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

Karan S. Shakya*

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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, high-resolution river and river basin data, and numerous remote-sensed data, I find that irrigation dams increase neonatal mortality in the river basins where they are constructed 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 points out 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

*Department of Agricultural, Environmental and Development Economics, The Ohio State University. Email: shakya.11@osu.edu. I am grateful to Leah Bevis, Daniela Miteva, Abdoul Sam, and participants of the Agricultural & Applied Economics Association 2024 and Camp Resource 2024 for their feedback on this paper.

"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 Shastry 2023). Thorough evaluations of these costs are necessary to better assess the long-term returns of agricultural investments on society.

Among the various agricultural investments, 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.[1] 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. A 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.

[1] 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 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 indicators, 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% higher 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 show that these irrigation dams increase malaria incidences in both local (0.7 percentage points) and downstream (1.0 percentage points) river basins. I then 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. 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 for children in India. I find corroborating evidence when assessing water quality levels through the monitoring stations across India, where areas with a high number of irrigation dams had higher levels of nitrate in their rivers and groundwater.

To further demonstrate that dam-induced increases in chemical fertilizers can lead to greater child health risks, I exploit variations in the timing of conception. Specifically, I assess whether children whose first trimester – when in-utero exposure to agrichemicals is expected to have the most severe impact – coincided with their district's wet or dry sowing period, the month when fertilizer application is highest. I find that neonatal mortality is approximately 0.8 percentage points higher for children whose first trimester overlapped with the sowing period in districts with both high fertilizer use and high irrigation dam intensity. This provides additional evidence that irrigation dams, by increasing agrichemical exposure, impose significant health costs on children.

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 a 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 are 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 lead to an increase in inundated and standing water areas, increase the incidence 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 Shastry 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 hydroelectric 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 (Brainerd and Menon 2014).[2] 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. 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.[3] 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.[4] 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

[2] 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.

[3] 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.

[4] 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.

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 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.[5]

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

[5]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.

includes details such as the year of completion, dam dimensions (height and length), and the primary purpose of construction.[6]

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 into this category.[7] 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.[8]

However, district boundaries have a key disadvantage: regions within a district can vary

[6] I use the most recent: 'GDAT_data_v1.zip' version of the database accessed through Zenodo.

[7] Figure A4 illustrates the distribution of irrigation dams across dam height.

[8] 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.

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 locations within a single district can function as both upstream and downstream areas.[9] 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.[10] 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.[11]

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 agri-

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[9] 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.

[10] All maps and products are publicly available through the HydroSHEDS website.

[11] 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.

cultural 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 resolution.[12] 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.[13] 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.[14] 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.

[12] 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.

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

[14] The surveys are maintained on the ICRISAT website District Level Database.

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.[15] From this database, I use two key indicators: (i) the parasite rate, which 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.[16]

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.[17] 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.

[15] Data can be downloaded from the Malaria Atlas website

[16] 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.

[17] The website for the CPCB Water Quality records can be accessed through their website. However, this newly updated website only records information from 2012 onward. Data from 2007 can be accessed through the old website.

4 Identification Strategy

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

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

where, Y_{ibt} indicates the early-childhood mortality status for child i in region basin b and year t.[18] Dam_{ibt} represents the total number of irrigation dams within each river basin, while LDam_{ibt}^{U} denotes the number of large irrigation dams upstream of the river basin. 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. μ_b represents region fixed-effects that capture all time-invariant unobserved heterogeneity specific to each region, and ϕ_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 β_1 and β_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 gradients 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 boundary.[19] Figure A7 graphically illustrates the likelihood of irrigation dams across these river gradient bins. As expected, the high

[18] 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.

[19] 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.

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, so I interact them with a measure of 'predicted dams' to ensure they are not absorbed by the region fixed effects (Duflo and Pande 2007). This predicted dam variable 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 impact regions based on their river gradient characteristics and historical state-share of dam construction, after accounting for region and year-specific factors.

Formally, my first stage takes the following form:

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

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, ν_b and ϕ_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 designs by either arguing for 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.[20]

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

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

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 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 through 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.

Another component of this paper is to examine the potential channels through which irrigation dams affect children's health. One key pathway I focus on is the increased exposure of pregnant women to agrichemicals. Previous literature highlights that when

[20]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.

babies are exposed to large quantities of agrichemicals during the first trimester, they are at risk for birth defects and mortality. I build on this observation by investigating whether a child's first trimester coincided with the local wet or dry season sowing period – times when fertilizer applications are highest – and whether irrigation dams exacerbate these effects.

Calculating the months of the first trimester for each child is straightforward, but determining the sowing periods for both the wet and dry seasons in each district requires additional steps. There is no official calendar marking the start of the sowing season, as it depends on the crop composition and local climate of each district. To estimate the wet and dry sowing periods efficiently, I pool the raw NDVI values for each district to analyze the seasonality in NDVI. Typically, the sowing period marks the start of the agricultural cycle, a period when crops are planted and begin to germinate. During this time, NDVI values are low but begin to rise rapidly by the end of this period.

For each season in every district, I calculate the point at which the NDVI values are at their lowest. Instead of relying on raw NDVI values, which can fluctuate erratically across months, I use predicted NDVI values generated using a flexible trigonometric polynomial function. These predictions result in smoother, more cyclical NDVI curves that better capture the seasonality of vegetation changes.[21] Figure A8 graphically illustrates this process. For each season, the month with the lowest predicted NDVI values is identified as the sowing period, which corresponds to the time when fertilizer application is at its highest.

I then estimate the following equation.

$$\begin{gathered} Y_{idt} = \gamma_0 + \gamma_1 \text{Sow}_{idt} + \gamma_{2n} \text{Nit}^n_{idt} + \gamma_3 \text{HighDam}_{idt} + \\ \gamma_{4n} (\text{Sow}_{idt} \times \text{Nit}^n_{idt} \times \text{HighDam}_{idt}) + X_{idt} + \mu_d + \phi_t + \varepsilon_{ibt} \end{gathered} \tag{4}$$

Here, Y represents the incidence of neonatal mortality for a child i in district d in year t. Sow is a binary variable indicating whether the child's first trimester coincided with the district's sowing period. Nit is a categorical variable that divides districts into three terciles based on their average nitrogen fertilizer application rate (low, medium, high). HighDam is a binary variable indicating districts with a high number of irrigation dams, which I define as districts with more than 20 dams. The key parameter of interest is γ_4, which represents the triple interaction among a child being born during the sowing period, the nitrogen fertilizer load in the district, and whether the district has a high

[21] Specifically, I use a second-order trigonometric polynomial with the following functional form: $Y_t = \alpha_1 \sin\left(\frac{2\pi t}{1}\right) + \alpha_2 \cos\left(\frac{2\pi t}{1}\right) + \alpha_3 \sin\left(\frac{2\pi t}{0.5}\right) + \alpha_4 \cos\left(\frac{2\pi t}{0.5}\right) + \varepsilon_t$. This function is flexible enough to capture two peaks in NDVI, which is required to estimate the peaks of both the wet and dry seasons for each district. The benefits of using this trigonometric approach over comparing raw means are discussed elsewhere (Shakya, Bevis, and Thorne-Lyman 2024).

number of irrigation dams. Specifically, this estimates the additional risk to neonatal mortality for children whose first trimester overlaps with the sowing period in districts that have both high fertilizer use and a high number of irrigation dams, beyond what would be expected from the sum of their individual effects and pairwise interactions (these pairwise interactions are lumped in X). A significant increase in γ_4 would suggest that the presence of irrigation dams amplifies the harmful effects of agrichemical exposure during critical periods of fetal development, particularly in regions with high nitrogen fertilizer loads.

The identifying variation used to isolate the additional impact of high agrichemical fertilizer exposure in the presence of irrigation dams relies on the assumption that, in India, the timing of conception and births is plausibly random.[22] However, to ensure that seasonal factors and household characteristics do not bias the results, X also includes a set of household controls (identical to those in Equation 3) and environmental controls (rainfall and temperature) to account for potential omitted variable bias.

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

[22] Table A1 presents the balance table comparing children whose first trimester coincided with their districts sowing season and those whose first trimester did not. The differences in key variables are not significant, suggesting that household and district characteristics do not statistically differ between these two groups of children.

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 A9 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.

The effects of irrigation dams on early childhood mortality are not significant when using district boundaries (Table A2). None of the mortality indicators, whether the dams are constructed locally or upstream, show significant changes at the district level. However, as noted earlier, districts in India are large administrative units that aggregates considerable local heterogeneity in household and geographical characteristics, which may obscure any effects that irrigation dams have on child health outcomes.

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 local regions. First, I assess how irrigation dams affect the incidence of malaria indicators. Second, I provide an overview of the land use compositions in the river basins, focusing on three major land classifications: urban, cropland, and forested areas. Third, I test how these irrigation dams impact agricultural productivity and potential changes in agricultural inputs. Finally, I show whether children experience elevated risks when their in-utero development overlapped with periods of high agrichemical exposure.

Most of these channels are estimated using the same instrumental variable strategy as in Equation 3. These analyses are now at the river basin level rather than the child level, so household-specific controls are replaced with broader basin-level controls for the environment (rainfall and temperature).

Table 5 presents the changes to malaria parasite rate and incidence rates at the river basins. Only the IV estimates are presented. Column 2 indicates that irrigation dams in the basin and large irrigation dams upstream increase parasite rate by 0.30 and 0.45 percentage points respectively. A similar result is observed for malaria incidence rates, where these irrigation dams in basin and large irrigation dams upstream increase rates by 0.73 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 areas show increased malaria risk suggests that additional health risk factors may be responsible for the localized health costs generated by irrigation dams.

Table 6 presents the results of how irrigation dams change land use composition at the river basin level. As expected, irrigation dams increase cropland area (column 1), 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 2) and forested areas (column 3). 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, possibly explaining why irrigation dams increased the rates of malaria indicators locally and in downstream river basins.

Table 6 also 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 4) but they significantly increase dry season productivity by approximately 25% (column 5). There are no noticeable dam-induced changes in agricultural productivity 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.

Despite validation exercises showing that local changes in NDVI can serve as a suitable proxy for changes in actual crop yields, there are arguments that, in our sample, NDVI – being a remote measure of vegetation with a spatial resolution of only 500 meters – might not strongly correlate with regional changes in actual crop yields. To internally validate the link between crop yields and NDVI, I compare district-level changes in NDVI with actual crop yield information. The ICRISAT surveys record district-level yields for key crops across India, allowing me to compute wet and dry season yields for each district throughout the sample period.[23]

Table A3 presents district-level changes in both wet season and dry season agricultural yields using both the ICRISAT and NDVI indicators. Columns 1 and 2 present the wet season results, where there is some correlation between the two indicators of productivity, with irrigation dams slightly reducing both wet season yields and NDVI in districts where the dams are constructed. However, large irrigation dams upstream decrease yields while increasing NDVI values, though these discrepancies account for only a small portion of district-level yield changes. Columns 3 and 4 present the results for the dry season, where the relationships between yields and NDVI are more consistent. Irrigation dams constructed in the basin increase yields by approximately 140 kg/ha, with NDVI also rising by roughly 20%. Irrigation dams upstream reduce yields by a smaller amount, which is similarly reflected by a smaller decrease in NDVI. These district-level estimates provide confidence that, in our setting, there are strong correlations between dam-induced changes in yields and NDVI, particularly during 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 7 shows 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

[23] The survey contains information on 10 crops. I define wet season crops as: cotton, groundnut, maize, pigeonpea, pulses, rice, sorghum, soyabean, and sugarcane, and the dry season crops as: barley, castor, chickpea, millet, fruits/vegetables, linseed, oilseeds, onion, millet, potatoes, rapeseed, safflower, sesamum, sorghum (boro season), sunflower, and wheat.

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 7 these results as well. I find that in river basins where irrigation dams are constructed, nitrate levels in the water increase (column 4), 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 5). 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 6), 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.

To further link dam-induced agrichemical increases to neonatal mortality, I estimate Equation 4, examining the effects of a child's first trimester coinciding with the sowing season, variations in fertilizer use, and dam intensity across districts. Table 8 presents results for the wet season (column 1) and dry season (column 2). In the wet season, children in high-nitrogen districts whose first trimester overlaps with the sowing season face a 0.2 percentage point increase in neonatal mortality risk. However, the triple interaction shows no significant variation based on dam intensity. In contrast, for the dry season, districts with high nitrogen levels show a reduced mortality effect. More notably, the triple interaction reveals a significant negative effect (0.8 percentage points), indicating that districts with high irrigation dam intensity and high nitrogen use pose greater risks to children exposed during the dry season sowing period. This finding supports the idea that irrigation dams, which boost dry season agriculture and chemical fertilizer use, increase health risks for children due to greater agrichemical exposure.

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-level 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 provides evidence of the unintended consequences of large agricultural investments and technologies on human health, and the need to account for these costs to ensure that such investments yield the greatest benefits for society.

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Tables and Figures

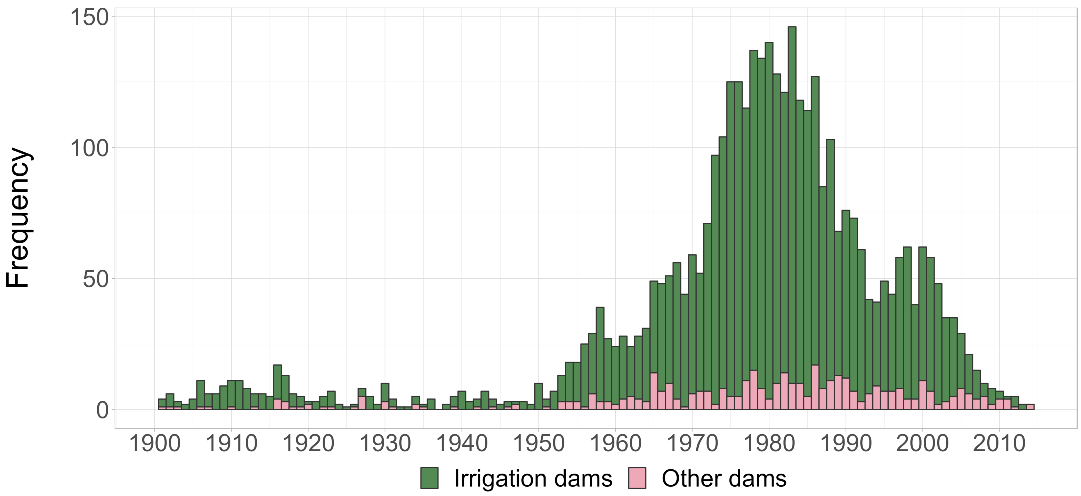
Table 1: Summary statistics of variables at the beginning and end of the sample period. [back]

	Start of Sample		End of Sample		
	Mean	Std.dev	Mean	Std.dev	Change (%)
Child health outcomes					
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
Dam frequency					
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
Agricultural variables					
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
Other variables					
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

For most variables, start of sample indicates values at 1990 and the end of sample indicates values at 2014. The exception, due to data availability, is NDVI values (1990-2013), Urban/Cropland/Forest pixels (2001-2014), and malaria indicators (2000-2014).

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

	Mean	Std.Dev	Min	Max
Mother's characteristics				
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
Household characteristics				
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
Dam characteristics				
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
Geographical characteristics				
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
Boundaries				
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, drinking water, and unspecified dams.

Figure 1: Frequency of dam constructed in India from 1900 onward. [back]

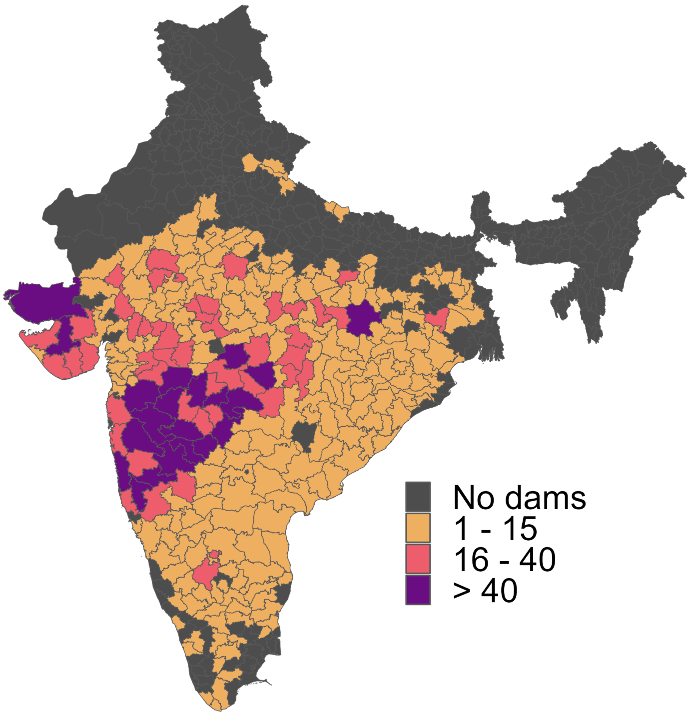
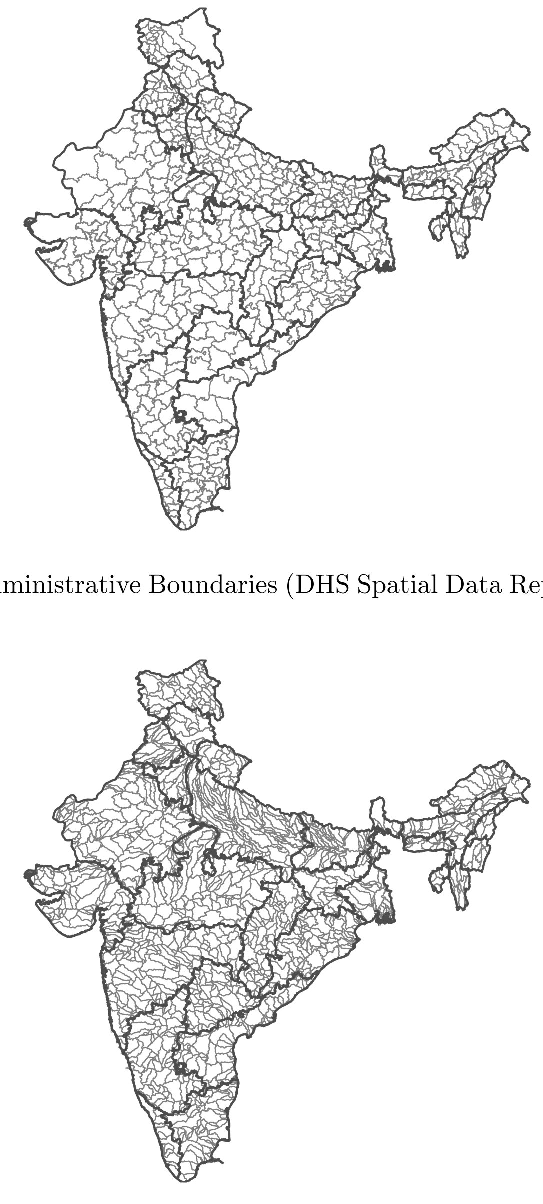


Figure 2: Spatial distribution of irrigation dams across districts. [back]



(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	-4.898**	-0.014	-0.004
	(2.607)	(1.928)	(0.016)	(0.006)
High gradient	16.908***	11.841***	0.046**	0.018***
	(2.086)	(1.649)	(0.021)	(0.006)
Steep gradient	2.361	-1.080	0.072**	0.033***
	(3.321)	(2.432)	(0.036)	(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 incidences at the river basin level. [back]

	Neonatal		Post-neonatal		Child	
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
Irrigation dams in basin	0.0007***	0.0025**	0.0004***	0.0002	0.0004	0.0005
	(0.0003)	(0.0010)	(0.0002)	(0.0004)	(0.0002)	(0.0007)
Large irrigation dams upstream	-0.0034***	-0.0010	0.0004	0.0040	0.0005	0.0006
	(0.0012)	(0.0052)	(0.0007)	(0.0028)	(0.0008)	(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 malaria indicators at the river basin level estimated using instrumental variables. [back]

	Parasite rate	Incidence rate
	(1)	(2)
Irrigation dams in basin	0.0030***	0.0073***
	(0.0010)	(0.0019)
Large irrigation dams upstream	0.0045***	0.0104***
	(0.0016)	(0.0035)
F-test for Riv.Grad	19.2	19.2
Fixed effects	Yes	Yes
Geographic controls	Yes	Yes
Riv.Grad trend	Yes	Yes
Climate controls	Yes	Yes
Non-irrigation dams	Yes	Yes
Dep. var. mean	0.004	0.008
Observations	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 6: Impacts of irrigation dam on land cover change and agricultural productivity (proxied using NDVI) at the river basin level estimated using instrumental variables. [back]

	Land cover changes (%)			log(NDVI)	
	(1) Cropland	(2) Urban	(3) Forest	(4) Wet season	(5) Dry season
Irrigation dams in basin	0.045***	-0.006*	-0.037***	0.010	0.252***
	(0.014)	(0.003)	(0.011)	(0.010)	(0.032)
Large irrigation dams upstream	0.078***	-0.017**	-0.052***	0.007	0.152
	(0.021)	(0.008)	(0.017)	(0.031)	(0.113)
F-test for Riv.Grad	13.2	13.2	13.2	128.7	127.9
Fixed effects	Yes	Yes	Yes	Yes	Yes
Geographic controls	Yes	Yes	Yes	Yes	Yes
Riv.Grad trend	Yes	Yes	Yes	Yes	Yes
Climate controls	Yes	Yes	Yes	Yes	Yes
Non-irrigation dams	Yes	Yes	Yes	Yes	Yes
Observations	15,939	15,939	15,939	28,487	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 7: Impacts of irrigation dam on chemical fertilizer application and water quality measures. [back]

	Fertilizer application (tons)			Water content (mg/L)		
	(1) Nitrogen	(2) Phosphorus	(3) Potassium	(4) Nitrate	(5) DO	(6) BOD
Irrigation dams in basin	1347.186**	540.117*	-132.529	0.065***	-0.008*	-0.071
	(595.368)	(285.286)	(258.873)	(0.014)	(0.005)	(0.049)
Large irrigation dams upstream	-275.007	-22.760	262.434*	-0.001	-0.006	0.078
	(180.268)	(127.059)	(140.745)	(0.026)	(0.009)	(0.092)
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	No	No	No
Climate controls	Yes	Yes	Yes	No	No	No
Non-irrigation dams	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,325	20,325	20,325	5,290	5,775	5,765

Asterisks indicates significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Note: due to data limitations, water quality outcomes (columns 4, 5, and 6) are estimated using OLS with State and Year fixed effects. Standard errors are clustered at the district 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 whether children's first trimester coincide with the district's sowing period across districts with varying irrigation dams and nitrogen fertilizer application intensities. [back]

	Neonatal mortality incidence	
	(1) Wet Season	(2) Dry Season
Sowing season	-0.0000	0.0004
	(0.0006)	(0.0008)
Sowing season × Medium nitrogen	0.0012	-0.0007
	(0.0010)	(0.0011)
Sowing season × High nitrogen	0.0022**	-0.0048***
	(0.0011)	(0.0012)
Sowing season × High dam	0.0010	-0.0043*
	(0.0040)	(0.0025)
Sowing season × Medium nitrogen × High dam	-0.0009	0.0035
	(0.0043)	(0.0032)
Sowing season × High nitrogen × High dam	-0.0010	0.0082***
	(0.0043)	(0.0030)
Constant	0.0465	0.0475
	(0.0366)	(0.0366)
Fixed effects	Yes	Yes
Controls	Yes	Yes
Observations	1,217,373	1,217,373

Asterisks indicates significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Standard errors are clustered at the district level. Fixed effects indicate district and year fixed effects. Controls include the pair-wise interaction between sowing season, nitrogen bins, and high dams. It also includes variables for household wealth index, rural residence, mother's age, mother's education, average rainfall and temperature (with its squared terms).

Appendix A: Supplementary Results

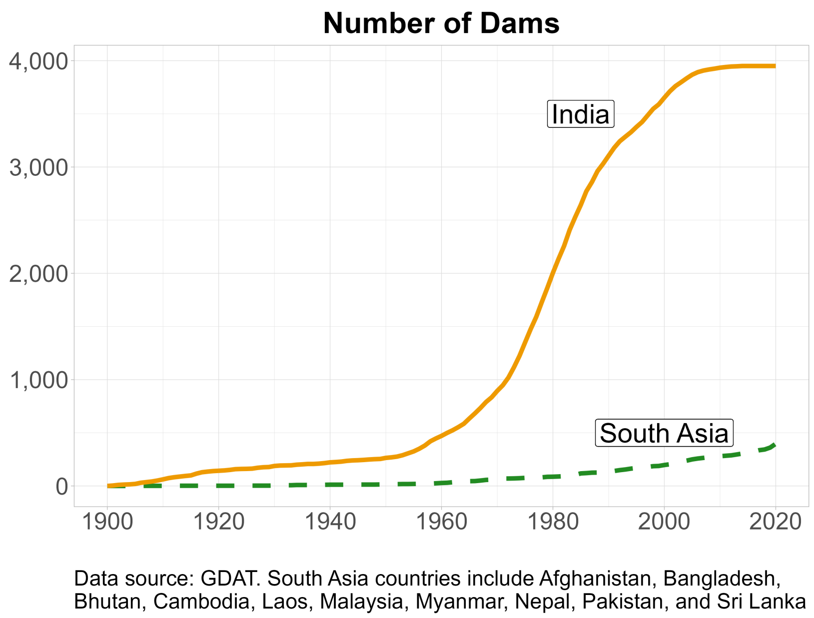


Figure A1: Trends in dam construction in India compared to the rest of it South Asian neighbors. [back]

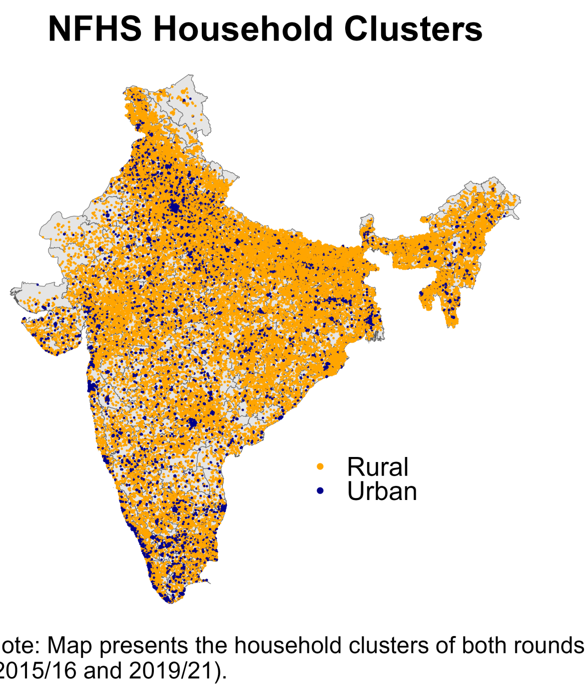


Figure A2: Location of the NFHS household clusters across India. Survey includes more than 58,000 household clusters with each cluster having roughly 20 households. [back]

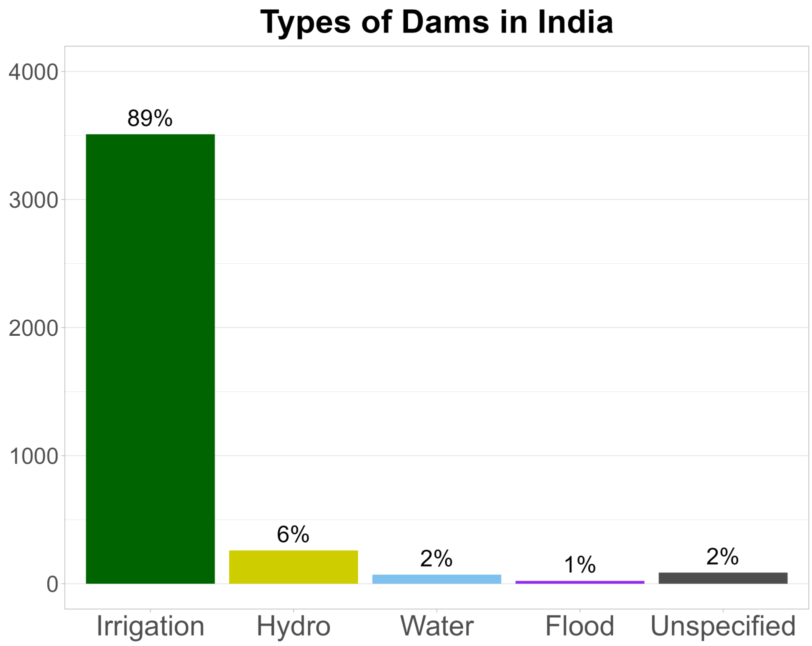


Figure A3: Frequency of dams in India by types. [back]

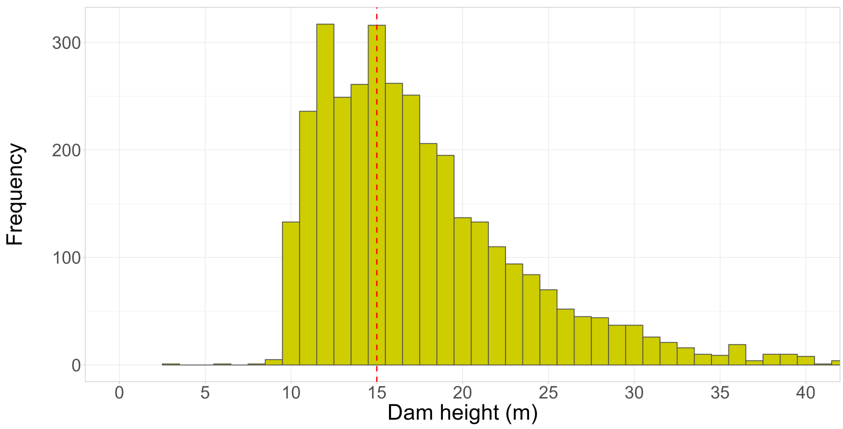


Figure A4: Distribution of irrigation dams, constructed from 1990-2014, across dam height. Dotted red line indicates the 15m cutoff used to designate large irrigation dams. [back]

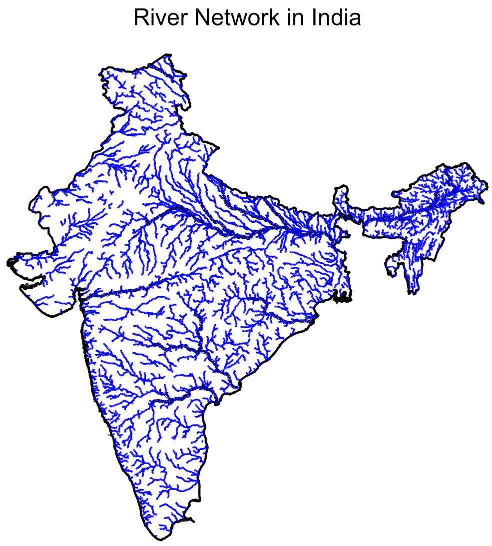


Figure A5: River network in India. Data is from the HydroRIVER database. Smaller rivers have been omitted for clarity. [back]

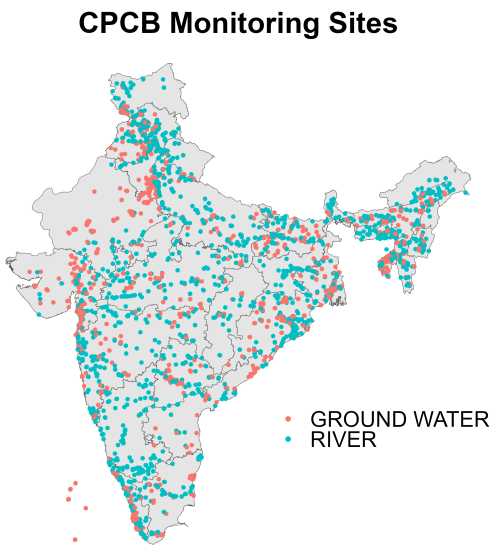


Figure A6: Central Pollution Control Board water quality monitoring sites across India. [back]

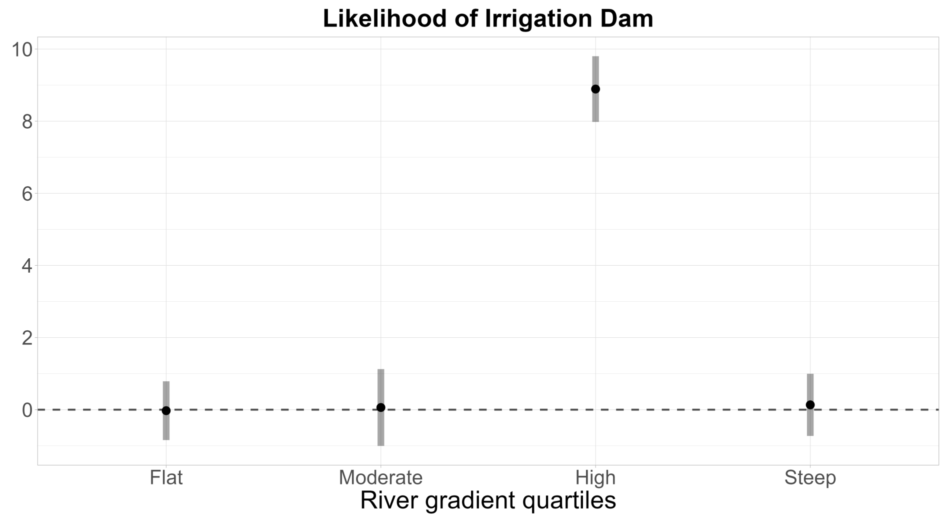


Figure A7: Likelihood of irrigation dam construction across different river gradient bins. [back]

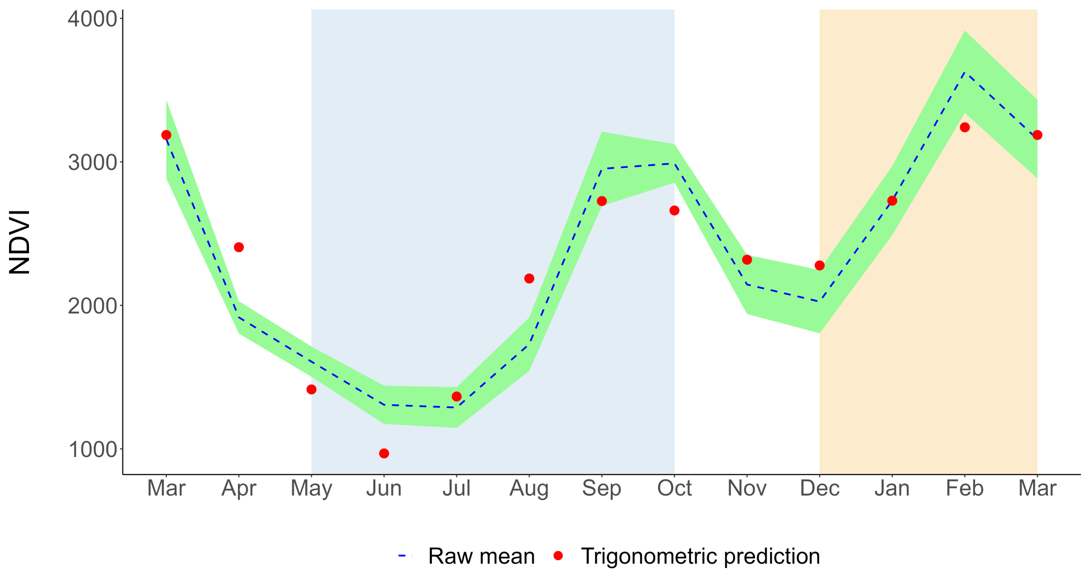


Figure A8: Graphical illustration of the seasonality in NDVI in the Etawah district (Uttar Predesh). Blue dashed line and green shade indicates the raw means and the 95% confidence interval. Red point indicates the predicted NDVI using the flexible trigonometric polynomial. The sowing period, where the predicted NDVI is the lowest during each season, is June for the wet season and December for the dry season. [back]

Table A1: Balance test between children whose first trimester did not coincide with the district sowing period (low-risk children) and children whose first trimester did coincide with the district sowing period (high-risk children). [back]

	Low-risk children		High-risk children		
	Mean	Sd	Mean	Sd	SMD
Neonatal mortality	0.035	0.183	0.035	0.183	0.001
Wealth index	2.484	1.317	2.479	1.324	0.004
Rural households	0.811	0.392	0.809	0.393	0.004
Mother's age	37.574	6.954	37.464	6.979	0.016
Mother's education	0.799	0.951	0.817	0.959	-0.019
Irrigation dams	6.676	12.713	6.095	12.280	0.046
Large irrigation dams	3.849	7.540	3.545	7.349	0.041
Non-irrigation dams	0.621	1.575	0.580	1.550	0.026
Nitrogen	25835.755	22911.187	26067.167	22759.182	-0.010
Phosphorus	10110.809	10197.402	10003.658	10029.697	0.011
Potassium	3577.735	5837.179	3572.307	5780.827	0.001

Standardized mean differences (SMD) < 0.1 indicates well-balanced, < 0.2 indicates moderate imbalanced, and ≥ 0.2 indicates highly imbalanced covariates.

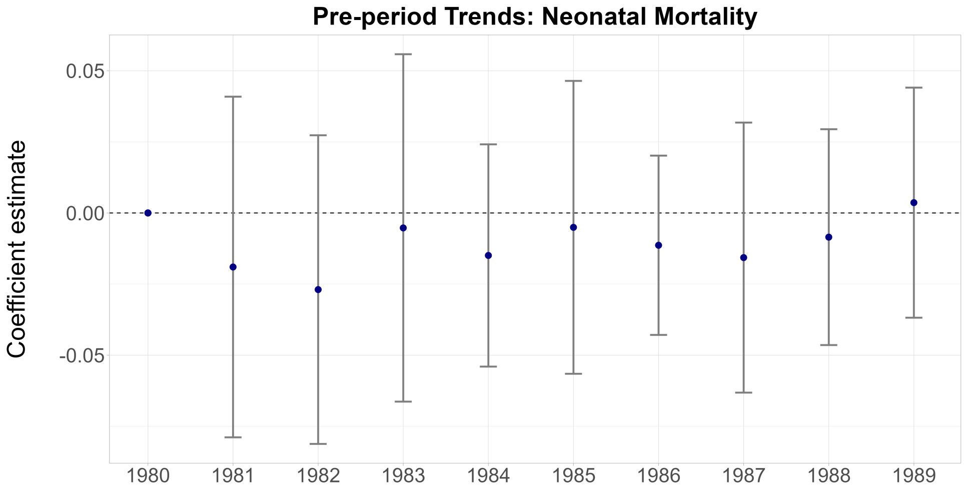


Figure A9: Pre-trends in neonatal mortality across states with high and low state-shares of irrigation dams. No significant pre-trend is also observed for post-neonatal and child mortality (provided upon request). [back]

Table A2: Impacts of irrigation dams on early childhood mortality using district boundaries. [back]

	Neonatal		Post-neonatal		Child	
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
Irrigation dams in basin	0.0001	0.0012	0.0001	-0.0001	0.0003***	0.0007
	(0.0002)	(0.0010)	(0.0001)	(0.0005)	(0.0001)	(0.0007)
Large irrigation dams upstream	0.0001	-0.0000	0.0001	0.0002	0.0002***	0.0001
	(0.0001)	(0.0004)	(0.0001)	(0.0002)	(0.0001)	(0.0003)
F-test for Riv.Grad		15.7		15.7		15.7
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	1,281,392	1,281,392	1,281,392	1,281,392	1,281,392	1,281,392

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-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 A3: Impacts of irrigation dams on agricultural productivity at the district level estimated using instrumental variables. [back]

	Wet season		Dry season	
	(1) Yields (kg/ha)	(2) log(NDVI)	(3) Yields (kg/ha)	(4) log(NDVI)
Irrigation dams in basin	-132.836	-0.017*	137.832***	0.188***
	(81.983)	(0.010)	(45.413)	(0.038)
Large irrigation dams upstream	-68.216**	0.008**	-88.155***	-0.047***
	(33.433)	(0.004)	(17.933)	(0.014)
F-test for Riv.Grad	22.9	26.6	22.9	26.6
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	10,254	10,920	10,254	10,920

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-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 the average of 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).