

# **Children of the Dam: Evaluating Impacts of Irrigation Dams on Children's Health in India**

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## **Abstract**

Dams are a key and costly investment in agricultural productivity. Despite controversies over environmental degradation and community displacement, dams continue to be built with the expectation that they will generate benefits for society. This paper explores an understudied link between irrigation dams and children's health in India. Using two recent rounds of the National Family Health Survey, a global dam database, a high-resolution river and river basin data, a comprehensive agricultural panel survey, and numerous remote-sensed data, I find that irrigation dams constructed within river basins increase neonatal mortality incidences by approximately 7.4 percent, while no changes are observed in downstream areas. I show that these results can be linked to dam-induced changes in agrichemical exposure, highlighting the role of agricultural pollutants in increasing child health risks. Given the established link between infant health and later-life productivity and well-being, this paper highlights that the long-term benefits of irrigation dams may be greatly overestimated and there is need to better manage the unintended consequences of these irrigation dams in India.

Keywords: irrigation dams, early childhood mortality, agrichemicals, India

JEL Classifications: O13, I15, Q15

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*“Bhakra-Nangal is not a work of this moment only, because the work which we are doing at present is not only for our own times but for coming generations and future times.”*

- Jawaharlal Nehru, the first prime minister of independent India, on the construction of the Bhakra dam.

## 1 Introduction

Investments in agricultural technologies can be crucial for economic development and growth, but they can also impose significant social and environmental costs. India exemplifies this trade-off, where the investments and infrastructure introduced during the Green Revolution significantly increased agricultural output, reduced poverty levels, improved nutrition and consumption, and enhanced economic productivity (Gollin, Hansen, and Wingender 2021; Bharadwaj et al. 2020; von der Goltz et al. 2020). However, these agricultural advancements also introduced notable short-term and long-term costs, exacerbating social inequality, environmental degradation, and health risks (Dhanagare 1987; Brainerd and Menon 2014; Sekhri and Shastray 2023). Thorough evaluations of these costs are necessary to better assess the long-term returns of agricultural investments on society.

Among the various agricultural technologies, irrigation dams stand out as some of the most expensive, grandiose, and contentious. These dams are designed to improve water resource infrastructure for farmers and have contributed to increasing agricultural productivity, while also making it more resilient to rainfall shocks (Duflo and Pande 2007; Strobl and Strobl 2011; Hansen, Libecap, and Lowe 2009). Yet, debate persists over whether they truly enhance community welfare as concerns about environmental degradation and community displacement call into question the benefits these irrigation dams may provide (Dillon and Fishman 2019; WCD 2001). These concerns are particularly relevant in India, which has constructed over 4,000 irrigation dams, far exceeding the total number built by its South and Southeast Asian neighbors.<sup>1</sup> Despite the scale of dam construction, there is limited empirical research on the health impacts of irrigation dams, particularly on vulnerable populations, such as children.

This paper examines the spatially varying impacts of irrigation dams on children’s health in India and the potential channels that explain these effects. Focus on spatial effects is necessary, as irrigation dams typically have different impacts on agricultural and economic outcomes in the areas where they are built compared to downstream areas. To analyze this relationship, I combine data from multiple sources. I use two rounds of the National Family Health Survey (NFHS), which is nationally representative and geo-referenced.

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<sup>1</sup>Figure A1 illustrates the number of dams constructed in India and other countries in South and Southeast Asia.

I incorporate spatially explicit data on dams from the Global Dam Database, which provides detailed information on individual dams and their completion dates. To isolate spatial spillover effects, I use a digitally constructed river basin boundaries that link each river basin to its respective upstream and downstream basin. Additionally, I draw on a district-level agricultural panel survey, a national water quality monitoring database, and various remote-sensed measures of land use, climatic variables, malaria incidence, and agricultural productivity to examine the channels through which irrigation dams may influence children's health.

Since dam placements can be driven by endogenous factors, my identification strategy follows the use of instrumental variables and fixed effects. This approach is motivated by [Duflo and Pande 2007](#), who demonstrate that some river gradients strongly predict dam construction locations, where high gradients are more suitable for irrigation dams as opposed to flatter or steeper gradients. Additionally, because my sample includes time-varying trends in child health outcomes, the empirical design adopts a shift-share-like method that accounts for potential exogenous variation in dam construction over time and across states with varying shares of dams.

I find that irrigation dams increase early childhood mortality – an indicator of the vulnerability in children's growing environment – in the regions where they are constructed. The most significant impact is observed for neonatal mortality (the probability that a child dies before reaching 1 month), which increases by 0.25 percentage points (approximately 7.4% greater than the sample mean). This effect is strongly identified using river basin boundaries, highlighting the importance of finer units of analysis in detecting potential health costs of irrigation dams. Post-neonatal and child mortality, which represent health risks to older children, do not change, suggesting that the impacts of irrigation dams on children may be limited to in-utero or post-pregnancy shocks. Notably, irrigation dams upstream did not lead to any changes in mortality, suggesting that the health costs of these dams are typically localized, with no spatial spillover effects across river basin boundaries in India.

In examining the channels, I first analyze changes in land use composition, where I find that irrigation dams increase cropland areas in both local and downstream river basins, by approximately 5% and 8% respectively. This increase in cropland area comes at the expense of a reduction in urban and forested areas. Similarly, I find that these dams increase malaria incidences in both local (0.7pp) and downstream river basins (1.0pp) as well. However, when assessing agricultural productivity through a remote-sensed measure of NDVI, I find that irrigation dams increase productivity only in local river basins, particularly during the dry season, where productivity rises by approximately 25%. Local wet season and downstream basin agricultural productivity appeared to be unaffected by irrigation dams.

This increase in productivity is linked to higher chemical fertilizer use, with irrigation dams increasing nitrogen and phosphorus – two of the most commonly used components of chemical fertilizers – by approximately 1350 and 550 tons respectively, in local areas. Given the sensitivity of neonatal mortality to excessive agrichemical exposure, this provides suggestive evidence that dam-induced increases in agrichemical exposure may explain some of the observed health costs on children in India. I find corroborating evidence when assessing water quality levels through the monitoring stations across India, where areas with high number of irrigation dams had higher level of nitrate in their rivers and groundwater.

This paper contributes to the literature on the health consequences of large irrigation infrastructures in three significant ways. First, to the best of my knowledge, it is the first study to examine the impacts of irrigation dams on children’s health outcomes using nationally representative samples from India. Previous studies have linked dam construction to child mortality, primarily in the African context, where women’s involvement in agriculture and concerns about agrichemical exposure are lower compared to India ([Mettetal 2019](#); [Chakravarty 2011](#)). These papers highlight pollution externalities as a potential channel, and my paper extends these findings by showing strong associations between irrigation dams and agrichemical exposures in regions where they are constructed. I also provide spatially finer assessment of the spatial spillover effects of irrigation dams on children by using river basin boundaries. In my sample, most effects on children’s health are localized to local river basins where the dams are constructed, rather than in downstream basins. This contrasts with [Duflo and Pande 2007](#), who, using an older dataset and larger district boundaries, found that agricultural and economic outcomes improved primarily in downstream regions. The lack of significant effects on health and productivity in downstream areas may be due to the large saturation of dams built in India, where more recent irrigation dams focus primarily on localized impacts. These findings also contribute to the broader literature that connects large irrigation infrastructures with improved health and income ([Giordano, Namara, and Bassini 2019](#); [Domènech 2015](#); [Okyere and Usman 2021](#)), while also acknowledging negative externalities, such as increased water pollution ([Srinivasan and Reddy 2009](#)).

My second contribution is to the understanding of agrichemical exposure as a key mechanism affecting children’s health in India. Chemical fertilizers and pesticides are key inputs in modern agriculture, and exposure to these chemicals – both for pregnant mothers and infants – is linked to immediate and long-term health costs ([Brainerd and Menon 2014](#); [Li et al. 2023](#); [Zaveri et al. 2020](#); [Heeren, Tyler, and Mandeya 2003](#)). I find that dam-induced increases in agrichemical exposure correspond with observed changes in children’s health outcomes in India, emphasizing the urgent need to manage the externalities from chemical fertilizers. Additionally, agrichemical related illnesses is not the only health risks

linked to irrigation dams, as I find that malaria incidence increases in both local and downstream regions of a dam. This aligns with numerous studies from Asian and African contexts where irrigation infrastructures, which leads to an increase in inundated and standing water areas, increases the incidences of vector-borne and water-related illnesses (Kibret 2018; Mary et al. 2023).

The third contribution is to discussions around the welfare effects of structural and national agricultural transformations. In India, the Green Revolution fundamentally transformed the agricultural sector by introducing ‘high-yielding variety’ seeds, irrigation infrastructure, and increased fertilizer application. These advancements have undoubtedly led to greater agricultural productivity, economic growth, and significant improvements in household health (Bharadwaj et al. 2020; von der Goltz et al. 2020; Gollin, Hansen, and Wingender 2021). However, concerns have been raised about the unequal distribution of benefits and costs in income generation (Dhanagare 1987; Prahladachar 1983), greater exposure to agrichemicals (Brainerd and Menon 2014), and long-term health consequences due to changing dietary patterns (Sekhri and Shastray 2023). I find that irrigation dams, a key component of India’s transforming agricultural sector, have unintended consequences on children’s health. It is well documented in the human-capital literature that children’s health during infancy has strong links to later-life productivity, income, and educational attainment (Currie and Almond 2011; Currie and Vogl 2013; Lambiris et al. 2022). My findings highlight a significant gap in the discourse on dams, as most assessment frameworks rarely consider their effects on children. Without accounting for these impacts, current assessments risk overestimating the benefits of irrigation dams while overlooking key inefficiencies related to the health costs they impose on children.

The paper proceeds as follows: Section 2 summarizes key background information on dams and how agrichemical exposure can affect children’s health. Section 3 describes all the data used in this study. Section 4 illustrates the empirical strategy used to estimate the effects of dams on children. Section 5 presents the results and discussions, and finally, Section 6 concludes.

## 2 Background

### 2.1 Dams and Households

Dams have been constructed worldwide to better manage increasingly vital water resources within countries. Their capacity to ensure year-round water availability and facilitate further inland water distribution helps meet the growing demands for food, energy, and income (Shi et al. 2019). In recent years, dams have also been used for hy-

droelectric power generation and as safeguards against climate-induced floods and severe droughts (Boulange et al. 2021; Edwards, Sanchez, and Sekhri 2024).

Dams can affect households in various ways, with the most direct impact being changes in agricultural productivity. The seminal paper by Duflo and Pande 2007, one of the first to empirically evaluate the impacts of dams, finds that dams have spatially varying effects on agricultural productivity across the districts where they are constructed and in downstream districts. The study finds that dams increase agricultural productivity only in downstream districts, with no notable changes observed in the districts where the dams are built. Similar spatial heterogeneity is documented in Africa as well (Strobl and Strobl 2011; Blanc and Strobl 2014).

The primary reason for this spatial variability is that downstream regions do not experience the significant costs associated with dams. Dams often inundate large areas, leading to increased waterlogging and salinization in surrounding regions (WCD 2001; Pradhan and Srinivasan 2022). These issues are commonly linked to soil degradation, which reduces the potential for agricultural growth. In contrast, downstream districts typically benefit from dams through irrigation canals, which rely primarily on gravity. Moreover, dams reduce the sensitivity of agricultural yields to climatic variations in downstream regions (Sarsons 2015).

In India, dams have played a crucial role in ensuring the country's food production meets the demands of its growing population. Following the Bengal Famine of 1943, which caused millions of deaths due to food shortages in eastern India, the government made substantial investments in the agricultural sector (Sen 1977). India embraced the Green Revolution during the 1960s, leading to a significant increase in food supply, reduced crop prices, and higher farmer incomes (Evenson and Gollin 2003). At the same time, India began constructing dams to enhance irrigation and support the newly introduced high-yield variety crops. Since the early 1960s, the number of dams has surged from around 400 to over 4,000, far surpassing the number in other South and Southeast Asian countries. Although dam construction has slowed in recent years, ongoing discussions around national "river-linking projects", aimed at increasing irrigation, improving drinking water access, and reducing flood risks, indicate that dams remain integral to India's economic vision (Misra et al. 2007; Shah and Amarasinghe 2016).

The most common types of dams in India are irrigation dams, typically built alongside rivers or lakes. These dams connect households to water through gravity-driven canals, forming extensive networks across villages. These canals have significantly increased agricultural output, wealth, and population density in rural areas (Blakeslee et al. 2023). This elevation-based technology inherently introduces a spatial dimension to the distribution of benefits and costs, making it an ideal case for studying spatial inequalities and

spillovers.

## 2.2 Agrichemical Exposure

This paper narrows down one pathway through which dams impact households: changes in agrichemical exposure, particularly through chemical fertilizer application. Fertilizers are essential for achieving high yields in modern agricultural systems and are crucial for maintaining productivity in both developed and developing countries (McArthur and McCord 2017). Global fertilizer application currently stands at approximately 195 million tons, with nitrogen fertilizers comprising the majority (FAO 2023). Nitrogen, along with phosphorus and potassium, are key components of chemical fertilizers, providing essential nutrients for plant growth. However, the over-application and mismanagement of fertilizers have been linked to significant environmental costs, including ecosystem disruption, soil imbalances, and severe short-term and long-term health impacts on mothers and children (Devi, Manjula, and Bhavani 2022; Innes 2013; Keeler et al. 2016).

The biomedical literature identifies several pathways through which agrichemical exposure impacts health, particularly among infants. One of the most significant pathways involves in-utero exposure to agrichemicals, which can lead to birth defects, low birth weight, and even mortality (Manassaram, Backer, and Moll 2006; Brender and Weyer 2016; Restrepo et al. 1990). Excessive exposure can cause ‘blue baby syndrome’, in which high nitrate levels bind with a baby’s hemoglobin, disrupting the normal transfer of oxygen (Knobeloch et al. 2000). Additionally, exposures during pregnancy can lead to neural tube defects, affecting the baby’s spinal cord and overall development (Brender et al. 2004).

It is important to note that alarmingly high nitrate exposure is not necessary to observe adverse effects on children’s health. Economic and public health literature also links agrichemical exposure to negative child health outcomes by comparing regions or periods of high and low chemical fertilizer use. Recent studies in China, a major user of fertilizers and pesticides, show strong associations between in-utero agrichemical exposure and increased mortality rates, particularly in intensive agricultural regions (Li et al. 2023) and among lower socio-economic households (Lin et al. 2022). Similarly, in India, rising agrichemical exposure has been associated with higher neonatal mortality rates (Brainard and Menon 2014).<sup>2</sup> Consistent findings have been documented in Africa (Heeren, Tyler, and Mandeya 2003) and even in developed countries like the United States, despite stricter regulations and monitoring of agrichemical exposure sources (Stayner et al.

<sup>2</sup>An unpublished preliminary manuscript by Zaveri et al. 2020 also examines the potential long-term effects of agrichemical exposure on adults. Their results suggest that high exposure during childhood can negatively impact adult height in developing countries worldwide.

2017; Winchester, Huskins, and Ying 2009; Jones 2019).

## 3 Data

My data consists of household demographic surveys, a georeferenced dam database, a global hydrological dataset on rivers and river basins, district-level agricultural surveys, and various remote-sensed products to measure agricultural productivity, land use changes, and climate indicators. Although most of the data represent India at the national level, they vary in temporal coverage. To make the best use of all these datasets, the sample period spans 25 years, from 1990 to 2014.

### 3.1 Demographic and Health Survey

Information on children's health outcomes and household characteristics comes from the Indian National Family Health Survey (NFHS). These surveys are the DHS equivalent for India and are designed using a two-stage cluster sampling design. In the first stage, enumeration areas within each region are selected using census data. Then, within each area, a sample is drawn from a complete list of households.<sup>3</sup> I use the two most recent rounds of the NFHS (2015-16 and 2019-21), which provide district-level representative samples and GPS coordinates for household clusters.<sup>4</sup> [Figure A2](#) shows the location of household clusters from both survey waves, illustrating comprehensive sample coverage across India.

The NFHS collects detailed birth histories from all interviewed mothers, which I use to construct measures of early childhood mortality over my sample period. Early childhood mortality is a key indicator of children's well-being and development. I define three mortality measures: (i) neonatal mortality, the probability of death before 1 month of age, (ii) post-neonatal mortality, the probability of death between 1 and 11 months, and (iii) child mortality, the probability of death between 1 and 5 years. These measures reflect different risk factors, with neonatal mortality indicating in-utero stressors, post-neonatal mortality capturing early childhood risk factors, and child mortality reflecting persistent external and environmental pressures during childhood ([MDS 2010](#)).

[Table 1](#) summarizes changes in these health outcomes over the sample period. All three

<sup>3</sup>All surveys are publicly available through the [DHS website](#). An account must be registered with the DHS to access these surveys. A brief proposal is also required to access both the household and GPS data of household clusters.

<sup>4</sup>To ensure confidentiality, GPS coordinates for each household cluster are randomly displaced. In urban areas, clusters are displaced by up to 2 km; in rural areas, by up to 5 km, with an additional 1% of rural clusters displaced by up to 10km.

mortality rates declined significantly, with child mortality dropping by 79%, and both neonatal and post-neonatal mortality decreasing by about 45%. While these reductions are notable, largely due to improvements in India’s healthcare infrastructure, concerns persist that these improvements remain insufficient to fully mitigate the substantial child health risks in India ([Claeson et al. 2000](#)). Among the three indicators, neonatal mortality was the highest in 2014, approximately three times higher than post-neonatal mortality and seven times higher than child mortality, indicating that deaths occurring within the first month of life present the greatest burden in early childhood mortality.

To ensure accurate mortality measures, I limit the sample to children born in locations where their mothers resided at the time of the survey. The NFHS tracks how long mothers have lived in their current locations and when they moved. In this sample, only 6.5% of women had remained in the same location since birth, which is expected due to marriage-related migration. On average, mothers had moved about 17 years prior to the survey. Using this information, I restrict the analysis to children born after their mothers relocated, resulting in a sample of around 1.7 million children (approximately 77% of the total observations).

[Table 2](#) presents statistics on mothers and household characteristics. The average mother had completed secondary education, and about half of the children were girls. The NFHS also collects data on household wealth through a composite index based on assets and physical attributes of homes. Around three-fourths of the households in the sample lived in rural areas, with approximately 90% having access to electricity and improved drinking water sources. However, only 60% had access to improved sanitation facilities.<sup>5</sup>

### 3.2 Dam Database

To identify the locations of irrigation dams in India, I use the Global Dam Tracker (GDAT) database, which provides spatially explicit information on dams worldwide ([Zhang and Gu 2023](#)). The GDAT compiles data from existing global dam databases and validates each dam using local government reports and satellite images. This database includes details such as the year of completion, dam dimensions (height and length), and the primary purpose of construction.<sup>6</sup>

Focusing on India, the GDAT contains information on 4,367 dams up to 2014, with approximately 89% classified as irrigation dams ([Figure A3](#)). Typically, dams higher than 15 meters are categorized as ‘large dams’, and over half of the irrigation dams fall

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<sup>5</sup>The definition of improved drinking water and sanitation facilities is based on a comparison of multiple sources, with certain sources falling under the improved and preferred categories.

<sup>6</sup>I use the most recent: ‘GDAT\_data\_v1.zip’ version of the database accessed through [Zenodo](#).

into this category.<sup>7</sup> The remaining dams serve purposes such as hydroelectricity (6%), flood control (1%), water supply (2%), or are undefined (2%). During the sample period, about 700 irrigation dams were constructed, representing a 25% increase in irrigation dams and a 31% increase in large irrigation dams.

[Figure 1](#) shows the frequency of irrigation dam construction since 1900. Most of these dams were constructed during the 1960s, coinciding with the start of the Green Revolution in India, when there was significant governmental and international focus on increasing agricultural productivity. Another peak in dam construction occurred in the late 1990s, coinciding with large economic reforms in India that increased both international and federal funding for agricultural infrastructure ([Mohan Rao and Krishna Dutt 2006](#)). Since then, the construction of both irrigation and non-irrigation dams has declined.

[Figure 2](#) illustrates the spatial distribution of irrigation dams at the district level. While most districts have at least one dam, notable spatial clustering exists. Northern India, for example, has no irrigation dams, largely due to geographical factors that make the terrain either too steep or too flat for dam construction. The fact that dams require a moderate incline for feasibility plays an important role in isolating the impacts of dams on child outcomes.

### *3.3 Geographic Unit*

I use of two geographical boundaries – district and river basin boundaries – as units of analysis in this study. [Figure 3](#) shows both boundaries. District boundaries are an intuitive choice because the NFHS surveys are representative at this level. Although household clusters are randomly displaced to preserve confidentiality, the displacement occurs within the same district, ensuring households are not misidentified across districts. To account for changes in district and state boundaries over time, I use the administrative boundaries defined in the NFHS 2015 survey, which includes 623 districts and 32 states.<sup>8</sup>

However, district boundaries have a key disadvantage: regions within a district can vary significantly. Despite being smaller administrative units, the average district covers approximately 5,000 square kilometers, which limits the ability to capture spatial heterogeneity. Additionally, districts often have non-uniform elevation and slope, making it difficult to distinguish between upstream and downstream regions, which is crucial for understanding how dams impact households. While I use river network directions to classify upstream and downstream districts, the large size of districts means that loca-

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<sup>7</sup>[Figure A4](#) illustrates the distribution of irrigation dams across dam height.

<sup>8</sup>Union territories are considered separate states in these surveys. To ensure comparability in state size, I merge smaller states with neighboring ones, resulting in a final set of 27 revised states.

tions within a single district can function as both upstream and downstream areas.<sup>9</sup> This makes it more challenging to capture the spatially varying effects of dams accurately.

To address this issue, I use digitally constructed river basin boundaries from the World Wildlife Fund's HydroSHEDS database ([Lehner and Grill 2013](#)). These boundaries are generated remotely using elevation and hydrological models and are available at different spatial resolutions.<sup>10</sup> Each basin includes detailed geographical attributes such as slope, gradient, elevation, and the length of all rivers within the basin. The main advantage of using river basin boundaries is that they are directly linked to their respective upstream and downstream basins, making it easier to identify a dam catchment and downstream command areas.<sup>11</sup>

### *3.4 Agricultural Data*

Since irrigation dams introduce significant changes to local agricultural systems, it is essential to account for shifts in agricultural inputs and outputs when studying their impacts on households. The first outcome of interest is changes in cropland area, which are measured using the MODIS land cover type classification product. This publicly available dataset provides land cover classifications at 500-meter resolution from 2001 onward, categorizing land pixels into various types. I focus on changes in urban, cropland, and forested pixels to assess whether irrigation dams influence these land use classifications.

The second outcome of interest is agricultural productivity, arguably the primary reason for constructing irrigation dams. Given that I use river basin boundaries, I require a productivity measure that can be represented at the river basin level. Unfortunately, India lacks nationally representative data on agricultural productivity at scales smaller than district boundaries. In the absence of such data, I rely on remote-sensed measures of agricultural productivity, specifically the Normalized Difference Vegetation Index (NDVI).

NDVI is calculated by measuring changes in the surface reflection of near-infrared light and is widely used in economic literature as a proxy for agricultural productivity. It has been validated in both African ([Lobell et al. 2020](#)) and Asian ([Son et al. 2014](#)) contexts. The advantage of satellite-based vegetation measures is their high spatial and temporal

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<sup>9</sup>Data on river networks comes from the HydroSHEDS database. This database contains detailed information on rivers, including attributes and flow direction. [Figure A5](#) maps the river networks in India.

<sup>10</sup>All maps and products are publicly available through the HydroSHEDS [website](#).

<sup>11</sup>There is a valid concern about the potential misidentification of households across multiple river basins. However, I select a river basin boundary resolution that minimizes this error. While I could filter out household clusters overlapping multiple river basins, I choose to retain them, as the average displacement of just 5km is unlikely to introduce significant bias. The results are robust to dropping these overlapping household clusters from the analysis.

resolution.<sup>12</sup> I extract monthly NDVI values to construct a measure of agricultural productivity for India's main growing seasons: Kharif (wet season) and Boro (dry season). Following [Asher and Novosad 2020](#), I define each season's agricultural productivity by subtracting the mean NDVI of the first six weeks from the maximum NDVI reached during that season.<sup>13</sup> This method ensures the productivity indicator excludes non-agricultural vegetation, such as forests, which do not fluctuate significantly within a growing season.

For agricultural inputs, I use district-level surveys conducted by the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), which provide detailed information on agricultural inputs and outputs.<sup>14</sup> I use the 'unapportioned' district boundaries, which align closely with NFHS district boundaries. The primary indicator of interest from these surveys is the total annual application of fertilizers. The survey measures the total amount of nitrogen, phosphorus, and potassium (NPK) applied in tons for each district. These three components make up NPK fertilizers, which are widely used to supplement soil nutrients and increase yields but also contribute to environmental imbalances both globally and in India ([Randive, Raut, and Jawadand 2021](#)).

[Table 1](#) shows trends in these agricultural variables over the sample period. As expected, wet season NDVI values are considerably higher than dry season values, as the monsoon season is India's larger agricultural period. However, during the sample period, wet season NDVI increased by roughly 15%, while dry season NDVI grew by a substantial 120%, indicating greater productivity gains during the dry season. This suggests significant efforts have been made to enhance agricultural productivity in the dry season.

Similarly, the application of chemical fertilizers increased considerably. Among the three components of NPK fertilizers, nitrogen is the most widely applied, followed by phosphorus and potassium. Nitrogen fertilizer saw the largest increase, rising by nearly 50%, while phosphorus and potassium increased by approximately 30% on average.

### 3.5 Other Data

I also use a remote-sensed measure of malaria prevalence to assess whether irrigation dams affect malaria incidence in surrounding regions. Data comes from the Malaria Atlas, which combines on-the-ground records with climatic factors to estimate malaria risk levels. From this database, I use two key indicators: (i) the parasite rate, which

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<sup>12</sup>In this study, NDVI data is derived from the AVHRR sensor maintained by the National Oceanic and Atmospheric Administration, available globally from 1981 to 2013 at a resolution of 0.05 degrees. This product was accessed and extracted using Google Earth Engine. Link to [NDVI data](#).

<sup>13</sup>In India, the Kharif season typically runs from late May to October, while the Boro season runs from late December through March ([Selvaraju 2003](#)).

<sup>14</sup>The surveys are maintained on the ICRISAT website [District Level Database](#).

measures malaria-related parasite prevalence in an area, and (ii) the malaria incidence rate, which tracks the number of malaria cases in a region. Both indicators decreased by approximately 20%, on average, during the sample period in India.

In addition, I incorporate satellite-based measures of climatic conditions, specifically rainfall and temperature. Rainfall data is sourced from CHIRPS (Climate Hazards Group InfraRed Precipitation with Station data), while temperature data is obtained from ECMWF (European Centre for Medium-Range Weather Forecasts). Both climate products provide high-resolution grids interpolated using ground observations, ensuring availability at fine spatial and temporal scales.<sup>15</sup>

Finally, to assess whether irrigation dams affect local water quality, I use water quality reports from the Central Pollution Control Board (CPCB), which operates under the Ministry of Environment, Forest, and Climate Change.<sup>16</sup> The CPCB maintains an online database that monitors the quality of water resources across India. These water quality are recorded using monitoring sites scattered across India and I make sure of monitoring sites collecting data on river and groundwater ([Figure A6](#)). These record numerous water quality measures and I focus on nitrate content, dissolved oxygen (DO), and biochemical oxygen demand (BOD). Nitrate and DO levels are sensitive to agricultural pollutants; an increase in nitrate and a decrease in DO typically indicates greater agrichemical pollution in the region. BOD, on the other hand, is a broader indicator of water health, often reflecting wastewater contamination in water bodies.

## 4 Identification Strategy

A simple empirical framework to estimate the effects of irrigation dams on children's health is illustrated in the following equation:

$$Y_{ibt} = \beta_0 + \beta_1 \text{Dam}_{ibt} + \beta_2 \text{LDam}_{ibt}^{Up} + M_{ibt} + X_{bt} + \mu_b + \phi_t + \varepsilon_{ibt} \quad (1)$$

where,  $Y_{ibt}$  indicates the early-childhood mortality status for child  $i$  in region basin  $b$  and year  $t$ .<sup>17</sup>  $\text{Dam}_{ibt}$  represents the total number of irrigation dams within each river basin, while  $\text{LDam}_{ibt}^U$  denotes the number of large irrigation dams upstream of the river basin.

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<sup>15</sup>All satellite information is accessed and extracted using Google Earth Engine. Links to these products can be accessed through the following links: [land cover](#), [rainfall](#), and [temperature](#).

<sup>16</sup>The website for the CPCB Water Quality records can be accessed through this [link](#). However, this newly updated website only records information from 2012 onward. Data from 2007 can be accessed through the old website [here](#).

<sup>17</sup>Three different mortality indicators are considered (neonatal, post-neonatal, and child mortality), which equals 1 depending on if and when the child passed away. Additionally, region primarily represents river basins, which is the preferred unit of analysis, but results using district boundaries are also assessed.

I only consider large irrigation dams upstream, as these dams are large enough to likely to have command areas spanning to downstream regions.  $M_{ibt}$  represents a vector of child-level, mother-level, and household-level controls known to impact child mortality rates, and  $X_{bt}$  represents regional geographic characteristics.  $\mu_b$  represents region fixed-effects that capture all time-invariant unobserved heterogeneity specific to each region, and  $\phi_t$  represents year fixed-effects that account for common temporal shocks affecting all regions in any given year.

Even with the unit and year fixed effects along with household and geographic controls, the coefficients  $\beta_1$  and  $\beta_2$  may still be biased due to non-random placements of dams. For instance, if dams are strategically built in agriculturally prosperous regions to optimize benefits, and if children in these areas have better access to food and health facilities that lowers mortality rates, then the two dam coefficients could underestimate any negative effects that irrigation dams have on children.

To address this bias, I use an instrumental variable strategy, leveraging river gradients to predict the construction of irrigation dams. This approach is motivated by [Duflo and Pande 2007](#), who demonstrate that river gradients exhibit a non-monotonic relationship with the construction of dams. Specifically, flatter river gradients and steeper gradient are less likely to have irrigation dams due to higher construction costs. This follows the expectation that irrigation dams, which primarily distribute water through gravity-driven canals, require a high incline to be cost-efficient.

I calculate the proportions of four river gradient quartiles: low, moderate, high, and steep, within each river basin or district boundaries.<sup>18</sup> [Figure A7](#) graphically illustrates the likelihood of irrigation dams across these river gradient bins. As expected, the high gradient bin is strongly correlated with the presence of irrigation dams. Therefore, river basins or districts with a greater proportion of high gradient areas are more likely to have irrigation dams, as these regions are more cost-effective for dam construction.

Since my sample spans from 1990 to 2014, I need time-varying predictions of dam construction. River gradient bins are time-invariant, thus I interact it with a measure of ‘predicted dams’ to ensure it is not absorbed by the region fixed effect ([Duflo and Pande 2007](#)). This predicted dam is constructed by multiplying the total number of yearly dams in India by the state’s share of dams in 1989 (the year before the sample period). Now, the instrument identifies the causal effects by exploiting how national-level changes in dam construction differentially impacts regions based on their river gradient characteristics and historical state-share of dams construction, after accounting for region and year-specific factors.

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<sup>18</sup>River gradients below 5 decimeters per km are categorized as low, between 5 to 20 decimeters per km as moderate, between 20 to 66 decimeters per km as high, and above 66 decimeters per km as steep.

Formally, my first stage takes the following form:

$$\begin{aligned} \text{Dam}_{ibst} = & \alpha_1 + \sum_{k=2}^4 \alpha_{2k} (\text{RivGradient}_{bs}^k \times \bar{D}_{st}) + \alpha_3 (G_{bs} \times T_t) + \\ & \sum_{k=2}^4 \alpha_{4k} (\text{RivGradient}_{bs}^k \times T_t) + M_{ibt} + X_{bs}\nu_b + \phi_t + \omega_{bst} \end{aligned} \quad (2)$$

Here, Dam represents the number of irrigation dams in region  $b$  within state  $s$  at year  $t$ . RivGradient $_{bs}$  represents the proportion of each river gradient bins within each region. These river gradient bins are interacted with  $\bar{D}_{st}$ , which is the predicted dam incidence measure.  $G_{bs}$  represents other geographical characteristics, such as region elevation, average land gradient, total river length, and region area, all of which could influence the likelihood of dam construction. Since these geographical variables are time-invariant, they are interacted with year dummies  $T_t$ . River gradient bins are also interacted with year dummies to account for time-varying effects specific to certain gradient bins. Finally, along with all the relevant controls from the second stage regression,  $\nu_b$  and  $\phi_t$  represent the region and year fixed effects respectively.

This design resembles a shift-share-like methodology, leveraging national trends in dam construction (the *shift*) and the pre-determined, state-specific shares (the *shares*) to create an instrument that varies over time and across regions. Recent studies emphasize the need to justify the identification assumption in such shift-share-like design by either arguing that exogeneity in shares (Goldsmith-Pinkham, Sorkin, and Swift 2020) or exogeneity in the shift variable (Borusyak, Hull, and Jaravel 2022). I follow Goldsmith-Pinkham, Sorkin, and Swift 2020, who show that a shift-share design is similar to a pooled exposure design, where industry shares measure differential exogenous exposure to a common shock. For valid identification, I show that regions with different state shares do not exhibit pre-existing trends. In other words, only the common shock during the sample period affects changes in outcomes, not any pre-existing trends.<sup>19</sup>

I then estimate the second-stage using the predicted values of irrigation dams using the following equation:

$$Y_{ibt} = \beta_0 + \beta_1 \widehat{\text{Dam}}_{ibt} + \beta_2 \widehat{\text{Dam}}_{ibt}^{Up} + M_{ib} + X_{bt} + \mu_b + \phi_t + \varepsilon_{ibt} \quad (3)$$

Now,  $\widehat{\text{Dam}}$  and  $\widehat{\text{Dam}}^{Up}$  hat represents the predicted irrigation dams in the region and predicted large irrigation dams in upstream regions.  $Z_{ibt}$  represents a set of geographical

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<sup>19</sup>More rigorous tests for the exogeneity of shares exist, but these are under the framework of a conventional shift-share design consisting of multiple industry shares within a region. Since we only have one share (state shares of irrigation dams), we cannot compute the Rotemberg weights for these tests, so we rely on the pre-existing trend test to justify the validity of our state share.

and river gradient trend controls described earlier. In addition, I also control for the number of non-irrigation dams constructed in a region and its respective upstream regions to account for any effects these dams could have on households. Since we are using an instrumental variable strategy, the coefficients now represent the local average treatment effect of dams primarily constructed due to geographical suitability.

One concern is that river gradient bins, the primary instrument, can influence child health outcomes through other channels beyond irrigation dam construction. In fact, these gradients are strong predictors of household wealth and infrastructure, potentially violating the exogeneity assumption. To address this, I include a comprehensive set of household controls in Equation 3, such as household wealth index, rural residence, access to improved sanitation and drinking facilities, electricity, child's sex, and mother's education level.

I estimate Equation 3 for various early childhood mortality incidences using both district and river basin fixed effects. I also use this same equation to examine the potential channels by which irrigation dams may impact mortality incidences. To address potential heteroskedasticity in our panel data, I employ the commonly used two-step Generalized Method of Moments (GMM) estimator. This method provides robust standard errors that account for heteroskedastic error structures common in our dataset. Standard errors for all regressions are clustered at the river basin (or district) level, which is the level where irrigation dams vary across household groups. The GMM estimator also enhances the efficiency of our estimates by utilizing an optimal weighting matrix, ensuring more reliable and precise inference in the presence of clustered data.

## 5 Results and Discussion

### 5.1 Early Childhood Mortality Results

[Table 3](#) presents the relationship between river gradient bins and irrigation dams, using both district and river basin boundaries. In all models, the omitted river gradient bin is ‘low gradient’. Columns 1 and 2 show the cross-sectional relationship, where the coefficient for the high gradient bin is significant and positive, while the other river gradient bins do not display significant effects relative to the reference level. This result aligns with the expected non-monotonic relationship between river gradients and dam construction, where some degree of steepness is necessary to make dams cost-efficient. Columns 3 and 4 show the interaction of these river gradient bins with predicted dam incidence in a panel setting, representing the full first-stage results when considering irrigation dams constructed within a region. For both districts and river basins, the F-

test for river gradients indicates that the instrument is strong, with values exceeding the rule-of-thumb threshold of 10 ([Stock and Yogo 2005](#)).

To validate the shift-share-like design, I demonstrate that the effects of irrigation dams across different state shares observed during my sample period (1990-2014) are not driven by changes that occurred prior to my analysis. I test for pre-existing differential trends in early childhood mortality outcomes across states with varying dam shares. Specifically, I examine mortality incidences from 1980 to 1989 by regressing each mortality outcome on high and low state shares, using the same controls as in Equation 3. [Figure A8](#) shows no significant pre-trends in neonatal mortality, supporting the notion that pre-existing differences in state shares of dams do not predict changes in neonatal mortality through channels other than post-1990 dam construction.

[Table 4](#) presents the OLS and IV results of the impacts of irrigation dams on early-childhood mortality indicators using river basin boundaries. Columns 1 and 2 present the results for neonatal mortality, where the OLS estimation indicates a small increase in mortality (0.07 percentage points) when irrigation dams are constructed in the basin and a larger decrease in mortality (0.34 percentage points) for large irrigation dams constructed upstream. However, as mentioned earlier, these estimates may be biased. The IV estimation leads to a slightly different result: irrigation dams constructed in a basin lead to a greater increase in mortality (0.25 percentage points), approximately 7.4% of the sample mean for neonatal mortality. Irrigation dams upstream no longer have any effect on neonatal mortality.

The IV results for post-neonatal mortality (column 4) and child mortality (column 6) are insignificant for both irrigation dams constructed within a river basin and those constructed upstream. Both of these mortality indicators measure risks to relatively older children, with child mortality assessing the cumulative risk for children between 1 and 5 years old. There could be several reasons why these mortality indicators show no significance. One possibility is that irrigation dams, regardless of their location, have no effect on mortality rates for older children, as dam-induced health risks could be more closely associated with in-utero conditions or those occurring immediately after birth – both of which are strongly linked to neonatal mortality. However, this lack of significance may also be due to limited variation in the post-neonatal and child mortality indicators. The majority of early childhood mortality in India is neonatal, comprising almost 60% of all child deaths, and thus the lower frequency of post-neonatal and child mortality might contribute to the null effect.

## 5.2 Examining Pathways

To explore the channels through which irrigation dams increase neonatal mortality in the river basins where they are constructed, I examine how these dams alter the broader environment in these basins. First, I provide an overview of the land use compositions in the river basins, focusing on three major land classifications: urban, cropland, and forested areas. Next, I assess how irrigation dams affect the incidence of malaria. Finally, I test how these irrigation dams impact agricultural productivity and potential changes in agricultural inputs in each river basin. All of these outcomes are estimated using the same instrumental variable strategy as in Equation 3. Since these analyses are at the river basin level, household controls are replaced with broader basin-level controls for the environment (average rainfall and temperature).

[Table 5](#) presents the results of how irrigation dams change land use composition at the river basin level. As expected, irrigation dams increase cropland area (column 2), with local areas experiencing a 4.5% increase and downstream basins a larger increase of 7.8%. This expansion of cropland is typically associated with decreases in urban areas (column 4) and forested areas (column 6). Urban areas and forested areas decreased by 0.6% and 3.7%, respectively in river basins where dams are constructed, and by slightly larger amounts of 1.7% and 5.2%, respectively in downstream river basins.

Dam-induced decreases in forested areas have been a concern not only in India but also worldwide. Deforestation resulting from dam construction and the subsequent expansion of cropland has been documented before ([Sudhakar Reddy et al. 2016](#); [Tian et al. 2014](#)). This decline in forest area is also strongly associated with increases in several vector-borne diseases, primarily malaria. Coupled with the rise of this disease due to greater irrigation infrastructure ([Guerra, Snow, and Hay 2006](#); [Mary et al. 2023](#)), malaria serves as an important channel through which dams could affect children's health.

[Table 6](#) confirms this, showing that irrigation dams increase parasite rates (column 2) and malaria incidence rates (column 4) in local river basins by 0.3 and 0.7 percentage points respectively. Interestingly, downstream river basins also exhibit increases in parasite rates and malaria incidence rates by slightly larger amounts, 0.4 and 1.0 percentage points respectively. While this rise in malaria could contribute to higher neonatal mortality rates, the fact that both local and downstream show increased malaria risk suggests that additional health risk factors may be responsible for the localized health costs generated by irrigation dams.

[Table 7](#) presents the changes in log NDVI, a proxy for agricultural productivity, in the river basins. Local irrigation dams do not appear to affect wet season agricultural productivity (column 2) but they significantly increase dry season productivity by approximately 25% (column 4). There are no noticeable dam-induced changes in agricultural produc-

tivity for downstream river basins, suggesting that similar to the effects on child health, the impacts of dams on agricultural productivity are more localized and concentrated in the dry season.

However, increases in agricultural productivity are often associated with higher household income and improved diet quality, so the fact that irrigation dams both increase local agricultural productivity and raise child mortality rates seems contradictory. To better understand the changes introduced by greater agricultural productivity, I assess the impact of irrigation dams on chemical fertilizer applications. [Table 8](#) shows that changes in key fertilizer components at the district level, indicating that irrigation dams increase the application of nitrogen (column 2) and phosphorus (column 4) by approximately 1350 and 550 tons respectively. This represents an increase of roughly 5% from the respective sample mean. Interestingly, potassium – another key component of NPK chemical fertilizers – does not increase in districts where dams are constructed, but it does increase in downstream districts. However, in India, potassium represents a relatively small proportion of total chemical fertilizer use.

The increase in chemical fertilizer use, particularly in regions where irrigation dams are constructed, aligns with the rise in neonatal mortality rates despite the gains in agricultural productivity. India faces significant challenges with the over-application of chemical fertilizers, which has already led to substantial health costs for children ([Brainerd and Menon 2014](#)). Similarly, studies in China, one of the largest consumers of chemical fertilizers, have linked greater fertilizer exposure to higher child mortality rates, even in regions where agricultural productivity has increased ([Li et al. 2023; Lin et al. 2022](#)).

Since the chemical fertilizer application data is at the district level, I also use water pollution monitoring data from the Central Pollution Control Board (CPCB) to assess whether irrigation dams affect local water quality. However, due to data limitations and a lack of comprehensive monitoring sites across India during the sample period, the analysis of these water quality measures is conducted using OLS with state and year fixed effects, along with river basin controls and the non-irrigation dams indicator used in previous analyses. [Table A1](#) presents these results. I find that in river basins where irrigation dams are constructed, nitrate levels in the water increase (column 1), providing corroborative evidence that dam-induced increases in chemical fertilizer use are associated with higher agrichemical pollution in local water bodies. Dissolved oxygen, another indicator of water health, also declines (column 2). However, biochemical oxygen demand (BOD), a common measure of water quality linked to non-agricultural activities such as wastewater contamination, does not increase in river basins with dams (column 3), indicating that water quality is not generally poorer in high irrigation dam regions. Irrigation dams do not appear to alter water quality measures in downstream river basins.

## 6 Conclusion

This paper investigates whether irrigation dams impose health costs on children in India and whether these effects vary spatially. Using river gradients as instrumental variables and river basin boundaries to identify spatial effects, I find that irrigation dams significantly increase neonatal mortality in the basins where they are constructed. However, I find no evidence that these irrigation dams affect the mortality of children in downstream basins. In examining the mechanisms, I find that irrigation dams increase cropland area in both local and downstream basins, at the expense of urban and forested areas. Incidences of malaria also rise in both local and downstream basins. Interestingly, agricultural productivity increases only in the basins where the dams are constructed, with no productivity gains observed downstream. This increase in productivity is closely linked to higher use of chemical fertilizers (nitrogen and phosphorus). Given the sensitivity of neonatal mortality to agrichemical exposure, the increased use of chemical fertilizers may explain part of the heightened health risks in basins where irrigation dams are constructed.

The results of this paper have several policy implications. First, I provide evidence that irrigation dams in India impose substantial health costs on children. Conventional cost-benefit analyses conducted before dam construction, or assessments made after the dams are built, rarely consider the health effects on children. This omission tends to overestimate the societal benefits of dams, thereby limiting the recognition of the unintended consequences on children's development.

Second, the increase in neonatal mortality persists despite gains in local agricultural productivity. Irrigation dams constructed in India after 1990 were effective in increasing agricultural productivity, particularly during the dry season. However, this productivity gain comes at the cost of greater chemical fertilizer use. In India, the use of chemical fertilizers continues to rise at an alarming rate, even though corresponding increases in crop yields are not being observed. There is an urgent need for better management of chemical fertilizers to prevent health externalities arising from their overuse.

It is important to acknowledge the limitations of this study, primarily driven by data constraints. Much of the analysis of the channels through which irrigation dams affect children relies on remote-sensing measures. While these measures have been validated in prior studies, they are not as precise as ground-based estimates, which would likely provide more accurate results. This paper also identifies agrichemical exposure as one possible pathway and is in no way the only pathway by which dams could affect child health outcomes. For instance, these irrigation dams could also change the number of hours women work in agriculture, which could also be linked to the outcomes of their children's health.

Finally, this paper highlights the need to address additional questions to better understand the effects of irrigation dams on human welfare. A more thorough investigation into the long-term health consequences of irrigation dams on children is required to assess the true return on these investments for local communities. In this regard, examining heterogeneous effects across household characteristics, regions, and behaviors could shed light on the differential risks faced by sub-populations and how large agricultural investments may have distributional effects across groups. Answering these questions will require additional data, which was not available at the time of this study. Nonetheless, this paper underscores the unintended consequences of large agricultural investments and technologies on human health, and the need to acknowledge these effects to ensure that such investments yield the greatest benefits for society.

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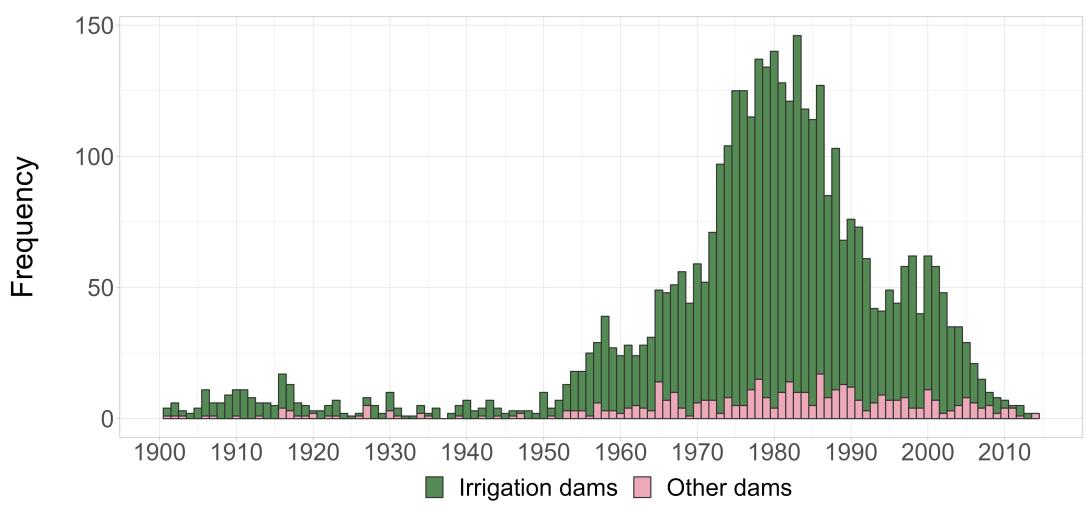
## Tables and Figures

**Table 1:** Summary statistics of variables at the beginning and end of the sample period. [\[back\]](#)

	Start of Sample		End of Sample		Change (%)
	Mean	Std.dev	Mean	Std.dev	
<b>Child health outcomes</b>					
Neonatal mortality (death before 1 month)	0.047	0.212	0.027	0.162	-43.1
Post-neonatal mortality (death between 1-11 months)	0.015	0.123	0.008	0.091	-46.4
Child mortality (death between 1-5 years)	0.020	0.140	0.004	0.065	-79.0
<b>Dam frequency</b>					
Irrigation dams	2,763	-	3,455	-	25.0
Large irrigation dams	1,583	-	2,078	-	31.3
Other types of dams	297	-	406	-	36.7
<b>Agricultural variables</b>					
Nitrogen (tons)	21,245	21,423	31,250	28,573	47.1
Phosphorus (tons)	8,669	8,282	11,223	11,275	29.5
Potassium (tons)	3,507	5,196	4,680	7,310	33.4
Wet season NDVI	1,552	679	1,794	805	15.5
Dry season NDVI	285	315	624	710	118.8
<b>Other variables</b>					
Urban area pixel (%)	0.039	0.131	0.031	0.108	-21.0
Cropland area pixel (%)	0.807	0.315	0.790	0.320	-2.1
Forest area pixel (%)	0.154	0.303	0.180	0.315	16.4
Average rainfall (mm)	3,262	1,807	2,973	1,768	-8.9
Average temperature (c)	21.863	8.682	21.995	8.972	0.6
Malaria parasite rate (%)	0.006	0.017	0.004	0.017	-21.5
Malaria incidence rate (%)	0.012	0.031	0.009	0.032	-23.5

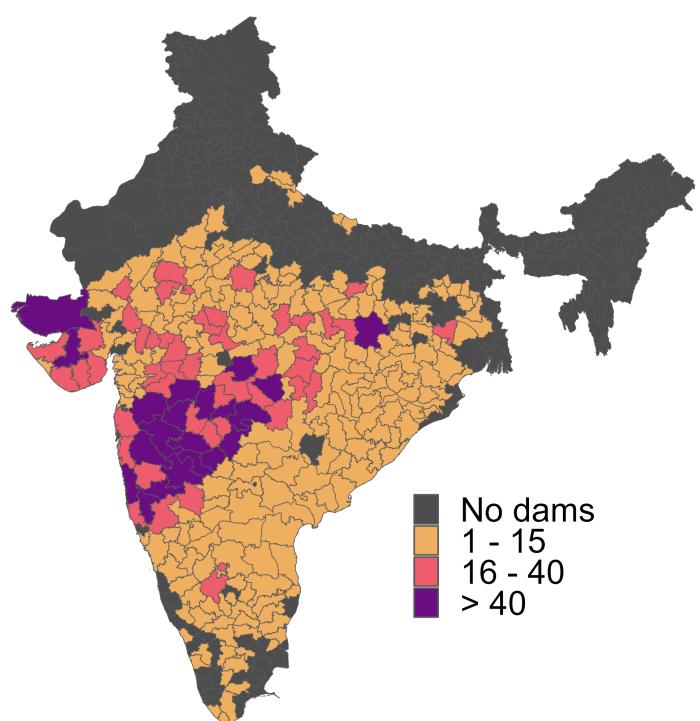
**Table 2:** Summary statistics of time-invariant variables. [back]

	Mean	Std.Dev	Min	Max
<b>Mother's characteristics</b>				
Proportion of mothers who lived in the same home	0.065	0.247	0.0	1.0
Number of years since moving homes	17.249	8.829	0.0	49.0
Proportion of children born in another location	0.234	0.423	0.0	1.0
Mother's education level (factor 0-3)	0.968	0.988	0.0	3.0
<b>Household characteristics</b>				
Wealth index (factor 1-5)	2.722	1.371	1.0	5.0
Proportion of rural households	0.763	0.425	0.0	1.0
Proportion of households with electricity	0.894	0.308	0.0	1.0
Proportion of households with improved drinking water	0.896	0.306	0.0	1.0
Proportion of households with improved sanitation	0.615	0.487	0.0	1.0
<b>Dam characteristics</b>				
Proportion of irrigation dams	0.887	0.316	0.0	1.0
Proportion of irrigation dams defined as large	0.594	0.491	0.0	1.0
Proportion of hydroelectric dams	0.068	0.252	0.0	1.0
Proportion of flood control dams	0.005	0.071	0.0	1.0
Proportion of water supply dams	0.018	0.134	0.0	1.0
<b>Geographical characteristics</b>				
Flat river gradient	0.309	0.220	0.0	1.0
Moderate river gradient	0.275	0.166	0.0	1.0
High river gradient	0.238	0.191	0.0	0.7
Steep river gradient	0.174	0.239	0.0	0.9
Average elevation (m)	471.693	674.703	0.0	4,821.5
Average land gradient	99.771	200.884	0.0	1,269.6
<b>Boundaries</b>				
Basin area (sq.km)	2,102	1,823	6	21,004
District area (sq.km)	5,013	4,616	20.6	47,810.3
State area (sq.km)	158,296	100,164	10,754.5	346,474.7



Note: Data source is from the GDAT database. Other dams include hydroelectric, flood control, drinkir and unspecified dams.

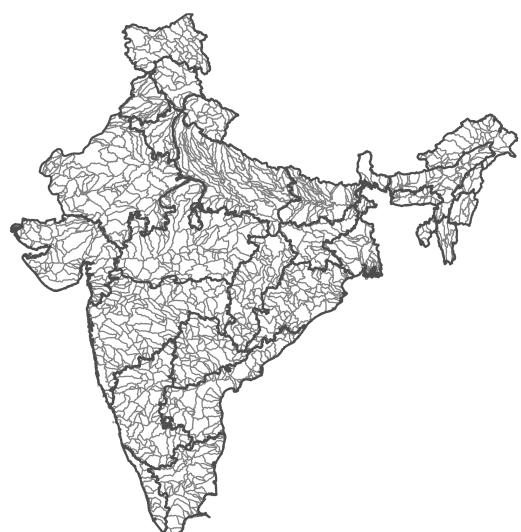
**Figure 1:** Frequency of dam constructed in India from 1900 onward. [\[back\]](#)



**Figure 2:** Spatial distribution of dams across districts. [\[back\]](#)



(a) Administrative Boundaries (DHS Spatial Data Repository)



(b) River Basin Boundaries (HydroSHEDS Database)

**Figure 3:** District and river basin boundaries. Bolder lines represents revised State boundaries.  
[\[back\]](#)

**Table 3:** Relationship between river gradient bins and irrigation dams at the district and basin level. [\[back\]](#)

	Cross-sectional (1989)		Panel (1990-2014)	
	(1)	(2)	(3)	(4)
Moderate gradient	-4.280 (2.607)	-4.898** (1.928)	-0.014 (0.016)	-0.004 (0.006)
High gradient	16.908*** (2.086)	11.841*** (1.649)	0.046** (0.021)	0.018*** (0.006)
Steep gradient	2.361 (3.321)	-1.080 (2.432)	0.072** (0.036)	0.033*** (0.011)
F-test for Riv.Grad	24.5	23.2	12.2	15.9
Unit	District	Basin	District	Basin
Geographic controls	No	No	Yes	Yes
Riv.Grad trend	No	No	Yes	Yes
Household controls	No	No	Yes	Yes
Non-irrigation dams	No	No	Yes	Yes
Observations	13,244	13,235	1,281,392	1,279,576

Asterisks indicates significance: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ . Standard errors are clustered at the unit level (District for columns 1 and 3, River basin for columns 2 and 4). The reference river gradient bin ‘Low gradient’ is omitted. Cross-sectional models (Column 1 and 2) include state and year fixed effects. Panel models include district (column 3) or basin (column 4) and year fixed effects. Geographical controls include: area of region, three average elevations bins, two average land gradient bins, and the total area of rivers within each region. Each of these variables is interacted with year dummies. Household controls include: wealth index, rural residence status, access to improved sanitation and drinking facilities, mother’s education level, mother’s age, and child’s sex. Non-irrigation dams are the number of dams in the region built for purposes other than irrigation (e.g., hydroelectricity, flood control, drinking water, or unspecified).

**Table 4:** Impacts of irrigation dams on early childhood mortality using the river basin boundaries. [\[back\]](#)

	Neonatal		Post-neonatal		Child	
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
Irrigation dams in basin	0.0007*** (0.0003)	0.0025** (0.0010)	0.0004*** (0.0002)	0.0002 (0.0004)	0.0004 (0.0002)	0.0005 (0.0007)
Large irrigation dams upstream	-0.0034*** (0.0012)	-0.0010 (0.0052)	0.0004 (0.0007)	0.0040 (0.0028)	0.0005 (0.0008)	0.0006 (0.0030)
F-test for Riv.Grad		12.1		12.1		12.1
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Geographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Riv.Grad trend	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes
Non-irrigation dams	Yes	Yes	Yes	Yes	Yes	Yes
Dep. var. mean	0.034	0.034	0.011	0.011	0.012	0.012
Observations	1,279,576	1,279,576	1,279,576	1,279,576	1,279,576	1,279,576

Asterisks indicates significance: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ . Standard errors are clustered at the river basin level. The F-test represents the Sanderson-Windmeijer Multivariate F-test statistic, which is a diagnostic tool for models with multiple endogenous variables. Geographical controls include: area of region, three average elevations bins, two average land gradient bins, and the total area of rivers within each region. Each of these variables is interacted with year dummies. Household controls include: wealth index, rural residence status, access to improved sanitation and drinking facilities, mother's education level, mother's age, and child's sex. Non-irrigation dams are the number of dams in the region built for purposes other than irrigation (e.g., hydroelectricity, flood control, drinking water, or unspecified).

**Table 5:** Impacts of irrigation dam on land cover change the river basin boundaries. [\[back\]](#)

	Cropland		Urban		Forest	
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
Irrigation dams in basin	-0.005*** (0.002)	0.045*** (0.014)	0.002 (0.001)	-0.006* (0.003)	0.003** (0.001)	-0.037*** (0.011)
Large irrigation dams upstream	0.005** (0.003)	0.078*** (0.021)	-0.000 (0.003)	-0.017** (0.008)	-0.005* (0.002)	-0.052*** (0.017)
F-test for Riv.Grad		13.2		13.2		13.2
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Geographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Riv.Grad trend	Yes	Yes	Yes	Yes	Yes	Yes
Climate controls	Yes	Yes	Yes	Yes	Yes	Yes
Non-irrigation dams	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,939	15,939	15,939	15,939	15,939	15,939

Asterisks indicates significance: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ . Standard errors are clustered at the river basin level. The F-test represents the Sanderson-Windmeijer Multivariate F-test statistic, which is a diagnostic tool for models with multiple endogenous variables. Geographical controls include: area of region, three average elevations bins, two average land gradient bins, and the total area of rivers within each region. Each of these variables is interacted with year dummies. Climate controls include average rainfall and temperature and its squared term. Non-irrigation dams are the number of dams in the region built for purposes other than irrigation (e.g., hydroelectricity, flood control, drinking water, or unspecified).

**Table 6:** Impacts of irrigation dam on malaria rates using the river basin boundaries. [\[back\]](#)

	Parasite rate		Incidence rate	
	(1) OLS	(2) IV	(3) OLS	(4) IV
Irrigation dams in basin	-0.0010*** (0.0002)	0.0030*** (0.0010)	-0.0020*** (0.0004)	0.0073*** (0.0019)
Large irrigation dams upstream	-0.0012* (0.0006)	0.0045*** (0.0016)	-0.0021* (0.0012)	0.0104*** (0.0035)
F-test for Riv.Grad		19.2		19.2
Fixed effects	Yes	Yes	Yes	Yes
Geographic controls	Yes	Yes	Yes	Yes
Riv.Grad trend	Yes	Yes	Yes	Yes
Climate controls	Yes	Yes	Yes	Yes
Non-irrigation dams	Yes	Yes	Yes	Yes
Dep. var. mean	0.004	0.004	0.008	0.008
Observations	17,745	17,745	17,745	17,745

Asterisks indicates significance: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ . Standard errors are clustered at the river basin level. The F-test represents the Sanderson-Windmeijer Multivariate F-test statistic, which is a diagnostic tool for models with multiple endogenous variables. Geographical controls include: area of region, three average elevations bins, two average land gradient bins, and the total area of rivers within each region. Each of these variables is interacted with year dummies. Climate controls include average rainfall and temperature and its squared term. Non-irrigation dams are the number of dams in the region built for purposes other than irrigation (e.g., hydroelectricity, flood control, drinking water, or unspecified).

**Table 7:** Impacts of irrigation dam on log(NDVI) using the river basin boundaries. [\[back\]](#)

	Wet Season		Dry Season	
	(1) OLS	(2) IV	(3) OLS	(4) IV
Irrigation dams in basin	0.009*** (0.003)	0.010 (0.010)	0.048*** (0.010)	0.252*** (0.032)
Large irrigation dams upstream	0.008 (0.008)	0.007 (0.031)	0.013 (0.027)	0.152 (0.113)
F-test for Riv.Grad		128.7		127.9
Fixed effects	Yes	Yes	Yes	Yes
Geographic controls	Yes	Yes	Yes	Yes
Riv.Grad trend	Yes	Yes	Yes	Yes
Climate controls	Yes	Yes	Yes	Yes
Non-irrigation dams	Yes	Yes	Yes	Yes
Observations	28,487	28,487	28,481	28,481

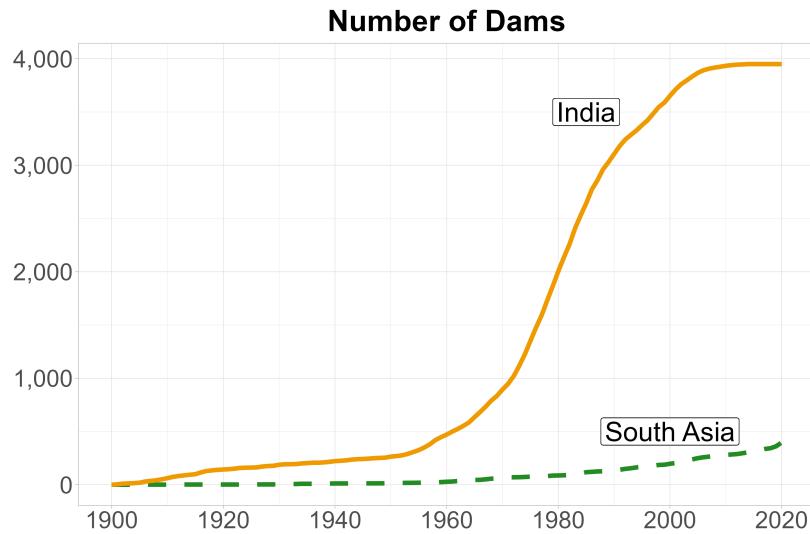
Asterisks indicates significance: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ . Standard errors are clustered at the river basin level. The F-test represents the Sanderson-Windmeijer Multivariate F-test statistic, which is a diagnostic tool for models with multiple endogenous variables. Geographical controls include: area of region, three average elevations bins, two average land gradient bins, and the total area of rivers within each region. Each of these variables is interacted with year dummies. Climate controls include average rainfall and temperature and its squared term. Non-irrigation dams are the number of dams in the region built for purposes other than irrigation (e.g., hydroelectricity, flood control, drinking water, or unspecified).

**Table 8:** Impacts of irrigation dam on chemical fertilizer application using the district boundaries. [\[back\]](#)

	Nitrogen		Phosphorus		Potassium	
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) f5	(6) f6
Irrigation dams in basin	344.3 (219.7)	1347.2** (595.4)	266.0* (136.7)	540.1* (285.3)	111.4 (94.1)	-132.5 (258.9)
Large irrigation dams upstream	42.3 (100.7)	-275.0 (180.3)	62.8 (62.9)	-22.8 (127.1)	90.4 (59.4)	262.4* (140.7)
F-test for Riv.Grad		26.4		17.5		17.5
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Geographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Riv.Grad trend	Yes	Yes	Yes	Yes	Yes	Yes
Climate controls	Yes	Yes	Yes	Yes	Yes	Yes
Non-irrigation dams	Yes	Yes	Yes	Yes	Yes	Yes
Dep. var. mean	24,786	24,786	10,095	10,095	4,388	4,388
Observations	20,325	20,325	20,325	20,325	20,325	20,325

Asterisks indicates significance: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ . Standard errors are clustered at the district level. The F-test represents the Sanderson-Windmeier Multivariate F-test statistic, which is a diagnostic tool for models with multiple endogenous variables. Geographical controls include: area of region, three average elevations bins, two average land gradient bins, and the total area of rivers within each region. Each of these variables is interacted with year dummies. Climate controls include average rainfall and temperature and its squared term. Non-irrigation dams are the number of dams in the region built for purposes other than irrigation (e.g., hydroelectricity, flood control, drinking water, or unspecified).

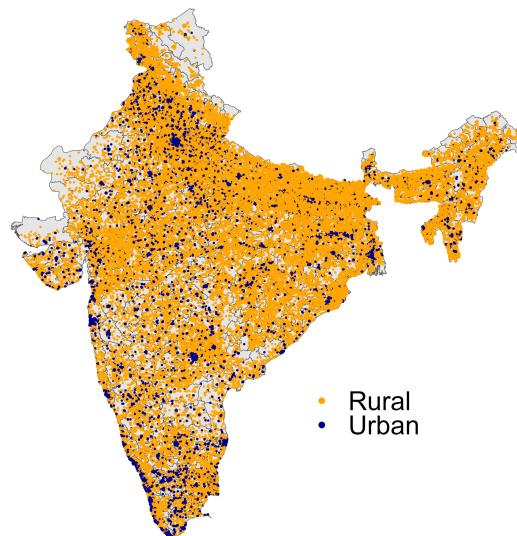
## Appendix A: Supplementary Results



Data source: GDAT. South Asia countries include Afghanistan, Bangladesh, Bhutan, Cambodia, Laos, Malaysia, Myanmar, Nepal, Pakistan, and Sri Lanka

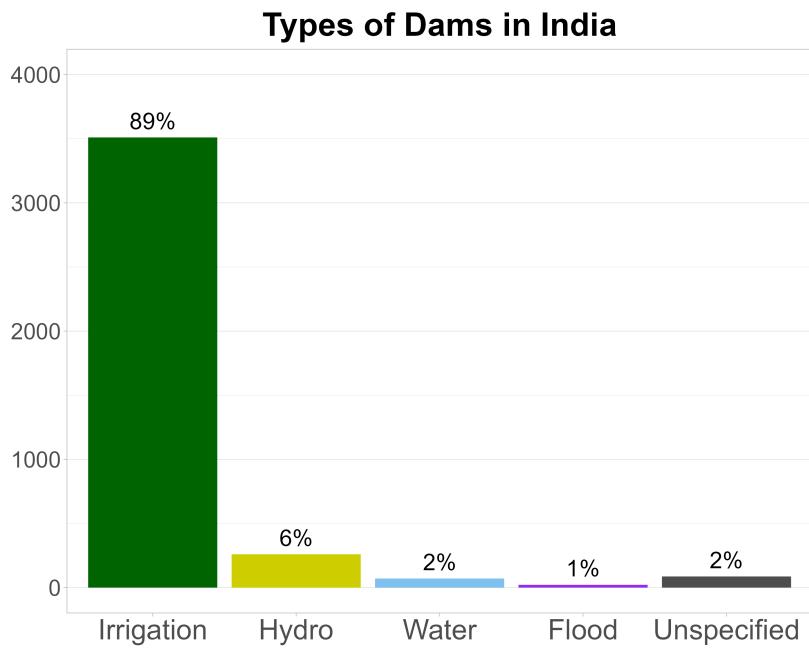
**Figure A1:** Trends in dam construction in India compared to the rest of its South Asian neighbors. [\[back\]](#)

### NFHS Household Clusters

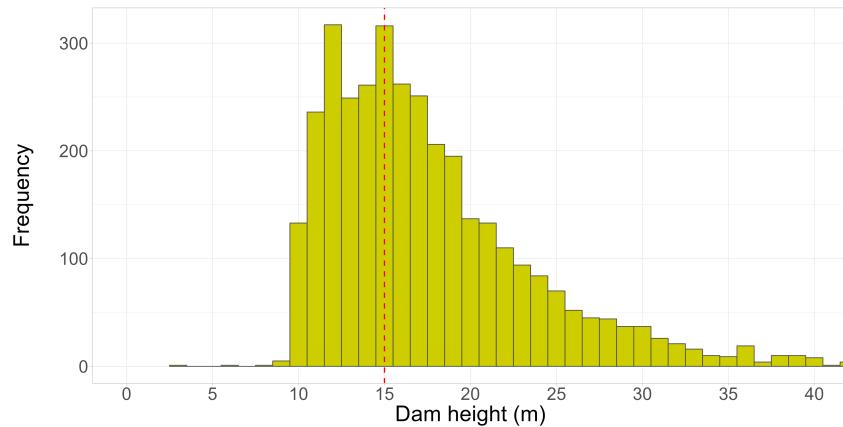


Note: Map presents the household clusters of both rounds (2015/16 and 2019/21).

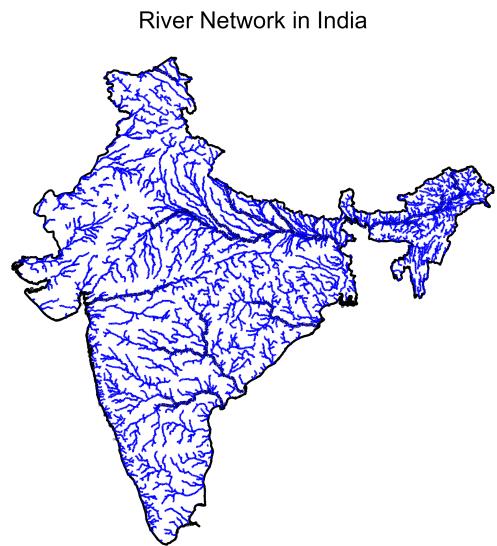
**Figure A2:** Location of the NFHS household clusters across India. Survey includes more than 58,000 household clusters with each cluster having roughly 20 households. [\[back\]](#)



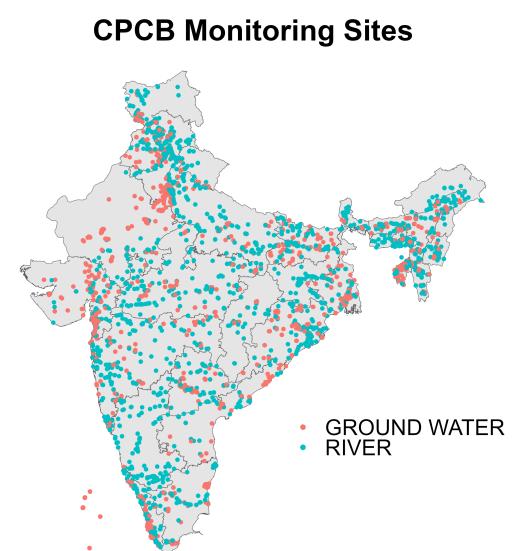
**Figure A3:** Frequency of dams in India by types. [\[back\]](#)



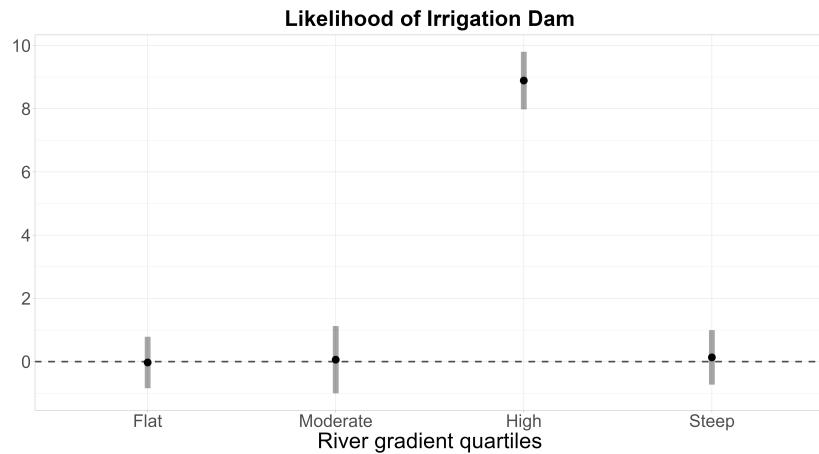
**Figure A4:** Distribution of irrigation dams, constructed from 1990-2014, across dam height. Dotted red line indicates the 15m cutoff used to designate large irrigation dams. [\[back\]](#)



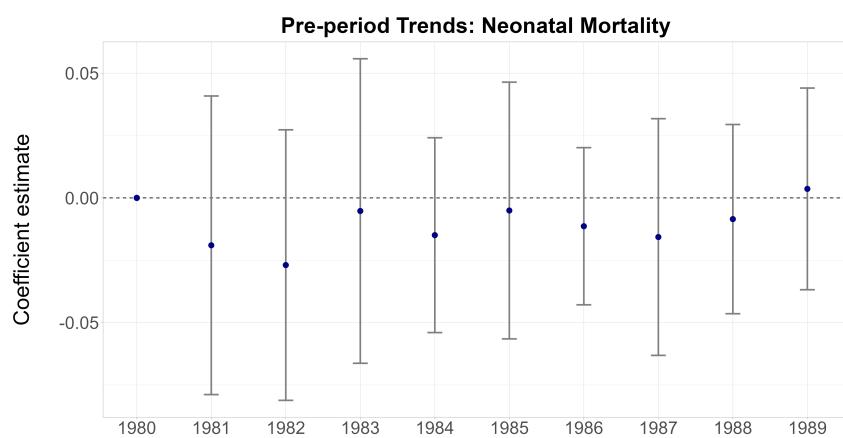
**Figure A5:** River network in India. Data is from the HydroRIVER database. Smaller rivers have been omitted for clarity. [\[back\]](#)



**Figure A6:** Central Pollution Control Board water quality monitoring sites across India. [\[back\]](#)



**Figure A7:** Likelihood of irrigation dam construction across different river gradient bins. [\[back\]](#)



**Figure A8:** Pre-trends in neonatal mortality across states with high and low state-shares of irrigation dams. No significant pre-trend is also observed for post-neonatal and child mortality (provided upon request). [\[back\]](#)

**Table A1:** Links between irrigation dams and water quality. [\[back\]](#)

	Nitrate (mg/L)	Dissolved Oxygen (mg/L)	BOD (mg/L)
	(1)	(2)	(3)
Irrigation dams in basin	0.065*** (0.014)	-0.008* (0.005)	-0.071 (0.049)
Irrigation dams upstream	-0.001 (0.026)	-0.006 (0.009)	0.078 (0.092)
Fixed effects	State + Year	State + Year	State + Year
Geographic controls	Yes	Yes	Yes
Non-irrigation dams	Yes	Yes	Yes
Observations	5,290	5,775	5,765

Asterisks indicates significance: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ . Standard errors are robust to heteroskedasticity. Geographical controls include: area of region, average elevation, average land gradient, and total area of rivers within regions. Non-irrigation dams include the number of non-irrigation dams (e.g., hydroelectricity, flood control, drinking water, and unspecified) constructed in the region.