996	61	87	0	0	252	1513	2648	0	0	0
1997	63	91	0	0	247	1622	2966	0	0	0
1998	62	91	0	0	251	1660	3069	0	0	0
1999	56	79	0	0	261	1719	3271	0	0	0
2000	59	85	0	0	257	1807	3588	0	0	0
2001	66	99	0	0	253	1709	3333	0	0	0
2002	78	125	0	0	263	1831	3886	0	0	0
2003	68	102	0	0	257	1802	3751	0	0	0
2004	71	114	0	0	255	1805	3764	0	0	0
2005	60	91	0	0	257	1785	3740	0	0	0
2006	74	118	0	0	254	1819	3793	0	0	0
2007	78	122	0	0	257	1822	3883	0	0	0
2008	90	154	0	0	260	1846	4035	0	0	0
2009	98	178	0	0	255	1852	3912	0	0	0
2010	106	194	3	3	263	1850	3926	15	106	184
2011	101	195	6	17	258	1814	3780	25	191	355
2012	110	209	8	20	261	1835	4035	39	254	493
2013	101	196	17	33	261	1866	4058	53	392	788
2014	106	192	24	46	258	1828	3900	68	510	1061
2015	110	206	29	64	245	1468	2990	83	562	1064
2016	110	214	34	73	230	1030	2089	92	442	905
2017	116	236	44	88	235	1020	2030	101	474	950
2018	127	256	57	119	230	1011	2096	119	524	1087
2019	133	273	64	133	202	759	1330	111	473	856
2020	115	243	55	115						
Total		4261		711			89273			7743

Notes: Columns 1A and 2A tabulate the total number of urban areas in each year, while columns 1C and 2C tabulate the number of urban areas that treat wastewater in each year. Column 1B tabulates the total number of monitoring stations in each year, while column 1D tabulates the number of monitoring stations located within or downstream an urban area that treats wastewater in this year. Column 2B tabulates the number of NFHS clusters downstream an urban area in each year, while column 2E tabulates the number of NFHS clusters downstream an urban area that treats wastewater in this year. Column 2C tabulates the number of children born downstream an urban area in each year, while column 2F tabulates the number of children born downstream an urban area that treats wastewater in this year. I subject the full sample to two restrictions before analysis, both of which applied here. (i) If there is an outcome data (water pollution measure or birth) from a monitoring station or NFHS cluster related to an urban area after it has started wastewater treatment, then that monitoring station or NFHS cluster is only included if it has at least one data point before the urban area starting wastewater treatment. (ii) If the urban area doesn't treat wastewater in 2020, then the monitoring station or the NFHS cluster is only included if it has at least two outcome data points. A monitoring station or a NFHS cluster is only included in the subsequent regressions if it has outcome data for the specific dependent variable of that given regression.

Table 2: Effect on Fecal coliforms levels

Dependent Variable:	Log(Average Fecal coliforms)			
	(1)	(2)	(3)	(4)
Estimator : Gardner (2022)	-0.5245**	-0.5302**	-0.5492**	-0.5535**
	(0.2361)	(0.2359)	(0.2247)	(0.2280)
Estimator : S & A (2021)	-0.5041**	-0.4953**	-0.5383**	-0.5310**
	(0.2342)	(0.2342)	(0.2336)	(0.2325)
Estimator : TWFE	-0.3718	-0.3651	-0.4252	-0.4209
	(0.2854)	(0.2783)	(0.2940)	(0.2902)
Weather controls		X		X
River distance			X	X
Urban area FE			X	X
Monitoring station FE	X	X		
Year-Main basin FE	X	X	X	X
Observations	4,261	4,261	4,261	4,261
Period	1991-2020	1991-2020	1991-2020	1991-2020
Number of Stations	313	313	313	313
Number of Urban areas	142	142	142	142

Notes: The table presents the coefficients of the estimators according to the Gardner [2022], Sun and Abraham [2021] and classic TWFE methodologies. Dependent variables are annual monitoring stations measures. In each regression, treated monitoring stations have at least one observation pre-treatment and one observation post-treatment and control monitoring stations have at least two observations. The model in columns (1) and (2) includes monitoring station fixed effects and main basin-by-year fixed effects while the model in columns (3) and (4) includes urban area fixed effects and controls for the river distance between the monitoring station and the urban area. Columns (2) and (4) add controls for precipitation and temperature. Standard errors are clustered at the urban area level. Asterisks denote p-value < 0.10 (*), < 0.05 (**), or < 0.01 (***).

Table 3: Effect on organic pollution measures

	Highest pollution			Lowest pollution		
Dependent Variable:	Log(Max Fcoli) (1)	Log(Max BOD) (2)	Min DO (3)	Log(Min Fcoli) (4)	Log(Min BOD) (5)	Max DO (6)
Estimator : Gardner (2022)	-0.5575**	-0.2362***	0.3580**	-0.1420	0.0013	-0.2085*
	(0.2477)	(0.0600)	(0.1563)	(0.1866)	(0.0524)	(0.1212)
Estimator : S & A (2021)	-0.5024**	-0.1134	0.4637***	-0.1205	0.1612**	-0.1637
	(0.2445)	(0.0721)	(0.1635)	(0.2110)	(0.0780)	(0.1365)
Estimator : TWFE	-0.3825	-0.1803***	0.4835***	-0.0608	0.0318	-0.0685
	(0.2945)	(0.0593)	(0.1454)	(0.2073)	(0.0767)	(0.1507)
Weather controls	X	X	X	X	X	X
Monitoring station FE	X	X	X	X	X	X
Year-Main basin FE	X	X	X	X	X	X
Observations	4,261	5,952	5,820	4,261	5,952	5,820
Period	1991-2020	1991-2020	1991-2020	1991-2020	1991-2020	1991-2020
Number of Stations	313	395	390	313	395	390
Number of Urban areas	142	166	164	142	166	164
Mean of Dep. Variable			5.603			8.085

Notes: The table presents the coefficients of the estimators according to the Gardner [2022], Sun and Abraham [2021] and classic TWFE methodologies. Dependent variables are annual monitoring stations measures. In each regression, treated monitoring stations have at least one observation pre-treatment and one observation post-treatment and control monitoring stations have at least two observations. Contrary to fecal coliforms and biological oxygen demand (BOD) levels, dissolved oxygen (DO) levels are inversely proportional to pollution. All specificationq include controls for precipitation and temperature, monitoring station fixed effects and main basin-by-year fixed effects. Standard errors are clustered at the urban area level. Asterisks denote p-value < 0.10 (*), < 0.05 (**), or < 0.01 (***).

Table 4: Effect on Downstream Mortality

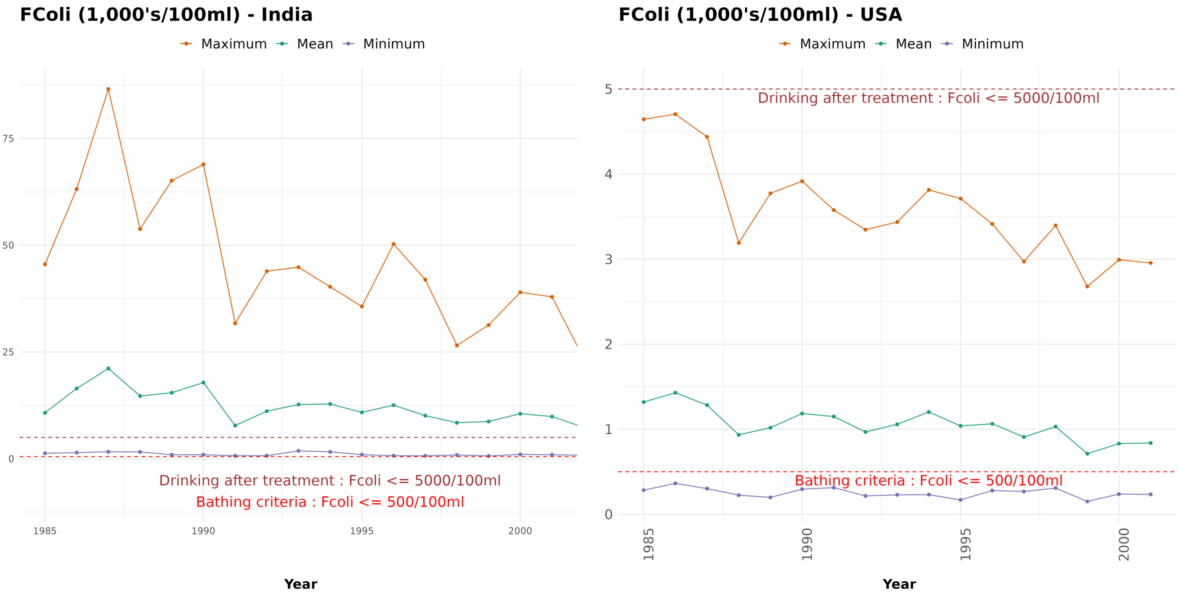
Dependent Variable:	Child died before the age of six months			
	(1)	(2)	(3)	(4)
Estimator : Gardner (2022)	-7.132**	-8.091**	-5.367	-5.750*
	(3.463)	(3.514)	(3.416)	(3.369)
Estimator : S & A (2021)	-8.531	-10.19	-7.374	-8.929
	(7.069)	(6.977)	(7.090)	(6.970)
Estimator : TWFE	-9.496***	-10.49***	-6.968**	-7.497**
	(3.383)	(3.378)	(3.360)	(3.302)
Extended controls		X		X
Urban area FE			X	X
NFHS Cluster FE	X	X		
Birth year FE + Birth month FE	X	X	X	X
Observations	89,273	84,916	89,273	84,916
Period	1991-2019	1991-2019	1991-2019	1991-2019
Number of NFHS Clusters	2387	2348	2387	2348
Number of Urban areas	272	272	272	272
Mean of Dep. Variable	40.863	41.182	40.863	41.182

Notes: The table presents the coefficients of the estimators according to the Gardner [2022], Sun and Abraham [2021] and classic TWFE methodologies. The model in columns (1) and (2) includes NFHS cluster fixed effects while the model in columns (3) and (4) includes urban area fixed effects, all models include birth year and birth month fixed effects. Mortality variables are scaled as described in the text to generate coefficients that indicate impacts on rates $\times$ 1,000 (deaths per 1,000 children). Child controls include indicators for the child being a female, being a multiple birth, being the first born, being the fourth or more born. Controls at the mother level include indicators for the mother being either under 18 years old or over 35 years old at the time of the child's birth, educational attainment (primary, secondary education or higher education), religious affiliation (being Muslim, neither Hindu nor Muslim), and caste affiliation (scheduled caste, scheduled tribe, or other backward caste). Household controls include indicators for first, second, fourth and fifth wealth quintiles. Weather controls include the logarithmic transformation of the sum of precipitation felt in one year within a 20km radius of the cluster coordinates and the daily mean temperature over the year within a 20km radius of the cluster coordinates. Standard errors are in parentheses and clustered by urban area. Asterisks denote p-value < 0.10 (*), < 0.05 (**), or < 0.01 (***).

Appendices

A Additional Results

Figure A1: Comparison of fecal coliforms levels over the period 1985-2001 in India versus in the USA (Author's computation based on Greenstone and Hanna [2014] (India) and Keiser and Shapiro [2019] (USA) data)



Notes: Dashed lines correspond to Indian designated best-use water quality criteria under the National Water Quality Monitoring Programme (Figure D1).

Figure A2: Densities of maximum organic pollution readings

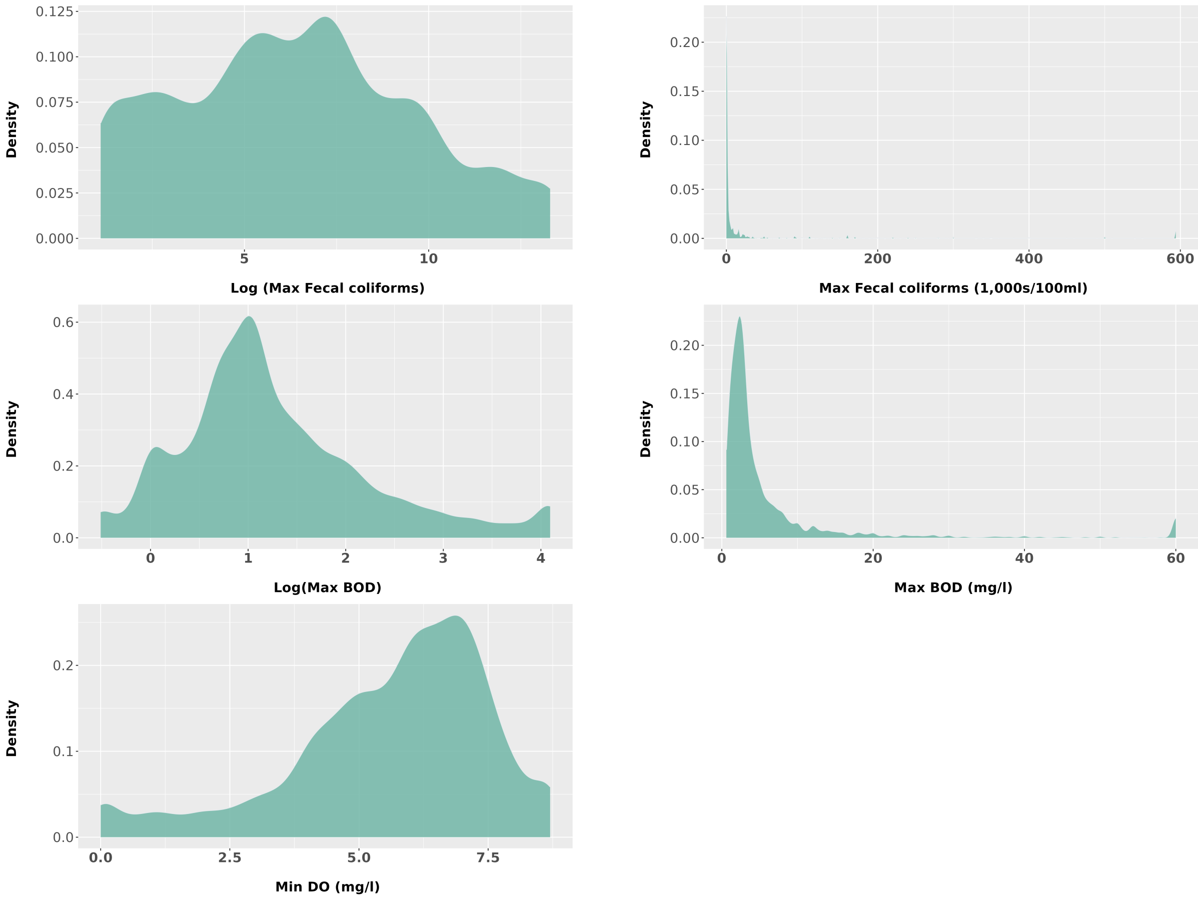


Figure A3: Measures of pollution from Greenstone and Hanna [2014] extended over the period 2005-2020

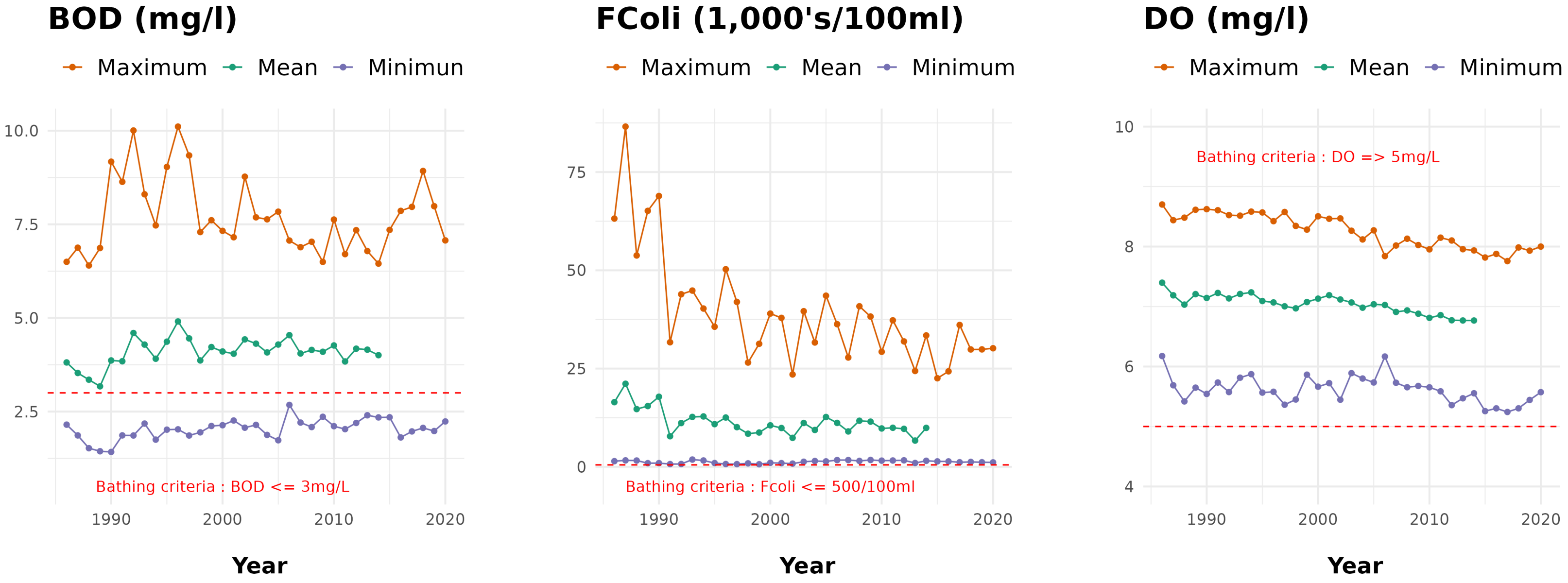


Figure A4: Annual means of average fecal coliforms in the surface water quality dataset

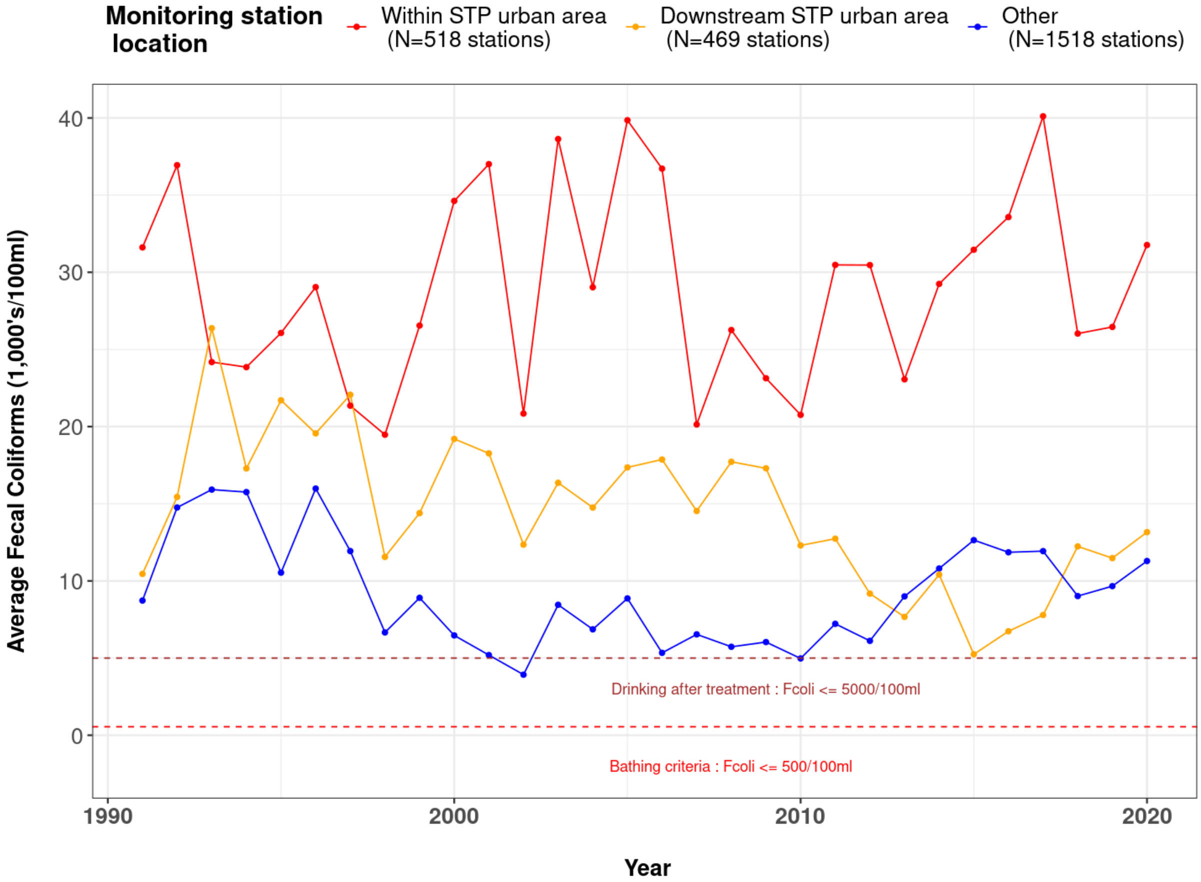
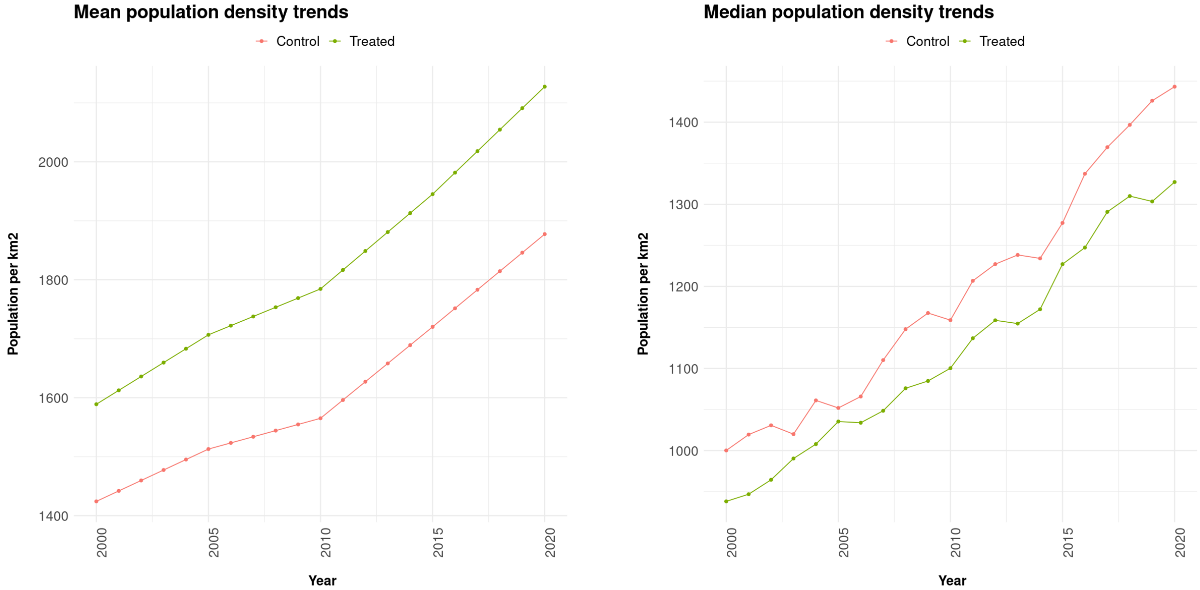


Figure A5: Average (left) and Median (right) population density annual means by treatment group computed on WorldPop estimates



x

Figure A6: Annual means of the logartithmic transformation of fecal coliforms levels by treatment group

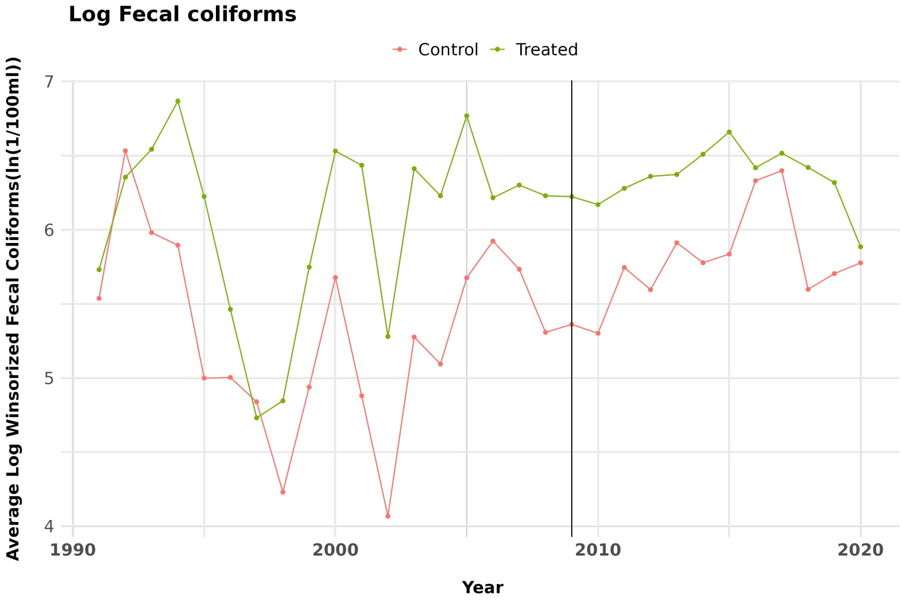
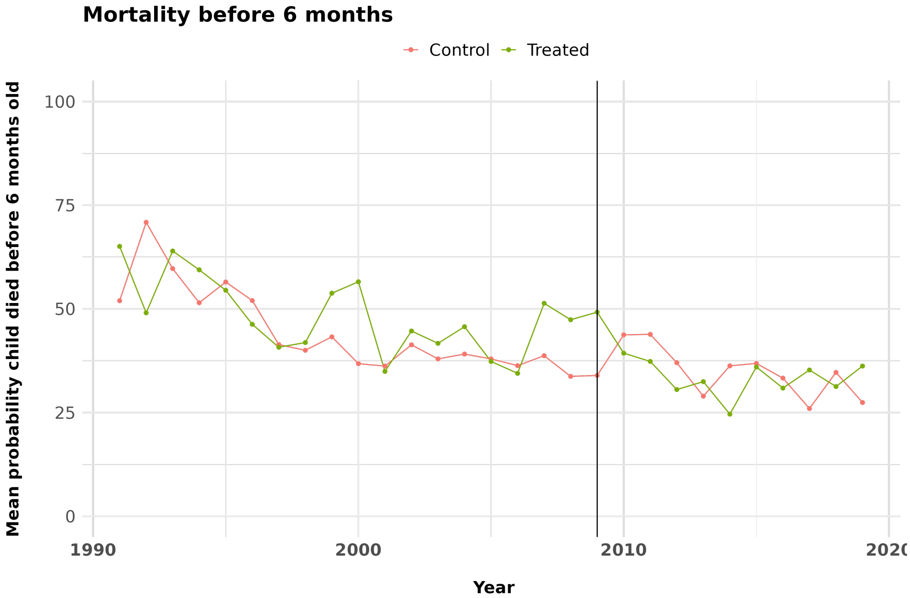


Figure A7: Annual means of mortality in the first six months of life by treatment group



Notes: The mortality variable is an indicator for death in the first six months of life × 1,000.

Table A1: Water summary statistics

	Means		Difference	p-value	N. Obs.	
	Control	Treated		(t-test)	Control	Treated
Panel A. 1991-2009						
Log(average fecal coliforms)	5.259	6.046	0.787	0	737	1,202
Log(min fecal coliforms)	3.375	4.058	0.683	0	737	1,202
Log(max fecal coliforms)	5.731	6.513	0.782	0	737	1,202
Log(min BOD)	-0.220	0.108	0.328	0	1,170	1,721
Log(max BOD)	1.018	1.291	0.273	0	1,170	1,721
Min DO (mg/L)	6.183	5.550	-0.633	0	1,144	1,808
Max DO (mg/L)	8.576	8.085	-0.491	0	1,144	1,808
Log Rainfall	27.956	27.805	-0.151	0	1,217	1,851
Air Temperature (°C)	25.548	24.886	-0.662	0	1,217	1,851
Panel B. 2010-2019						
Log(average fecal coliforms)	5.820	6.343	0.523	0	1,193	1,429
Log(min fecal coliforms)	4.245	4.848	0.604	0	1,193	1,431
Log(max fecal coliforms)	6.267	6.790	0.523	0	1,193	1,429
Log(min BOD)	0.197	0.352	0.154	0	1,627	1,767
Log(max BOD)	1.202	1.507	0.305	0	1,626	1,767
Min DO (mg/L)	5.690	5.128	-0.562	0	1,554	1,716
Max DO (mg/L)	8.144	7.595	-0.549	0	1,554	1,717
Log Rainfall	27.993	27.886	-0.108	0	1,638	1,797
Air Temperature (°C)	25.199	24.954	-0.245	0.008	1,638	1,797

Notes: Panel A compares the summary statistics between monitoring stations within or downstream urban areas where wastewater treatment started between 2010 and 2020 and monitoring stations within or downstream urban area where wastewater treatment is in project in 2020 before wastewater treatment started in the sample (before 2010), while Panel B compares the summary statistics since 2010 when the first operation of sewage treatment plants were observed in the data. The unit of observations is the monitoring station level. Contrary to fecal coliforms and biological oxygen demand (BOD) levels, dissolved oxygen (DO) levels are inversely proportional to pollution.

Table A2: Mortality summary statistics

	Means		Difference	p-value	N. Obs.	
	Control	Treated		(t-test)	Control	Treated
Panel A. 1991-2009						
Mortality before 6 months	41.950	45.224	3.275	0.028	35,781	39,293
Child female	0.477	0.467	-0.009	0.012	35,781	39,293
Child multiple birth	0.013	0.013	-0.0001	0.925	35,781	39,293
Child first born	0.327	0.342	0.015	0	35,781	39,293
Child birth order sup 4	0.195	0.174	-0.021	0	35,781	39,293
Mother under 18 at birth	0.090	0.083	-0.008	0	35,781	39,293
Mother older 35 at birth	0.017	0.013	-0.004	0	35,781	39,293
Mother no educ	0.569	0.497	-0.072	0	35,781	39,293
Mother primary educ	0.156	0.166	0.010	0	35,781	39,293
Mother secondary educ	0.252	0.308	0.056	0	35,781	39,293
Mother higher educ	0.022	0.029	0.006	0	35,781	39,293
Mother hindu	0.737	0.798	0.060	0	35,781	39,293
Mother muslim	0.184	0.130	-0.054	0	35,781	39,293
Mother scheduled caste (SC)	0.205	0.261	0.056	0	33,369	38,371
Mother scheduled tribe (ST)	0.148	0.053	-0.094	0	33,369	38,371
Mother other backward caste (OBC)	0.455	0.465	0.010	0.007	33,369	38,371
HH wealth lowest quintile	0.272	0.136	-0.136	0	35,781	39,293
HH wealth second quintile	0.256	0.237	-0.019	0	35,781	39,293
HH wealth fourth quintile	0.157	0.203	0.046	0	35,781	39,293
HH wealth highest quintile	0.095	0.184	0.089	0	35,781	39,293
Log Rainfall	27.807	27.549	-0.258	0	35,781	39,293
Air Temperature (°C)	24.670	24.950	0.280	0	35,781	39,293
Panel B. 2010-2019						
Mortality before 6 months	36.357	32.347	-4.010	0.038	16,943	18,858
Child female	0.479	0.473	-0.007	0.207	16,943	18,858
Child multiple birth	0.016	0.016	0.00003	0.981	16,943	18,858
Child first born	0.347	0.366	0.019	0	16,943	18,858
Child birth order sup 4	0.170	0.150	-0.020	0	16,943	18,858
Mother under 18 at birth	0.036	0.027	-0.009	0	16,943	18,858
Mother older 35 at birth	0.040	0.035	-0.004	0.029	16,943	18,858
Mother no educ	0.352	0.279	-0.074	0	16,943	18,858
Mother primary educ	0.148	0.140	-0.009	0.019	16,943	18,858
Mother secondary educ	0.433	0.474	0.040	0	16,943	18,858
Mother higher educ	0.066	0.108	0.042	0	16,943	18,858
Mother hindu	0.725	0.782	0.057	0	16,943	18,858
Mother muslim	0.196	0.156	-0.040	0	16,943	18,858
Mother scheduled caste (SC)	0.221	0.268	0.046	0	15,830	18,435
Mother scheduled tribe (ST)	0.164	0.053	-0.112	0	15,830	18,435
Mother other backward caste (OBC)	0.439	0.466	0.027	0	15,830	18,435
HH wealth lowest quintile	0.294	0.139	-0.155	0	16,943	18,858
HH wealth second quintile	0.248	0.229	-0.019	0	16,943	18,858
HH wealth fourth quintile	0.160	0.205	0.045	0	16,943	18,858
HH wealth highest quintile	0.093	0.188	0.095	0	16,943	18,858
Log Rainfall	27.833	27.576	-0.256	0	16,943	18,858
Air Temperature (°C)	24.759	25.130	0.371	0	16,943	18,858

Notes: Panel A compares the summary statistics between children born downstream urban areas where wastewater treatment started between 2010 and 2020 and children born downstream urban area where wastewater treatment is in project in 2020 before wastewater treatment started in the sample (before 2010), while Panel B compares the summary statistics since 2010 when the first operation of sewage treatment plants were observed in the data. Mortality before 6 months is the number of deaths among children less than six months old, scaled per 1,000 births. The unit of observations is the child level.

Table A3: Comparison of surface area and population of urban areas reporting the first year of sewage treatment

	Urban areas reporting sewage treatment plants				
	Under construction in 2020	Starting to operate between 2010 and 2020		Starting to operate before 2010	
	N=185	N=273		N=117	
Variable	Mean (1)	Mean (2)	Diff (2)-(1)	Mean (3)	Diff (3)-(1)
Surface (km^2)	46.3	58.6	12.3**	94.8	48.5**
WorldPop population					
2000	76,529	148,567	72,038*	453,028	376,4995**
2010	84,036	164,155	80,119*	535,273	451,237**

Notes: Asterisks denote p-value < 0.10 (*), < 0.05 (**), or < 0.01 (***) for the t-test.

Table A4: Effect on Mortality - Heterogeneity analysis (1)

Dependent Variable:	Child died before the age of six months			
	Female	Male	Low wealth quintile	High wealth quintile
	(1)	(2)	(3)	(4)
Estimator : Gardner (2022)	-6.228	-9.770*	-12.55*	-7.578
	(4.685)	(5.544)	(6.766)	(4.642)
Estimator : S & A (2021)	-7.629	-12.06	-19.13	-7.520
	(10.37)	(8.062)	(12.22)	(6.457)
Estimator : TWFE	-8.033*	-13.08**	-13.52**	-11.51***
	(4.227)	(5.287)	(6.549)	(4.174)
Extended controls	X	X	X	X
NFHS Cluster FE	X	X	X	X
Birth year FE + Birth month FE	X	X	X	X
Observations	40,205	44,711	39,648	45,268
Period	1991-2019	1991-2019	1991-2019	1991-2019
Number of NFHS Clusters	2386	2385	1960	2291
Number of Urban areas	272	272	258	272
Mean of Dep. Variable	37.060	44.888	48.704	34.594

Notes:The table presents the coefficients of the estimators according to the Gardner [2022], Sun and Abraham [2021] and classic TWFE methodologies. The model in columns (1) and (2) compares mortality among female and male children, while the model in columns (3) and (4) compares mortality among low wealth (first or second) quintile and high wealth (third, fourth and fifth) quintile children. All models include NFHS cluster fixed effects, birth year and birth month fixed effects. Mortality variables are scaled as described in the text to generate coefficients that indicate impacts on rates × 1,000 (deaths per 1,000 children). Extended controls are the same as in the baseline regressions, except that the child female control is excluded in columns (1) and (2). Standard errors are in parentheses and clustered by urban area. Asterisks denote p-value < 0.10 (*), < 0.05 (**), or < 0.01 (***).

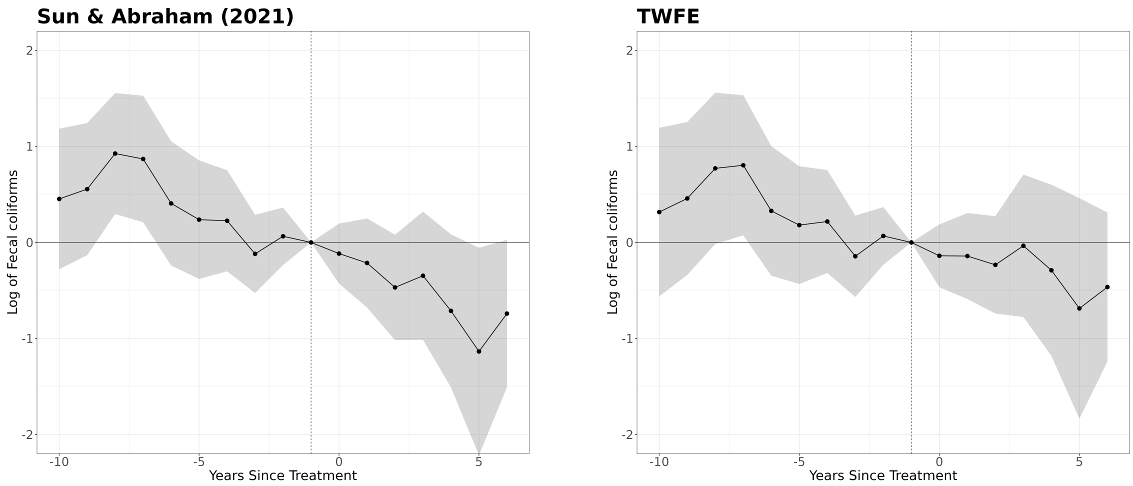
Table A5: Effect on Mortality - Heterogeneity analysis (2)

Dependent Variable:	Child died before the age of six months					
	Treating water (1)	Not treating water (2)	Drinking groundwater (3)	Drinking other sources (4)	Having a toilet (5)	Not having a toilet (6)
Estimator : Gardner (2022)	-6.383	-8.525**	-5.879	-9.323*	-4.824	-21.63***
	(6.313)	(4.079)	(5.524)	(4.906)	(4.182)	(7.687)
Estimator : S & A (2021)	-3.279	-11.30	-9.634	-6.658	-8.915	-17.07
	(10.30)	(8.250)	(11.99)	(8.564)	(7.832)	(11.45)
Estimator : TWFE	-7.609	-12.03***	-11.30**	-11.02**	-8.043**	-21.73***
	(5.692)	(3.954)	(5.427)	(4.473)	(3.886)	(7.794)
Extended controls	X	X	X	X	X	X
NFHS Cluster FE	X	X	X	X	X	X
Birth year FE + Birth month FE	X	X	X	X	X	X
Observations	25,370	59,542	44,008	40,908	57,202	27,714
Period	1991-2019	1991-2019	1991-2019	1991-2019	1991-2019	1991-2019
Number of NFHS Clusters	1951	2219	1745	1962	2266	1609
Number of Urban areas	268	271	240	272	272	247
Mean of Dep. Variable	33.938	44.271	47.537	34.345	36.939	49.939

Notes:The table presents the coefficients of the estimators according to the Gardner [2022], Sun and Abraham [2021] and classic TWFE methodologies. The model in columns (1) and (2) compares mortality among children born in households that treat water before drinking versus those that do not treat water before drinking. The model in columns (3) and (4) compares mortality among children born in households that primarily drink groundwater versus other sources of water. The model in columns (5) and (6) compares mortality among children born in households that have access to a toilet versus those that practice open defecation at the time of interview. All models include NFHS cluster fixed effects, birth year and birth month fixed effects. Mortality variables are scaled as described in the text to generate coefficients that indicate impacts on rates $\times$ 1,000 (deaths per 1,000 children). Extended controls are the same as in the baseline regressions, except that the child female control is excluded in columns (1) and (2). Standard errors are in parentheses and clustered by urban area. Asterisks denote p-value < 0.10 (*), < 0.05 (**), or < 0.01 (***).

B Robustness

Figure B1: Pollution Event Study with Alternative Estimators



Sun and Abraham [2021] estimator

TWFE estimator

Notes: This figure shows the coefficients of the estimators according to the Sun and Abraham [2021] (left column) and the classic two-way fixed effects (right column) methodology. The 95% confidence intervals bands are shown. Data include years 1991-2020. The model includes monitoring station fixed effects and main basin-by-year fixed effects, as well as controls for precipitation and temperature. Standard errors are clustered at the urban area level. All observations more than 10 years before treatment are set at 10 years before treatment and all observations more than 6 years after treatment are set at 6 years after treatment.

Figure B2: TWFE negative weights in classic TWFE regression reported in Column (2) of Table 2

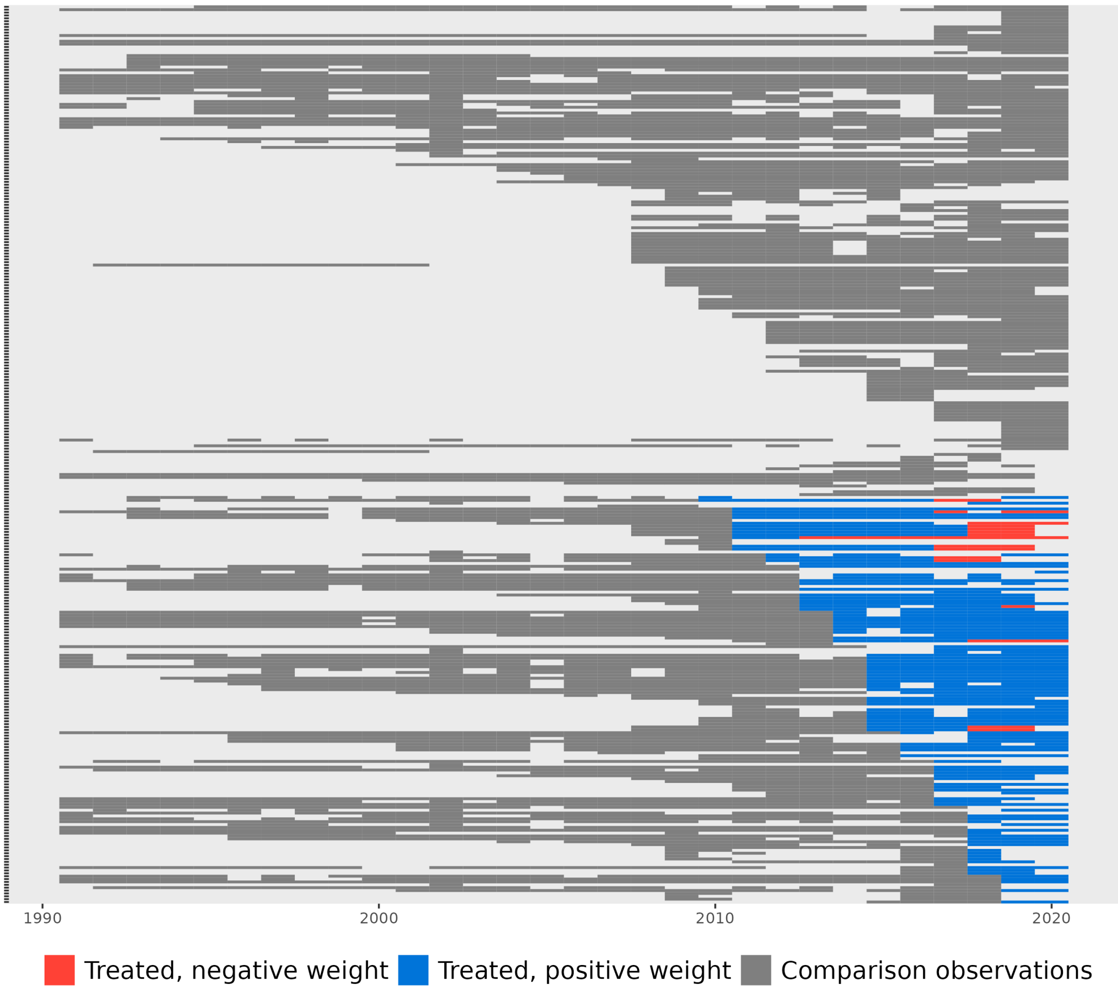
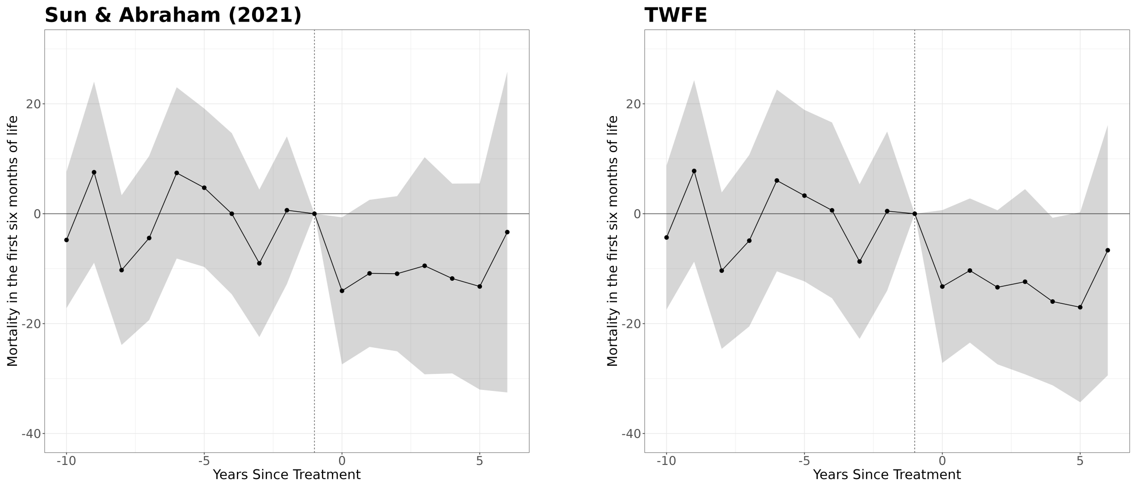


Figure B3: Mortality Event Study with Alternative Estimators

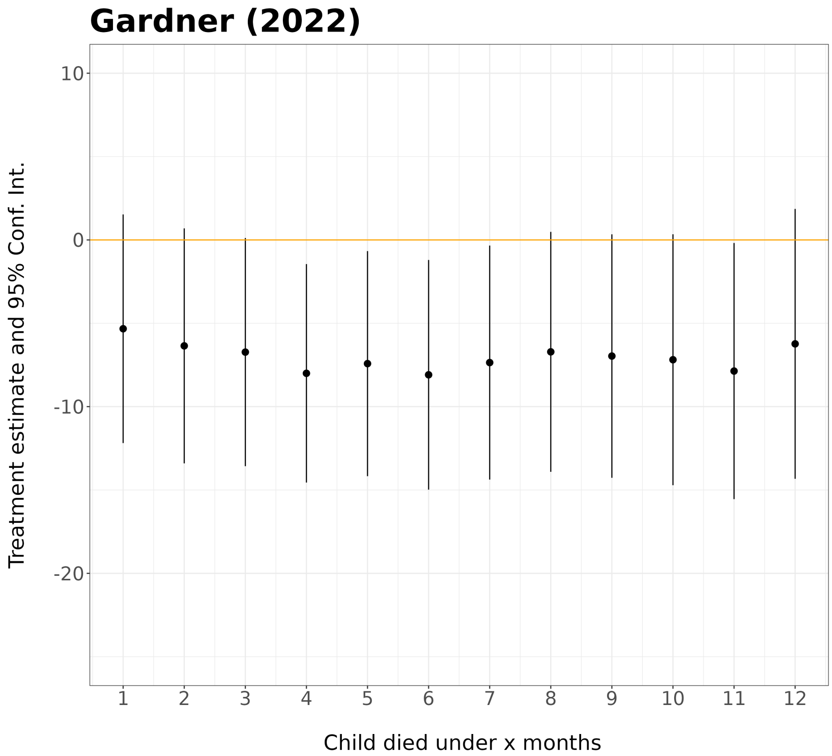


Sun and Abraham [2021] estimator

TWFE estimator

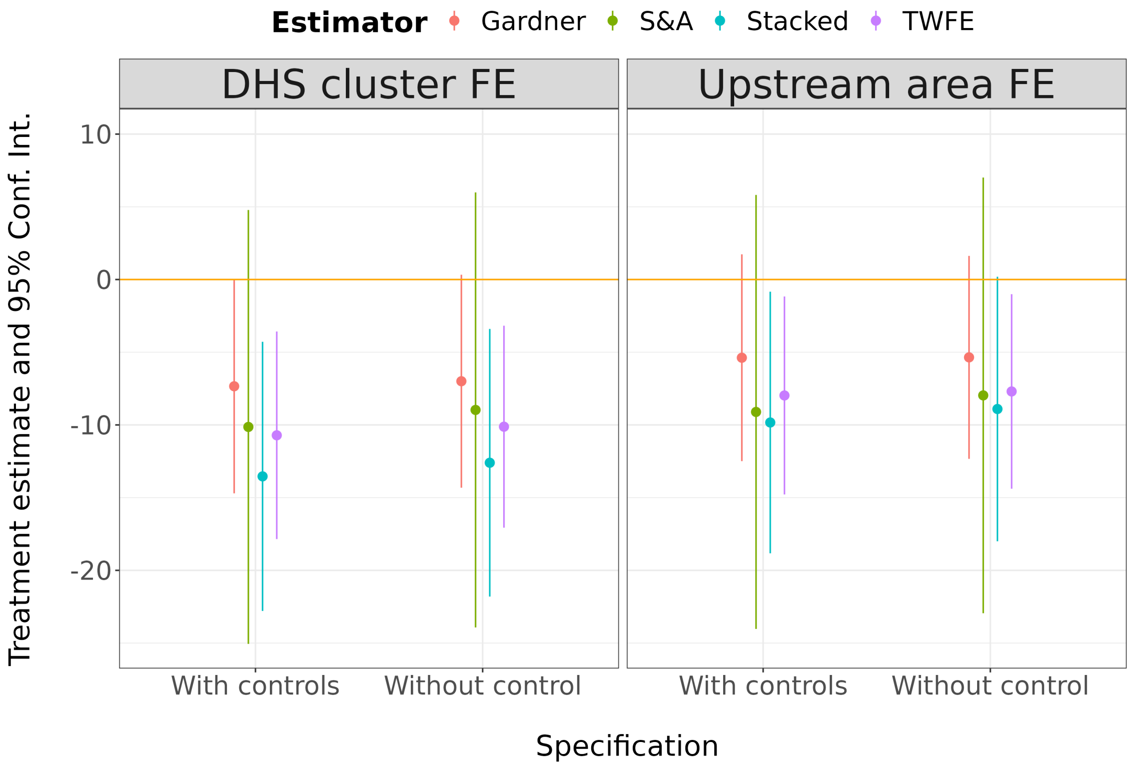
Notes: This figure shows the coefficients of the estimators according to the Sun and Abraham [2021] (left column) and the classic two-way fixed effects (right column) methodology. The dependent variable is an indicator for death in the first six months of life $\times$ 1,000. The 95% confidence intervals bands are shown. Data include years 1991-2019. The model includes cluster fixed effects and year fixed effects, as well as controls for child-level, mother-level, household-level and weather determinants of health. Child controls include indicators for the child being a female, being a multiple birth, being the first born, being the fourth or more born. Controls at the mother level include indicators for the mother being either under 18 years old or over 35 years old at the time of the child's birth, educational attainment (primary, secondary education or higher education), religious affiliation (being Muslim, neither Hindu nor Muslim), and caste affiliation (scheduled caste, scheduled tribe, or other backward caste). Household controls include indicators for first, second, fourth and fifth wealth quintiles. Weather controls include the logarithmic transformation of the sum of precipitation felt in one year within a 20km radius of the cluster coordinates and the daily mean temperature over the year within a 20km radius of the cluster coordinates. Standard errors are clustered by urban area. All observations more than 10 years before treatment are set at 10 years before treatment and all observations more than 6 years after treatment are set at 6 years after treatment.

Figure B4: Effect on Mortality - Comparison from neonatal mortality to infant mortality at the monthly level



Notes: The figure presents the coefficients of the estimators according to the Gardner [2022] methodology. The model includes NFHS cluster fixed effects and year fixed effects as well as child, mother, household and weather controls. The coeffcient estimate for the mortality under 6 months is the one presented in column (2) of Table 4. Mortality variables are scaled as described in the text to generate coefficients that indicate impacts on rates × 1,000 (deaths per 1,000 children). Standard errors are in parentheses and clustered by urban area.

Figure B5: DiD mortality results summary excluding children born from mother with higher education



Notes: Figures plot coefficient estimates and 95% confidence intervals for the difference-in-differences on the mortality under six months based on different estimators: Gardner [2022], Sun and Abraham [2021], stacked regression and classic TWFE with and without controls, as well as with NFHS cluster fixed effect or urban area fixed effects.

Figure B6: DiD Upstream mortality results summary

Notes: Figures plot coefficient estimates and 95% confidence intervals for the difference-in-differences on the mortality under six months based on different estimators: Gardner [2022], Sun and Abraham [2021], stacked regression and classic TWFE with and without controls, as well as with NFHS cluster fixed effect or urban area fixed effects.

Table B1: Effect on Fecal coliforms levels

Dependent Variable:	Log(Average Fecal coliforms)			
	(1)	(2)	(3)	(4)
Stacked regression	-0.4963	-0.4954*	-0.5746*	-0.5570*
	(0.3015)	(0.2963)	(0.3076)	(0.3037)
Weather controls		X		X
River distance			X	X
Urban area FE			X	X
Monitoring station FE	X	X		
Year-Main basin FE	X	X	X	X
Observations	15,950	15,950	15,950	15,950
Period	1991-2020	1991-2020	1991-2020	1991-2020
Number of Stations	307	307	307	307
Number of Urban areas	139	139	139	139

Notes: The table presents the coefficients of the estimators according to the stacked difference-in-diferences methodology. The model in columns (1) and (2) includes monitoring station fixed effects and main basin-by-year fixed effects while the model in columns (3) and (4) includes urban area fixed effects and controls for the river distance between the monitoring station and the urban area. Columns (2) and (4) add controls for precipitation and temperature. Standard errors are clustered at the urban area level. Asterisks denote p-value < 0.10 (*), < 0.05 (**), or < 0.01 (***).

Table B2: Effect on Mortality

Dependent Variable:	Child died before the age of six months			
	(1)	(2)	(3)	(4)
Stacked regression	-11.68***	-12.79***	-8.588*	-9.779**
	(4.383)	(4.333)	(4.409)	(4.265)
Extended controls		X		X
Urban area FE			X	X
NFHS Cluster FE	X	X		
Birth year FE + Birth month FE	X	X	X	X
Observations	238,065	225,579	238,065	225,579
Period	1991-2019	1991-2019	1991-2019	1991-2019
Number of NFHS Clusters	2386	2344	2386	2344
Number of Urban areas	272	272	272	272
Mean of Dep. Variable	36.813	37.167	36.813	37.167

Notes: The table presents the coefficients of the estimators according to the stacked difference-in-diferences methodology. The model in columns (1) and (2) includes NFHS cluster fixed effects while the model in columns (3) and (4) includes urban area fixed effects, all models include birth year and birth month fixed effects. Mortality variables are scaled as described in the text to generate coefficients that indicate impacts on rates $\times$ 1,000 (deaths per 1,000 children). Child controls include indicators for the child being a female, being a multiple birth, being the first born, being the fourth or more born. Controls at the mother level include indicators for the mother being either under 18 years old or over 35 years old at the time of the child's birth, educational attainment (primary, secondary education or higher education), religious affiliation (being Muslim, neither Hindu nor Muslim), and caste affiliation (scheduled caste, scheduled tribe, or other backward caste). Household controls include indicators for first, second, fourth and fifth wealth quintiles. Weather controls include the logarithmic transformation of the sum of precipitation felt in one year within a 20km radius of the cluster coordinates and the daily mean temperature over the year within a 20km radius of the cluster coordinates. Standard errors are in parentheses and clustered by urban area. Asterisks denote p-value < 0.10 (*), < 0.05 (**), or < 0.01 (***).

Table B3: Effect on Mortality with mother fixed effects

Dependent Variable:	Child died before the age of six months	
	(1)	(2)
Estimator : Gardner (2022)	-6.464	-7.646
	(7.012)	(7.025)
Estimator : S & A (2021)	-19.84	-18.53
	(12.14)	(12.17)
Estimator : TWFE	-11.26*	-11.32*
	(6.332)	(6.375)
Extended controls		X
Urban area FE	X	X
Birth year FE + Birth month FE	X	X
Observations	55,618	55,618
Period	1991-2019	1991-2019
Number of NFHS Clusters	2249	2249
Number of Urban areas	266	266
Mean of Dep. Variable	42.882	42.882

Notes: The table presents the coefficients of the estimators according to the Gardner [2022] methodology and the canonical TWFE model. The model in columns (1) and (3) includes NFHS cluster fixed effects while the model in columns (2) and (4) includes urban area fixed effects, all models include birth year and birth month fixed effects. In each regression, mothers downstream treated urban areas gave birth at least to one child before treatment and one child post-treatment and mothers downstream control urban areas gave birth to at least two children. Child controls include indicators for the child being a female, being a multiple birth, and only for columns (3) and (4) being the first born, being the fourth or more born. Mother controls include indicators for the mother being under 18 years old when the child is born, being over 35 years old when the child is born. Weather controls include the logarithmic transformation of the sum of precipitation felt in one year within a 20km radius of the cluster coordinates and the daily mean temperature over the year within a 20km radius of the cluster coordinates. Standard errors are in parentheses and clustered by urban area. Asterisks denote p-value < 0.10 (*), < 0.05 (**), or < 0.01 (***).

Table B4: Effect on Child controls

Dependent Variable:	Child female (1)	Child multiple birth (2)	Child first born (3)	Child birth order sup 4 (4)
Estimator : Gardner (2022)	4.674	4.169	13.60	-6.773
	(9.809)	(3.033)	(9.773)	(9.147)
Estimator : S & A (2021)	13.70	7.328	10.48	14.44*
	(15.58)	(5.126)	(18.11)	(8.045)
Estimator : TWFE	4.510	3.787	23.44***	-10.62
	(9.400)	(2.769)	(8.864)	(9.111)
NFHS FE	X	X	X	X
Birth month FE	X	X	X	X
Birth year FE	X	X	X	X
Observations	89,273	89,273	89,273	89,273
Period	1991-2019	1991-2019	1991-2019	1991-2019
Number of NFHS Clusters	2387	2387	2387	2387
Number of Urban areas	272	272	272	272
Mean of Dep. Variable	473.60	14.260	341.90	176.66

Notes: The table presents the coefficients of the estimators according to the Gardner [2022], Sun and Abraham [2021] and classic TWFE methodologies. All models include NFHS cluster fixed effects, birth year and birth month fixed effects. Dependent variables are scaled to generate coefficients that indicate impacts on rates $\times$ 1,000 (number per 1,000 children). Standard errors are in parentheses and clustered by urban area. Asterisks denote p-value < 0.10 (*), < 0.05 (**), or < 0.01 (***).

Table B5: Effect on Mother controls

Dependent Variable:	Mother underage 18 (1)	Mother overage 35 (2)	Mother primary educ (3)	Mother secondary educ (4)	Mother higher educ (5)	Mother muslim (6)	Mother not hindu nor muslim (7)	Mother schedule caste (8)	Mother schedule tribe (9)	Mother OBC (10)
Estimator : Gardner	-1.017	-4.581	-19.86	-18.51	34.88***	3.199	2.759	-7.480	0.6248	3.515
	(4.661)	(4.143)	(12.13)	(15.11)	(10.02)	(5.211)	(2.771)	(7.852)	(5.167)	(8.221)
Estimator : S & A	3.650	-0.4641	-10.62	-21.20	17.25**	13.69***	2.705	-1.078	4.303	0.7417
	(5.979)	(4.807)	(10.86)	(13.46)	(8.607)	(4.914)	(4.046)	(9.243)	(5.115)	(12.21)
Estimator : TWFE	-0.2059	-3.444	-18.57*	-11.93	30.96***	0.6318	2.957	-6.145	-0.6210	4.256
	(4.383)	(4.094)	(10.71)	(14.39)	(9.137)	(4.766)	(2.704)	(7.216)	(4.452)	(7.743)
NFHS Cluster FE	X	X	X	X	X	X	X	X	X	X
Birth month FE	X	X	X	X	X	X	X	X	X	X
Birth year FE	X	X	X	X	X	X	X	X	X	X
Observations	89,273	89,273	89,273	89,273	89,273	89,273	89,273	84,916	84,916	84,916
Nb NFHS Clusters	2387	2387	2387	2387	2387	2387	2387	2387	2387	2387
Nb Urban areas	272	272	272	272	272	272	272	272	272	272
Mean of Dep. Var.	68.207	21.899	157.38	334.77	45.344	163.77	79.565	236.93	103.61	454.34

Notes: The table presents the coefficients of the estimators according to the Gardner [2022], Sun and Abraham [2021] and classic TWFE methodologies. All models include NFHS cluster fixed effects, birth year and birth month fixed effects. Dependent variables are scaled to generate coefficients that indicate impacts on rates $\times$ 1,000 (number per 1,000 children). Standard errors are in parentheses and clustered by urban area. Asterisks denote p-value < 0.10 (*), < 0.05 (**), or < 0.01 (***).

Table B6: Effect on Household controls

Dependent Variable:	HH wealth lowest (1)	HH wealth second (2)	HH wealth fourth (3)	HH wealth highest (4)
Estimator : Gardner	-6.396	4.134	8.141	-0.9390
	(7.074)	(8.386)	(7.960)	(6.789)
Estimator : S & A	-1.106	-3.014	22.67*	-6.993
	(7.640)	(12.28)	(12.00)	(7.678)
Estimator : TWFE	-6.046	1.441	4.331	-0.8002
	(6.689)	(7.709)	(7.111)	(5.936)
NFHS Cluster FE	X	X	X	X
Birth month FE	X	X	X	X
Birth year FE	X	X	X	X
Observations	89,273	89,273	89,273	89,273
Nb NFHS Clusters	2387	2387	2387	2387
Nb Urban areas	272	272	272	272
Mean of Dep. Var.	221.00	243.44	176.03	135.12

Notes: The table presents the coefficients of the estimators according to the Gardner [2022], Sun and Abraham [2021] and classic TWFE methodologies. All models include NFHS cluster fixed effects, birth year and birth month fixed effects. Dependent variables are scaled to generate coefficients that indicate impacts on rates $\times$ 1,000 (number per 1,000 children). Standard errors are in parentheses and clustered by urban area. Asterisks denote p-value < 0.10 (*), < 0.05 (**), or < 0.01 (***).

Table B7: Effect on Downstream Mortality excluding children born from mother with higher education

Dependent Variable:	Child died before the age of six months			
	(1)	(2)	(3)	(4)
Estimator : Gardner (2022)	-6.994*	-7.405*	-5.353	-5.379
	(3.736)	(3.880)	(3.560)	(3.628)
Estimator : S & A (2021)	-8.968	-10.14	-7.968	-9.106
	(7.597)	(7.577)	(7.609)	(7.579)
Estimator : TWFE	-10.12***	-10.71***	-7.697**	-7.973**
	(3.527)	(3.625)	(3.397)	(3.458)
Extended controls		X		X
Urban area FE			X	X
NFHS Cluster FE	X	X		
Birth year FE + Birth month FE	X	X	X	X
Observations	84,224	80,040	84,224	80,040
Period	1991-2019	1991-2019	1991-2019	1991-2019
Number of NFHS Clusters	2339	2298	2339	2298
Number of Urban areas	270	270	270	270
Mean of Dep. Variable	41.817	42.129	41.817	42.129

Notes: The table presents the coefficients of the estimators according to the Gardner [2022], Sun and Abraham [2021] and classic TWFE methodologies. The model in columns (1) and (2) includes NFHS cluster fixed effects while the model in columns (3) and (4) includes urban area fixed effects, all models include birth year and birth month fixed effects. Mortality variables are scaled as described in the text to generate coefficients that indicate impacts on rates $\times$ 1,000 (deaths per 1,000 children). Child controls include indicators for the child being a female, being a multiple birth, being the first born, being the fourth or more born. Controls at the mother level include indicators for the mother being either under 18 years old or over 35 years old at the time of the child's birth, educational attainment (primary or secondary education education), religious affiliation (being Muslim, neither Hindu nor Muslim), and caste affiliation (scheduled caste, scheduled tribe, or other backward caste). Household controls include indicators for first, second, fourth and fifth wealth quintiles. Weather controls include the logarithmic transformation of the sum of precipitation felt in one year within a 20km radius of the cluster coordinates and the daily mean temperature over the year within a 20km radius of the cluster coordinates. Standard errors are in parentheses and clustered by urban area. Asterisks denote p-value < 0.10 (*), < 0.05 (**), or < 0.01 (***).

Table B8: Effect on Downstream Mortality excluding children born from mother with higher education

Dependent Variable:	Child died before the age of six months			
	(1)	(2)	(3)	(4)
Stacked regression	-12.60***	-13.54***	-8.905*	-9.832**
	(4.673)	(4.701)	(4.619)	(4.568)
Extended controls		X		X
Urban area FE			X	X
NFHS Cluster FE	X	X		
Birth year FE + Birth month FE	X	X	X	X
Observations	238,065	225,579	238,065	225,579
Period	1991-2019	1991-2019	1991-2019	1991-2019
Number of NFHS Clusters	2336	2292	2336	2292
Number of Urban areas	270	270	270	270
Mean of Dep. Variable	36.813	37.167	36.813	37.167

Notes: The table presents the coefficients of the estimators according to the stacked difference-in-diferences methodology. The model in columns (1) and (2) includes NFHS cluster fixed effects while the model in columns (3) and (4) includes urban area fixed effects, all models include birth year and birth month fixed effects. Mortality variables are scaled as described in the text to generate coefficients that indicate impacts on rates $\times$ 1,000 (deaths per 1,000 children). Child controls include indicators for the child being a female, being a multiple birth, being the first born, being the fourth or more born. Controls at the mother level include indicators for the mother being either under 18 years old or over 35 years old at the time of the child's birth, educational attainment (primary or secondary education education), religious affiliation (being Muslim, neither Hindu nor Muslim), and caste affiliation (scheduled caste, scheduled tribe, or other backward caste). Household controls include indicators for first, second, fourth and fifth wealth quintiles. Weather controls include the logarithmic transformation of the sum of precipitation felt in one year within a 20km radius of the cluster coordinates and the daily mean temperature over the year within a 20km radius of the cluster coordinates. Standard errors are in parentheses and clustered by urban area. Asterisks denote p-value < 0.10 (*), < 0.05 (**), or < 0.01 (***).

Table B9: Effect on Upstream Mortality

Dependent Variable:	Child died before the age of six months			
	(1)	(2)	(3)	(4)
Estimator : Gardner (2022)	2.841	3.131	3.128	3.983
	(2.849)	(2.734)	(2.535)	(2.515)
Estimator : S & A (2021)	-1.804	-1.225	-0.2068	0.5038
	(5.414)	(5.531)	(5.056)	(5.197)
Estimator : TWFE	1.990	2.518	3.062	3.853
	(2.841)	(2.789)	(2.499)	(2.459)
Extended controls		X		X
Urban area FE			X	X
NFHS Cluster FE	X	X		
Birth year FE + Birth month FE	X	X	X	X
Observations	144,495	140,162	144,495	140,162
Period	1991-2019	1991-2019	1991-2019	1991-2019
Number of NFHS Clusters	3814	3814	3814	3814
Number of Urban areas	177	177	177	177
Mean of Dep. Variable	41.005	41.195	41.005	41.195

Notes: The table presents the coefficients of the estimators according to the Gardner [2022], Sun and Abraham [2021] and classic TWFE methodologies. The model in columns (1) and (2) includes NFHS cluster fixed effects while the model in columns (3) and (4) includes urban area fixed effects, all models include birth year and birth month fixed effects. Mortality variables are scaled as described in the text to generate coefficients that indicate impacts on rates $\times$ 1,000 (deaths per 1,000 children). Child controls include indicators for the child being a female, being a multiple birth, being the first born, being the fourth or more born. Controls at the mother level include indicators for the mother being either under 18 years old or over 35 years old at the time of the child's birth, educational attainment (primary, secondary education or higher education), religious affiliation (being Muslim, neither Hindu nor Muslim), and caste affiliation (scheduled caste, scheduled tribe, or other backward caste). Household controls include indicators for first, second, fourth and fifth wealth quintiles. Weather controls include the logarithmic transformation of the sum of precipitation felt in one year within a 20km radius of the cluster coordinates and the daily mean temperature over the year within a 20km radius of the cluster coordinates. Standard errors are in parentheses and clustered by urban area. Asterisks denote p-value < 0.10 (*), < 0.05 (**), or < 0.01 (***).

Table B10: Comparison of upstream versus downstream mortality

Dependent Variable:	Child died before the age of six months	
	(1)	(2)
Estimator : Gardner (2022)	-4.335	-5.854
	(3.776)	(3.750)
Estimator : S & A (2021)	-9.600	-9.917
	(7.354)	(6.160)
Estimator : TWFE	-4.663	-6.413*
	(3.580)	(3.569)
Extended controls		X
Urban area FE	X	X
Birth year FE + Birth month FE	X	X
Observations	70,765	68,924
Period	1991-2019	1991-2019
Number of NFHS Clusters	2033	2027
Number of Urban areas	66	66
Mean of Dep. Variable	39.398	39.928

Notes: The table presents the coefficients of the estimators according to the Gardner [2022], Sun and Abraham [2021] and classic TWFE methodologies. The model in columns (1) and (2) includes urban area fixed effects, birth year and birth month fixed effects. Mortality variables are scaled as described in the text to generate coefficients that indicate impacts on rates $\times$ 1,000 (deaths per 1,000 children). Child controls include indicators for the child being a female, being a multiple birth, being the first born, being the fourth or more born. Controls at the mother level include indicators for the mother being either under 18 years old or over 35 years old at the time of the child's birth, educational attainment (primary or secondary education education), religious affiliation (being Muslim, neither Hindu nor Muslim), and caste affiliation (scheduled caste, scheduled tribe, or other backward caste). Household controls include indicators for first, second, fourth and fifth wealth quintiles. Weather controls include the logarithmic transformation of the sum of precipitation felt in one year within a 20km radius of the cluster coordinates and the daily mean temperature over the year within a 20km radius of the cluster coordinates. Standard errors are in parentheses and clustered by urban area. Asterisks denote p-value < 0.10 (*), < 0.05 (**), or < 0.01 (***).

Table B11: Parental behavior summary statistics - Children aged 0-6 months

	Means			N. Obs.		
	Control	Pre-Treated	Post-Treated	Control	Pre-Treated	Post-Treated
Panel A. Interviews 2015-2016						
Child age in months	3.421	3.279	3.496	604	204	409
Water and sanitation behavior						
Water treatment	0.291	0.238	0.215	632	210	427
Open defecation	0.509	0.419	0.445	632	210	427
Shared toilets	0.177	0.139	0.169	310	122	237
Liquids given to the child						
Currently breastfed	0.957	0.946	0.958	601	202	407
Plain water	0.441	0.436	0.485	610	202	412
Juice	0.052	0.064	0.063	610	202	412
Milk	0.180	0.203	0.211	610	202	412
Baby formula	0.026	0.064	0.029	610	202	412
Soup	0.051	0.054	0.046	610	202	412
Other liquid	0.048	0.045	0.034	610	202	412
Panel B. Interviews 2019						
Child age in months	3.255	4	3.358	365	3	358
Water and sanitation behavior						
Water treatment	0.349	0	0.330	378	3	367
Open defecation	0.216	0	0.174	379	3	367
Shared toilets	0.101	0.333	0.129	297	3	303
Liquids given to the child						
Currently breastfed	0.947	1	0.960	361	3	353
Plain water	0.400	0	0.292	365	3	356
Juice	0.088	0	0.045	365	3	356
Milk	0.167	0	0.154	365	3	356
Baby formula	0.071	0	0.053	365	3	356
Soup	0.085	0	0.053	365	3	356
Other liquid	0.071	0	0.065	365	3	356

Notes: Panel A compares summary statistics for children aged under 6 months at the time of the NFHS-4 interviews, while Panel B compares summary statistics for children born in 2019 and aged under 6 months at the time of the NFHS-5 interviews. The unit of observations is the child level.

Table B12: Effect on Air pollution

Dependent Variable:	PM 2.5		
	Minimum (1)	Mean (2)	Maximum (3)
Estimator : Gardner (2022)	0.0332	0.0745	0.0911
	(1.114)	(1.119)	(1.130)
Estimator : S & A (2021)	-0.4437	-0.4425	-0.4521
	(0.4109)	(0.4117)	(0.4085)
Estimator : TWFE	0.0921	0.1375	0.1597
	(1.055)	(1.063)	(1.077)
Urban area FE	X	X	X
Year FE	X	X	X
Observations	10,442	10,442	10,442
Period	1998-2020	1998-2020	1998-202O
Number of Urban areas	454	454	454
Mean of Dep. Variable	50.173	51.318	52.410

Notes: The table presents the coefficients of the estimators according to the Gardner [2022], Sun and Abraham [2021] and classic TWFE methodologies. All models include state fixed effects and year fixed effects. Standard errors are in parentheses and clustered by state. Asterisks denote p-value < 0.10 (*), < 0.05 (**), or < 0.01 (***).

C Other Health Outcomes

As NFHS surveys are cross-sectional, few health variables, apart from mortality, can be studied in a panel at the NFHS cluster level. Using NFHS cluster fixed effect is important because it controls for unobserved birthplace characteristics such as access to healthcare services and road infrastructure.

Birth weight and height-for-age z-score, which measures chronic malnutrition, are the only health variables that can be studied in a panel according to NFHS cluster and birth year. Table C1 presents the regression samples, which are subject to the same restrictions as the mortality sample. (i) If there is a birth in a NFHS cluster related to an urban area after it has started wastewater treatment, then that NFHS cluster is only included if it has at least one data point before the urban area starting wastewater treatment. (ii) If the urban area doesn't treat wastewater in 2020, then the NFHS cluster is only included if it has at least two outcome data points.

C.1 Birth weight

Literature shows that maternal exposure to fecal pathogens can reduce the quality of maternal nutrition during gestation, in turn reducing uterine growth and birth weight [Prendergast et al., 2014, Spears, 2020, Coffey and Spears, 2021]. In the US, Flynn and Marcus [2021] show that CWA grants to municipal wastewater treatment plants increased average birth weight by 8 grams in counties downstream of the plants.

In NFHS surveys, birth weight was recorded from either a written record or the mother's report. Figure C1 shows that birth weight in the sample is not normally distributed and presents big peaks at rounded values every 500 grams. This rounding raises concerns about a loss of precision which may mask substantial differences or trends in the data.

In columns (3) and (4) of Table C2, I examine birth weight given in grams and the number of children with low birth weight (inferior to 2.5kg). Following Equation 3, I use as treatment variable the same binary indicator than in mortality regressions that is equal to one if the upstream urban area treats the wastewater in the birth year of the child. According tot he Gardner [2022]'s estimator, I observe no significant result. Surprisingly, the estimates are negative. Column 3 suggests a 30g reduction in birth weight after wastewater treatment. This result is possibly due to the poor precision of the birth weight report described in the previous paragraph, and is therefore inconclusive.

C.2 Chronic malnutrition

A related pathway from exposure to fecal pathogens to death is poor net nutrition, which is calories consumed net of calories lost to diarrheal disease and parasites as well as expended in combating infections. If wastewater treatment is reducing deaths via infection, malnutrition should also be reduced.

I use height-for-age z-score (HAZ), the number of standard deviations (SD) above or below the gender- and age-specific median height-for-age to measure chronic malnutrition. Low height-for-age is known as stunting. It is the result of chronic or recurrent undernutrition. Stunting can be due to repeated fecal contamination that, through an inflammatory response, increases the small intestine's permeability to pathogens while reducing nutrient absorption. Chronic malnutrition holds children back from reaching their physical and cognitive potential [Black et al., 2013]. A child with an HAZ below -2 SD is considered to be stunted. Since HAZ and the proportion of stunted children reflect long-term exposure, I distinguish children born downstream of treated areas between those who have lived more than half their lives with treatment and those who have lived less than half their lives with treatment. Figure C2 presents the HAZ distribution in the sample and suggests that children who have lived more than half their lives with treatment suffer less from chronic malnutrition than others.

In columns (1) and (2) of Table C2, I examine chronic malnutrition measured respectively by the height-for-age z-score (HAZ) and the number of stunted children with a binary indicator equal to one if the child has lived more than half his life with upstream wastewater treatment. The results are inconclusive, possibly due to a reduction in statistical power.

C.3 Description of other health outcomes

Water pollution by untreated sewage, and in particular contamination by faecal pathogens, has other health effects that need to be measured to assess the extent of wastewater treatment. NFHS data allow us to study three other morbidity variables, which correspond to short-term symptoms:

Diarrhea : Fecal pathogens cause gastrointestinal diseases of which a major symptom is diarrhea.

Acute malnutrition : Weight-for-height z-score (WHZ), the number of standard deviations (SD) above or below the gender- and age-specific median weight-for-height, measures acute malnutrition. Low weight-for-height is known as wasting. It usually indicates recent and severe weight loss, because a person has not had enough food to eat and/or they have had an infectious disease, such as diarrhoea, which has caused them to lose weight. A young child who is moderately or severely wasted has an increased risk of death, but treatment is possible. A child with a WHZ below -2 SD is considered to be wasted.

Hemoglobin level/Anemia : Anemia defined as low levels of blood hemoglobin, can be caused by diets lacking iron, vitamin B12, and folic acid, all of which are necessary for the production of red blood cells. Intestinal parasites also contribute to low blood hemoglobin in developing country settings [Geruso and Spears, 2018] In children, a hemoglobin level below 11mg/L corresponds to anemia.

Table C3 presents descriptive statistics for children age 0-59 months for whom weight-for-height and hemoglobin level were measured by the NFHS interviewers and/or diarrhea in the last two weeks was reported by the mother. This compares children according to upstream water treatment at the date of the interview and not at the date of birth as in mortality regressions. The means suggest that children living in NFHS clusters downstream of urban areas that treat wastewater suffer less from acute malnutrition. There is no noteworthy difference in hemoglobin levels or anemia. Means for the incidence of diarrhea, fever and cough suggest that children in areas downstream of wastewater treatment are sicker than others. However, these results should be treated with caution due to the problems with survey-reported diarrhea, as highlighted by Geruso and Spears [2018].

In the end, other health variables do not allow us to reliably assess the effect of wastewater treatment, due to biases associated with the reporting of morbidity variables and low statistical power.

C.4 Figures and Tables

Figure C1: Density of birth weight

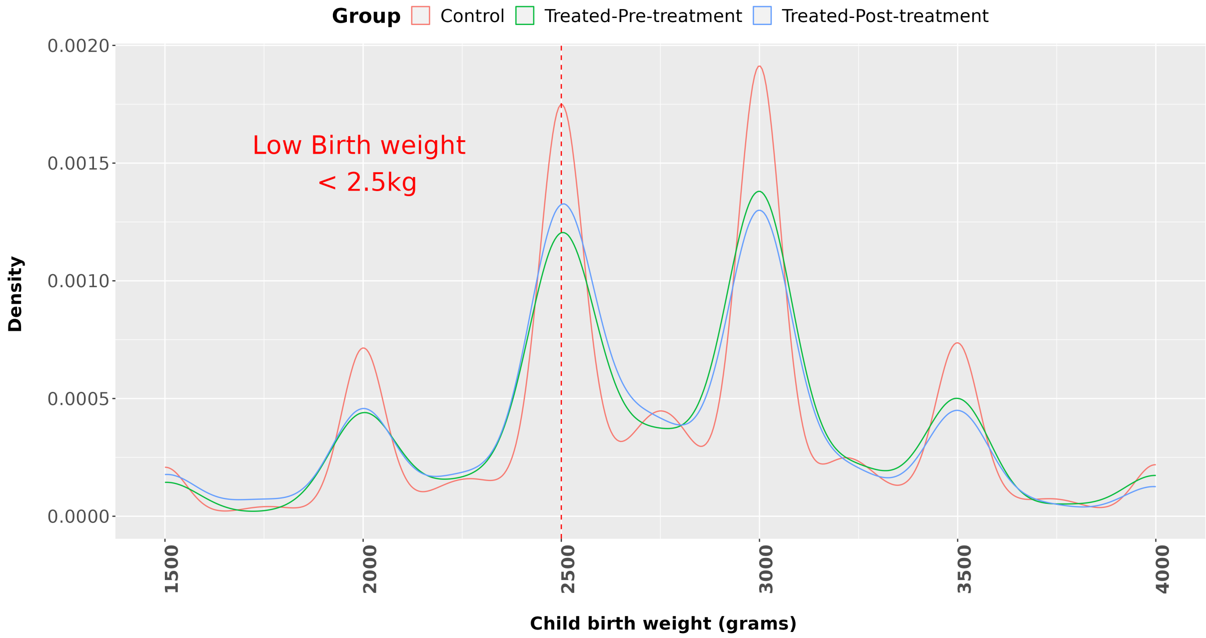
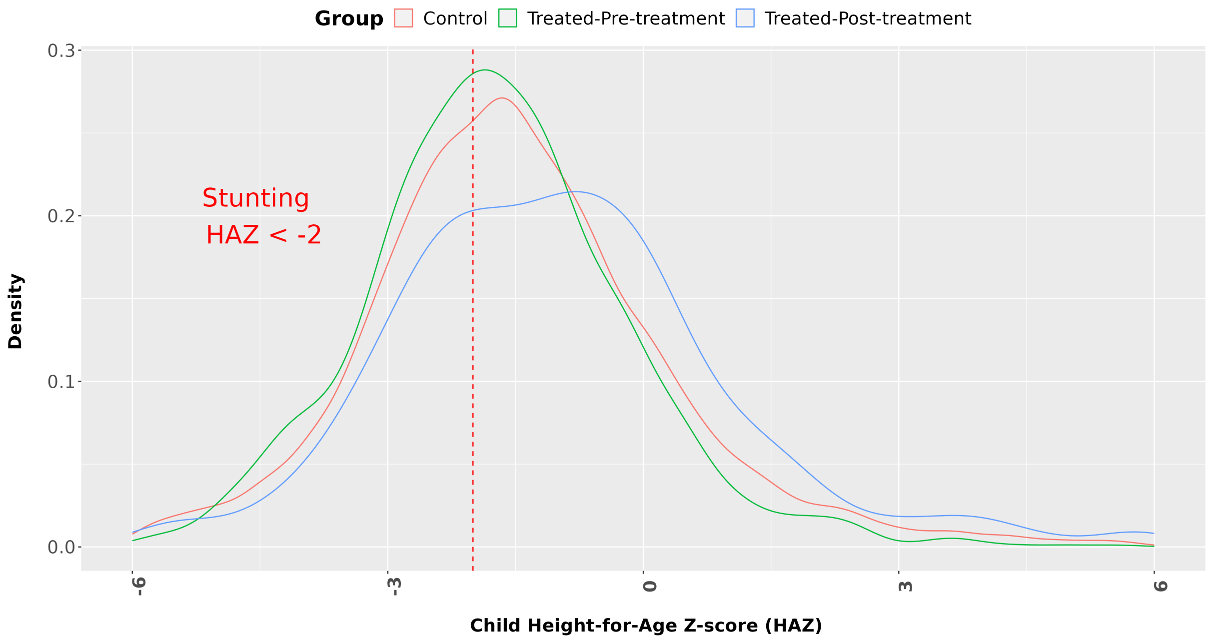


Figure C2: Density of Height-for-Age Z-score(HAZ)



Notes: A child is considered post-treated if it has lived more than half its life with upstream wastewater treatment.

Table C1: Presentation of the height-for-age z-score and birth weight regression samples

	Height-for-Age Z-score (HAZ)						Birth weight					
	All urban areas	All NFHS clusters	All births	Treated urban areas	Treated NFHS clusters	Treated births	All urban areas	All NFHS clusters	All births	Treated urban areas	Treated NFHS clusters	Treated births
2010	83	264	440	0	0	0	80	235	358	0	0	0
2011	145	589	1145	1	5	15	150	547	929	6	11	20
2012	153	670	1422	8	44	90	156	633	1216	14	21	39
2013	157	678	1459	15	73	141	157	642	1260	23	74	124
2014	171	812	1589	23	105	208	171	784	1462	33	106	199
2015	181	911	1722	29	98	176	195	956	1775	38	125	225
2016	148	631	1117	24	48	76	172	717	1286	31	72	111
2017	139	505	949	18	48	84	152	580	1115	20	53	101
2018	136	504	981	18	39	63	152	595	1170	41	125	246
2019	129	458	782	24	70	100	146	552	1007	42	144	285
Total			11606			953			11578			1350

Notes: Columns 1A and 2A tabulate the total number of urban areas in each year, while columns 1C and 2C tabulate the number of urban areas that treat wastewater in each year. Columns 1B and 2B tabulate the number of NFHS clusters downstream an urban area in each year, while columns 1E and 2E tabulate the number of NFHS clusters downstream an urban area that treats wastewater in this year. Columns 1C and 2C tabulate the number of children born downstream an urban area in each year, while columns 1F and 2F tabulate the number of children born downstream an urban area that treats wastewater in this year. I subject the full sample to two restrictions before analysis, both of which applied here. (i) If there is a birth in a NFHS cluster related to an urban area after it has started wastewater treatment, then that NFHS cluster is only included if it has at least one data point before the urban area starting wastewater treatment. (ii) If the urban area doesn't treat wastewater in 2020, then the NFHS cluster is only included if it has at least two outcome data points. A NFHS cluster is only included in the subsequent regressions if it has outcome data for the specific dependent variable of that given regression.

Table C2: Effect on Height-for-Age Z-score (HAZ) and Birth Weight

Dependent Variable:	HAZ	Stunted (HAZ < -2)	Birth weight	Low birth weight (. < 2.5kg)
	(1)	(2)	(3)	(4)
Estimator : Gardner (2022)	0.0362	9.755	-30.59	21.75
	(0.1025)	(34.09)	(33.75)	(23.54)
Estimator : S & A (2021)	0.2898	-7.539	-48.76*	29.15
	(853.9)	(264,286.5)	(29.07)	(20.37)
Estimator : TWFE	0.0737	-0.1370	-47.69*	28.77
	(0.1088)	(30.75)	(24.32)	(17.84)
Extended controls	X	X	X	X
NFHS Cluster FE	X	X	X	X
Birth year FE + Birth month FE	X	X	X	X
Observations	10,913	10,913	10,924	10,924
Period	2010-2019	2010-2019	2010-2019	2010-2019
Number of NFHS Clusters	1542	1542	1634	1634
Number of Urban areas	202	202	222	222
Mean of Dep. Variable	-1.5063	397.97	2,772.3	185.74

Notes: The table presents the coefficients of the estimators according to the Gardner [2022], Sun and Abraham [2021] and classic TWFE methodologies. The model in columns (1) and (2) uses a binary treatment indicator for whether or not the urban area upstream the NFHS cluster where anthropometric measures for the child are taken treat wastewater for more than half the child's life while the model in columns (3) and (4) uses the binary treatment indicator that indicates whether the urban area upstream treat wastewater since the birth year of the child. All models include urban area, birth month and birth year fixed effects. Stunted and Low birth weight variables are scaled to generate coefficients that indicate impacts on rates × 1,000 (cases per 1,000 children). For birth weight regressions, the controls are the same than for mortality regressions. For HAZ regressions, the controls are the following. Child controls include indicators for the child being a female, being the first born and child age in months. Mother controls include indicators for the mother having primary education, having secondary education, having higher education, being muslim, being nor hindu neither muslim, belonging to scheduled caste, belonging to scheduled tribe, belonging to other backward caste. Household controls include indicators for wealth quintiles. Standard errors are in parentheses and clustered by urban area. Asterisks denote p-value < 0.10 (*), < 0.05 (**), or < 0.01 (***).

Table C3: Morbidity summary statistics - Children aged 0-59 months

	Means			N. Obs.		
	Control	Pre-Treated	Post-Treated	Control	Pre-Treated	Post-Treated
Panel A. Interviews 2015-2016						
Child age in months	29.646	29.700	29.747	6,125	1,887	3,758
Weight-for-Height Z-score	-1.029	-0.981	-0.957	5,677	1,695	3,517
Child is wasted	218.425	209.440	192.778	5,677	1,695	3,517
Hemoglobin level (g/L)	104.718	104.394	104.755	5,380	1,604	3,303
Child is anemic	615.799	591.646	607.024	5,380	1,604	3,303
Child had diarrhea	89.335	94.480	103.945	6,123	1,884	3,752
Child had fever	128.434	145.280	144.812	5,824	1,769	3,508
Child had cough	111.073	139.205	130.597	5,771	1,760	3,484
Panel B. Interviews 2019						
Child age in months	30.022	29.661	30.132	2,575	109	1,283
Weight-for-Height Z-score	-0.915	-0.976	-0.886	2,333	99	1,154
Child is wasted	217.317	181.818	199.307	2,333	99	1,154
Hemoglobin level (g/L)	100.850	99.107	101.283	2,186	84	1,086
Child is anemic	715.005	666.667	720.074	2,186	84	1,086
Child had diarrhea	79.705	110.092	79.501	2,572	109	1,283
Child had fever	154.129	200	171.311	2,446	100	1,220
Child had cough	121.237	140	151.115	2,425	100	1,211

Notes: Panel A compares the summary statistics between children born downstream urban areas where wastewater treatment started between 2010 and 2020 and children born downstream urban area where wastewater treatment is in project in 2020 based on interviews conducted in the NFHS-4 survey over the period 2015-2016, while Panel B compares the summary statistics in 2019 based on NFHS-5 interviews. The unit of observations is the child level. Wasted, anemic, diarrhea, fever and cough variables indicate rates $\times$ 1,000 (cases per 1,000 children). Treatment is based on the interview year and not on the birth year considered for infant mortality regression.

D Data Details

D.1 Sewage Treatment Plants

D.1.1 Description of the national inventory

The 2020 national inventory of sewage treatment plants (STPs) highlights the gap between sewage generation and treatment capacity, estimating that less than 28% or urban wastewater is actually treated by the STPs. For each STP, the report tabulates the installed treatment capacity, the capacity actually used, the capacity complying to discharge norms prescribed by the Central Pollution Control Board (CPCB), as well as treatment technology and potential reuse of wastewater[25]

Among the 1,632 STPs listed in the inventory[26], I identify 1,097 operational STPs, 103 non-operational STPs, 270 STPs under construction and 150 STPs proposed for construction[27].

The total installed capacity reported in the inventory is 36,710 megaliters per day (MLD). The operational capacity corresponds to 26,910MLD. Out of the operational 26,314MLD capacity with non-missing used capacity values, 19,252MLD (73%) is actually utilized.

Among the 1,097 operational STPs, compliance status of 754 STPs is available and only 553 STPs, having a combined capacity of 12,264 megaliters per day (MLD), are found complying with the consented norms prescribed by the CPCB. Figure D4 shows the installed capacity and actual utilization according to the compliance status of the 1,045 operational STPs reported in the inventory with non-missing used capacity.

D.1.2 Merging at the urban area level

I manually matched each sewage treatment plant (STP) according to the administrative descriptors provided in the CPCB inventory (state, town and an accompanying string description of location) to the India Village-Level Geospatial Socio-Economic (IVLGSE) Data Set [Meiyappan et al., 2018]. This dataset provides village/town level boundaries

[25] Some data is missing, and the reporting of this information is not uniform across all states. Full code for pdf data extraction and data cleaning for the analysis is replicable on R.

[26] The inventory reports 1,631 STPs and I identify one row corresponding to two STPs commissioned in different years with information for installed capacity each year: row 38 of state Karnataka.

[27] I am not able to determine the operation status of 12 STPs.

from the official cadastral maps published by the Survey of India for 2001.

Of the 1631 STPs reported in the inventory, I match respectively 1606 STPs to the boundary of a town or of a village in the IVLGSE dataset. In total, 848 village/town polygons contain at least one STP.

To account for the evolution of administrative boundaries over time and for the fact that wastewater from a town may be treated in a nearby area, I aggregated the data by merging the boundaries of neighbouring polygons containing STPs up to a distance of 2km.[28]

This final merging results in 684 urban areas. The average area of one of these urban areas is 56km^2, while the median is 15km^2.

Of these 684 urban areas determined from the list of 1631 STPs reported in the national inventory, I exclude 109 urban areas that have at least one operational STP in 2020, but commissioned year is missing for one of them which doesn't allow to determine the year in which wastewater treatment began. Keeping only urban areas for which the year of commission of operational STP is known or urban area without operational STP, the dataset contains 575 urban areas.

Current work consists in providing exact plant geolocation based on Google Maps identification (Figure 1). So far, I have identified 564 of the 1631 stations that are correctely located in the urban areas.

D.2 Water quality

D.2.1 Data sources

This section provides additional information on the data then explains how I extract and clean it.

I use water pollution readings from four data repositories: the GEMS database [29], the India-WRIS platform [30], the published database from Greenstone and Hanna [2014] and the public database from the Central Pollution Control Board (CPCB) [31].

In this section, I describe steps taken to make the four repositories comparable.

[28] I create a buffer of 1km around each polygon and merge intersecting polygons.

[29] https://gemstat.org/, accessed in March 2021

[30] https://indiawris.gov.in/wris/#/RiverMonitoring, accessed in March 2021

[31] http://www.cpcbenvis.nic.in/water_quality_data.html, accessed first in March 2021 and in February 2022 for the 2020 data

Ambient Monitoring in Rivers, Lakes and Canals. The analysis includes only rivers, lakes and canals. This excludes pond, creek, drain, and coast because these other surface water types are uncommon in the pollution data.

The GEMS, CPCB and Greenstone and Hanna [2014] data comes from the National Water Quality Monitoring Network (NWMP), established by the CPCB in collaboration with State Pollution Control Boards (SPCBs) in the States and Pollution Control Committees (PCCs) in Union Territories. All the NWMP stations have a unique identifier consistent across the databases. I then match all the NWMP measures to their stations geo-coordinates based on the station list provided on the CPCB website.[32] I distinguish streams and lakes in the NWMP station data using the provided monitoring location type name field in the station list. Of the 4111 monitoring stations maintained in 2020 through the NWMP, there are 2016 river monitoring stations, 341 lake monitoring stations and 65 canal monitoring stations.

The WRIS data comes from the Central Water Commission monitoring water quality at 390 locations covering all the major river basins of India.[33] Data from WRIS are all related to rivers.

Measures of Water Pollution and Sample Exclusions.

The GEMS, WRIS and Greenstone and Hanna [2014] databases provide monthly measures, while the CPCB data are aggregated at the yearly level. For consistency, I then aggregate all the monitoring station readings at the yearly level.

To limit the influence of outliers, I winsorize data below the 2.5th percentile and above the 97.5th percentile. It means that for each reading below the 2.5th percentile of the distribution of readings, I recode the result to equal the 2.5th percentile and for each reading above the 97.5th percentile of the distribution of readings, I recode the result to equal the 97.5th percentile.

[32] https://cpcb.nic.in/wqm/WQMN_list.pdf, accessed in March 2021

[33] https://indiawris.gov.in/wiki/doku.php?id=river_water_quality_monitoring

D.2.2 Measurement error

To check if water quality measures were performed correctly, I use methods from the geochemistry theory.

In first approximation, the use of charge imbalance (CI) is regularly used to check the quality of water analyses [Federation et al., 2005]. The charge balance is based on the principle of electrical neutrality, meaning that the equivalent concentration of positively charged ions, the cations, is equal to the equivalent concentration of negatively charged ions, the anions. Major anions, such as bicarbonates (HCO_3^-), carbonates (CO_3^{2-}), chlorides (Cl^-), fluoride (F^-), nitrate ($NO3^-$) and sulfates (SO_4^{2-}), as well as major cations, such as calcium (Ca^{2+}), magnesium (Mg^{2+}), sodium (Na^+) and potassium (K^+), usually represent most of the dissolved ions in water, so the sum in milliequivalents of major cations and anions should be nearly equal.

However, when a large charge imbalance exists, there is no indication whether the error is caused by a cation or an anion. A second constraint is helpful to identify the constituent most likely in error. That's why I use an approximation of the electrical conductivity method proposed by McCleskey et al. [2011] as a quality control method for checking water analyses. If measures were performed correctly, both the anion and cation sums should be approximately 1/100 of the measured electrical conductivity value. If either of the two sums does not meet this criterion, that sum is suspect.

I can only compare the respective sums of anions and cations to the electrical conductivity for the data from the WRIS platform because the other data do not give the concentrations of all major anions. As the anions correspond to the elements characterizing the pollution (notably the nitrates), it is specifically important that there is no significant measurement error on the anion concentrations.

Of the 8907 annual station-level measurements from the WRIS platform, about half (4312) are complete and allow the calculation of major ion sums. Of these, 70% (2986) seem to be good quality data as the anion sum is approximately 1/100 of the measured electrical conductivity value with a tolerance of 20%. However, it means that 30% of the data could be unreliable.

Spatially, it appears that the measurements in eastern India are not assessable and those in the south are of particularly good quality (Figure D7).

Temporally, there is no significant difference in the quality of the measurements, which is counter-intuitive as one might have expected an improvement in the measurements over time (Figure D8).

D.3 Health data

The National Family Health Survey, equivalent to the Indian Demographic Health Survey, uses a stratified two-stage sampling design. First, enumeration areas (EAs) are randomly selected from census files, stratifying by state and urban/rural residence. Within the selected EAs, herein referred to as clusters, households are randomly selected for interviewing. Within these households, all women of reproductive age (15–49 years) are interviewed. Enumerators also collect coordinates of the cluster location allowing me to link the NFHS data to other geo-coded data at the cluster level. To maintain confidentiality of respondents, NFHS randomly displaces the coordinates of the clusters up to 2 km in urban areas and up to 5 km in rural areas, with a further 1% of rural clusters displaced up to 10 km. The direction of displacement is randomly chosen, with the caveat that coordinates are not displaced outside of the state. This displacement introduces classical measurement error. However, in this study, which uses the difference-in-differences method, there is no reason for the error to be greater in the treatment group than in the control group, and it is not a priori a cause for concern.

D.4 Data figures

Figure D1: India designated best-use water quality criteria under the National Water Quality Monitoring Programme (NWMP) (Source : Central Pollution Control Board)

Designated Best Use Water Quality Criteria		
Designated-best-Use/ Beneficial Use	**Classification of water**	**Criteria**
Drinking water source without conventional treatment but after disinfection	A	1. Total Coliforms Organism MPN/100 ml shall be 50 or less 2. pH between 6.5 and 8.5 3. Dissolved Oxygen 6 mg/l or more 4. Biochemical Oxygen Demand 5 days 20 °C 2 mg/l or less
Outdoor bathing (organised)	B	1. Total Coliforms Organism MPN/100 ml shall be 500 or less 2. pH between 6.5 and 8.5 3. Dissolved Oxygen 5 mg/l or more 4. Biochemical Oxygen Demand 5 days 20 °C 3 mg/l or less
Drinking water source after conventional treatment and disinfection	C	1. Total Coliforms Organism MPN/100 ml shall be 5000 or less 2. pH between 6 and 9 3. Dissolved Oxygen 4 mg/l or more 4. Biochemical Oxygen Demand 5 days 20 °C 3 mg/l or less
Propagation of wild life and fisheries	D	1. pH between 6.5 and 8.5 2. Dissolved Oxygen 4 mg/l or more 3. Free Ammonia (as N) 1.2 mg/l or less
Irrigation, industrial cooling, controlled waste disposal	E	1. pH between 6.0 and 8.5 2. Electrical Conductivity at 25 °C micro mhos/cm maximum 2250 3. Sodium absorption ratio maximum 26 4. Boron maximum 2 mg/l

Figure D2: Government agencies responsible for urban wastewater management in India (in January 2019). (Source: Reymond et al. [2020])

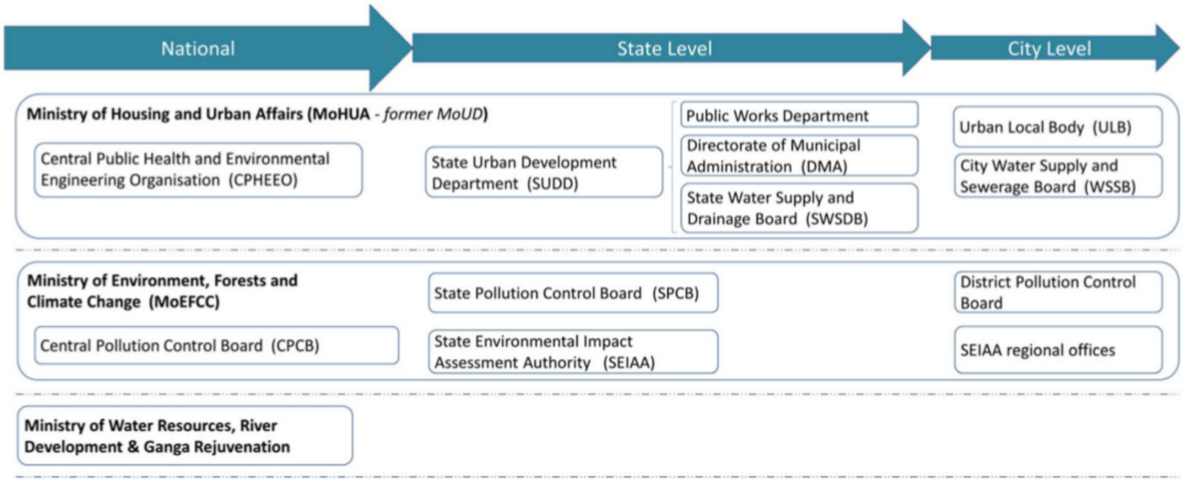


Figure D3: Comparison of responsibilities in the large-scale and small-scale sanitation sectors; the governmental agencies highlighted in brown fall under MoHUA and the ones in green under MoEFCC (Source : Reymond et al. [2020])

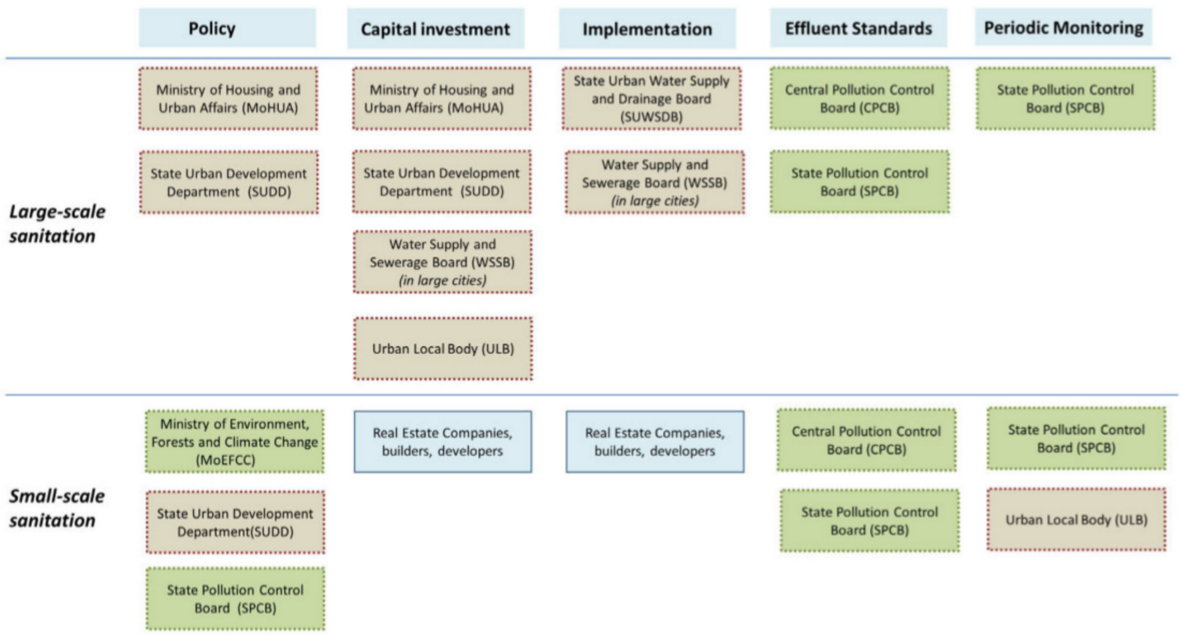


Figure D4: Capacity, utilization and compliance status of 1045 operational STPs reported in the 2020 inventory

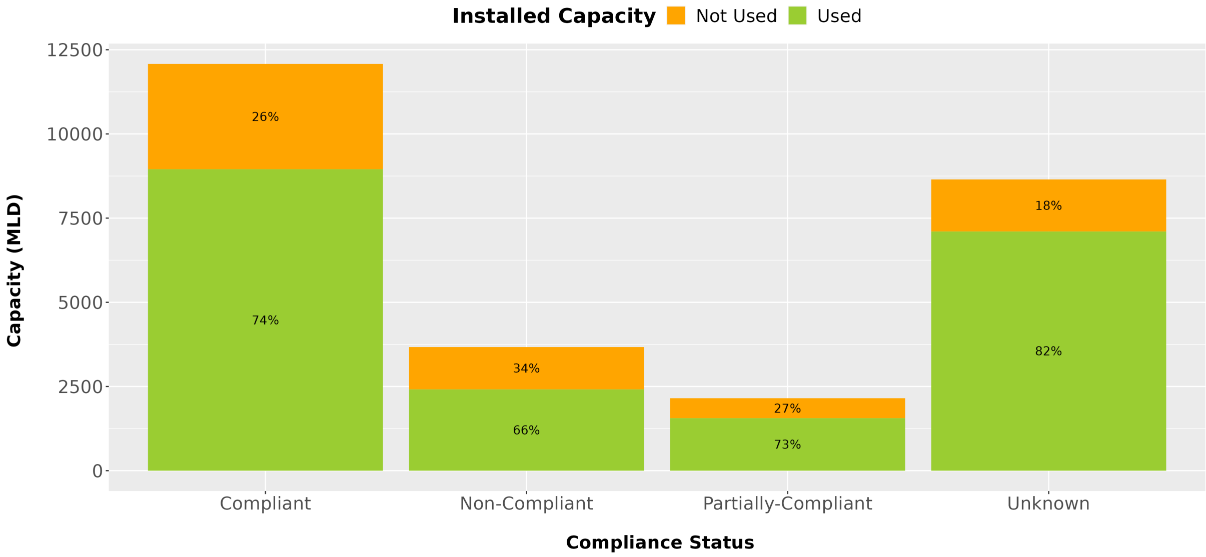


Figure D5: Examples of urban areas

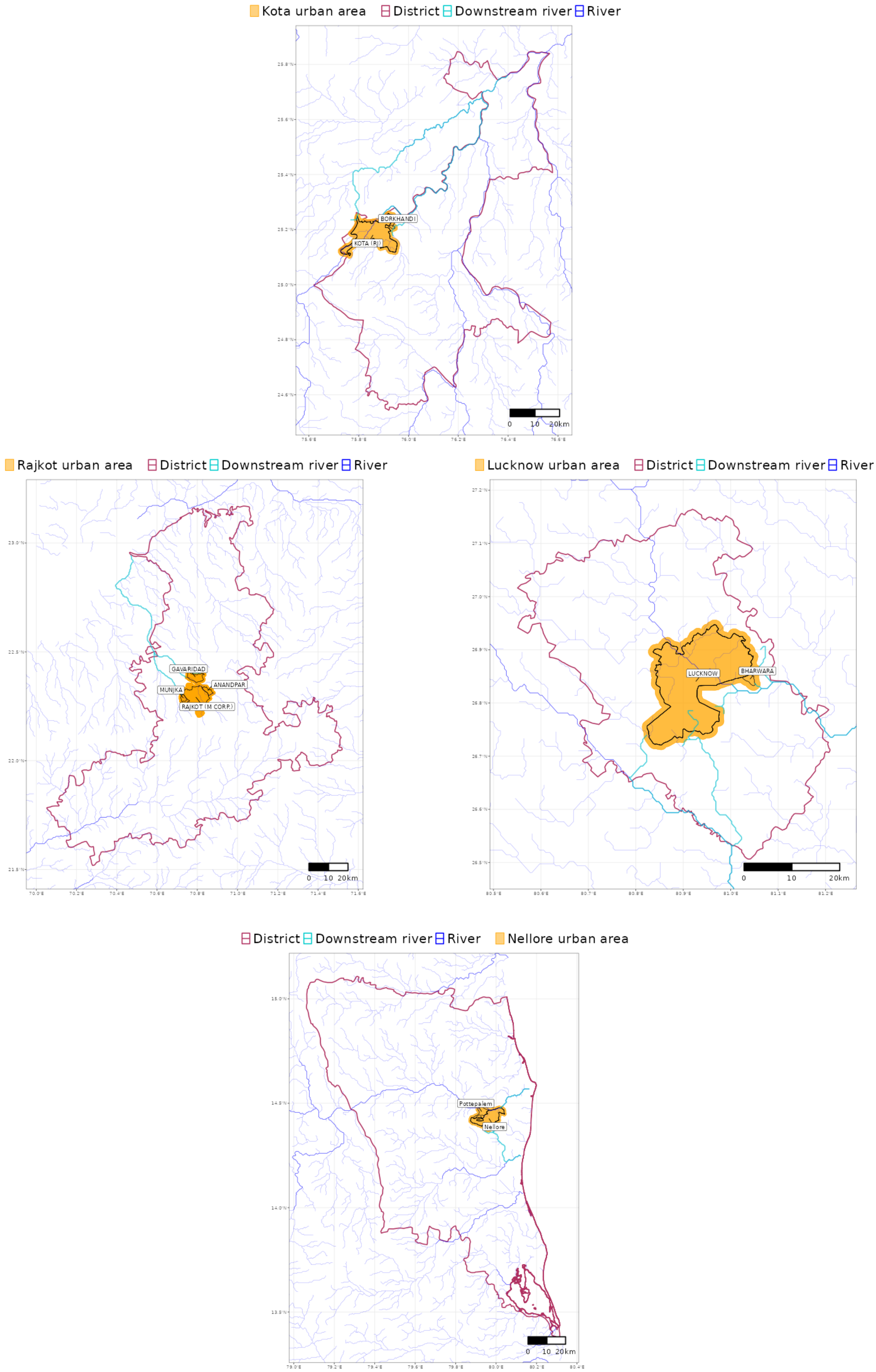
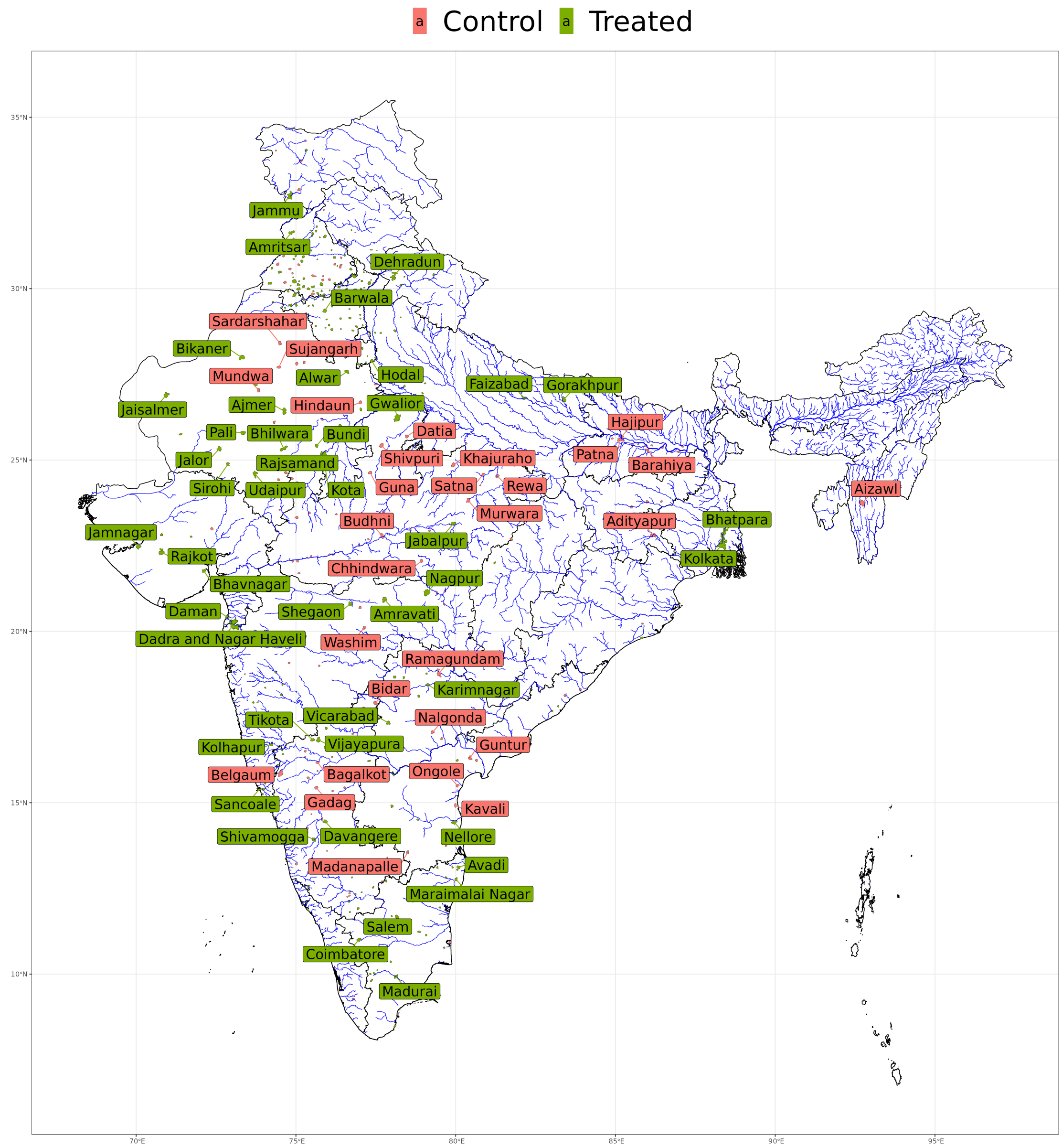


Figure D6: Map of the 458 urban areas kept in the analysis



Urban area labels are provided only for urban area of 70 km^2 or more

Figure D7: Map of WRIS monitoring stations (left) and assessment of the water quality measurement error (right)

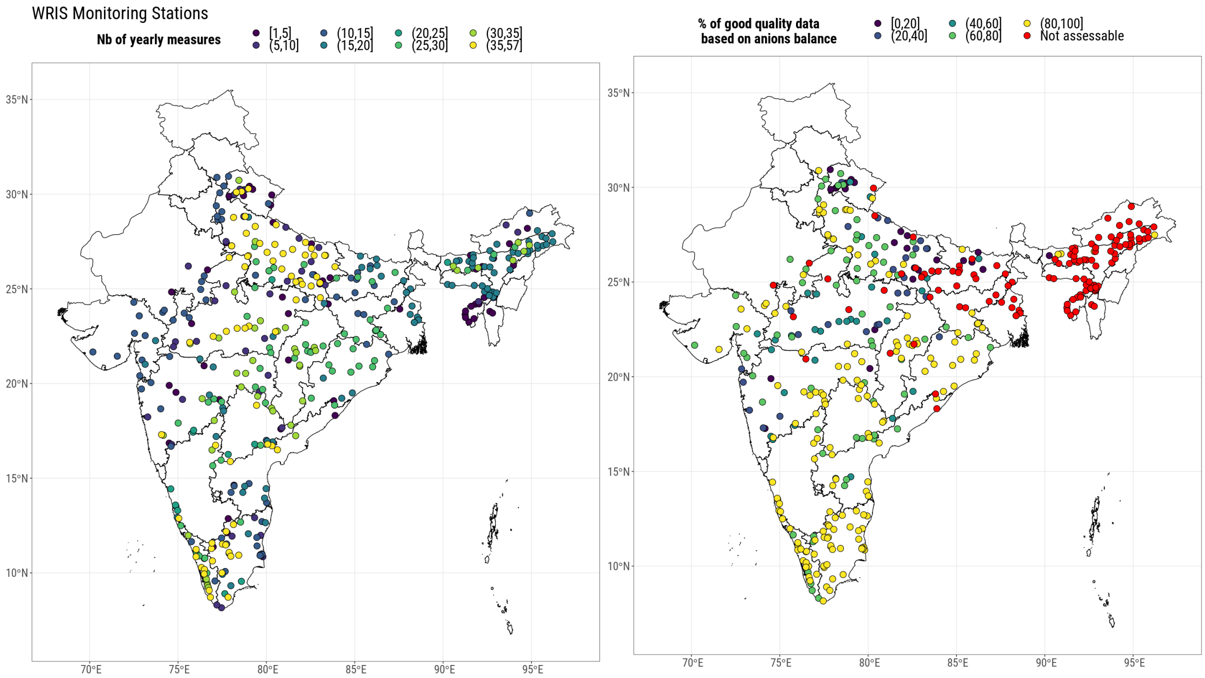
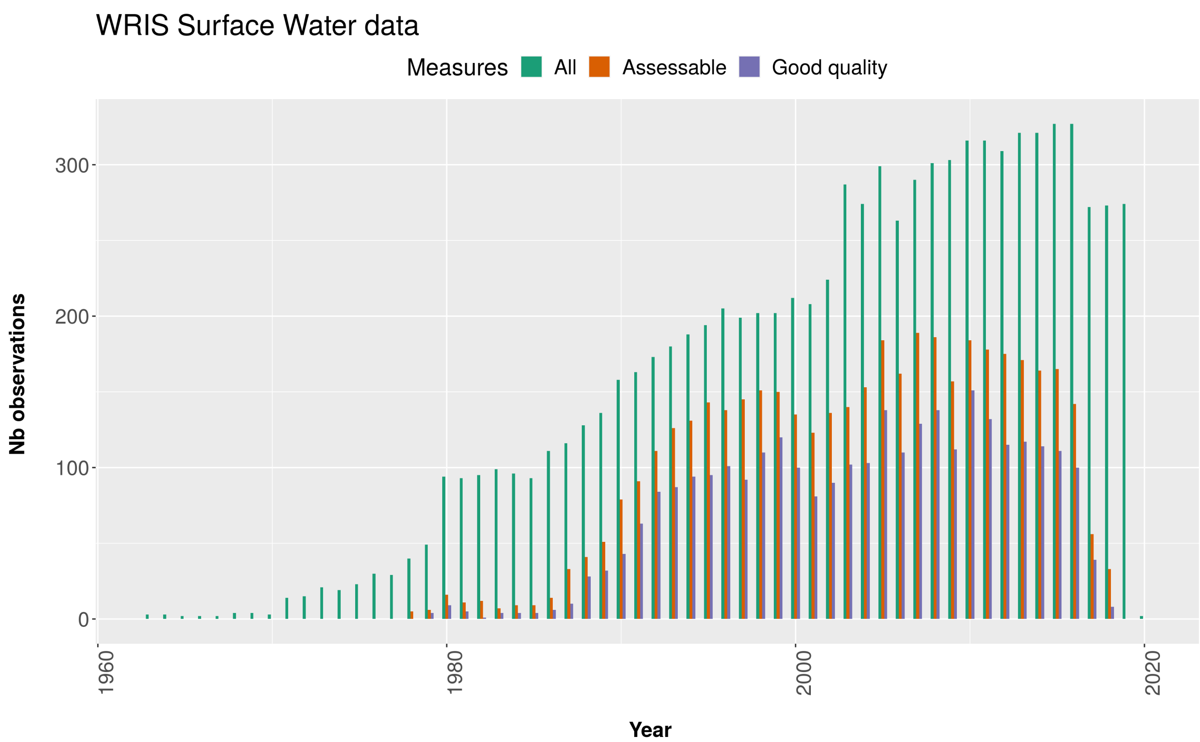


Figure D8: Histogram of the WRIS measures quality over time based on the anion imbalance



E Spatial Matching Across Datasets

Conducting the analysis of this paper requires linking several datasets thanks to the hydrological network HydroSHEDS [Linke et al., 2019].

E.1 HydroSHEDS

HydroSHEDS (Hydrological data and maps based on SHuttle Elevation Derivatives at multiple Scales, Linke et al. [2019]) offers a suite of geo-referenced datasets in raster and vector format, including stream networks, watershed boundaries, drainage directions, and ancillary data layers such as flow accumulations, distances, and river topology information.

HydroSHEDS version 1 is derived primarily from elevation data of the Shuttle Radar Topography Mission (SRTM) at 3 arc-second (approximately 90 meters at the equator) resolution and has been developed by World Wildlife Fund (WWF), in partnership or collaboration with universities and institutions [34].

I use two HydroSHEDS products to perform the spatial matching of sewage treatment plants to water quality monitoring stations and child births, that are respectively HydroRIVERS and HydroBASINS.

HydroRIVERS represents a vectorized line network of all global rivers that have a catchment area of at least 10 km^2 or an average river flow of at least 0.1 m^3/sec, or both. I use the phrase "river segment" to describe what HydroSHEDS calls a "HyrivID". A "HyrivID" is a unique identifier code for a specific line segment in HydroSHEDS. On average a HyrivID is 4.2 kilometers long.

HydroBASINS represents a series of vectorized polygon layers that depict sub-basin boundaries at a global scale. I use the highest level of sub-basin breakdown, that corresponds to the Pfafstetter level 12. I use the word "sub-basin" to describe what HydroSHEDS calls a "HybasID". A "HybasID" is a unique identifier code for an individual sub-basin polygon in HydroSHEDS. At the Pfafstetter level 12, a HybasID has an average area of 130.6 km^2. I use the phrase "main basin" to identify the entire river basin that a

[34] McGill University, Montreal, Canada; the U.S. Geological Survey (USGS); the International Centre for Tropical Agriculture (CIAT); The Nature Conservancy (TNC); the Australian National University, Canberra, Australia; and the Center for Environmental Systems Research (CESR), University of Kassel, Germany

sub-basin belongs to [35] (see Figure 2).

E.2 Matching datasets

I matched each of the 684 urban area polygon containing sewage treatment plants (STP) to both the HydroRIVERS and HydroBASINS datasets.

First, I identify all the river segments crossing each urban area polygon boundaries. Only 25 urban areas out of 684 are not crossed by rivers. In total, 4928 distinct rivers segments cross urban areas with a mean length of 4.8 kilometers. I construct chains of downstream rivers segments from an urban area up to 100km.

I match each monitoring station to a river segment. Based on the matching of urban areas to river segments, I can then identify monitors that located within or downstream urban areas up to a river distance of 100km^2. Figure E1 illustrates for example the matching of river segments and monitoring stations to urban areas containing STPs in Uttar Pradesh.

Second, I define the sub-basins downstream an urban area as the ones containing the corresponding downstream river segments. I then identify NFHS clusters located in sub-basins downstream urban areas. Figure E2 maps for example the sub-basins containing STPs in Uttar Pradesh, the related downstream sub-basins and the NFHS clusters within these sub-basins.

[35] In HydroSHED, the main basin is identified with the "MainBas" column that provides the HybasID of the most downstream sink, i.e. the outlet of the main river basin.

E.3 Matching figures

Figure E1: Map of urban areas containing STPs and downstream-related monitoring sites and river segments in Uttar Pradesh

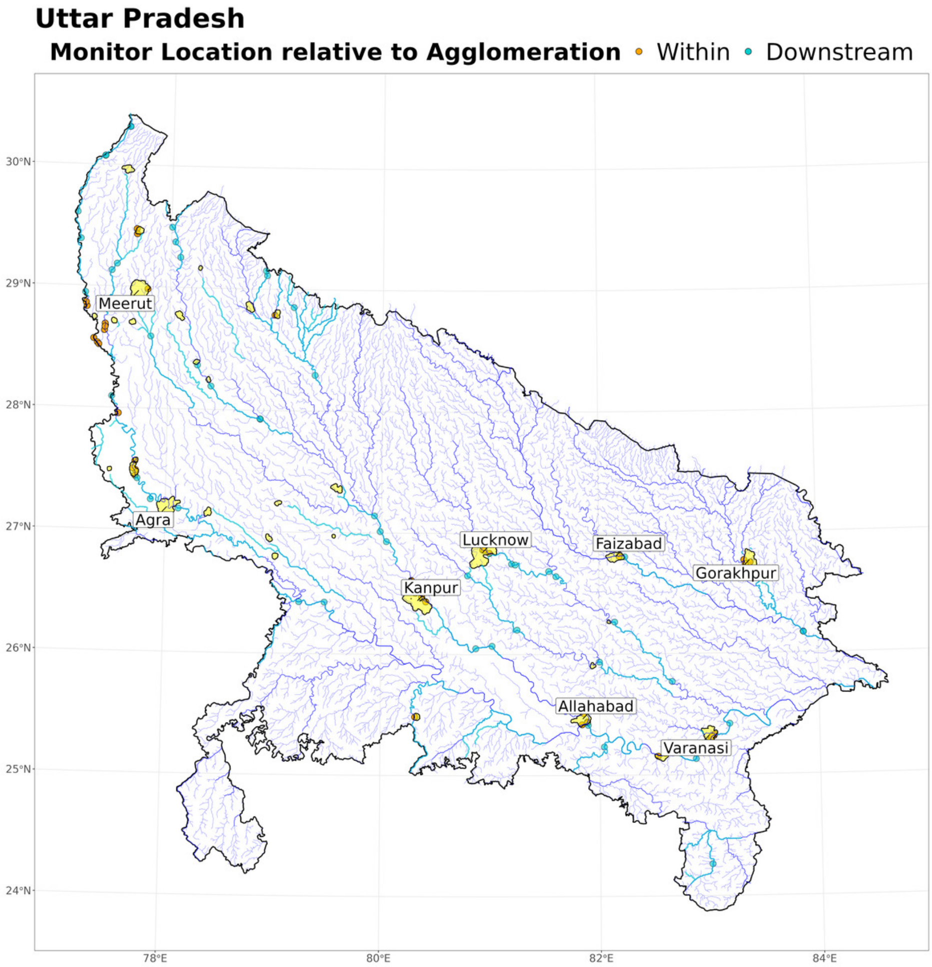


Figure E2: Map of sub-basins containing STPs and downstream-related NFHS clusters in state Uttar Pradesh

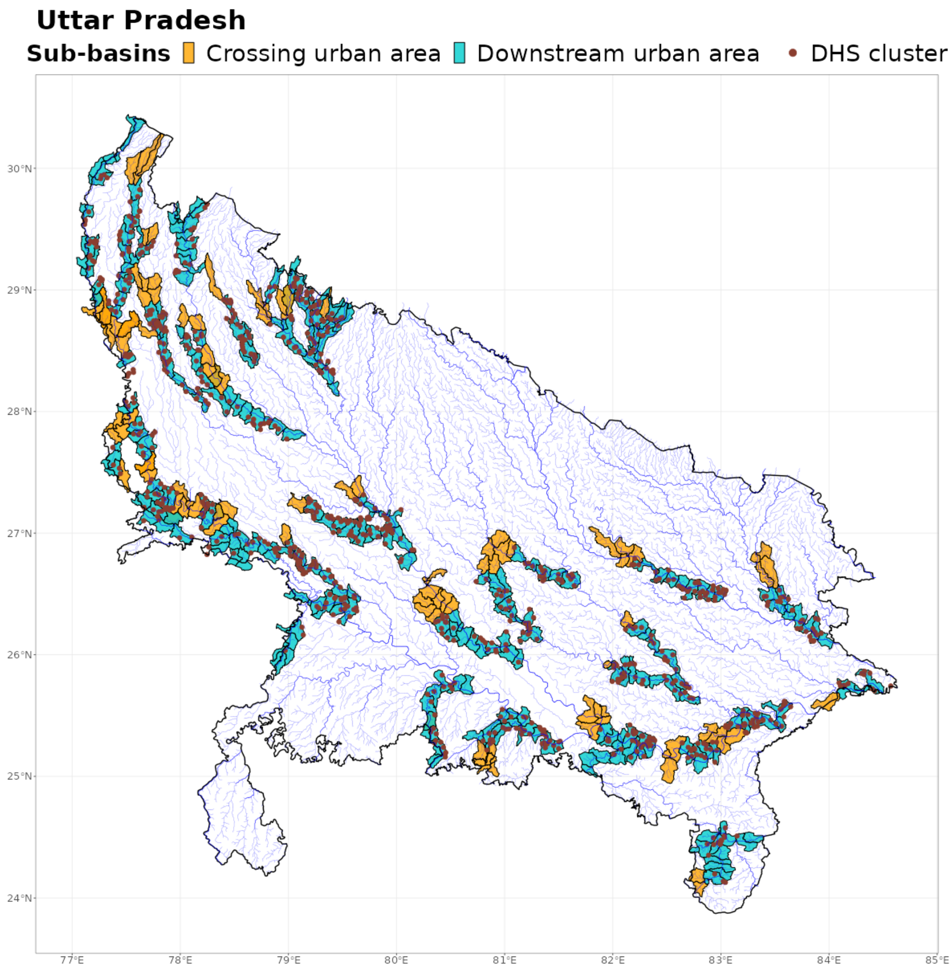
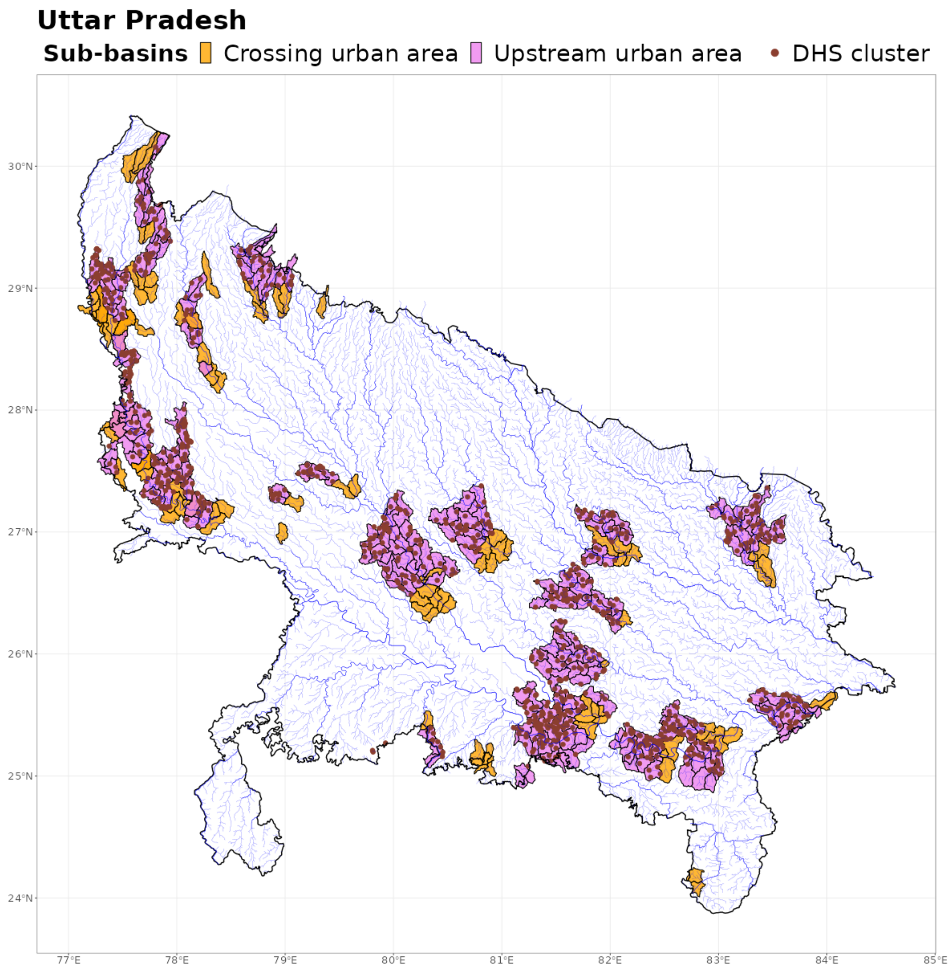
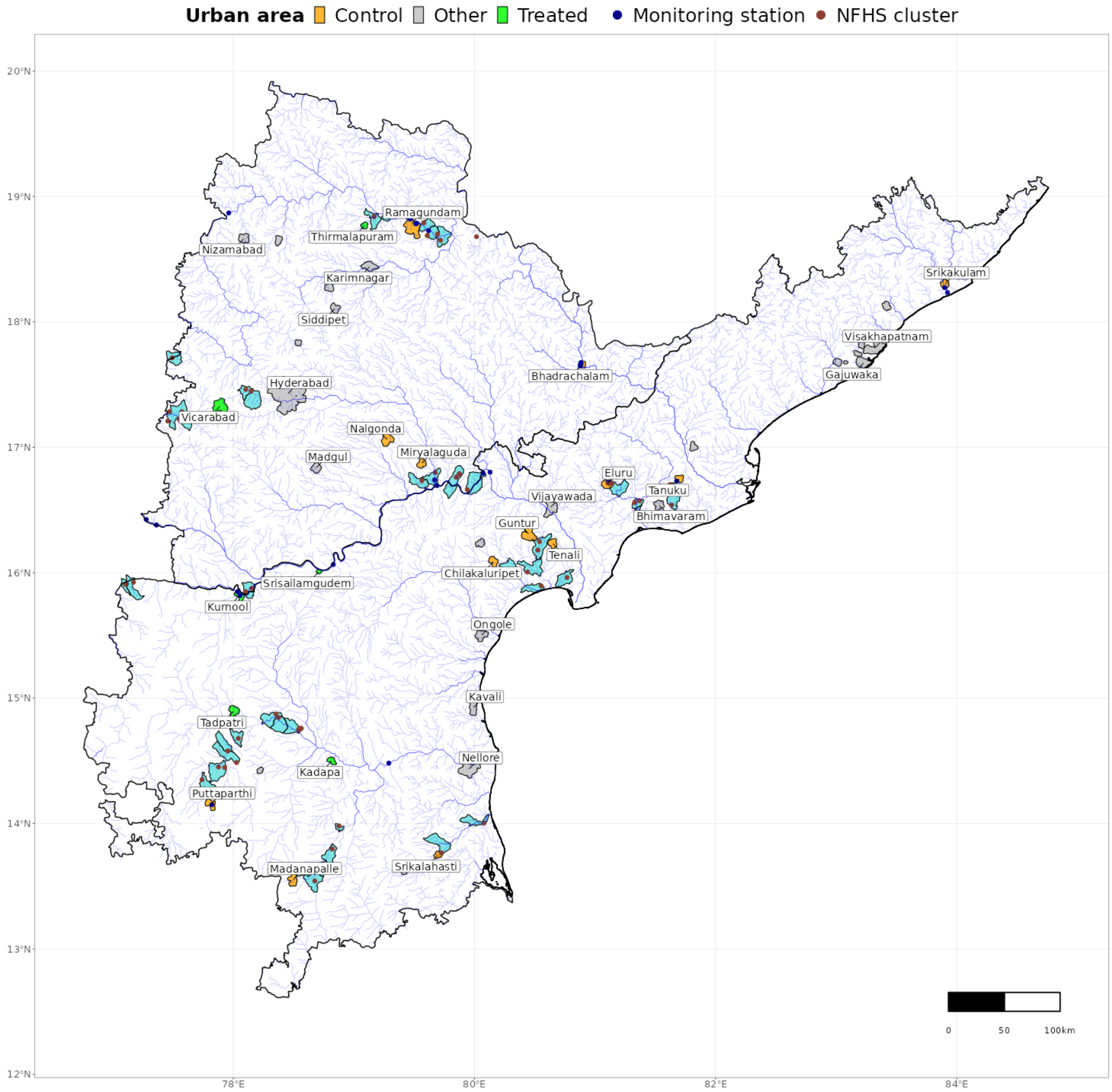


Figure E3: Map of sub-basins containing STPs and upstream-related NFHS clusters in state Uttar Pradesh



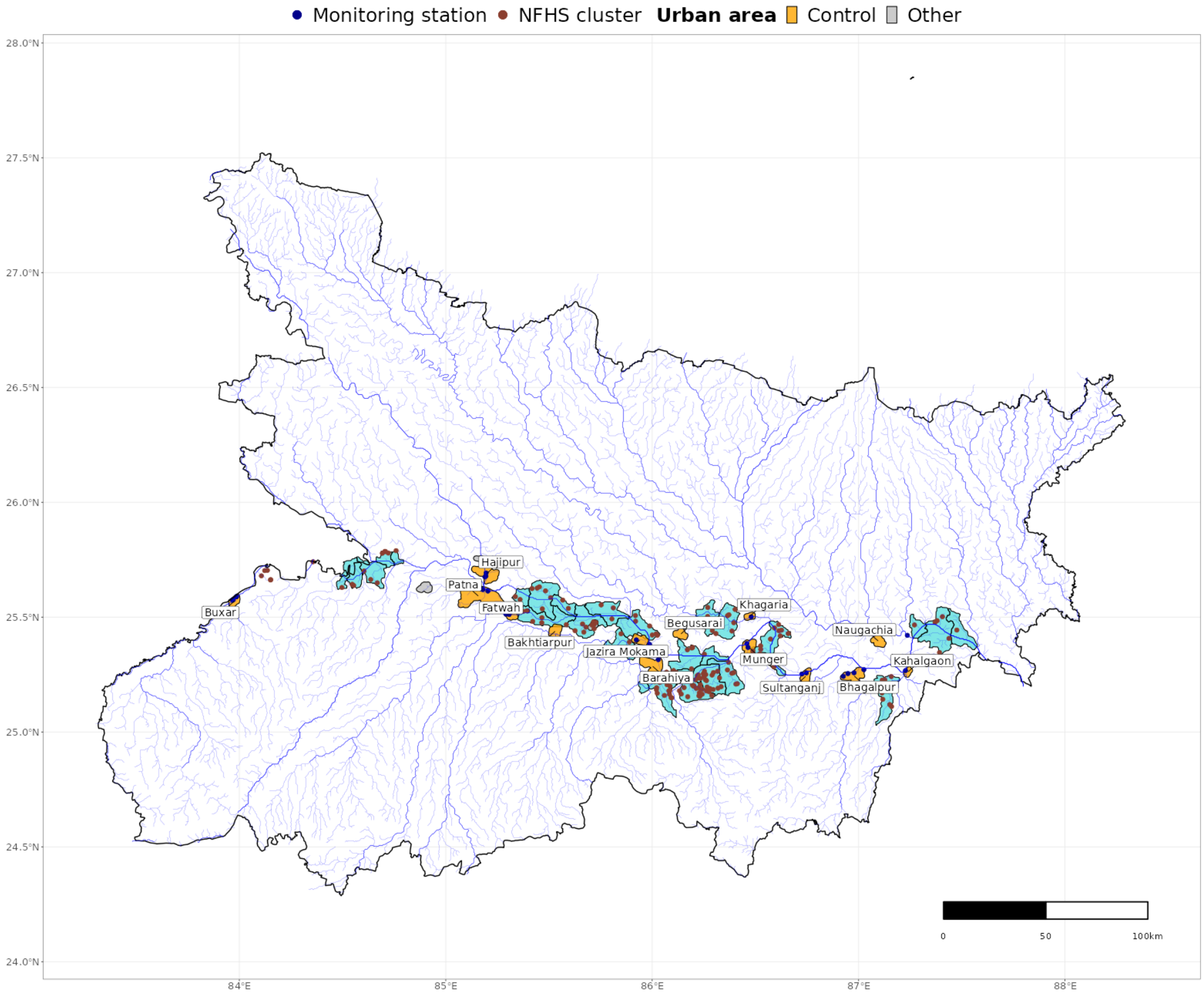
F Maps state by state

Andhra Pradesh, Telangana



Notes: The blue polygons represent the hydrological sub-basins that contain NFHS clusters and river segments located within 100km downstream of segments that cross the urban areas listed in the sewage treatment plant inventory.

Bihar



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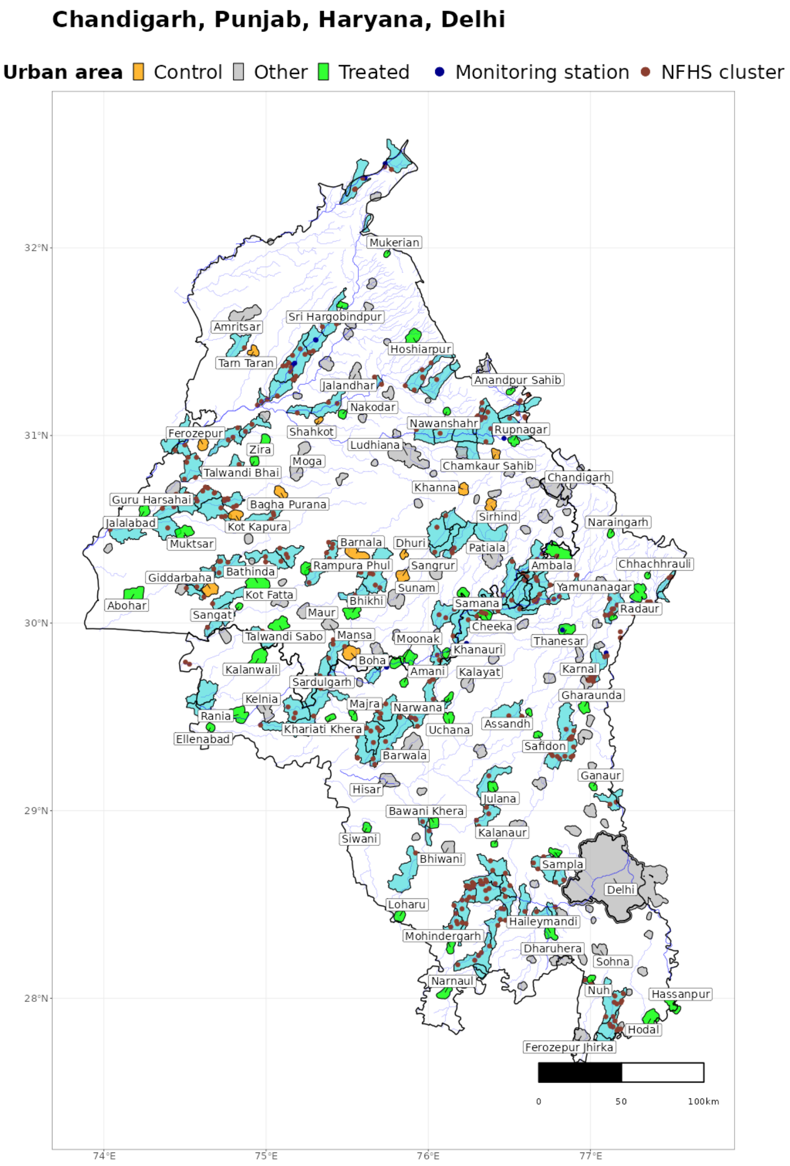
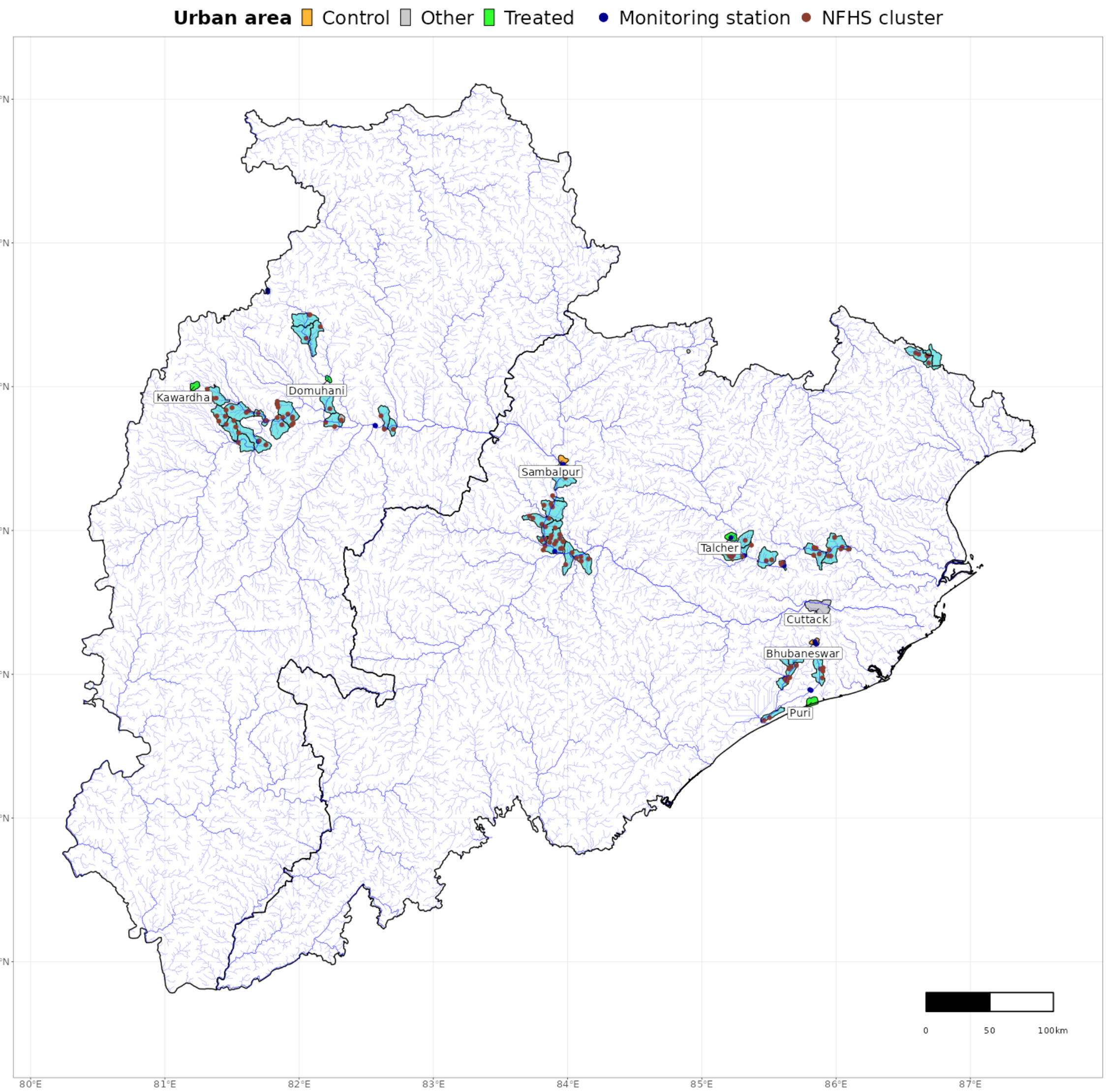


Notes: The blue polygons represent the hydrological sub-basins that contain NFHS clusters and river segments located within 100km downstream of segments that cross the urban areas listed in the sewage treatment plant inventory.

Chhattisgarh, Orissa



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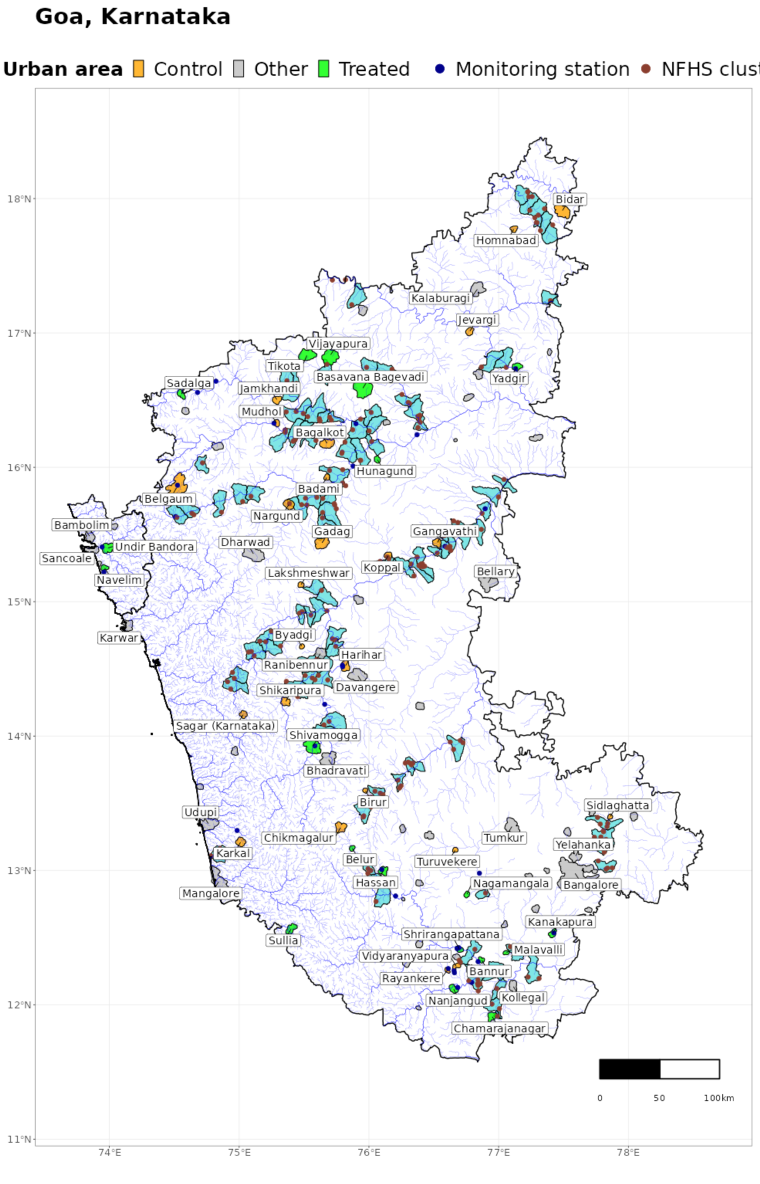
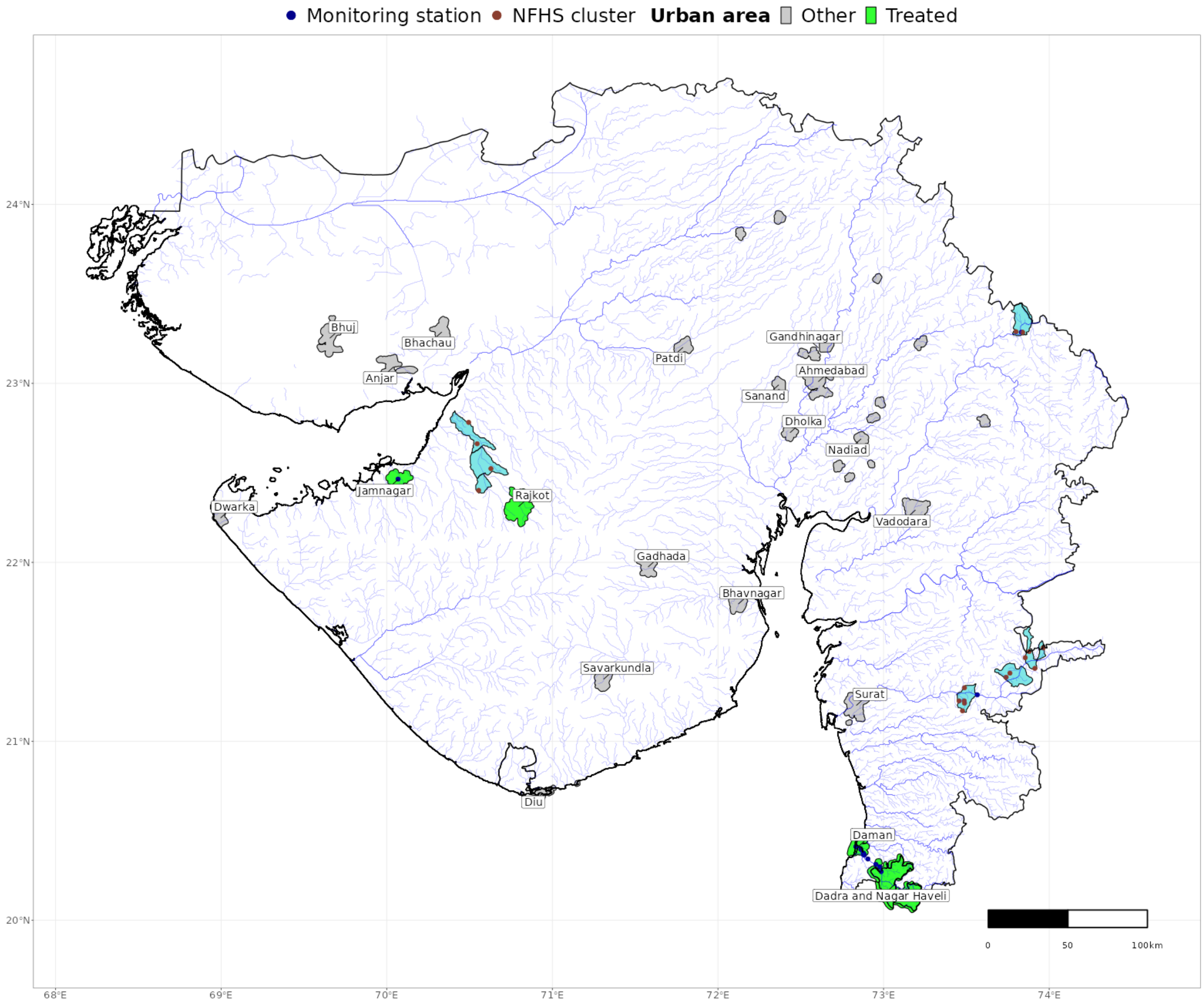


Notes: The blue polygons represent the hydrological sub-basins that contain NFHS clusters and river segments located within 100km downstream of segments that cross the urban areas listed in the sewage treatment plant inventory.

Gujarat, Daman and Diu, Dadra and Nagar Haveli



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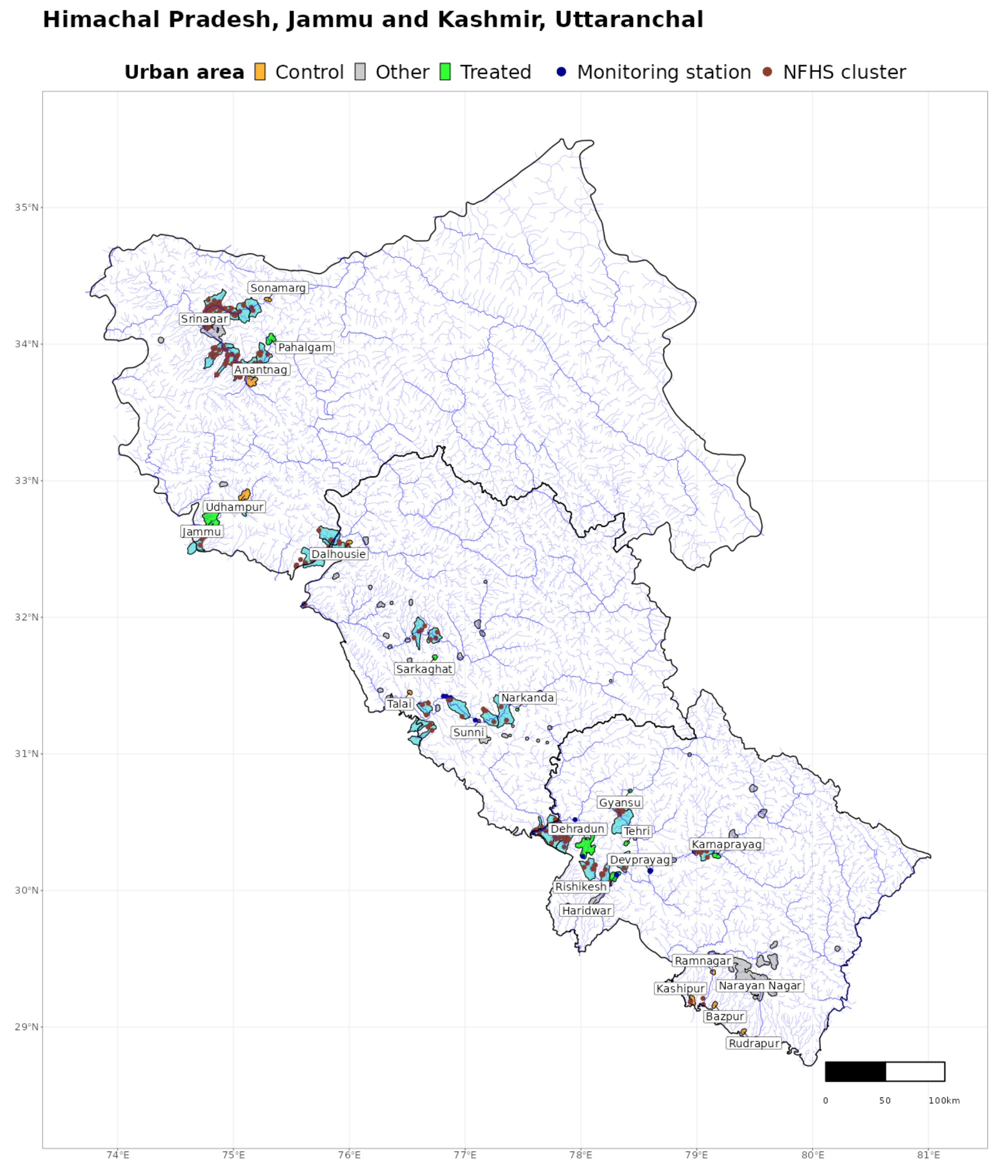
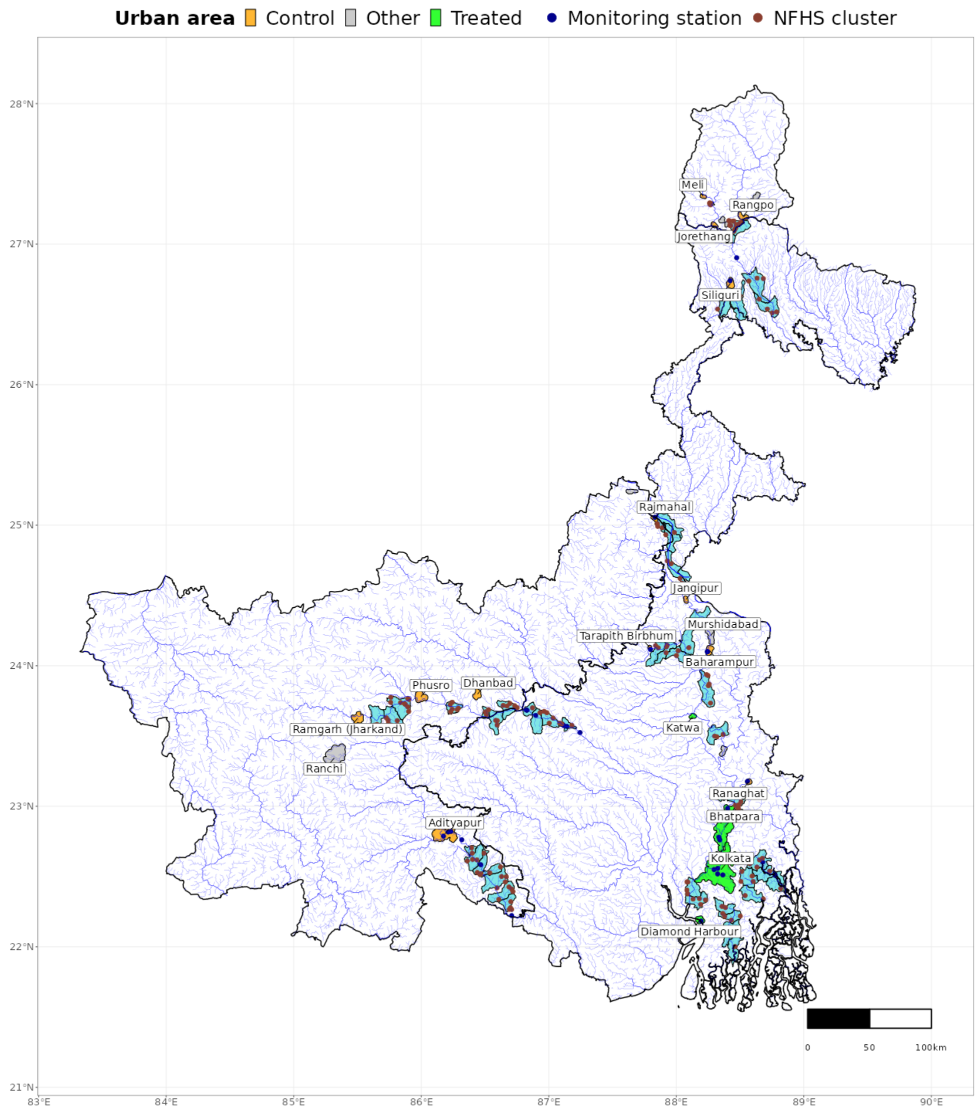
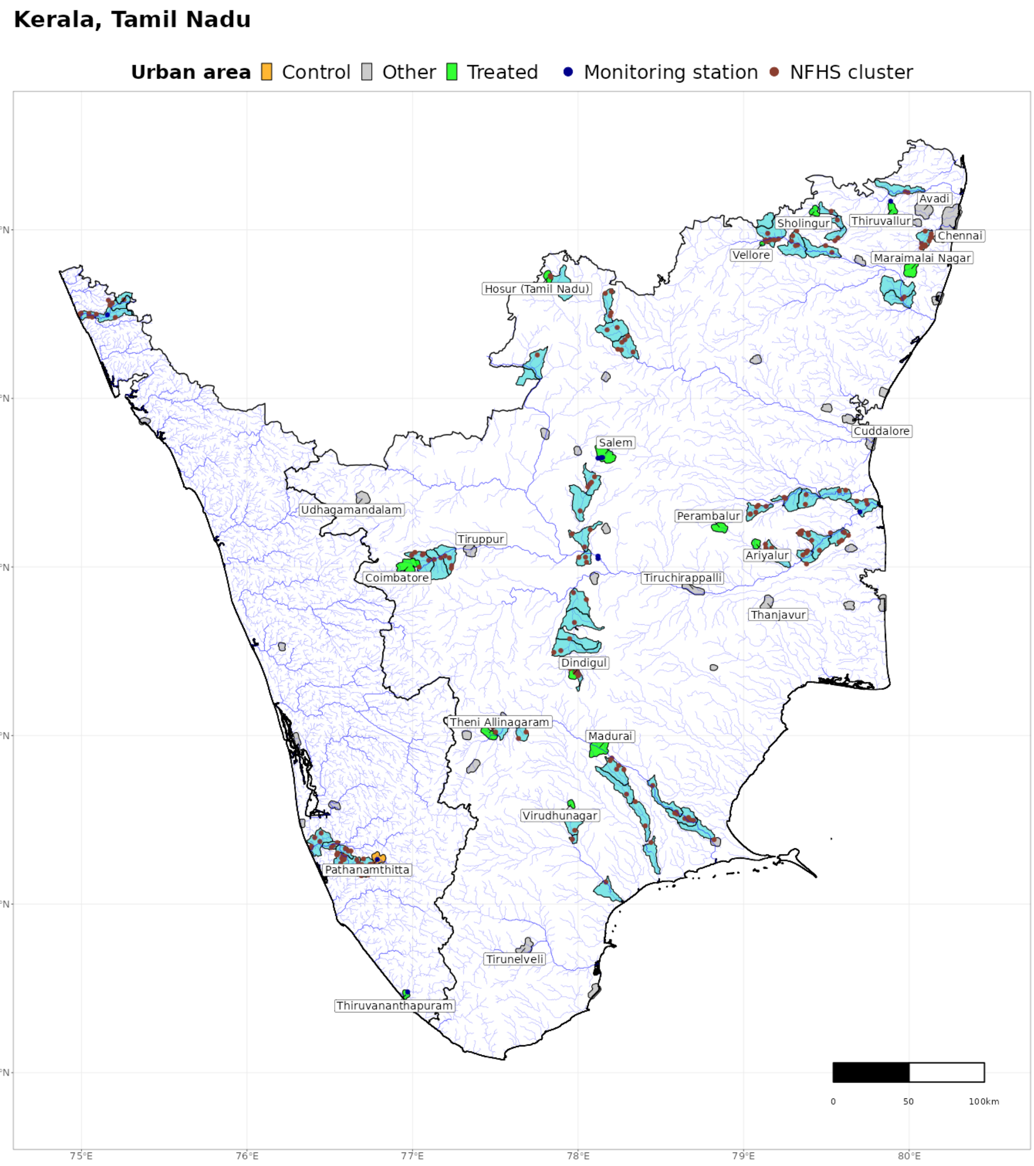


Notes: The blue polygons represent the hydrological sub-basins that contain NFHS clusters and river segments located within 100km downstream of segments that cross the urban areas listed in the sewage treatment plant inventory.

Jharkhand, Sikkim, West Bengal

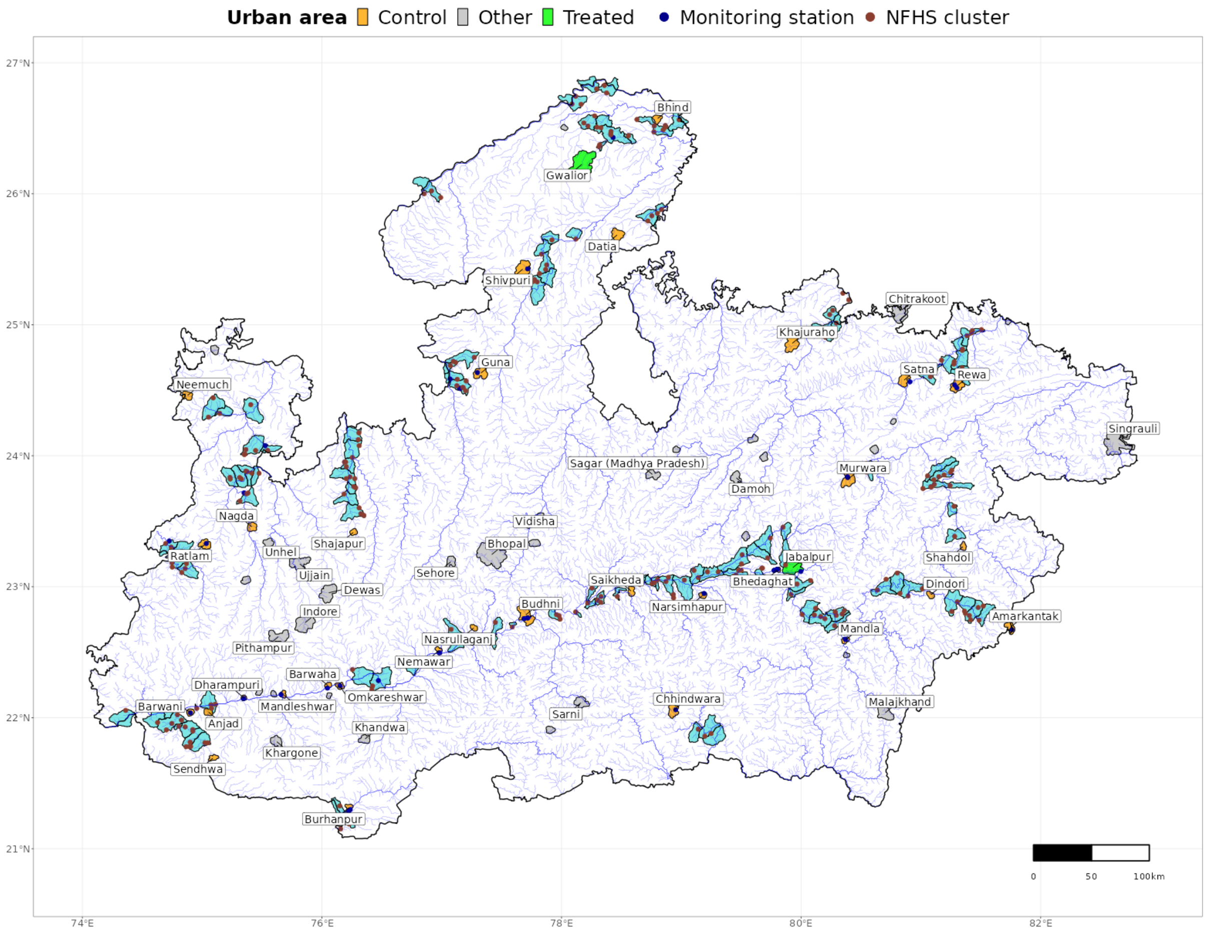


Notes: The blue polygons represent the hydrological sub-basins that contain NFHS clusters and river segments located within 100km downstream of segments that cross the urban areas listed in the sewage treatment plant inventory.



Notes: The blue polygons represent the hydrological sub-basins that contain NFHS clusters and river segments located within 100km downstream of segments that cross the urban areas listed in the sewage treatment plant inventory.

Madhya Pradesh



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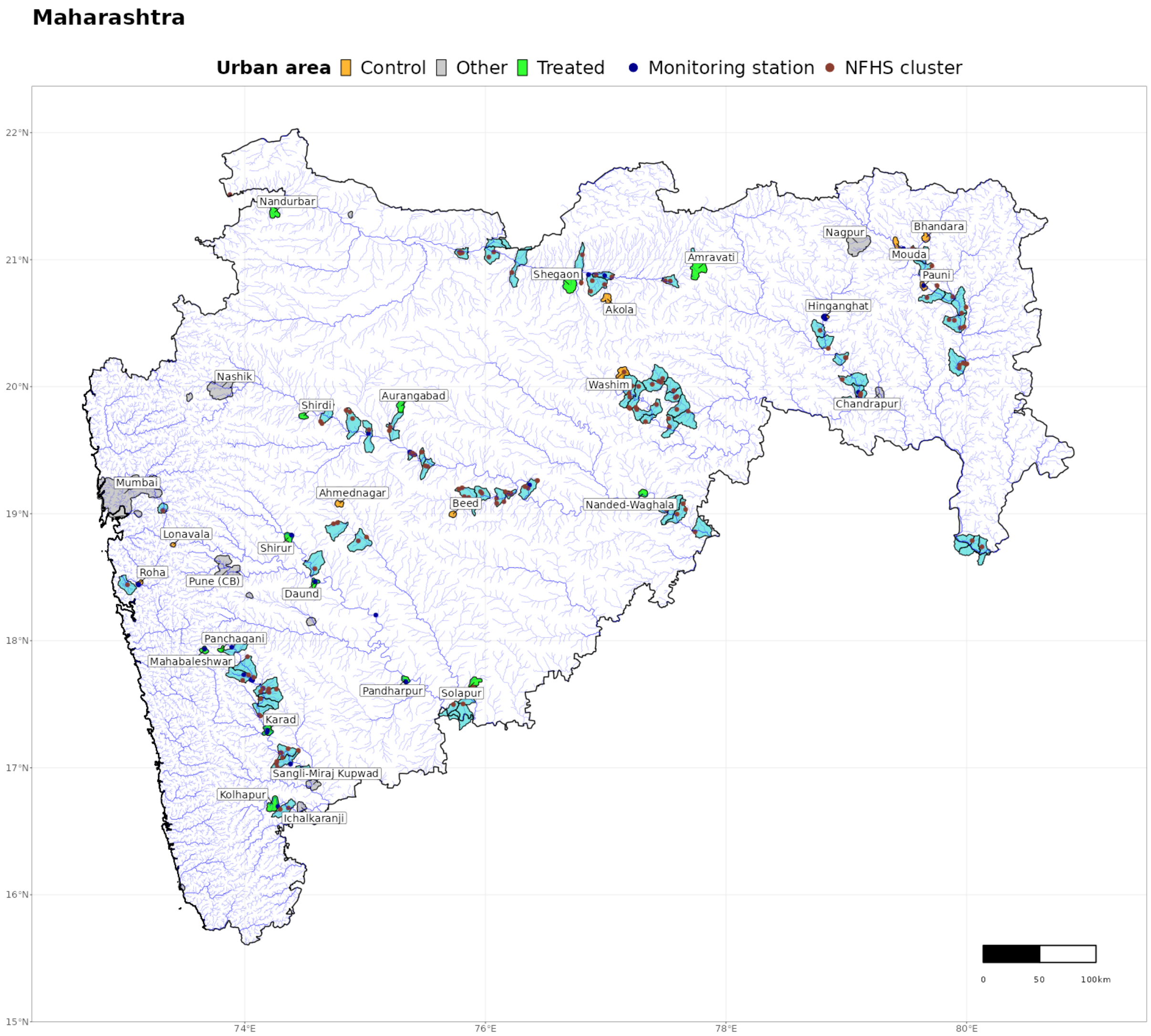
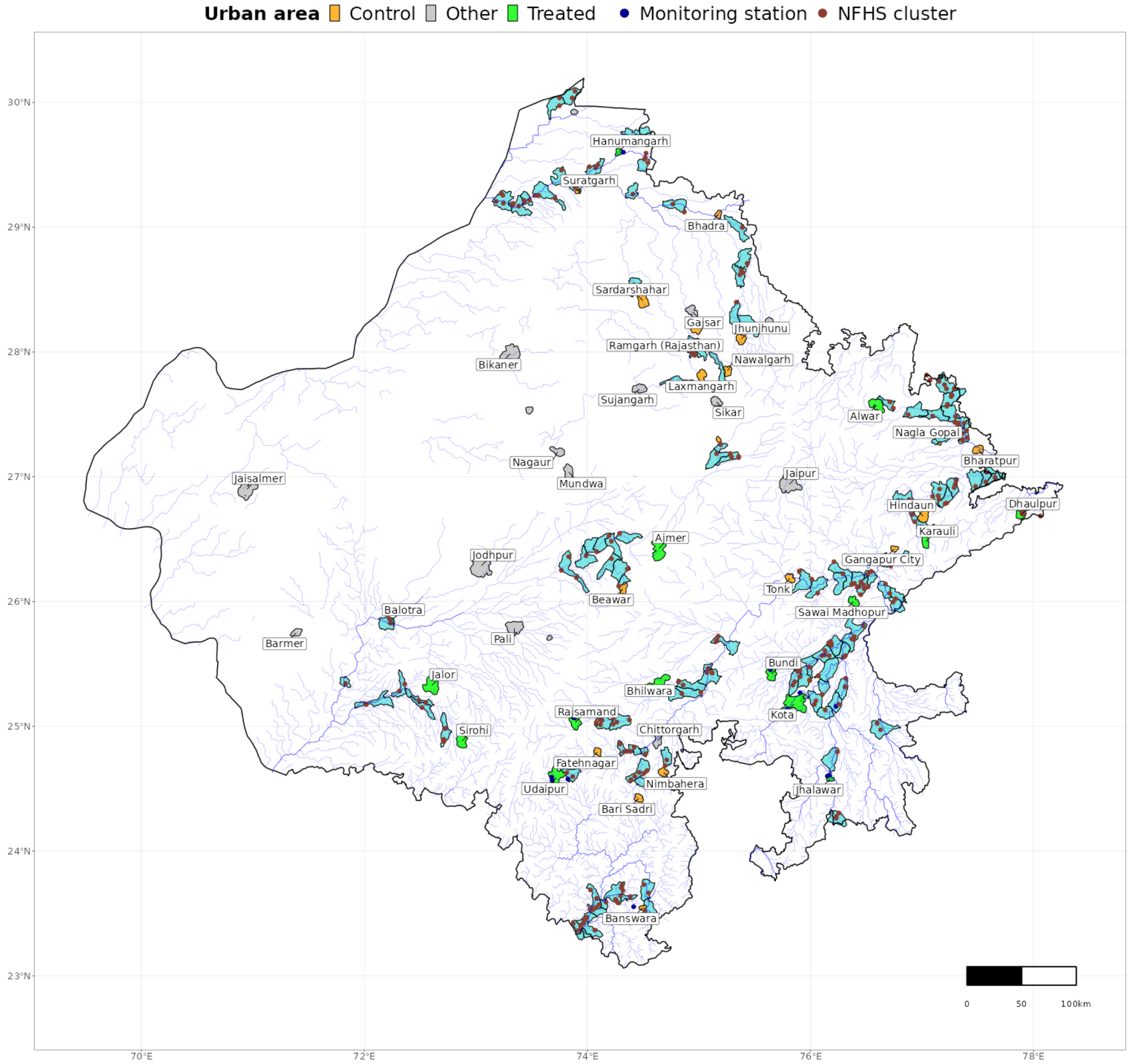


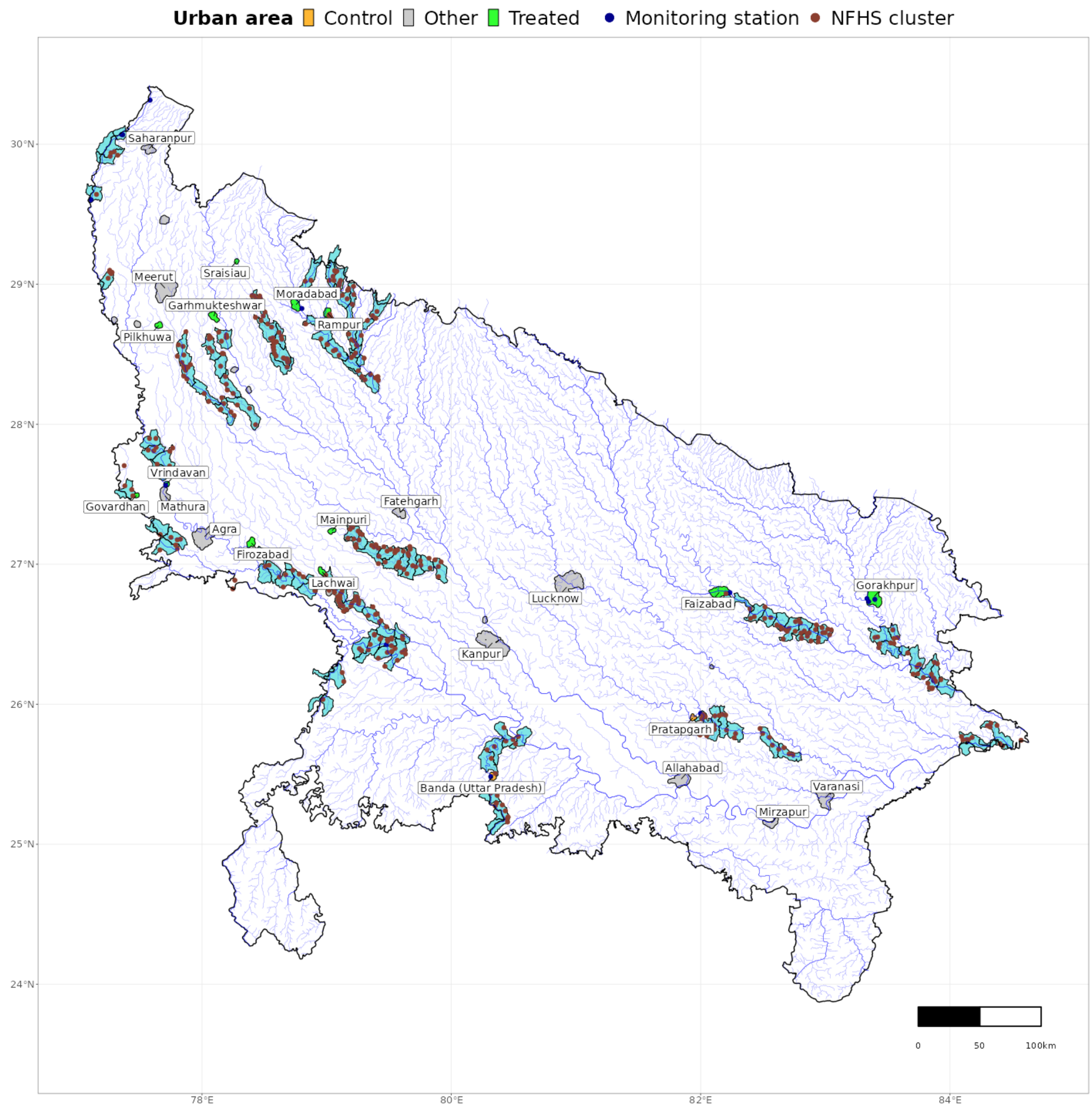
Notes: The blue polygons represent the hydrological sub-basins that contain NFHS clusters and river segments located within 100km downstream of segments that cross the urban areas listed in the sewage treatment plant inventory.

Rajasthan

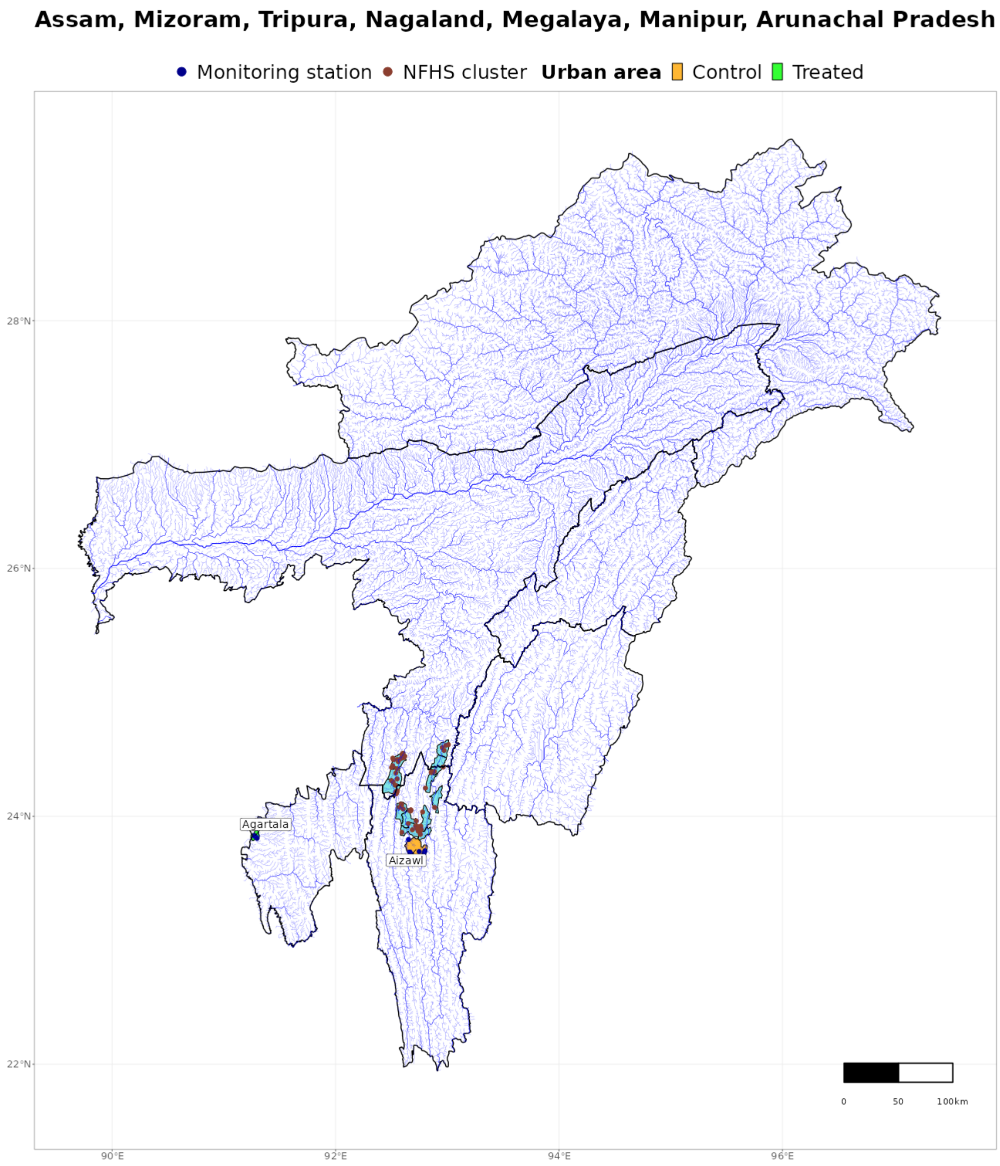


Notes: The blue polygons represent the hydrological sub-basins that contain NFHS clusters and river segments located within 100km downstream of segments that cross the urban areas listed in the sewage treatment plant inventory.

Uttar Pradesh



Notes: The blue polygons represent the hydrological sub-basins that contain NFHS clusters and river segments located within 100km downstream of segments that cross the urban areas listed in the sewage treatment plant inventory.



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