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Glyphosate Use, Water Contamination, and Neonatal Health in the United States

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Abstract

This study investigates the impact of glyphosate, the most widely used herbicide, on birth outcomes in the US Corn Belt. Using water flow mechanisms to identify causal effects, the study shows that glyphosate affects populations far from application sites through waterborne transmission. The results suggest that a 10 kg/km^2 increase in upstream glyphosate use led to a 4.6 percent rise in neonatal deaths in lower-income areas, with no observed effects in higher-income regions. The research design also incorporates variations in spatial distances, seasonal exposure patterns, and rainfall data to ensure that the observed health impacts are attributable to glyphosate. Evidence suggests avoidance behaviors and water treatment are potential mechanisms of the heterogeneous effects.

Herbicides are widely used in modern agriculture, with glyphosate—commonly known by its trade name, Roundup—being the most extensively applied worldwide. Since the introduction of genetically modified (GM) glyphosate-tolerant crops in 1996, global glyphosate use has surged fifteenfold (Benbrook, 2016). As of 2024, more than 90 percent of soybeans and corn grown in the US are GM herbicide-tolerant crops, with most treated with glyphosate. By providing an easy method for weed control, glyphosate has contributed to food production (Duke and Powles, 2008). However, despite its widespread use and agricultural benefits, research on its potential health risks remains largely limited

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to animal and laboratory studies. Ongoing debates over glyphosate's effects on human health continue to fuel scientific and regulatory discussions (Tiramani et al., 2017; Mendez et al., 2022).

This study provides empirical evidence of glyphosate's health impacts on the general population through its presence in water systems. Glyphosate can be transported to surface and groundwater through mechanisms such as rainfall and leaching, potentially affecting populations far from the application sites. In the United States, which uses nearly 20 percent of the world's glyphosate, the Environmental Protection Agency (EPA) has assessed that current usage levels do not pose significant health risks. In contrast, some countries have adopted more stringent regulations. For example, the European Union's standards for glyphosate in drinking water are 7,000 times stricter than those in the US. Over the past decade, studies have also called for a reevaluation of its toxicity (Myers et al., 2016).

Investigating glyphosate's causal health effects presents challenges typical of pollution studies. Pollution levels and outcomes often correlate with unobserved socioeconomic factors, leading to endogeneity issues (Chay and Greenstone, 2005). For instance, factors such as land use, genetically modified crops, and glyphosate use decisions may not be independent of local agricultural development and socioeconomic conditions (Osawa et al., 2016), such as land ownership, farm sizes (Wang et al., 2017), income, and attitudes towards pesticide and genetically modified crops (Useche et al., 2009). These conditions can also influence health outcomes. Given the impossibility of randomly assigning glyphosate to humans, causal evidence on its health effects remains limited.

To address this identification challenge, this study employs a quasi-experimental framework using water flow mechanisms to investigate the effects of upstream glyphosate on downstream birth outcomes. This approach builds on the work of previous studies, such as those by Dias et al. (2023) and Skidmore et al. (2023). This design mitigates endogeneity concerns, as the correlation between socioeconomic factors of each county and upstream pesticide use is low. I construct a panel dataset covering 13 states from 2001 to 2014 in the US Corn Belt. The US is a major glyphosate user in the world, with the Corn Belt accounting for two-thirds of its glyphosate use.

The study also takes advantage of the distinct rise in glyphosate use during the sample period. Figure 1 illustrates trends in major pesticide use, while Figure 2 depicts fertilizer use. While glyphosate use increased dramatically during the study period, the use of other agricultural chemicals remained relatively stable. This sharp variation in glyphosate use, combined with water flow data, allows for the isolation of its effects, making it unlikely that other socioeconomic factors or chemicals confound the results. The research

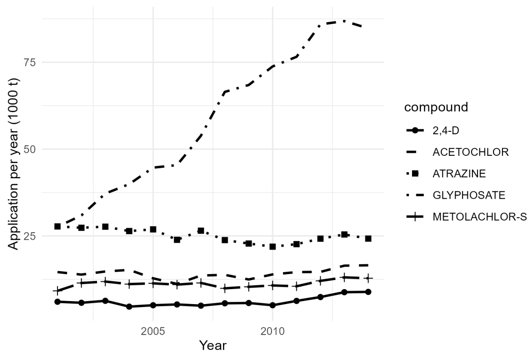

Figure 1: Main pesticide use in the US Corn Belt, 2001-2014. Source: USGS.

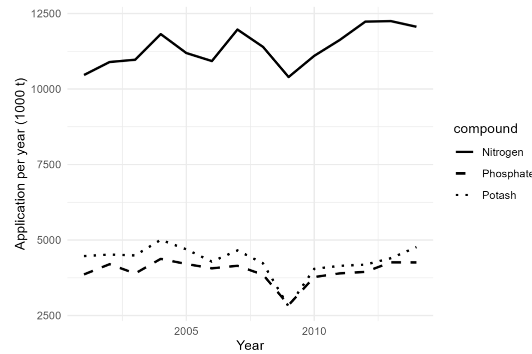

Figure 2: Fertilizer use in the US, 2001-2014. Source: USDA.

design further incorporates variations in spatial distances, seasonal exposure patterns, and rainfall data to ensure that the observed health impacts are attributable to glyphosate water contamination rather than coincidental factors.

This quasi-experimental design reveals that a 10 kg/km^2 increase in glyphosate use in upstream watersheds within 200km leads to 0.153 neonatal deaths per thousand births or a 4.6 percent neonatal mortality rate increase in lower-income areas, with no discernible effects in higher-income areas. Considering that annual glyphosate use upstream on average is 23.46 kg/km^2 from 2001 to 2014 and the average annual number of newborns is 243,645 in the lower-income areas of the Corn Belt, glyphosate use in the study period corresponds to 87.6 annual neonatal deaths (90% confidence interval [32.2, 142.9]). The effects are more pronounced in areas with younger, less educated mothers, higher proportions of white residents, and greater reliance on private wells, but are weaker in areas with timely water system violation notifications. These findings suggest that avoidance behaviors and water treatment may mitigate glyphosate's health impacts. Additionally, the results suggest that glyphosate leads to a higher preterm birth rate. It's worth noting that this study focuses solely on glyphosate's impact on infants and does not consider its effects on older individuals, implying that the overall health impacts may be larger than indicated by the aforementioned numbers.

Prior studies have sought to understand glyphosate's health impacts. However, beyond laboratory experiments, most studies only investigate correlations between glyphosate and birth outcomes, rather than establishing causation (Lacroix and Kurrasch, 2023). These studies primarily examine the relationship between urinary glyphosate concentrations and birth outcomes in humans, often relying on small, regional samples with limited diversity in racial/ethnic and socioeconomic characteristics. The non-random nature of glyphosate exposure makes it challenging to address confounders and provide causal evidence, while the lack of sample diversity limits the ability to explore heterogeneous effects (Parvez et al., 2018; Silver et al., 2021; Gerona et al., 2022; Lesseur et al., 2022).

One exception is Dias et al. (2023), who leverage water flow patterns in Brazil to identify a causal effect: 10 kg/km^2 of upstream glyphosate use in Brazil results in 0.39 additional infant deaths per 1,000 births. Building on their foundation, this study examines the health impacts of glyphosate in the US and further explores heterogeneous effects across socioeconomic contexts. The effects in US low-income areas are smaller than the average effects in Brazil, and the effects are insignificant in US high-income areas.

Studying waterborne glyphosate's impact in a developed country such as the US, as well as its heterogeneous effects, has several important implications. First, the health impacts of pollution are likely to highly depend on government regulations and individual behaviors. Differences in the magnitude of glyphosate's effects across and within countries not only add to our understanding of environmental justice but also shed light on the underlying mechanisms and potential mitigation strategies. Prior research shows that pollution disproportionately affects low-income and minority communities (Banzhaf et al., 2019). This study contributes to this body of knowledge by demonstrating that glyphosate more negatively impacts lower-income areas in the US, despite these areas experiencing lower levels of upstream glyphosate use. Intermediate factors, such as water treatment infrastructure and avoidance behaviors, may play critical roles in explaining these heterogeneous effects, and improving them could mitigate the health impacts.

Second, glyphosate remains at the center of political and scientific debates. Uncovering evidence of glyphosate's impacts across multiple countries reinforces the potential widespread effects, while disentangling exposure mechanisms is essential for effective regulation and targeted mitigation. Although few studies offer causal evidence on glyphosate's health effects, most focus on developing countries (Camacho and Mejía, 2017; Dias et al., 2023; Skidmore et al., 2023). An exception is Reynier and Rubin (2025), who estimate that local glyphosate use reduces birthweight and gestational length in rural US counties using an instrumental variables strategy. However, their analysis does not isolate specific exposure pathways-it remains unclear whether the observed effects result from direct contact, drift, or waterborne transmission. In an appendix, they attempt to assess waterborne exposure using machine learning-predicted glyphosate concentrations, but the predictions have limited accuracy.[1] In contrast, my study directly links upstream glyphosate application to downstream birth outcomes using hydrological flow, providing

[1] Reynier and Rubin (2025)'s out-of-sample R^2 values are 0.59 (random forest) and 0.31 (LASSO), indicating some degree of noise in predicted glyphosate concentrations. They find no significant waterborne effects on birthweight-consistent with my results-and do not examine glyphosate water exposure effects on other birth outcomes.

a more transparent and policy-relevant proxy for waterborne exposure. This approach allows me to isolate the health effects of glyphosate transmitted through water and to focus on neonatal mortality—an outcome not examined in Reynier and Rubin (2025).

Third, developed countries such as the US typically have better-quality data than developing countries. This study benefits from access to fine-grained glyphosate usage data, whereas Dias et al. (2023) imputed local usage from national-level glyphosate use and relied on estimated potential yield gains from the adoption of genetically modified seeds to correct measurement errors. The availability of more precise data in this study allows for a more direct link between glyphosate exposure and health outcomes.

Beyond the literature on health impacts and environmental justice, this study makes two specific economic contributions. First, it advances the economics of water pollution, a field often constrained by limited data on chemical concentrations in water (Keiser and Shapiro, 2019). By focusing on glyphosate application rather than concentration, I identify agricultural externalities that would otherwise remain undetectable due to sparse monitoring data. Second, this study refines the cost-benefit analysis of GM crop and biofuel policies. GM crops and biofuel production are significant sources of glyphosate use. While previous research emphasizes the benefits of these technologies for farm income and rural development (Qaim, 2009; Ali and Abdulai, 2010), the paper highlights an important uncounted cost. The results suggest that glyphosate-induced adverse birth outcomes constitute a significant negative externality that must be weighed against the economic benefits of these policies.

The remainder of this paper is structured as follows: Section 1 provides the changes in glyphosate use in the US, and elucidates the mechanism linking glyphosate contamination to infant health via water sources. Section 2 elaborates on the identification strategies, empirical model, and the dataset employed in the analysis. Section 3 presents the findings and includes detailed robustness checks. Finally, Section 4 discusses the implications and limitations of the study's findings and offers concluding remarks.

1 Background

This section outlines the relationship between glyphosate usage in the US, water contamination, and potential health impacts, providing background and supporting evidence for this study.

1.1 Glyphosate use in the US

Glyphosate serves as a broad-spectrum herbicide used for weed control. The US is a major glyphosate user, accounting for nearly 20 percent of global usage. Since its introduction in 1974, over 1.6 billion kilograms of glyphosate have been used in the US. The introduction and adoption of GM glyphosate-resistant seeds accelerated glyphosate usage starting in 1996. Approximately 67 percent of the total glyphosate used in the US from 1974 to 2014 was applied in the last 10 years of that period (Benbrook, 2016). Glyphosate is mainly sprayed on corn and soybeans, which are predominantly planted in the Corn Belt. In 2014, glyphosate comprised over 40 percent of all pesticide use in the Corn Belt, according to the USGS. The Corn Belt accounts for about two-thirds of glyphosate use in the US. The expansion of the Renewable Fuel Standard in 2007 led to a marked increase in demand for corn ethanol, resulting in more land being planted with corn and further driving up glyphosate use. Figure 1 displays the top-utilized pesticides in the US Corn Belt. It reveals that glyphosate use surged with the adoption of GM crops and had an additional increase around 2007 due to the expansion of corn-based biofuels.

Glyphosate application primarily occurs from April to September. The planting season for corn in the Corn Belt is from April to early June, while for soybeans it spans from May to early July (USDA, 2010). For corn, glyphosate is recommended to be broadcast on the top of the corn plants until they reach 30 inches in height, and applied using drop nozzles when the plants are between 30 and 48 inches tall, typically within 60 days after planting (Ransom and Endres, 2020; Bayer Crop Science, 2020; Bayer Crop Science, 2024). For soybeans, it is generally advised to apply no later than the second reproductive stage, typically within 46 to 83 days after planting (Jhala, 2017; Naeve, 2018; Endres and Kandel, 2021).

1.2 Glyphosate and Water

Glyphosate has been increasingly detected in water sources. Several studies have examined the connection between agricultural activities and glyphosate concentrations in water (Aparicio et al., 2013; Medalie et al., 2020). For instance, Coupe et al. (2012) identified glyphosate in water within agricultural basins such as Iowa and Mississippi, noting that concentrations align with crop application patterns. Although glyphosate monitoring has been infrequent and limited in spatial coverage, its detection in US water systems has risen since the 2000s (Battaglin et al., 2014; Shoda et al., 2020). The Water Quality Portal (WQP) compiles glyphosate data from agencies including the US Geological Survey (USGS), the USDA Agricultural Research Service (ARS), and the EPA. Appendix Figure A1 shows a clear seasonal pattern in glyphosate concentrations in natural water systems, and Tables A1–A3 demonstrate strong correlations between these concentrations and upstream agricultural use. Glyphosate's half-life in water varies between 2 to 91 days, averaging around 40 days (Coupe et al., 2012; Battaglin et al., 2014), depending on factors such as light exposure, microbial activity, and soil absorption (Mallat and Barcelo, 1998).

When glyphosate enters water systems, it can contaminate drinking water (Rendon-von Osten and Dzul-Caamal, 2017; Lima et al., 2022; Brown and Farenhorst, 2024). The US EPA regulates glyphosate, along with over 90 other chemicals, in drinking water.[2] Since 1992, the maximum contamination level (MCL) for glyphosate has been set at 700 $\mu g/L$, compared to 500 $\mu g/L$ in Brazil, 280 $\mu g/L$ in Canada, and 0.1 $\mu g/L$ in the European Union. Public water systems are required to monitor glyphosate once or twice every three years after the initial compliance period, depending on the population served.[3] No public water system exceeded the MCL during the study period, and systems are not obligated to publicly report if detections are below this threshold, leaving exact contamination data for drinking water unavailable.

States are responsible for enforcing water regulations and can adopt stricter standards. However, enforcement stringency varies due to factors such as state budgets, congressional voting patterns, and community characteristics (Sigman, 2005; Grant and Grooms, 2017; Elrod et al., 2019). Public water systems can apply for waivers to reduce monitoring requirements.

Water systems may treat water through various treatments. Studies suggest that methods like adsorption, advanced oxidation processes, and filtration can reduce glyphosate in water supplies (Jönsson et al., 2013; Espinoza-Montero et al., 2020). However, in 2006, about 31 percent of public water systems, or 17 percent of those using their own sources, did not treat their water. Approximately 75 percent of systems rely on groundwater, with nearly half using only disinfection (EPA, 2009). Drinking water quality remains a major environmental concern in the US (Keiser and Shapiro, 2019). Violations among public water systems are prevalent, particularly in lower-income, rural, and non-white communities (Allaire et al., 2018; Mueller and Gasteyer, 2021; Teodoro et al., 2018) and in smaller water systems (Rubin, 2013; EPA, 2014).

Public water systems are required to notify residents about violations. While violations may signal poor water quality, they can also prompt information and potentially trigger avoidance behaviors. For Maximum Contaminant Level (MCL) violations, notifications

[2] Appendix D provides detailed information on monitoring procedures and the full list of regulated chemicals.

[3] Title 40: Code of Federal Regulations, Chapter I, Subchapter D, Part 141, Subpart C, §141.24.

must be sent within 30 days—or within 24 hours for certain chemicals. In contrast, Monitoring and Reporting (MR) violations only require notification within one year. Marcus (2022) find that immediate notifications (within 24 hours) of coliform MCL violations increase bottled water consumption and mitigate adverse health impacts. Hadachek (2024) observe higher bottled water consumption and even reduced infant mortality rates following nitrate MCL violations, particularly in areas with lower poverty rates. The finding suggests that public notifications can lead some individuals to consume safer water, improving health outcomes.

On the other hand, some Americans rely on private water sources rather than public water supplies. According to USGS estimates, from 2000 to 2015, approximately 18.5 percent of the population across the thirteen Corn Belt states primarily sourced their water from private wells. These sources are not regulated by the EPA under the Safe Drinking Water Act (Pieper et al., 2015; Malecki et al., 2017), making private owners responsible for their water quality. Studies suggest private water quality could be poor, though wealthier individuals tend to test and treat their water more frequently and effectively, resulting in better water quality (Smith et al., 2014; Flanagan et al., 2015; Malecki et al., 2017).

1.3 Glyphosate and Birth Outcomes

Through drinking water, glyphosate can affect people far from its application sites. Curwin et al. (2006) and Connolly et al. (2022) detected glyphosate in human urine, finding it not only among farmers and workers directly involved in its application but also among the general population. Grau et al. (2022) found lower glyphosate detection associated with filtered water consumption. In a study by Ospina et al. (2022), glyphosate was quantified in urine samples from 2,310 individuals in the US during 2013-2014, with glyphosate detected in 81 percent of the samples. Moreover, glyphosate exposure extends to pregnant women. Several studies found that more than 90 percent of urine samples from pregnant women in the Midwest and other regions of the US contained glyphosate residues (Gerona et al., 2022; Parvez et al., 2018; Lesseur et al., 2022). Some studies tracking human exposure to glyphosate over time have reported increasing proportions of individuals with detectable levels of glyphosate in their urine (Mills et al., 2017; Gillezeau et al., 2019).

Glyphosate can reach pregnant women and ultimately affect the fetus. Studies have detected glyphosate in the serum of pregnant women at childbirth and in umbilical cord serum (Kongtip et al., 2017) and shown that glyphosate can cross the placental barrier (Mose et al., 2008; Poulsen et al., 2009). In vitro experiments show that glyphosate exposure can trigger apoptosis and necrosis in embryonic and placental cells (Benachour et al., 2007; Tajai et al., 2023), even at concentrations far lower than typical agricultural use and corresponding to levels of indirect exposure (Richard et al., 2005; Benachour and Séralini, 2009). Additionally, glyphosate exposure could induce oxidative stress and inflammation, potentially leading to preterm births (Lesseur et al., 2022).

In summary, this background section underscores the nexus between glyphosate usage, water contamination, and potential health implications, notably regarding birth outcomes. The following section on methodologies will detail the analytical approaches I employ to investigate the causal link between glyphosate exposure and neonatal health outcomes.

2 Methods

2.1 Identification Strategy

To construct an empirical model for identifying the birth impacts of glyphosate, I leverage the glyphosate use changes observed in the 13 states comprising the Corn Belt from 2001 to 2014.[4] Glyphosate use in the Corn Belt drastically increased during the study period. The use of glyphosate in 2014 was three times the amount in 2001. Over this period, these 13 Corn Belt states collectively used 822.4 million kilograms of glyphosate active ingredient, accounting for 66 percent of the total glyphosate use in the United States.

Estimating the impact of glyphosate on health outcomes requires addressing endogeneity issues, as socioeconomic factors often influence planting and pesticide choices. I leverage water flows to examine the effects of upstream pesticide use changes on downstream health outcomes, following Dias et al. (2023) and Skidmore et al. (2023). This design mitigates endogeneity concerns as upstream pesticide adoption is less likely to correlate with socioeconomic factors in downstream areas. Specifically, I use the following equation to identify glyphosate's impact on birth outcomes:

$$Y_{it} = \theta up\_gly_{it} + \boldsymbol{X'_{it}}\boldsymbol{\beta} + \alpha_i + \delta_{st} + \mu_{it}. \tag{1}$$

where Y_{it} denotes a specific birth outcome in county i in year t, up_gly captures the amount of glyphosate use upstream from county i, $\boldsymbol{X_{it}}$ is a set of time-varying control variables, and α_i and δ_{st} denote county and state-year fixed effects, respectively. The base model uses state-year fixed effects because states implement and determine the stringency of water

[4]These states include Illinois, Indiana, Iowa, Kansas, Kentucky, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin. This timeframe was selected based on data availability and to capture a balanced period before and after the 2007 RFS expansion.

regulations, which may change over time. The Appendix Table F2 provides estimates using year fixed effects. To further address endogeneity concerns, the model includes a comprehensive set of time-varying controls. These controls encompass demographics (mother's age, race, marital status, country of origin, hypertension, and diabetes ratios), economic factors (including income, unemployment rate, poverty rate, and agricultural employment share), industrial water pollution, and medical resources (hospital beds, other health providers per thousand population, and per square kilometer). This study not only considers medical resources per capita but also their density, as spatial distances are also a factor affecting birth outcomes (Blondel et al., 2011; Daysal et al., 2015).

Given potential heteroskedasticity—where the variance of the error term may differ across counties due to differences in population size—regressions are weighted by the mean number of newborns in each county over the study period. Counties with fewer births tend to exhibit greater variability in neonatal mortality rates because of small sample sizes. Weighting helps transform heteroskedastic errors into homoskedastic ones (Smith and Taylor, 2017) and make the regression close to the population target (Angrist and Pischke, 2009). Furthermore, because glyphosate exposure from upstream sources tends to be spatially correlated within watersheds, I apply robust standard errors clustered at the watershed level.

2.2 Data

To conduct the analysis, I compiled detailed data on glyphosate use, socioeconomic factors, medical resource metrics, and birth outcomes from 2001 to 2014. Below, I outline the sources of data and the methods used to construct variables.

Glyphosate and Watersheds County-level annual glyphosate usage estimates from 2001 to 2014 are sourced from the US Geological Survey (USGS). To identify glyphosate applied upstream, I connect the glyphosate use data with the Watershed Boundary Dataset (WBD) and Mainstem Rivers of the Conterminous United States (ver. 2.0, Feb 2023) from the USGS.

The WBD provides hydrologic units (HUs) that define drainage areas to streams and rivers based on topographic, hydrologic, and relevant landscape characteristics without regard for administrative or political boundaries. Six levels of HUs, ranging from 2- to 12-digit codes, constitute the hierarchical dataset. Two-unit hydrologic unit codes (HUC2) identify the highest level of drainage areas and are further divided into HUC4, HUC6, HUC8, HUC10, and HUC12. Mainstem Rivers of the Conterminous United States (ver. 2.0,

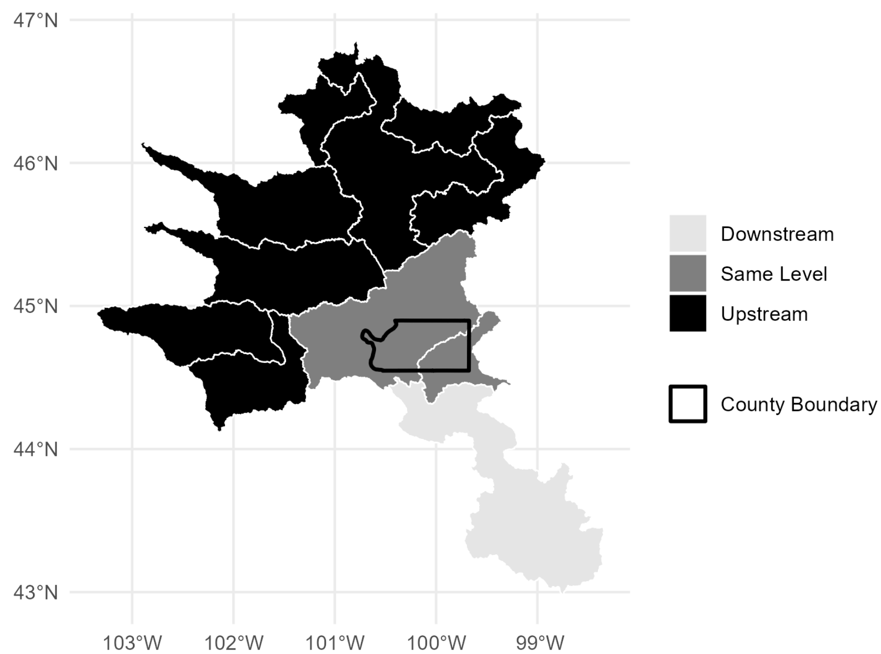

Figure 3: Illustrating the concepts of upstream, downstream, and local areas using Sully County, SD as an example.

Feb 2023) provides information on the hydrologic unit network, defining the upstream and downstream of each unit. HU8 is the smallest level with complete information, and this study employs HU8 units to define the upstream of each county. In total, 496 HU8s cover the counties in the Corn Belt, with an average area of 4,539.9 square kilometers and a median of 3,665.0 square kilometers.

Figure 3 illustrates the upstream and downstream concepts. To determine the hydrologic unit to which each county belongs, I overlay county boundaries with HU8 boundaries. HU8s that intersect with county boundaries are considered the same level for each county and are shown in dark gray. The upstream and downstream HU8s of the intersected HU8 represent the upstream and downstream areas relative to each county and are shown in black and light gray, respectively. This study primarily focuses on upstream areas defined as HU8s within a 200 km radius from the centroid of each county and HU8. Section 3.2 examines alternative definitions of upstream areas based on different distances.

Glyphosate use in each county's upstream is computed using the amount of glyphosate applied per square kilometer (tonne/km^2) in its upstream HU8s. I determine the glyphosate use for each HU8 by the amount applied per square kilometer across all intersecting counties, weighted by the proportion of the intersection area. I also incorporate the amount of glyphosate per square kilometer applied within each county as locally applied glyphosate, serving as a control.

Birth Outcomes Birth outcomes are extracted from the US National Center for Health Statistics (NCHS) vital statistics. The dataset comprises birth records with county-level geographical identifiers and comprehensive maternal information. The main focus is on the neonatal mortality rate (NMR), but I also investigate other birth outcomes, including infant mortality rate (IMR), preterm birth rates (PTBR), term birth weight, and low birth weight rate of term births (LBWR).

NMR is defined as the ratio of neonatal deaths before one week due to health causes per thousand newborns. I exclude deaths caused by external factors like accidents or assaults, as glyphosate is unlikely to influence these external deaths. However, I also examine external NMR for internal validity. IMR considers infant deaths due to health causes up to one year after birth. PTBR is the ratio of babies born alive before 37 weeks of pregnancy completion per 1,000 newborns. Term birth is defined as births occurring between 37 weeks and 41 weeks, and LBWR is the ratio of term birth babies weighing less than 2,500 g per thousand term births.

I calculate birth outcome variables using births conceived within the same calendar year to better match glyphosate exposure, as using birth years would misalign births with minimal exposure to glyphosate in that year. Since glyphosate affects unborn children in utero and most birth outcomes are measured at or shortly after birth, infants born early in a year are more exposed to glyphosate use from the previous year. Therefore, I compute birth outcomes using a conception-year approach, averaging the outcomes for births occurring from September of one year through August of the following year.[5] I also explore averaging the outcomes across different months and report the results in Section 3.3.

The dataset includes demographic information on the mother's age, marital status, race, education, birth country, health conditions (hypertension and diabetes), and details about newborns, such as birth order and plurality (single, twin, triplet, etc.). I use this information as controls.

Other Variables To control additional socioeconomic factors and consider regional health service availability, I incorporate data from the Bureau of Economic Analysis (BEA), the Bureau of Labor Statistics (BLS), and the Health Resources & Services Administration's (HRSA) Area Health Resource Files (AHRF) sourced from Griffith et al. (2021). These

[5]Appendix Figure G8 illustrates the timeline of glyphosate application, birth month, and conception month, showing how using conception year better matches births to the glyphosate application than using birth year. I also consider constructing the conception year using birth month and gestational length. However, since most counties have some missing data on gestational lengths, using only the counties with complete information results in missing observations. Relying solely on births with recorded gestational lengths can lead to inaccurate variables, especially when there are missing data in mortality files.

data provide information on the number of hospital beds, health providers other than hospitals, income, poverty rate, unemployment rate, and agricultural employment ratios at the county level. Income is deflated using the GDP deflator sourced from BEA.

Industrial water pollution serves as an important control to eliminate the possibility of health impacts from other pollutants besides glyphosate. The data are from the EPA's Risk-Screening Environmental Indicators (RSEI), which integrates information from the Toxics Release Inventory (TRI). TRI records toxic chemical releases reported by industrial and federal facilities, regulated by the EPA due to significant adverse health effects. EPA constructs the RSEI and calculates toxicity-weighted water pollution concentrations for each flowline in the US based on TRI data along with the chemical's fate and transport through the environment.[6] To estimate county-level industrial water pollution, this study averaged concentrations across flowlines, weighted by flowline length. I exclude outlier flowlines with a concentration exceeding the 99.99th percentile to address potential reliability issues with self-reported TRI data.[7] Table 9 shows the consideration of various outlier thresholds. Additionally, I examine other top pesticides used and corn and soybean areas in the Corn Belt to ensure the observed effects stem from glyphosate. I source pesticide data from the USGS and area data from the USDA. I compute the upstream use of each pesticide and upstream corn and soybean area using the same methods outlined in Section 2.2 for upstream glyphosate estimates.

Violation records of public water systems are sourced from the Safe Drinking Water Information System (SDWIS) of the EPA. This dataset encompasses basic information about all public water systems in the US. Information regarding water sources, specifically the percentage of people using private water sources, is obtained from the USGS. This data is presented on a 5-year basis. Monthly precipitation data for the Corn Belt is procured from the PRISM Climate Group, featuring a 4km resolution. I aggregate the data to the upstream watershed level for analysis. Water quality metrics—including dissolved oxygen deficit (DOD), nitrate and nitrite nitrogen, phosphorus, total suspended solids (TSS), Escherichia coli (E. coli), and total coliform—are sourced from the Water Quality Portal (WQP).

2.3 Descriptive Statistics

Table 1 provides descriptive statistics for 1126 counties in the Corn Belt from 2001 to 2014. The data are stratified by lower-income and higher-income areas due to significantly

[6] A flowline represents a segment of a stream. It is the basic unit of analysis in the RSEI water Microdata.

[7] https://www.epa.gov/system/files/documents/2022-07/rsei-documentation-geographic-microdata-july-2022.pdf

different glyphosate health effects observed in counties with varying income levels.[8]

Lower-income and higher-income counties exhibit systematic differences across most birth outcomes, glyphosate use, and socioeconomic factors. Lower-income counties tend to have worse birth outcomes compared to their higher-income counterparts. Neonatal mortality rates, infant mortality rates, and preterm birth rates are all higher while birth weight is lower in lower-income areas. The mean of external neonatal mortality rates does not differ between the two regions.

Unlike most pollution, on average, glyphosate use is lower in lower-income areas than in higher-income areas. In contrast, industrial water pollution tends to be more concentrated in lower-income areas, a pattern consistently observed in many studies (Currie, 2011; Banzhaf et al., 2019), although the difference is not statistically significant. Lower-income counties exhibit higher poverty and unemployment rates, with a slightly lower share of the population working in agriculture. There are notable differences in mothers' characteristics. Mothers in lower-income areas tend to be younger, single, and less likely to have college degrees compared to those in higher-income areas. Higher-income areas have slightly more non-Hispanic blacks and fewer non-Hispanic white individuals, likely due to greater racial diversity in urban areas. Lower-income areas have a higher prevalence of mothers with hypertension, while the incidence of diabetes is slightly lower.

In terms of medical resources, lower-income areas have fewer hospital beds and health providers per thousand persons and lower spatial density. They also have a higher proportion of residents relying on private water sources and violation records for both MR and MCL.

Geographically, many lower-income counties are located in the southeastern Corn Belt, while higher-income counties are concentrated in the northwest (Appendix Figures G1). Figures G2 present maps of changes in glyphosate use by income group. Counties with high glyphosate use changes are generally centered in the middle of the region, but both lower- and higher-income areas include counties with varying levels of change. In terms of hydrological characteristics, rivers in lower-income counties have higher average flow rates.[9] However, this difference is largely driven by a few counties through which the mainstem of the Mississippi River flows, resulting in extremely high flow values (Figures G5–G7). Figures G3–G4 show MCL and MR violation coverage by income group. While violations tend to be more common in lower-income areas on average, the spatial

[8] Lower-income areas are counties with average incomes lower than the median average income in the Corn Belt, encompassing 13 states.

[9] Flow rate data are from EPA's NHDPlus Version 2 dataset, which provides three estimates: QA (mean annual flow from runoff), QC (reference-gage regression), and QE (gauge-adjusted flow). County-level measures are constructed as flowline-length-weighted averages.

Table 1: Descriptive Statistics

	Lower-income		Higher-income		Diff
	mean	sd	mean	sd	
	(1)	(2)	(3)	(4)	(5)
Birth outcomes					
Number of newborns	434.70	1192.18	1090.38	3832.71	655.68*
Neonatal mortality rate	3.29	4.68	3.18	7.20	-0.11
External neonatal mortality rate	0.01	0.28	0.01	0.21	-0.00
Neonatal mortality rate (< 28 days)	4.16	5.23	3.80	7.56	-0.36*
Infant mortality rate (< 1 year)	6.24	6.58	5.36	9.07	-0.89*
Preterm birth rate	119.72	34.09	108.42	39.37	-11.30*
Birth weight	3379.71	67.48	3413.50	76.50	33.80*
Glyphosate					
Upstream glyphosate (tonne/km^2)	0.023	0.024	0.033	0.027	0.01*
Downstream glyphosate (tonne/km^2)	0.026	0.021	0.035	0.023	0.009*
Local glyphosate (tonne/km^2)	0.026	0.026	0.038	0.030	0.012*
Economic covariates					
Income per capita (thousand dollars)	32.82	4.38	43.41	8.96	10.59*
Unemployment rate	7.32	2.64	4.90	2.00	-2.42*
Poverty rate	16.14	6.12	10.78	3.04	-5.36*
% employment in agriculture	9.52	7.07	10.63	9.23	1.10
Demographic covariates					
% married	61.18	10.44	69.67	10.21	8.49*
% mothers born outside of the US	4.14	6.11	6.50	7.31	2.36*
% non-hispanic black	2.41	5.48	2.69	5.77	0.29
% non-hispanic white	89.28	15.97	87.76	12.05	-1.52
Mother's age	26.10	0.97	27.41	1.11	1.31*
% of mothers with a college degree	17.31	7.18	28.83	9.74	11.52*
Birth order	2.20	0.24	2.20	0.23	0.00
Number of plurality	1.032	0.02	1.035	0.03	0.003*
% diabetes	5.09	2.78	5.31	3.40	0.23*
% hypertension	7.11	3.10	6.40	3.32	-0.71*
Industrial water pollution					
Industrial pollution concentrations	13.22	175.59	6.37	103.34	-6.85
Medical resources					
Hospital beds per capita*1000	2.80	4.07	5.11	6.76	2.32*
Health providers per capita*1000	0.31	0.23	0.43	0.40	0.11*
Hospital beds density	0.08	0.22	0.21	0.64	0.13*
Health provider density	0.005	0.01	0.009	0.02	0.003*
Water quality					
% using private wells	31.98	24.11	26.28	17.11	-5.71*
MCL violation coverage (%)	8.26	18.30	6.86	17.33	-1.40*
MR violation coverage (%)	13.08	22.64	7.74	16.42	-5.34*
Other					
Monthly upstream precipitation in Apr-Sep	88.11	43.71	79.46	35.04	-8.64*
Monthly upstream precipitation in Oct-Mar	56.52	34.97	35.84	25.17	-20.68*
Flow rate (QA)	1263.47	5509.75	587.58	1835.87	-675.89*
Flow rate (QC)	1091.37	4978.60	468.41	1516.93	-622.96*
Flow rate (QE)	1431.59	6692.02	598.51	1924.74	-833.07*

Notes: Column (5) presents the differences in sample means between groups of counties by median income and test results of the null hypothesis of equality of means via regressions of each variable on a dummy variable representing higher-income areas. Standard errors are clustered at the watershed (HU8) level. * denotes significance at the 5 percent level. Approximately 9 percent of counties have missing data on mother's education. The statistics reported here pertain to the remaining data for the % of mothers with a college degree.

distribution of violations differs from income patterns and shows substantial variation within each group.

The high standard deviations of the birth outcomes are attributed to low population counts and newborn numbers in some counties, resulting in extreme values when only a few births occur and some have unfavorable birth outcomes. To address this issue, I exclude counties with fewer than 25 newborns in any year from the analysis. Different thresholds for extreme values are also explored, with results presented in Section 3.4.

3 Results

Table 2 presents the main estimates of upstream glyphosate on neonatal mortality rate (NMR). The results suggest that glyphosate has significant effects in lower-income areas, but not in higher-income areas. Column (1) demonstrates the estimates of glyphosate use upstream on local NMR for all counties in the Corn Belt. The estimate is small and insignificant, suggesting that glyphosate seems to not directly affect NMR. However, upon closer examination in Column (2), glyphosate actually exhibits heterogeneous effects on different income areas. The coefficients of interactions of upstream glyphosate with the first and second income quartiles are significantly positive. Columns (3) to (8) focus on lower-income areas, and upstream glyphosate estimates are consistently significant across various settings.

In more detail, the estimate in Column (3) comes from the model without any time-varying controls, while the estimates in Columns (4)-(7) are obtained from a model sequentially adding economic, demographic, industrial pollution, and medical resource covariates, excluding local glyphosate use. Column (8) further presents the results with local glyphosate added to the controls. The coefficient values in these six columns are similar. Column (8) reveals that a 1 tonne/km^2 increase in upstream glyphosate use is associated with approximately a 15.32 increase in neonatal deaths per thousand newborns. This translates to a 0.153 increase in the neonatal mortality rate per 10 kg/km^2 of glyphosate, which represents a 4.6 percent increase, based on the average neonatal mortality rate of 3.295 in lower-income areas. Considering the average annual glyphosate use of 23.46 kg/km^2 and an average annual birth count of 243,645 in lower-income areas of the Corn Belt, glyphosate use during the study period is associated with 87.6 neonatal deaths annually (90% confidence interval [32.2, 142.9]).

The minimal impact of controls also suggests that the correlation between upstream glyphosate use and observed socioeconomic factors and mothers' original characteristics in a county is low, reducing the likelihood of omitted variable biases. Appendix Table

Table 2: Glyphosate effects on neonatal mortality rate

	All counties		Lower-income areas					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Upstream glyphosate	1.847	-2.315	15.08**	15.78**	15.65***	15.55***	15.95***	15.32***
	(3.815)	(4.119)	(6.502)	(6.091)	(5.738)	(5.728)	(5.763)	(5.869)
Upstream glyphosate × income quartile 1		15.51*						
		(8.044)						
Upstream glyphosate × income quartile 2		9.166*						
		(4.838)						
Upstream glyphosate × income quartile 3		3.502						
		(4.612)						
Local glyphosate	2.983	2.357						1.538
	(3.359)	(3.304)						(5.503)
Observations	14,630	14,630	7,770	7,770	7,770	7,770	7,770	7,770
R-squared	0.026	0.027	0.031	0.032	0.038	0.038	0.038	0.038
Number of counties	1,045	1,045	555	555	555	555	555	555
Economic covariates	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
Demographic covariates	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Industrial pollution covariates	Yes	Yes	No	No	No	Yes	Yes	Yes
Medical resource covariates	Yes	Yes	No	No	No	No	Yes	Yes

Notes: The dependent variable is neonatal mortality rates. The first row shows the sample areas. See Table 1 for a full list of the economic, demographic, industrial, and medical resource control variables. The variable for mother's college education is excluded from the controls due to missing data. However, the results remain consistent when excluding these counties and including college education as a covariate in the regressions. All regressions incorporate county and state-year fixed effects, and within-R^2 values are reported. Robust standard errors clustered at the watershed (HU8) level are shown in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

F1 presents regressions of local glyphosate and upstream glyphosate on covariates. The estimates indicate that local glyphosate use is correlated with various covariates, including income and unemployment rate, while the correlations between upstream glyphosate and covariates are low, providing additional evidence to support this identification strategy. It's important to note that the estimated glyphosate contamination effect on birth outcomes could be considered a lower bound, as it only considers upstream glyphosate use, excluding local glyphosate use.

The estimate of local glyphosate use is positive but insignificant and small. Local glyphosate effects are likely confounded by the correlation between glyphosate adoption, agricultural development, and socioeconomic effects, as previous studies and the estimates in Table F1 suggest. Regarding the choice of fixed effects, I also explore different fixed effects for the lower-income areas and report the results in Table F2, with all estimates for control variables reported. The results suggest similarity across year fixed effects and state-year fixed effects. Standard errors are clustered at the HU8 level, which was used to determine glyphosate usage, though I also investigate broader watersheds to account for sufficient spatial correlation. Table F3 replicates Table 2, except that standard errors are clustered at the HU4 level, yielding similar values. [10]

For the differing effects of upstream glyphosate use on lower-income and higher-income areas, table 1 reveals some potential reasons. Although glyphosate is used upstream, whether it reaches humans and whether people take avoidance actions could be some key factors in the differing outcomes. Lower-income areas have more people relying on private water sources, which are often less likely to regularly be tested or treated (Pieper et al., 2015; Malecki et al., 2017). Individuals with higher incomes or other characteristics might be more inclined to use filters, possess better filtration systems, or opt for bottled water (Triplett et al., 2019; Hadachek, 2024). Also, whether one can access or afford medical resources might contribute to this variance. Lower-income areas exhibit fewer hospital beds and health providers in terms of both the number per thousand population and spatial density. Section 3.5 and Appendix E will discuss these potential mechanisms in detail and explore heterogeneity with regard to more dimensional factors. Hereafter, I focus on lower-income areas.

3.1 Internal Validity and other birth outcomes

The previous section reveals a correlation between glyphosate use and neonatal mortality rates (NMR). This section assesses the internal validity and explores biological mechanisms by examining glyphosate's effects on various birth outcomes. Table 3 provides estimates of glyphosate's impact on other birth outcomes, utilizing full control, and county and state-year fixed effects, same as the specification in Table 2 Column (8).

Column (1) presents a placebo test for internal validity, using external NMR—deaths from external causes such as accidents-which should remain unaffected by upstream glyphosate use. The result is a small, insignificant estimate, aligning with expectations. Column (2) shows that a 1 kg/km^2 increase in glyphosate use upstream is associated with approximately a 0.177 neonatal death increase per thousand newborns when considering NMR with deaths less than 28 days old. Compared to the point estimates of glyphosate effects on NMR within one week, about 86 percent of the NMR less than 28 days happens in one week, suggesting glyphosate has relatively mild effects on infants who already survive for a period. The estimate for glyphosate effects on infant mortality rates (IMR), accounting for infant deaths up to one year old, is positive as shown in Column (3), but with a p-value of 0.13 and with a smaller magnitude. One reason for this could be that higher mobility after giving birth compared to during pregnancy leads to less accurate glyphosate exposure variables. Additionally, prenatal glyphosate exposure has moderate

[10] In total, 72 HU4 cover the counties in the Corn Belt. HU2 is the largest hydrologic unit, with only eight of them covering the Corn Belt.

Table 3: Glyphosate on other birth outcomes in lower-income areas

	External NMR	Internal NMR (<28 days)	Internal IMR (<1 year)	PTBR	LBWR	Birth weight
	(1)	(2)	(3)	(4)	(5)	(6)
Upstream glyphosate	0.111	17.68***	13.25	106.0**	-19.48	11.38
	(0.313)	(6.797)	(8.816)	(52.34)	(24.55)	(86.44)
Local glyphosate	-0.282	1.766	1.715	45.22	38.35**	29.56
	(0.269)	(5.871)	(7.104)	(40.32)	(19.00)	(75.18)
Observations	7,770	7,770	7,770	7,770	7,770	7,770
R-squared	0.018	0.041	0.048	0.230	0.068	0.176
Number of counties	555	555	555	555	555	555
Full controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The first row indicates the dependent variable of each regression. See the notes to Table 2 for the controls. All regressions incorporate county and state-year fixed effects, and within-R^2 values are reported. Robust standard errors clustered at the watershed (HU8) level are shown in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

effects on infants who have already survived, and the deaths of other reasons may add noise when considering a longer period.

Preterm birth and low birth weight are some of the main causes of neonatal death.[11] I further examine glyphosate effects on preterm birth rate (PTBR), low birth weight rate (LBWR), and birth weight to identify the biological mechanisms. Column (4) shows a statistically significant association between increased glyphosate use and higher preterm birth rates, suggesting that preterm birth may be a pathway for increased mortality. However, in terms of LBWR and birth weight, the estimates appear inconsistent. For LBWR, the upstream glyphosate estimate is not significant, while a positively significant estimate appears for local glyphosate. As for birth weight, glyphosate seems to have no effect.

These findings suggest that birth weight may not be a primary pathway linking glyphosate water exposure to neonatal mortality. One explanation is that birth weight is not necessarily better when higher, as large for gestational age (LGA) is a risk factor for birth complications and long-term health issues (Weschenfelder et al., 2019). Additionally, birth weight is highly correlated with maternal pre-pregnancy weight and gestational weight gain (Zhao et al., 2018). Mothers may control weight gain not only for health reasons but also due to societal pressure (Keyser-Verreault, 2023). This pattern aligns with several studies that find glyphosate exposure is more strongly associated with preterm birth than with birth weight or low birth weight (Savitz et al., 1997; Ling et al., 2018;

[11] https://www.who.int/news-room/fact-sheets/detail/preterm-birth; https://www.who.int/publications/i/item/WHO-NMH-NHD-19.21

Table 4: Placebo test: Downstream glyphosate effects on neonatal mortality rate in lower-income areas

	(1)	(2)	(3)	(4)	(5)	(6)
Downstream glyphosate	-1.294	0.127	0.0916	-0.109	0.0166	-5.669
	(7.740)	(7.952)	(8.220)	(8.232)	(8.063)	(9.145)
Local glyphosate						7.739
						(6.196)
Observations	7,770	7,770	7,770	7,770	7,770	7,770
R-squared	0.030	0.031	0.037	0.037	0.037	0.038
Number of counties	555	555	555	555	555	555
Economic covariates	No	Yes	Yes	Yes	Yes	Yes
Demographic covariates	No	No	Yes	Yes	Yes	Yes
Industrial pollution covariates	No	No	No	Yes	Yes	Yes
Medical resource covariates	No	No	No	No	Yes	Yes

Notes: The dependent variable is neonatal mortality rates. See the notes to Table 2 for the controls. All regressions incorporate county and state-year fixed effects, and within-R^2 values are reported. Robust standard errors clustered at the watershed (HU8) level are shown in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Parvez et al., 2018). It is broadly consistent with Reynier and Rubin (2025), who also find that glyphosate shortens gestation, though they report more robust negative effects on birth weight. This divergence may reflect differences in exposure pathways: their study focuses on local glyphosate use in rural areas, which may capture more direct or multiple routes of exposure, while mine isolates effects transmitted through water, for which birth weight potentially might not be a key mechanism. Differences in population characteristics could also contribute to the heterogeneity.

Overall, the results indicate a correlation between upstream glyphosate use and neonatal deaths short after birth in lower-income areas, but not with mortality due to external causes. To validate the robustness of these findings and demonstrate that the effects are causal and indeed attributable to water contamination from agricultural glyphosate use rather than other factors, I conducted several checks focusing on NMR in lower-income areas. These exercises provide additional supporting evidence for the observed correlations.

3.2 Water Contamination

In this section, I demonstrate that the observed effects stem from water contamination rather than other spatial correlations or alternative channels. I first use available glyphosate concentration data to examine correlations between measured concentrations and glyphosate applications to support the water-contamination mechanism. Concentrations are significantly correlated with upstream use within 200 km, but not beyond, and not with downstream use (Appendix A), suggesting that upstream glyphosate application flows to nearby downstream areas.

If birth outcome effects were driven by other spatial channels rather than water contamination, downstream glyphosate use would still have an impact. Table 4 challenges this alternative channel hypothesis by testing the effects of downstream glyphosate in lower-income areas using the same specifications as Table 2, Columns (3)–(8). The results show that downstream glyphosate effects are consistently small and insignificant across all models, reinforcing the argument that waterborne contamination is the primary mechanism. Similarly, regressions incorporating glyphosate use in nearby areas as an independent variable yield insignificant estimates (Table B1).

I next examine glyphosate effects at greater upstream distances. The results indicate that effects are present within 200 km upstream but diminish beyond this distance, becoming small and insignificant (Table 5). This pattern closely aligns with the relationship between upstream glyphosate application and measured concentrations: concentrations are strongly correlated with glyphosate use within 200 km but not beyond (Table A3). This evidence suggests that the observed effects are not driven by broader agricultural conditions or methodological issues, but rather result from upstream contamination in nearby areas.

I also assess potential economic spillovers as an alternative pathway. Glyphosate use or the adoption of GM crops could impact local industries by boosting agricultural productivity, reducing labor demand for weed control, and reallocating labor to non-agricultural sectors or livestock production. Table F1 already shows correlations between upstream glyphosate and various local conditions are low, which mitigates this concern. However, to fully assess this, I regress various economic indicators on glyphosate use, with results and a detailed discussion in Appendix Section B and Table B2. Most estimates suggest no significant spillover effects, though a few are borderline significant. Notably, the results suggest, if spillovers exist, they may actually be beneficial for birth outcomes, implying that the main estimates could be conservative.

Airborne glyphosate transport is another alternative channel, but this is unlikely. Glyphosate degrades rapidly in the air, and its concentrations are generally too low to travel significant distances (Martins-Gomes et al., 2022). Camacho and Mejía (2017) found that aerial spraying negatively affects health, but these effects were observed from local applications. Since my regressions control for local glyphosate use, airborne exposure is already accounted for. Moreover, if air transport were a major factor, we would expect effects beyond downstream regions. The inclusion of nearby glyphosate use as a control

Table 5: Glyphosate effects on neonatal mortality rate by distance in lower-income areas

	Baseline: 0-200km	200-400km	400-600km	600-800km	All distances
	(1)	(2)	(3)	(4)	(6)
Upstream glyphosate	15.32***	7.678	0.557	3.652	
	(5.869)	(7.339)	(8.419)	(11.25)	
Upstream glyphosate (0-200km)					14.71**
					(6.255)
Upstream glyphosate (200-400km)					5.929
					(9.078)
Upstream glyphosate (400-600km)					-15.30
					(13.91)
Upstream glyphosate (600-800km)					12.12
					(17.01)
Observations	7,770	7,770	7,770	7,770	7,770
R-squared	0.038	0.038	0.038	0.038	0.039
Number of counties	555	555	555	555	555
Full controls	Yes	Yes	Yes	Yes	Yes

Notes: The first row shows the upstream distance of glyphosate being considered. For details on the controls, refer to the notes in Table 2. All regressions include county and state-year fixed effects, and within-R^2 values are reported. Robust standard errors clustered at the watershed (HU8) level are shown in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

further addresses this concern and again yields insignificant estimates, strengthening the case that the primary exposure pathway is through water.

3.3 Agricultural Glyphosate Use

In this section, I provide further evidence that the observed effects on birth outcomes are directly attributable to agricultural glyphosate use. While the previous section established that these effects stem from water contamination, it remains possible that other water contaminants could be responsible, such as co-occurring agricultural chemicals or industrial pollutants. I have included industrial water pollution as a control variable, which mitigates some of this concern. However, this does not fully account for other untracked pollutants.

To address this concern, I examine whether the effects align with glyphosate's unique application and transport patterns. Specifically, I analyze seasonal exposure variations, the role of rainfall in glyphosate runoff, and potential confounding by other agricultural chemicals.

Pesticide use exhibits seasonal variation, influencing environmental exposure and potential health effects (Calzada et al., 2023). Farmers in the U.S. Corn Belt apply glyphosate from April to September, and concentration data in Appendix A and prior studies have documented peak glyphosate concentrations in water during the application period (Coupe et al., 2012). Researchers have also found that exposure during early pregnancy has

Table 6: Glyphosate effects on neonatal mortality rate using different year definitions in lower-income areas

	Birth year	Feb-Jan	Mar-Feb	Apr-Mar	May-Apr	Jun-May	Jul-Jun	Aug-Jul	Sep-Aug	Oct-Sep	Nov-Oct	Dec-Nov	One year lead
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Upstream glyphosate	7.634	7.746	7.912	9.914	10.55	11.20*	14.85**	15.51***	15.32***	11.12*	11.48*	11.52*	10.06
	(6.517)	(6.604)	(6.645)	(6.409)	(6.584)	(6.426)	(6.210)	(5.877)	(5.869)	(6.223)	(6.188)	(6.112)	(6.186)
Local glyphosate	-0.318	2.062	3.539	2.514	2.385	2.765	1.015	1.225	1.538	0.772	-0.582	-0.989	-1.097
	(5.718)	(5.602)	(5.532)	(5.560)	(5.557)	(5.712)	(6.089)	(5.797)	(5.503)	(5.563)	(5.772)	(6.001)	(6.185)
Observations	7,770	7,770	7,770	7,770	7,770	7,770	7,770	7,770	7,770	7,770	7,770	7,770	7,770
R-squared	0.044	0.044	0.045	0.041	0.040	0.038	0.037	0.036	0.038	0.041	0.041	0.043	0.042
Number of counties	555	555	555	555	555	555	555	555	555	555	555	555	555
Full controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The first row reports the year definition of each regression. For example, Column (1) includes infants born in the same calendar year as glyphosate application, while Column (2) considers infants born from February to the following January. For details on the controls, see the notes in Table 2. All regressions include county and state-year fixed effects, and within-R^2 values are reported. Robust standard errors clustered at the watershed (HU8) level are shown in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

stronger effects on birth outcomes (Ling et al., 2018; Gerona et al., 2022). If glyphosate drives the observed effects, its impact should follow a seasonal pattern.

To test this, I redefine birth measurement periods and examine how glyphosate's estimated effects change across different definitions. Table 6 presents the results. When considering infants born in the same calendar year as glyphosate application (Column 1: Birth year), the estimates are small and statistically insignificant. However, when shifting the period to include births from later months (Columns 2 to 9), the effects become larger and more significant, revealing a clear seasonal trend.

This pattern supports the role of glyphosate exposure. Infants born early in the calendar year had no exposure to that year's glyphosate since they were born before the application period. Those born during the application season were primarily exposed in late pregnancy, when susceptibility is lower. The strongest effects emerge when considering birth cohorts from August to the following July or September to the following August—aligning with the conception year used in this study, when the cohorts match glyphosate exposure and exposure during early pregnancy is highest. Appendix Figure G8 illustrates this alignment, showing how using conception year better matches birth cohorts to the relevant glyphosate application period than using birth year.[12]

Further, the estimated effects diminish as additional later months are considered. The statistical significance disappears after one year (Column 13) as many infants are not affected by glyphosate used in the previous year. This provides evidence that the observed effects stem from glyphosate exposure rather than confounding factors that do not follow the same seasonal pattern. The results also serve as a placebo check: the effects only appear when birth cohorts match glyphosate exposure timing, reinforcing internal validity and

[12]Table F4 presents the results using the conception year computed by birth month and gestational length. The effects are similar to the main results with a slightly larger magnitude, likely because this method captures more direct glyphosate effects but at the cost of missing observations.

Table 7: Rainfall and seasonal heterogeneous effects on neonatal mortality rate in lower-income areas

	Rainfalls	
	April-Sep	Oct-Mar
	(1)	(2)
Upstream glyphosate	5.032	1.031
	(8.945)	(10.50)
Rainfall quartile 2 × upstream glyphosate	7.480	15.45
	(6.757)	(9.837)
Rainfall quartile 3 × upstream glyphosate	10.32	15.42
	(6.859)	(11.34)
Rainfall quartile 4 × upstream glyphosate	18.74**	13.56
	(7.662)	(11.51)
Local glyphosate	2.152	2.291
	(5.469)	(5.440)
Observations	7,770	7,770
R-squared	0.040	0.040
Number of counties	555	555
Full controls	Yes	Yes

Notes: Columns (1) and (2) show regression results with interactions between rainfall quartiles and glyphosate use. The regressions also control for unreported rainfall quartiles. The second row specifies the months of rainfall considered. For details on controls, see Table 2. All regressions include county and state-year fixed effects, and within-R^2 values are reported. Robust standard errors clustered at the watershed (HU8) level are shown in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

ruling out methodological coincidence.

Furthermore, glyphosate is transported into water systems primarily through runoff, making precipitation a key factor in determining exposure. If the observed health effects are driven by glyphosate contamination rather than other pollutants, we should observe stronger effects when upstream rainfall is higher during the application season.

To examine this, I interact glyphosate use with quartiles of monthly upstream precipitation data, both within and outside the application season. The precipitation quartiles are defined across counties and years, following Dias et al. (2023). Column (1) of Table 7 shows that the interaction between glyphosate and the highest quartile of rainfall during the application season yields a significantly positive coefficient. The estimate for the third quartile is also positive but smaller and statistically insignificant, while effects for the second quartile are even weaker. This suggests that significant rainfall amplifies glyphosate's impact, consistent with runoff-driven water contamination. In contrast, Column (2) finds no significant interactions between glyphosate and rainfall quartiles from October to

Table 8: Testing the effects of overall agricultural chemicals on neonatal mortality rates

	(1)	(2)
Corn and soybeans area	0.0341	0.0231
	(0.0273)	(0.0280)
Upstream glyphosate		14.31**
		(6.038)
Local glyphosate	5.531	1.678
	(5.465)	(5.506)
Observations	7,770	7,770
R-squared	0.038	0.039
Number of counties	555	555
Full controls	Yes	Yes

Notes: For details on the controls, see the notes in Table 2. All regressions include county and state-year fixed effects, and within-R^2 values are reported. Robust standard errors clustered at the watershed (HU8) level are shown in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

March, further confirming that glyphosate's effects depend on seasonal rainfall.

A remaining concern is whether other agricultural pollutants following seasonal patterns could be confounding the glyphosate estimates. However, this is unlikely. Glyphosate use surged during the study period due to GM crop adoption, while the use of other agricultural chemicals remained relatively stable. If other chemicals were driving the effects, we would expect NMR to correlate with overall agricultural activity, not just glyphosate use.

To test this, I analyze the relationship between NMR and upstream acreage of corn and soybeans—the primary crops treated with both glyphosate and other agricultural chemicals in the Corn Belt. Table 8 presents the results. Column (1) shows a weak, statistically insignificant correlation between NMR and upstream crop acreage ($p = 0.21$). In Column (2), when upstream glyphosate use is included, the coefficient for crop acreage becomes even less significant, while glyphosate use remains highly significant. This suggests that glyphosate, rather than other agricultural chemicals, is the primary driver of the observed health effects.

Further, I examine correlations between glyphosate use and various agricultural water quality measures (Hooda et al., 2000; Kato et al., 2009; Keiser and Shapiro, 2018; Liu et al., 2023). Regressions in Appendix Table C1 show no significant correlations. The results support the notion that glyphosate use increased distinctly during the study period and does not significantly covary with these water quality measures. However, weak positive

Table 9: Robustness checks on neonatal mortality rate by different outlier definitions in lower-income areas

	Births ≥ 50	Births ≥ 100	W/O RSEI > 99.95 percentile	W/ all RSEI
	(1)	(2)	(3)	(4)
Upstream glyphosate	14.60**	16.61***	15.60***	15.31***
	(6.020)	(5.859)	(5.870)	(5.882)
Local glyphosate	2.079	2.809	1.362	1.645
	(5.575)	(5.719)	(5.504)	(5.535)
Observations	7,336	6,230	7,770	7,770
R-squared	0.040	0.044	0.038	0.038
Number of counties	524	445	555	555
Full controls	Yes	Yes	Yes	Yes

Notes: The first row shows the considered subsample. For control details, refer to Table 2. All regressions include county and state-year fixed effects, and within-R^2 values are reported. Robust standard errors clustered at the watershed (HU8) level are shown in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

associations are found with phosphorus (p = 0.20) and nitrate/nitrite nitrogen (p = 0.14), which are linked to fertilizer use. To rule out confounding, I add nitrogen and phosphorus as controls in the NMR regressions. Table C2, Columns (1)-(4), shows that glyphosate's estimated effects remain stable regardless of these controls. Columns (5)-(6) further test other widely used pesticides, yet glyphosate's estimate remains consistently significant. These findings reinforce that glyphosate, rather than other agricultural pollutants, is responsible for the observed neonatal health effects.

3.4 Other robustness checks

Previous sections demonstrate that glyphosate impacts birth outcomes in lower-income areas due to agricultural glyphosate water pollution. The next step is to ensure the robustness of the chosen thresholds for extreme values. I test various thresholds to examine their impact on the conclusion of glyphosate effects. Table 9 displays the estimates obtained from different outlier definitions. The baseline models in the analysis consider counties with 25 or more births annually, as some neonatal mortality rates may be extremely high due to the small number of births in certain counties. Columns (1) and (2) present estimates with stricter criteria: counties with 50 or more births and those with 100 or more births, respectively. These results are consistent with the baseline findings.

Columns (3) and (4) address the outlier definition based on industrial water pollution indicators (RSEI). Column (3) presents the estimate with industrial water pollution averaged across flowlines below the 99.95th percentile, while Column (4) reports the estimates without any exclusions, whereas the baseline considers flowlines below the 99.99th percentile. Notably, all estimates remain similar across different threshold choices, indicating the robustness of the results.

3.5 Potential Mechanisms

Previous sections demonstrate the robust and significant effects of glyphosate on neonatal mortality rates in lower-income areas. A further consideration is why these effects are primarily observed in lower-income areas rather than in higher-income ones, with a detailed discussion provided in Appendix E.

Evidence indicates that water consumption behaviors and water treatment may play important roles in shaping exposure risks and contribute to the observed heterogeneity. Stronger impacts are observed in areas with younger, less educated, and more non-Hispanic white mothers (Table E1, Columns 1–3), populations that are more likely to rely on tap water directly (Yang and Faust, 2019; Triplett et al., 2019; Park et al., 2022). At the same time, higher-income individuals are more likely to use bottled water and filters (Pieper et al., 2015; Malecki et al., 2017). In addition, glyphosate's effects are stronger in areas that rely more heavily on private water sources (Table E1, Column 4), which lack regulation and systematic treatment. Because lower-income areas have a higher share of private water users, these patterns suggest that differential water treatment may also be an important contributor to the heterogeneous effects.

4 Conclusion

This study provides robust evidence of the impacts of glyphosate, the most commonly used herbicide, on birth outcomes through water contamination. By employing a quasi-experimental framework that considers water contamination mechanisms and various robustness checks, the research establishes a causal relationship between glyphosate and adverse birth outcomes. The evidence suggests that a 10 kg/km^2 increase in glyphosate application in upstream watersheds within 200km leads to a 4.6 percent increase in neonatal deaths per thousand births in lower-income areas, with no significant effects observed in higher-income areas. The average glyphosate use in the upstream regions of lower-income areas in the Corn Belt is 23.46 kg/km^2 per year in the study period, which corresponds to an estimated 87.6 additional neonatal deaths annually. This finding adds new information to the ongoing controversy surrounding glyphosate.

The two potential mitigation strategies include the use of bottled or filtered water by consumers and the treatment of public water systems to remove glyphosate. Although using filters and bottled water would have individuals pay the social costs. Using bottled water for drinking and cooking could cost a family between $983 and $4,757 annually (Javidi and Pierce, 2018), and the spending often accounts for a higher proportion of income for minorities (Gorelick et al., 2011). Moreover, without adequate contamination information, individual efforts may be inefficient. Enhancing water quality monitoring and providing timely contamination information could improve individual decision-making.

On the other hand, A review of US drinking water regulations indicates that treatment requirements for water systems often provide greater benefits than costs (Keiser and Shapiro, 2019). Methods such as adsorption, advanced oxidation processes (AOPs), and filtration can reduce glyphosate in water supplies (Jönsson et al., 2013; Espinoza-Montero et al., 2020). Among these, filtration is the most widely used but offers moderate glyphosate removal (Jönsson et al., 2013). AOPs are promising but require further research for large-scale deployment (Feng et al., 2020). Adsorption, such as via activated carbon, is both effective and already in use—one study finds that activated carbon can remove over 99 percent of glyphosate (Grant et al., 2018).

Based on estimated costs of granular activated carbon (GAC) ranging from $0.10 to $0.36 per 1,000 gallons (Heberling et al., 2015, 2022) and an average daily per capita water use of 86 gallons from USGS, annual per-person treatment costs would range from approximately $3 to $10.80—substantially lower than bottled water.[13] A back-of-the-envelope calculation suggests that reducing one neonatal death through this strategy would cost between $0.67 million and $2.4 million.[14] GAC also removes other harmful contaminants such as PFAS and pesticides, offering additional public health benefits (Belkouteb et al., 2020; DiStefano et al., 2022).[15] While more research is needed for a full cost-benefit analysis, these estimates suggest that public water treatment could be a cost-effective mitigation strategy.

Another potential strategy is to reduce glyphosate use at the source. This study

[13]GAC costs are reported in 2016 dollars. Average daily per capita water use is from the USGS (https://www.epa.gov/watersense/statistics-and-facts).

[14]This estimate is based on a population of 19.6 million in lower-income Corn Belt counties, 87.6 neonatal deaths annually, and the simplifying assumption that glyphosate removal averts all associated deaths. If one were to use the value of a statistical life as a benchmark for benefits, the implied benefit of preventing one neonatal death would be $9.9 million (2016$) in the US (https://www.transportation.gov/office-policy/transportation-policy/revised-departmental-guidance-on-valuation-of-a-statistical-life-in-economic-analysis), which is substantially larger than the estimated costs.

[15]https://www.epa.gov/sdwa/overview-drinking-water-treatment-technologies

shows that upstream applications can harm downstream populations, highlighting a clear externality. These findings offer economic justification for stronger upstream regulations, such as buffer zones or application limits. That said, tighter controls must consider the costs and benefits. This study does not quantify the full social cost of glyphosate use, but it presents evidence that the associated health costs may be substantial and should be considered in future regulatory evaluations.

Overall, this research contributes to the growing body of literature on glyphosate's health impacts on indirectly exposed populations, specifically in relation to birth outcomes. Further investigation is needed to explore the effects of glyphosate exposure on human health across different demographics.

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Appendix: Glyphosate Use, Water Contamination, and Neonatal Health in the United States

A Glyphosate concentration

To examine the relationship between glyphosate application and water concentrations, I use data from the Water Quality Portal (WQP), which compiles publicly available glyphosate concentration measurements from the USGS, USDA ARS, and EPA. However, glyphosate concentration data suffer from sparse coverage: over 80% of counties in the Corn Belt lack any glyphosate monitoring, and among those with data, about 70% have observations from only a single year.

Due to the limited number of repeated observations per county, it is not feasible to include county fixed effects to capture within-county temporal variation. I pool the data across counties and years and include fixed effects and covariates to account for both temporal (monthly) and spatial (geography) confounders. I estimate the following pooled cross-sectional model:

$$C_{ijtmh} = \alpha_0 + \alpha_1\, up\_gly_{it} + \alpha_h + \tau_m + \boldsymbol{X}_i'\gamma + fr_i + \varepsilon_{ijtmh}$$

where C_{itmh} denotes the glyphosate concentration record j in county i, year t, HU2 h, and month m, up_gly_{it} represents glyphosate application upstream of county i in year t, α_h captures HU2 fixed effects to account for shared hydrological conditions, and τ_m are month fixed effects to adjust for seasonal variation in glyphosate concentrations (see Figure A1). The vector $\boldsymbol{X}_i'$ includes geographical controls such as average slope, soil erodibility, and stream level, and fr_i accounts for average flow rate.[16]

[16] Slope and flow rate data are from the EPA's NHDPlus Version 2 dataset, which reports slope, stream level, and three types of flow rate estimates for each flowline. I construct county-level variables by averaging values across all flowlines within a county, weighted by flowline length. The flow metrics include: QA (mean annual flow from runoff), QC (mean annual flow estimated via reference-gage regression), and QE (mean annual flow from gage adjustment). These three estimates are highly correlated. Stream level identifies

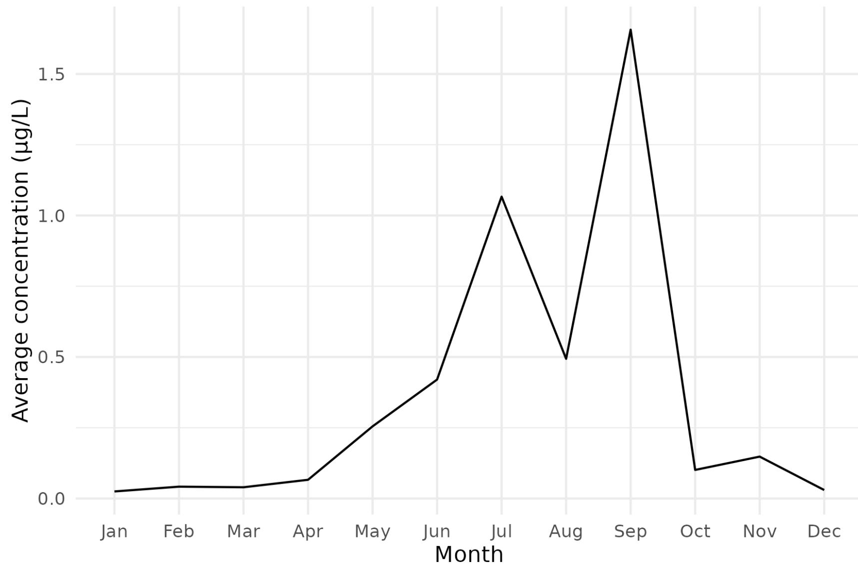

Figure A1: Average glyphosate concentration by month (2001-2014). Source: WQP.

Table A1 shows that glyphosate concentrations are significantly correlated with upstream glyphosate across all specifications. Interestingly, glyphosate concentration is not significantly correlated with local glyphosate use. Likely because local glyphosate captures the average glyphosate use in the county, but can't capture the application locations. Some applications may be downstream of monitoring stations, making the estimate noisy.

Table A2 repeats the same specification to downstream glyphosate. As expected, downstream glyphosate shows no significant relationship with glyphosate concentrations, supporting the validity of the model specification. Table A3 further includes upstream glyphosate use farther away and shows that glyphosate use beyond 200 km does not consistently correlate significantly to concentrations. This pattern closely aligns with the main finding that health effects are present within 200 km upstream but diminish beyond this distance.

To explore whether the heterogeneity in health effects is driven by geographic conditions differing by the income areas, I interact upstream glyphosate with income groups

whether a segment is part of the mainstem (lower values) or a tributary (higher values). Soil erodibility is obtained from the Gridded Soil Survey Geographic (gSSURGO) Database and averaged across all 30-meter cells within each county. I use readings from all monitoring stations for dissolved glyphosate. To avoid the influence of outliers, I drop readings of glyphosate above the 99.5th percentile.

Table A1: Relationship between glyphosate concentrations and upstream glyphosate applications

	(1)	(2)	(3)	(4)	(5)	(6)
Upstream glyphosate	3.386**	4.496***	4.503***	4.488***	4.478***	4.338***
	(1.413)	(1.584)	(1.582)	(1.580)	(1.580)	(1.371)
Local glyphosate	-1.267	-2.464	-2.530	-2.524	-2.506	-2.099
	(1.326)	(1.551)	(1.552)	(1.551)	(1.551)	(1.446)
Observations	3,099	3,099	3,099	3,099	3,099	3,099
R-squared	0.040	0.046	0.047	0.047	0.047	0.049
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Geogrophic covariates	No	Yes	Yes	Yes	Yes	Yes
Flow rate	No	No	QA	QC	QE	QA
HU2 FE	No	No	No	No	No	Yes

Notes: The dependent variable is glyphosate concentrations. Robust standard errors clustered at the watershed (HU8) level are shown in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

and flow rate. Table A4 presents the results. I find that the relationship between upstream glyphosate and concentrations does not differ between income regions (Column 1), suggesting the natural geography in these two regions does not lead to different concentrations and is not sufficient to explain the stronger health impacts in lower-income areas. Also, I found glyphosate concentrations are more strongly associated with upstream use in counties with moderate flow rates (Columns 2-4), likely because high flow rates dilute contaminants. However, this heterogeneity in concentration by flow rate does not align with the pattern across income levels: more lower-income counties have higher flow rates, yet still show stronger health impacts.

Column (5) discusses whether glyphosate is easier to transport through surface water or groundwater and shows no statistical difference in the sample, either from upstream glyphosate or local glyphosate. One possible reason is that groundwater and surface water highly interact in the US (Winter et al., 1998) and can be the source of contamination for each other (Duncan et al., 1991; Squillace et al., 1993; Malaguerra et al., 2012; Van Stempvoort et al., 2016).[17]

Table A5 presents the correlations between concentrations and upstream glyphosate

[17]The interaction of groundwater and upstream glyphosate shows a big magnitude. This may be due to sample selection. Groundwater monitoring data contains more extreme high values.

Table A2: Relationship between glyphosate concentrations and downstream glyphosate applications

	(1)	(2)	(3)	(4)	(5)	(6)
Downstream glyphosate	1.132	1.830	1.980	1.967	1.951	2.067
	(2.181)	(2.093)	(2.089)	(2.088)	(2.087)	(2.296)
Local glyphosate	0.114	-0.242	-0.387	-0.386	-0.367	-0.235
	(1.603)	(1.626)	(1.616)	(1.615)	(1.616)	(1.525)
Observations	3,099	3,099	3,099	3,099	3,099	3,099
R-squared	0.031	0.034	0.035	0.036	0.036	0.040
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Geographic covariates	No	Yes	Yes	Yes	Yes	Yes
Flow rate	No	No	QA	QC	QE	QA
HU2 FE	No	No	No	No	No	Yes

Notes: The dependent variable is glyphosate concentrations. Robust standard errors clustered at the watershed (HU8) level are shown in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

by rainfall quartile within and outside the application season, using the same quartile definitions applied in the health impact specifications. The results show that within-season precipitation increases the correlation between upstream glyphosate use and downstream concentrations, while outside-season rainfall has no significant effect. While the point estimate of the correlation in the highest rainfall quartile (Q4) is slightly lower than in Quartile 2, the difference is not statistically significant. This pattern suggests that dilution due to excessive rainfall is not a major concern in the study region. One possible reason is that precipitation levels in the Corn Belt, while variable, are generally moderate and do not reach levels that would overwhelm dilution thresholds.

Table A3: Relationship between glyphosate concentrations and upstream glyphosate applications by distances

	(1)	(2)	(3)	(4)	(5)	(6)
Upstream glyphosate (0-200km)	2.253*	3.280**	3.330**	3.316**	3.312**	3.193**
	(1.360)	(1.521)	(1.513)	(1.514)	(1.515)	(1.473)
Upstream glyphosate (200-400km)	1.921	1.943	1.934	1.938	1.938	2.106*
	(1.512)	(1.290)	(1.285)	(1.281)	(1.283)	(1.257)
Upstream glyphosate (400-600km)	-0.109	2.392	2.032	2.038	1.975	0.375
	(3.680)	(3.358)	(3.440)	(3.409)	(3.435)	(3.374)
Upstream glyphosate (600-800km)	-3.107	-4.353	-3.095	-3.101	-3.014	-1.378
	(3.570)	(3.280)	(3.665)	(3.580)	(3.650)	(3.604)
Local glyphosate	-1.127	-2.273	-2.337	-2.333	-2.320	-1.903
	(1.308)	(1.496)	(1.492)	(1.492)	(1.493)	(1.447)
Observations	3,099	3,099	3,099	3,099	3,099	3,099
R-squared	0.045	0.051	0.052	0.052	0.052	0.054
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Geogrophic covariates	No	Yes	Yes	Yes	Yes	Yes
Flow rate	No	No	QA	QC	QE	QA
HU2 FE	No	No	No	No	No	Yes

Notes: The dependent variable is glyphosate concentrations. Robust standard errors clustered at the watershed (HU8) level are shown in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Heterogeneity in glyphosate concentrations and upstream glyphosate applications

	Income (1)	Flow rate (QA) (2)	Flow rate (QC) (3)	Flow rate (QE) (4)	Water source (5)
Upstream glyphosate	3.912***	3.277*	3.335*	3.371*	3.669***
	(1.433)	(1.709)	(1.704)	(1.713)	(1.272)
Lower income × upstream glyphosate	1.323				
	(1.759)				
Quartile 1 × upstream glyphosate		-1.172	-0.727	-1.304	
		(1.260)	(1.228)	(1.646)	
Quartile 2 × upstream glyphosate		2.003**	1.853*	2.103**	
		(0.937)	(0.979)	(0.967)	
Quartile 3 × upstream glyphosate		2.336	2.599*	1.508	
		(1.564)	(1.556)	(1.411)	
Groundwater × upstream glyphosate					7.147
					(5.990)
Groundwater × local glyphosate					-2.863
					(4.931)
Local glyphosate	-2.144	-2.096	-2.114	-2.312	-2.449*
	(1.419)	(1.493)	(1.491)	(1.530)	(1.427)
Observations	3,099	3,087	3,087	3,087	2,988
R-squared	0.058	0.055	0.055	0.054	0.056
Controls	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is glyphosate concentration. The first row indicates the variable used for interaction in each column. All regressions include month fixed effects, HU2 fixed effects, geographic covariates, and flow rate. Unless otherwise noted in the first row, the QA flow rate is used. The results are similar using different flow rate measures. Robust standard errors clustered at the watershed (HU8) level are shown in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Heterogeneity in glyphosate concentrations by precipitation

	Apr-Sep	Oct-Mar
	(1)	(2)
Upstream glyphosate	-0.316	-2.109
	(1.295)	(4.231)
Quartile 2 × upstream glyphosate	6.697***	0.530
	(2.296)	(2.726)
Quartile 3 × upstream glyphosate	6.291**	3.230
	(2.436)	(4.572)
Quartile 4 × upstream glyphosate	6.062***	
	(1.833)	
Observations	2,579	520
R-squared	0.051	0.040
Controls	Yes	Yes

Notes: The dependent variable is glyphosate concentrations. The first row displays the season considered. All regressions include month fixed effects, HU2 fixed effects, geographic covariates, and QA flow rate. The results are similar using different flow rate measures. There is no concentration data available from October to March in counties with a rainfall quartile of 4. Robust standard errors clustered at the watershed (HU8) level are shown in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

B Economic Spillovers

To address economic spillovers, I run regressions adding glyphosate use in nearby areas as an independent variable, adapted from Dias et al. (2023), with results shown in Table B1. If economic spillovers exist, they are expected to affect nearby areas in non-specific directions rather than following water flow. The nearby glyphosate use is the sum of glyphosate in upstream, downstream, and any watersheds within 200 km. This variable captures spatial spillovers based purely on geographic proximity, allowing the upstream glyphosate coefficient to reflect the difference between upstream and non-upstream nearby effects. The estimates suggest that nearby glyphosate use, if it has any effects, may lead to spillovers that are actually beneficial for birth outcomes. However, these estimates are statistically insignificant.

I further explore spillovers by regressing local economic indicators on glyphosate use (Table B2). Local glyphosate use is negatively associated with agricultural employment and positively associated with manufacturing employment, suggesting a reallocation of labor potentially due to glyphosate or GM crop adoption. It is also positively correlated with agricultural GDP but shows no significant relationship with livestock sales. In contrast, upstream glyphosate use is generally statistically uncorrelated with these economic indicators, with two exceptions: small but borderline significant associations with total and manufacturing GDP. Given average upstream use of 0.023 tonne/km^2, these correlations translate to roughly 0.017% and 0.08% increases in total and manufacturing GDP, respectively, suggesting some economic spillovers. To assess whether these patterns reflect true spatial spillovers rather than upstream-specific effects, I include both upstream and nearby glyphosate use for the GDP equations. The results suggest some, but insignificant, spillover effects. There is no significant difference between upstream and non-upstream nearby effects—unlike the significant estimates observed for neonatal mortality.

Overall, while estimates suggest that economic spillovers from upstream glyphosate use are mostly insignificant, they cannot be fully ruled out. The identification strategy is designed to isolate waterborne transmission, but glyphosate use may still influence local economies through labor reallocation, productivity changes, or other indirect channels not fully captured in the empirical framework. Including nearby glyphosate use helps account for these possibilities and suggests that, if spillovers exist, the main health effect estimates may be conservative.

Table B1: Nearby glyphosate effects on neonatal mortality rate

	(1)	(2)	(3)	(4)	(5)	(6)
Upstream glyphosate	25.14**	24.81**	24.65**	24.64**	24.73**	26.68**
	(10.33)	(10.50)	(10.31)	(10.26)	(10.13)	(10.67)
Sum of nearby glyphosate	-6.748	-6.092	-6.069	-6.128	-5.948	-8.762
	(6.101)	(6.337)	(6.457)	(6.452)	(6.351)	(7.265)
Local glyphosate						5.360
						(6.277)
Observations	7,770	7,770	7,770	7,770	7,770	7,770
R-squared	0.031	0.032	0.038	0.038	0.039	0.039
Number of counties	555	555	555	555	555	555
Economic covariates	No	Yes	Yes	Yes	Yes	Yes
Demographic covariates	No	No	Yes	Yes	Yes	Yes
Industrial pollution covariates	No	No	No	Yes	Yes	Yes
Medical resource covariates	No	No	No	No	Yes	Yes

Notes: For details on the controls, see the notes in Table 2. All regressions include county and state-year fixed effects. Robust standard errors clustered at the watershed (HU8) level are shown in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table B2: Correlations between glyphosate and farm/non-farm economic conditions

	Farm employment (1)	Non-farm employment (2)	Animal sales (3)	Log ag GDP (4)	Log total GDP (5)	Log manuf. GDP (6)	Log ag GDP (7)	Log total GDP (8)	Log manuf. GDP (9)
Local glyphosate	-0.650**	225.1*	102.9	10.25***	-0.152	-0.868	8.660***	-0.344	-1.231
	(0.284)	(135.3)	(124.1)	(2.960)	(0.301)	(0.926)	(3.217)	(0.332)	(1.086)
Upstream glyphosate	-0.373	-95.76	193.5	4.500	0.705*	3.558*	-1.110	0.116	2.442
	(0.452)	(79.68)	(180.3)	(3.654)	(0.410)	(1.808)	(6.055)	(0.457)	(1.752)
Glyphosate use nearby							4.079	0.450	0.868
							(3.828)	(0.333)	(1.289)
Observations	7,770	7,770	7,686	3,262	7,770	6,510	3,262	7,770	6,510
R-squared	0.625	0.540	0.239	0.326	0.535	0.307	0.327	0.535	0.307
Number of counties	555	555	549	233	555	465	233	555	465

Notes: The first row shows the dependent variable of each regression. The data on animal sales are from the census of agriculture, which is only available every five years. I used linear interpolation to generate values in the years between censuses. The GDP data for some counties in specific years are unavailable due to confidentiality. All regressions include county and state-year fixed effects and economic covariates. For details on the controls, see the notes in Table 2. Robust standard errors clustered at the watershed (HU8) level are shown in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

C Other Agricultural Chemicals

To address other agricultural pollutants that could potentially confound the estimated effects of glyphosate, I examine the correlations between glyphosate use and various water quality measures associated with agricultural activity (Hooda et al., 2000; Kato et al., 2009; Keiser and Shapiro, 2018; Liu et al., 2023). These measures include dissolved oxygen deficit (DOD), nitrate and nitrite nitrogen, phosphorus, total suspended solids (TSS), Escherichia coli (E. coli), and total coliform. DOD is a widely used measure of water quality, as it reflects the amount of oxygen consumed by microorganisms breaking down pollutants. TSS captures solid particles in water and serves as an indicator of soil erosion. Nitrate and phosphorus represent nutrient pollution from sources such as fertilizers, livestock manure, and municipal sewage, with nitrate being the primary form of leached nitrogen from fertilizers in the Corn Belt (Bernhard, 2010). Coliform bacteria are indicators of harmful pathogens, often linked to human and animal fecal matter. Unfortunately, the water quality data is irregular in most regions and with limited spatial coverage.[18]

Table C1 reports correlations between upstream glyphosate use and water quality, while Table C2 controls for upstream phosphorus, nitrate/nitrite, and other pesticide use. Glyphosate's estimated effects on neonatal mortality remain robust after controlling for these substances, which themselves show no significant associations. Several factors may explain those insignificant estimates of other chemicals. First, many of the other chemicals (e.g., nitrate, atrazine, 2,4-D) are regulated under the Safe Drinking Water Act, and exceedances often prompt public notifications that trigger avoidance behaviors (Marcus, 2022; Hadachek, 2024). Second, MCLs vary substantially: glyphosate's is high (700 $\mu g/L$), whereas atrazine's is low (3 $\mu g/L$), making violations (and subsequent mitigation) more common for some substances than others (Warnemuende et al., 2007). Third, substances

[18]For water quality measures in each county, I use readings from all monitoring stations testing unfiltered/total water for DOD, nitrate and nitrite nitrogen, phosphorus, TSS, and water for total coliform and E. coli. Data from non-water media, such as soil and sediment, are excluded. To avoid the influence of outliers, I drop readings above the 99.5th percentile or below the 0.5th percentile in each county, following Liu et al. (2023). The remaining readings are averaged to generate county-year level variables for each water measure.

like phosphorus have little evidence of adverse effects in humans even at high doses.[19] Fourth, although other pesticides have been linked to adverse birth outcomes (e.g., atrazine with preterm birth and fetal growth restriction Chevrier et al., 2011; acetochlor with reduced birth weight Wickerham et al., 2012), these effects may not be strong enough to affect neonatal mortality, especially via waterborne exposure. Finally, glyphosate use increased substantially during the study period, while most other chemical use remained stable. This sharp variation improves identification and may explain why glyphosate emerges as the most policy-relevant factor in our setting.

Table C1: Correlations of water quality measures and glyphosate

	DOD (1)	Phosphorus (2)	Nitrate and nitrite (3)	TSS (4)	E. Coli (5)	Coliform (6)
Upstream glyphosate	55.20	13.58	19.70	-23.28	-8,594	-224,952
	(76.87)	(10.57)	(13.42)	(109.5)	(6,718)	(211,669)
Observations	2,209	5,394	3,673	2,691	3,154	346
R-squared	0.192	0.061	0.174	0.205	0.033	0.386
Number of counties	392	531	401	382	447	150

Notes: The first row shows the dependent variable of each regression. All regressions include county and state-year fixed effects but control for no covariates. Robust standard errors clustered at the watershed (HU8) level are shown in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

[19] https://ods.od.nih.gov/factsheets/Phosphorus-HealthProfessional/

Table C2: Glyphosate impacts on NMR with controlling of agricultural chemicals

	Phosphorus		Nitrate and nitrite		Pesticides	
	(1)	(2)	(3)	(4)	(5)	(6)
Upstream glyphosate	15.47**	15.40**	22.48***	22.96***	15.32***	15.56**
	(7.276)	(7.282)	(8.089)	(8.046)	(5.869)	(6.861)
Phosphorus		0.00588				
		(0.0103)				
Nitrate and nitrite				-0.0287		
				(0.0333)		
Upstream atrazine						2.766
						(19.71)
Upstream acetochlor						11.41
						(22.14)
Upstream metolachlor-s						17.33
						(25.41)
Upstream 2,4-D						15.09
						(29.27)
Local glyphosate	0.298	0.252	-0.989	-0.826	1.538	1.097
	(5.844)	(5.840)	(7.182)	(7.196)	(5.503)	(5.462)
Observations	5,394	5,394	3,673	3,673	7,770	7,770
R-squared	0.048	0.048	0.059	0.059	0.038	0.039
Number of counties	531	531	401	401	555	555
Full controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The first row indicates the agricultural chemical under consideration. The sample sizes for phosphorus and nitrate/nitrite are smaller due to data availability. For details on the controls, see the notes in Table 2. All regressions include county and state-year fixed effects. Robust standard errors clustered at the watershed (HU8) level are shown in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

D Public water system violations

The EPA sets legally enforceable limits (Maximum Contaminant Levels, or MCLs) on about 90 contaminants in drinking water (Table D1) and also prescribes water-testing schedules that public water systems must follow. Public water systems are required to monitor these contaminants based on EPA-specified schedules, though states may waive requirements. The frequency of monitoring depends on the type of contaminant, the water source, and the number of people served. For example, total coliforms must be monitored anywhere from once to 480 times per month, depending on population size. Nitrate must be tested annually in groundwater systems and quarterly in surface water systems. Some organic contaminants are monitored annually, while some are once or twice every three years.

A public water system is issued an MCL violation when contaminant levels exceed legal limits, and a Monitoring and Reporting (MR) violation if the system fails to conduct required testing or submit results to state or federal agencies on time.

To construct county-level violation exposure measures used in Section 3.5, I calculate the coverage of MCL and MR violations as the percentage of a county's population served by a public water system that had a given type of violation in a specific year. Since some systems serve multiple counties, I allocate their service populations across counties based on the proportion of each county's residents not already served by other systems. I exclude systems that were not operational during the study period, as well as transient non-community systems (e.g., campgrounds), which serve populations that are not necessarily the residents of that county.

Table D1: EPA-Regulated Drinking Water Contaminants by Category

Contaminant Group	**Chemicals**
Inorganic Chemicals	Antimony, Arsenic, Asbestos (fiber 10 μm), Barium, Beryllium, Cadmium, Chromium (total), Copper, Cyanide (free), Fluoride, Lead, Mercury (inorganic), Nitrate (as Nitrogen), Nitrite (as Nitrogen), Selenium, Thallium
Organic Chemicals (excluding PFAS)	Acrylamide, Alachlor, Atrazine, Benzene, Benzo(a)pyrene (PAHs), Carbofuran, Carbon tetrachloride, Chlordane, Chlorobenzene, 2,4-D, Dalapon, 1,2-Dibromo-3-chloropropane (DBCP), o-Dichlorobenzene, p-Dichlorobenzene, 1,2-Dichloroethane, 1,1-Dichloroethylene, cis-1,2-Dichloroethylene, trans-1,2-Dichloroethylene, Dichloromethane, 1,2-Dichloropropane, Di(2-ethylhexyl) adipate, Di(2-ethylhexyl) phthalate, Dinoseb, Dioxin (2,3,7,8-TCDD), Diquat, Endothall, Endrin, Epichlorohydrin, Ethylbenzene, Ethylene dibromide, Glyphosate, Heptachlor, Heptachlor epoxide, Hexachlorobenzene, Hexachlorocyclopentadiene, Lindane, Methoxychlor, Oxamyl (Vydate), PCBs, Pentachlorophenol, Picloram, Simazine, Styrene, Tetrachloroethylene, Toluene, Toxaphene, 2,4,5-TP (Silvex), 1,2,4-Trichlorobenzene, 1,1,1-Trichloroethane, 1,1,2-Trichloroethane, Trichloroethylene, Vinyl chloride, Xylenes (total)
Radionuclides	Alpha particles, Beta particles and photon emitters, Radium 226/228 (combined), Uranium
Disinfection Byproducts	Bromate, Chlorite, Haloacetic acids (HAA5), Total Trihalomethanes (TTHMs)
Microorganisms	Total Coliforms (including fecal coliform and *E. coli*)
Selected PFAS	Hazard Index PFAS (HFPO-DA, PFBS, PFHxS, PFNA), HFPO-DA (GenX Chemicals), PFBS, PFHxS, PFNA, PFOA, PFOS

Notes: Sourced from EPA (https://www.epa.gov/ground-water-and-drinking-water/national-primary-drinking-water-regulations#one).

E Other Heterogeneous Effects and Potential Mechanisms

This section investigates potential reasons why the effects of glyphosate on neonatal mortality rates are primarily observed in lower-income areas and not in higher-income ones.

One explanation could be geographic variation. Many lower-income counties are clustered in specific parts of the Corn Belt, and it is possible that certain geographic conditions affect glyphosate transport and drive the observed heterogeneity. However, this seems not to be the case. Table A4, Column (1), shows that upstream glyphosate use is positively associated with downstream concentrations in natural water systems, and this relationship does not differ significantly by income level. This suggests other mechanisms may be more relevant.

To explore further, I examine additional sources of heterogeneity. The suggestive results show avoidance behaviors may play a role. Even if glyphosate is present in drinking water, exposure can be mitigated through individual responses, such as using filters or bottled water. Roughly 20 percent of U.S. households rely exclusively on bottled water (Jaffee, 2024), reflecting persistent concerns over tap water quality (Keiser and Shapiro, 2019).

Studies show that higher-income, more educated, and older individuals are more likely to use water filters (Yang and Faust, 2019; Triplett et al., 2019; Park et al., 2022). Racial and ethnic differences also exist: non-Hispanic whites are more likely to trust tap water, whereas Hispanic and Black populations are more inclined to use bottled water for themselves and their children (Hobson et al., 2007; Viscusi et al., 2015; Javidi and Pierce, 2018; Rosinger et al., 2018).

The water consumption patterns align with observed heterogeneous effects across different demographic groups. Table E1 Columns (1)-(3) show stronger glyphosate impacts in areas with a higher incidence of less-educated, younger, and non-Hispanic white mothers. Like higher income, it is consistent with findings in the health literature that more-educated people are less affected by adverse conditions, as they have more resources

Table E1: Heterogeneous glyphosate effects on neonatal mortality rate by mother's demographics, private water sources, and flow rates

	Interacted variable						
	Age	Non-Hispanic whites	Education	Private Water sources	Flow rate (QA)	Flow rate (QC)	Flow rate (QE)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Upstream glyphosate	0.124	8.852*	-3.967	9.008*	-5.037	-4.370	-4.260
	(3.918)	(5.021)	(4.117)	(5.167)	(5.082)	(4.757)	(4.920)
Quartile 1 × upstream glyphosate	8.489**	-9.009**	9.525**	-9.183	9.520*	8.931*	7.988
	(4.147)	(4.427)	(4.509)	(5.987)	(4.901)	(4.795)	(4.955)
Quartile 2 × upstream glyphosate	3.683	-4.854	5.090	-8.376	17.19**	17.20***	12.99**
	(3.006)	(4.192)	(3.640)	(6.025)	(6.701)	(6.478)	(6.254)
Quartile 3 × upstream glyphosate	0.714	-1.249	3.909	-7.774	7.860*	7.005	8.706*
	(2.410)	(3.403)	(3.298)	(5.884)	(4.658)	(4.755)	(4.815)
Observations	14,630	14,630	13,370	14,630	14,616	14,616	14,616
R-squared	0.027	0.027	0.029	0.027	0.027	0.027	0.027
Number of counties	1,045	1,045	955	1,045	1,044	1,044	1,044

Notes: Each column presents regression results with interactions between glyphosate use and quartiles of the variable indicated in the second row. For control details, refer to Table 2. All regressions include county and state-year fixed effects. The sample analyzed for regional heterogeneous effects includes all counties, consistent with Table 2 Column (1). Column (2) in this table has a smaller sample size due to missing data on mother's education, which is measured as the proportion of mothers with a college degree. Columns (5)-(7) have a slightly smaller sample size due to missing data on flow rate. Robust standard errors clustered at the watershed (HU8) level are shown in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

to mitigate these factors or are better able to take avoidance actions (Currie, 2011; Currie et al., 2013; Greve et al., 2017). For example, studies also find that better-educated people are less affected by air pollution (Bharadwaj et al., 2017). However, it is unusual for non-Hispanic whites to be more severely impacted by air pollution (Chay and Greenstone, 2003; Banzhaf et al., 2019). This different finding, where glyphosate has stronger effects in areas with a higher proportion of non-Hispanic white mothers, may be explained by water usage behaviors, such as the decision to consume unfiltered tap water.[20] However, this is just correlation, not causation, as my data lacks random variation in interaction terms and cannot directly test this mechanism.

Water treatment may also play a role. Lower-income individuals are more likely to rely on private water sources, primarily wells, which are unregulated under the Safe Drinking Water Act. Private well users tend to test and treat their water less frequently than public

[20]The correlations between the non-Hispanic white share and income, age, and education are low, with correlation coefficients of -0.089, 0.061, and 0.072, respectively. These low correlations suggest that race and the associated water consumption patterns potentially contribute to the observed heterogeneous effects.

water systems (Pieper et al., 2015; Malecki et al., 2017). Table E1 Column (4) examines the interaction between glyphosate use and private water user quartiles, showing that glyphosate has a larger impact in areas with higher private water reliance. The magnitude and significance of the effect decline across private water use quartiles, although the first quartile remains marginally insignificant (p = 0.12). These results suggest that the lack of water treatment in private systems may amplify glyphosate's effects.

Columns (5)–(7) of Table E1 examine heterogeneity by river characteristics.[21] The results show that glyphosate's impact is larger in areas with relatively lower river flow rates across all measurements—likely because higher flow dilutes contaminants. This pattern aligns with findings in Appendix A, where glyphosate concentrations are more strongly associated with upstream use in areas with moderate flow. Importantly, lower-income areas have more counties with those high flow rates, reinforcing that geographic conditions are insufficient to explain the observed heterogeneity across income.

Public water system violations offer further insight. On one hand, violations may signal poor water quality; the resulting exposure risk may increase if individuals do not respond to these signals. On the other hand, violations can trigger mandatory public notices, prompting avoidance behaviors that mitigate health impacts. To disentangle these effects, I regress neonatal mortality on glyphosate use and an interaction between glyphosate and high violation coverage (defined as above-median share of the population served by systems with MCL or MR violations).[22] For MCL violations, notifications must be issued within 30 days or within 24 hours for certain chemicals. Whereas, MR violations only require notification within one year.

Table E2 shows that MCL violations are associated with reduced glyphosate effects (Column 1), particularly in higher-income areas (Column 5). In contrast, the mitigating effect is small and statistically insignificant in lower-income areas (Column 3). MR violations

[21] Flow rate data are from EPA's NHDPlus Version 2 dataset, which provides the three estimates: QA, QC, and QE. See the footnote 9 for more details.

[22] See Appendix D for detailed information on how the violation variable is constructed.

Table E2: Regression of NMR on violations

	All counties		Lower-income areas		Higher-income areas	
	MCL	MR	MCL	MR	MCL	MR
	(1)	(2)	(3)	(4)	(5)	(6)
Upstream glyphosate	3.342	1.566	15.45**	14.95**	-1.750	-4.207
	(3.878)	(3.806)	(6.159)	(6.353)	(4.564)	(4.587)
High violation x upstream glyphosate	-2.631*	0.498	-0.211	1.081	-2.900*	1.244
	(1.589)	(1.153)	(3.004)	(2.800)	(1.676)	(1.495)
Local glyphosate	2.857	3.009	1.530	1.770	2.792	3.189
	(3.348)	(3.353)	(5.510)	(5.510)	(4.013)	(4.033)
Observations	14,630	14,630	7,770	7,770	6,860	6,860
R-squared	0.027	0.026	0.038	0.039	0.048	0.048
Number of counties	1,045	1,045	555	555	490	490
Full controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The first row shows the considered sample, and the second row indicates the type of violations considered. For details on the controls, see the notes in Table 2. All regressions include county and state-year fixed effects. Robust standard errors clustered at the watershed (HU8) level are shown in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

show no significant interaction with glyphosate use (Columns 2, 4, and 6). These results align with prior research suggesting that timely public notification of MCL violations can prompt avoidance behaviors (Marcus, 2022), especially in higher-income areas with greater capacity to respond (Hadachek, 2024). In lower-income communities, financial constraints and limited access to media or timely notification may reduce the effectiveness of such warnings, leaving health risks elevated.[23] That said, these results should be interpreted with caution, as violations may correlate with unobserved confounders. More broadly, all heterogeneity analyses in this section are correlational, not causal, given the lack of random variation in interaction terms. Future research is needed to establish causality.

Finally, socioeconomic disparities in healthcare access may also contribute to differential glyphosate effects. Higher-income individuals have greater access to prenatal care and medical resources (Mocan et al., 2015), which can mitigate environmental health risks.

[23]Previous studies find that prompt violation notices lead to increased bottled water purchases and mitigate health impacts, particularly in areas with lower poverty rates. These behaviors may reduce exposure not only to the chemical causing the violation but also to others like glyphosate. Thus, violations unrelated to glyphosate may still inadvertently reduce its health impacts if they prompt broader avoidance behaviors.

Proximity to hospitals and healthcare providers improves birth outcomes (Blondel et al., 2011; Daysal et al., 2015). Descriptive statistics in Table 1 show that lower-income areas have fewer hospital beds and healthcare providers per capita, as well as lower spatial access to medical services. If glyphosate exposure affects both high- and low-income populations similarly, higher-income individuals may mitigate its effects through better healthcare access.

F Tables

Table F1: Regression of local glyphosate and upstream glyphosate on covariates

	(1) Local glyphosate	(2) Upstream glyphosate
Income per capita	-0.000436**	0.000223
	(0.000170)	(0.000192)
Unemployment rate	-0.00128***	-0.000241
	(0.000209)	(0.000355)
Poverty rate	-3.08e-05	0.000107
	(0.000138)	(0.000109)
% employment in agriculture	0.000344	-0.000265
	(0.000355)	(0.000407)
% married	-4.50e-05	8.09e-05
	(6.26e-05)	(6.35e-05)
% mothers born outside of the US	-0.000113	-8.39e-05
	(0.000212)	(0.000280)
% non-hispanic black	0.000294	0.000305
	(0.000298)	(0.000304)
% non-hispanic white	-7.55e-05	-0.000221
	(0.000156)	(0.000139)
Mother's age	0.00114**	0.000217
	(0.000530)	(0.000464)
Number of plurality	0.00282	-0.000301
	(0.00634)	(0.00549)
Birth order	-0.00157	-0.00127
	(0.00192)	(0.00185)
% diabetes	-9.47e-06	2.36e-05
	(0.000116)	(0.000110)
% hypertension	-0.000492***	5.43e-05
	(0.000104)	(9.25e-05)
Industrial water pollution	4.43e-05**	-2.37e-05
	(2.16e-05)	(2.00e-05)
Hospital beds per capita*1000	0.000435*	0.000260
	(0.000232)	(0.000208)
Health providers per capita*1000	-0.000524	-0.0115***
	(0.00471)	(0.00368)
Hospital beds density	-0.00248	0.00493
	(0.00627)	(0.00642)
Health provider density	-0.143***	0.0238
	(0.0295)	(0.0318)
Observations	7,770	7,770
R-squared	0.621	0.699
F stat	8.43	1.78
Number of counties	555	555
Fixed-Effects	County+State-Year FE	County+State-Year FE

Notes: F statistics report the results of the joint test of significance for all covariates, excluding fixed effects. Robust standard errors clustered at the watershed (HU8) level are shown in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table F2: Glyphosate effects on neonatal mortality rate using different FE and controls in lower-income areas

	No FE		County FE		County+Year FE		County+State-Year FE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Upstream glyphosate	-3.599	1.010	-2.606	10.58**	14.35***	13.08***	15.08**	15.32***
	(4.975)	(2.007)	(4.002)	(4.943)	(4.947)	(4.913)	(6.502)	(5.869)
Income per capita		-0.0299*		-0.0367		-0.0234		-0.0327
		(0.0174)		(0.0238)		(0.0276)		(0.0294)
Unemployment rate		0.0253		0.0494**		0.109**		0.0876*
		(0.0203)		(0.0195)		(0.0427)		(0.0509)
Poverty rate		-0.00380		-0.0296		-0.00652		-0.0113
		(0.0101)		(0.0219)		(0.0256)		(0.0244)
% employment in agriculture		-0.0175		-0.121**		-0.181***		-0.164**
		(0.0115)		(0.0583)		(0.0627)		(0.0731)
% married		-0.00308		0.00708		-0.00918		-0.00466
		(0.0101)		(0.0116)		(0.0131)		(0.0137)
% mothers born outside of the US		-0.00393		-0.0218		-0.0165		-0.0220
		(0.00921)		(0.0332)		(0.0332)		(0.0337)
% non-hispanic black		0.0237***		-0.000936		-0.00863		0.0140
		(0.00897)		(0.0423)		(0.0431)		(0.0458)
% non-hispanic white		-0.00790		-0.00839		-0.0195		-0.0214
		(0.00659)		(0.0275)		(0.0285)		(0.0293)
Mother's age		-0.192**		-0.346***		-0.357**		-0.403***
		(0.0792)		(0.114)		(0.145)		(0.147)
Number of plurality		15.14***		14.53***		14.82***		14.94***
		(2.876)		(3.039)		(3.033)		(3.087)
Birth order		0.604***		0.458		0.308		0.321
		(0.213)		(0.342)		(0.570)		(0.539)
% diabetes		-0.0225		-0.00616		0.000999		0.0178
		(0.0224)		(0.0264)		(0.0270)		(0.0292)
% hypertension		-0.0106		-0.0225		-0.0239		-0.0205
		(0.0195)		(0.0254)		(0.0257)		(0.0260)
Industrial water pollution		0.00200		-0.000410		-0.00384		-0.00321
		(0.00448)		(0.00726)		(0.00532)		(0.00656)
Hospital beds per capita*1000		-0.0340*		-0.0939*		-0.0979*		-0.102*
		(0.0204)		(0.0499)		(0.0505)		(0.0531)
Health providers per capita*1000		0.213		-0.657		-0.526		-0.367
		(0.326)		(0.978)		(0.993)		(1.026)
Hospital beds density		0.461***		0.349		0.298		0.515
		(0.0936)		(0.511)		(0.570)		(0.660)
Health provider density		-7.241***		-6.211		-6.112		-0.210
		(1.910)		(3.870)		(3.778)		(4.110)
Local glyphosate		2.177		-1.026		1.998		1.538
		(1.910)		(5.032)		(5.228)		(5.503)
Observations	7,770	7,770	7,770	7,770	7,770	7,770	7,770	7,770
R-squared	0.001	0.077	0.000	0.012	0.006	0.015	0.031	0.038
Economic covariates	No	Yes	No	Yes	No	Yes	No	Yes
Demographic covariates	No	Yes	No	Yes	No	Yes	No	Yes
Industrial pollution covariates	No	Yes	No	Yes	No	Yes	No	Yes
Medical resource covariates	No	Yes	No	Yes	No	Yes	No	Yes

Notes: The dependent variable is neonatal mortality rates. The first row shows the fixed effect considered. Robust standard errors clustered at the watershed (HU8) level are shown in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table F3: Glyphosate effects on neonatal mortality rate with clustered standard errors at the HUC4 level

	All counties		Lower-income areas					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Upstream glyphosate	1.847	-2.315	15.08**	15.78***	15.65***	15.55***	15.95***	15.32***
	(3.619)	(3.757)	(6.343)	(5.815)	(5.626)	(5.574)	(5.681)	(5.486)
Upstream glyphosate × income quartile 1		15.51*						
		(8.018)						
Upstream glyphosate × income quartile 2		9.166*						
		(4.612)						
Upstream glyphosate × income quartile 3		3.502						
		(4.880)						
Local glyphosate	2.983	2.357						1.538
	(3.275)	(3.192)						(5.369)
Observations	14,630	14,630	7,770	7,770	7,770	7,770	7,770	7,770
R-squared	0.026	0.027	0.031	0.032	0.038	0.038	0.038	0.038
Number of counties	1,045	1,045	555	555	555	555	555	555
Economic covariates	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
Demographic covariates	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Industrial pollution covariates	Yes	Yes	No	No	No	Yes	Yes	Yes
Medical resource covariates	Yes	Yes	No	No	No	No	Yes	Yes

Notes: This table replicates Table 1, but uses robust standard errors clustered at the HU4 watershed level. Standard errors are reported in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table F4: Upstream glyphosate effects on neonatal mortality rate using conception year computing by gestational length

	(1)	(2)	(3)	(4)	(5)	(6)
Upstream glyphosate	20.78***	21.25***	20.96***	20.65***	22.04***	20.60***
	(5.771)	(5.674)	(5.535)	(5.517)	(5.619)	(5.945)
Local glyphosate						3.643
						(6.236)
Observations	6,018	6,018	6,018	6,018	6,018	6,018
R-squared	0.034	0.035	0.040	0.040	0.042	0.042
Number of counties	552	552	552	552	552	552
Economic covariates	No	Yes	Yes	Yes	Yes	Yes
Demographic covariates	No	No	Yes	Yes	Yes	Yes
Industrial pollution covariates	No	No	No	Yes	Yes	Yes
Medical resource covariates	No	No	No	No	Yes	Yes

Notes: This table replicates Table 1 columns (3) to (8), but uses a sample constructed by gestational length. Robust standard errors clustered at the watershed (HU8) level are shown in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

G Figures

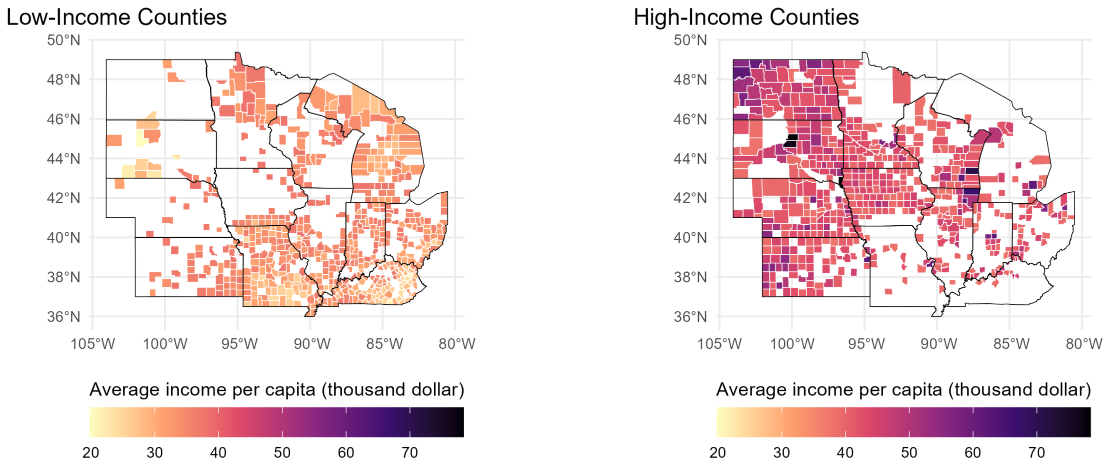

Figure G1: Average per capita income over the study period, by income group.

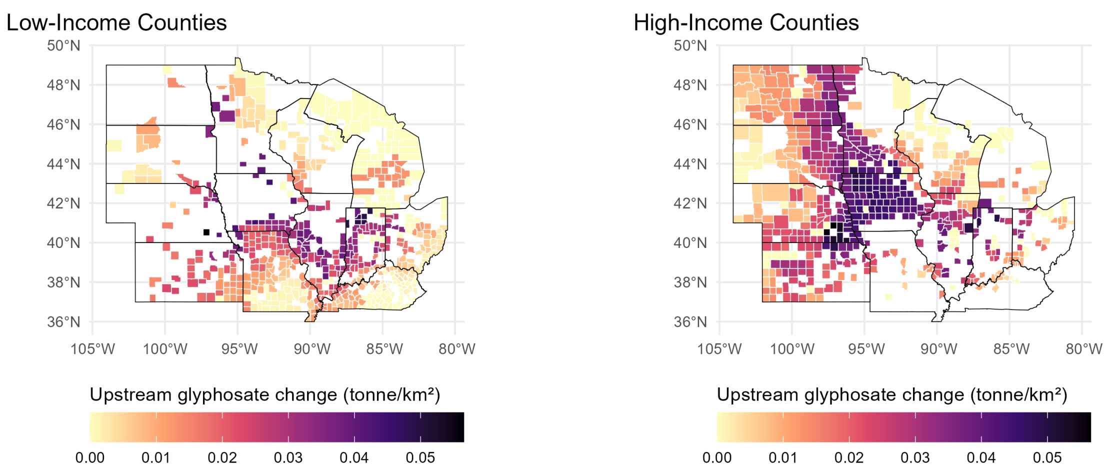

Figure G2: Change in upstream glyphosate use by income group. The figure shows the difference in average use between the first and second half of the study period.

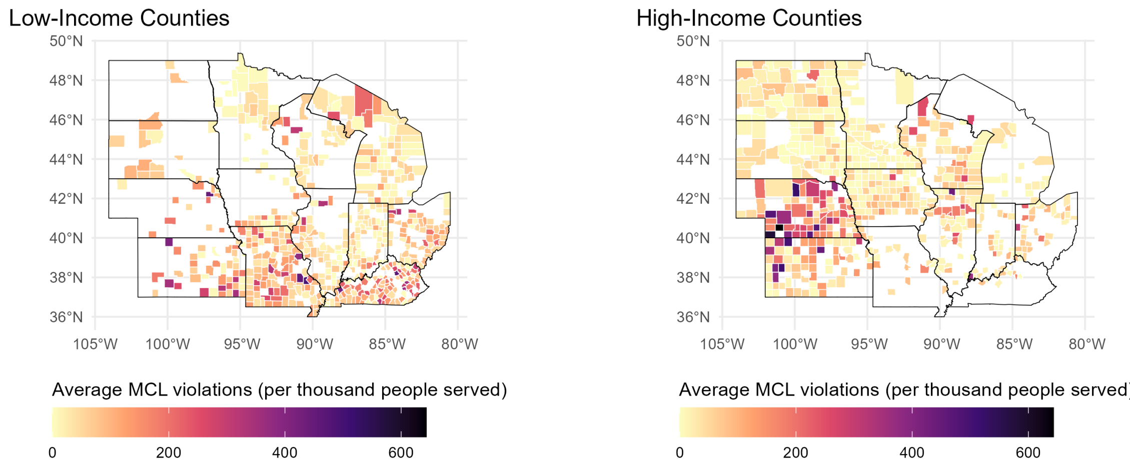

Figure G3: Average MCL violation coverage over the study period, by income group.

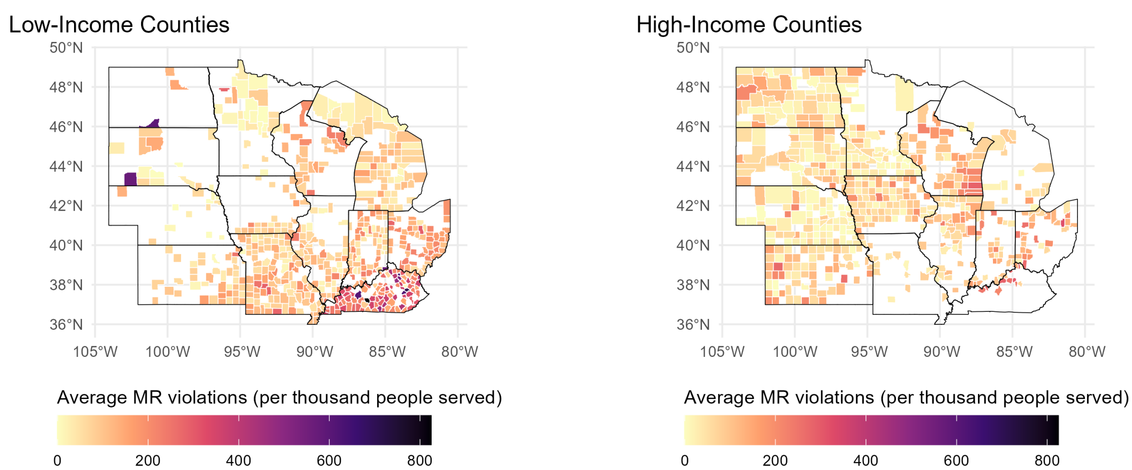

Figure G4: Average MR violation coverage over the study period, by income group.

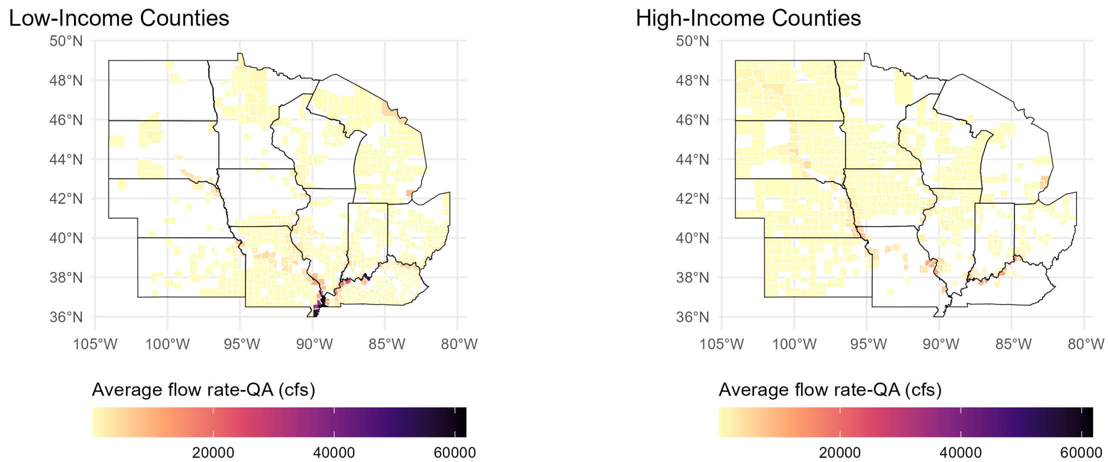

Figure G5: Average annual flow rate (QA: mean annual flow from runoff) by income group. Source: EPA's NHDPlus Version 2 dataset, which reports QA, QC, and QE metrics. These estimates are highly correlated.

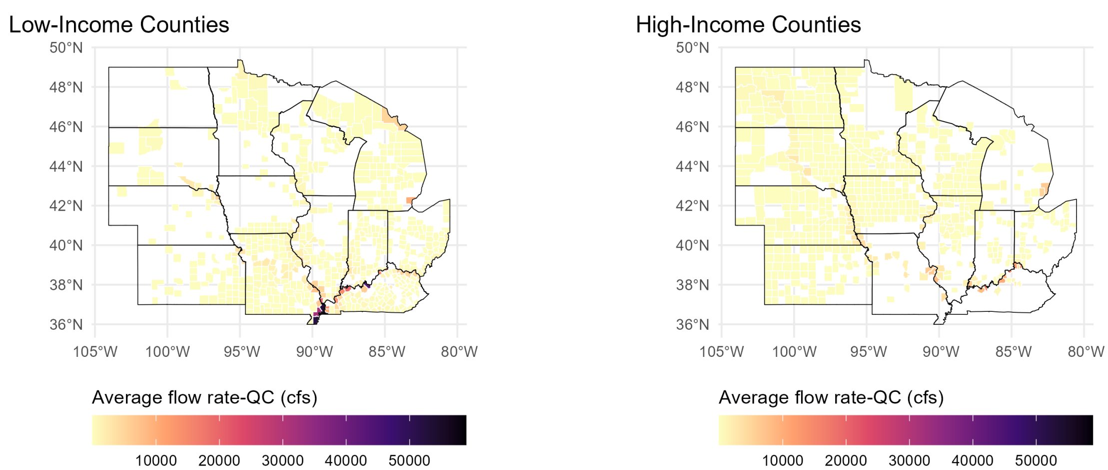

Figure G6: Average annual flow rate (QC: mean annual flow estimated via reference-gage regression) by income group. Source: EPA's NHDPlus Version 2 dataset, which reports QA, QC, and QE metrics. These estimates are highly correlated.

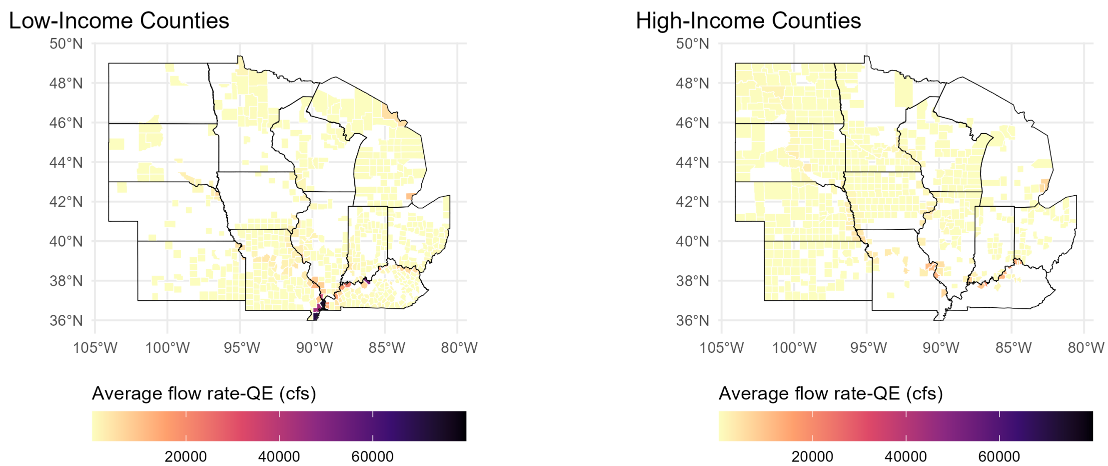

Figure G7: Average annual flow rate (QE: mean annual flow from gage adjustment) by income group. Source: EPA's NHDPlus Version 2 dataset, which reports QA, QC, and QE metrics. These estimates are highly correlated.

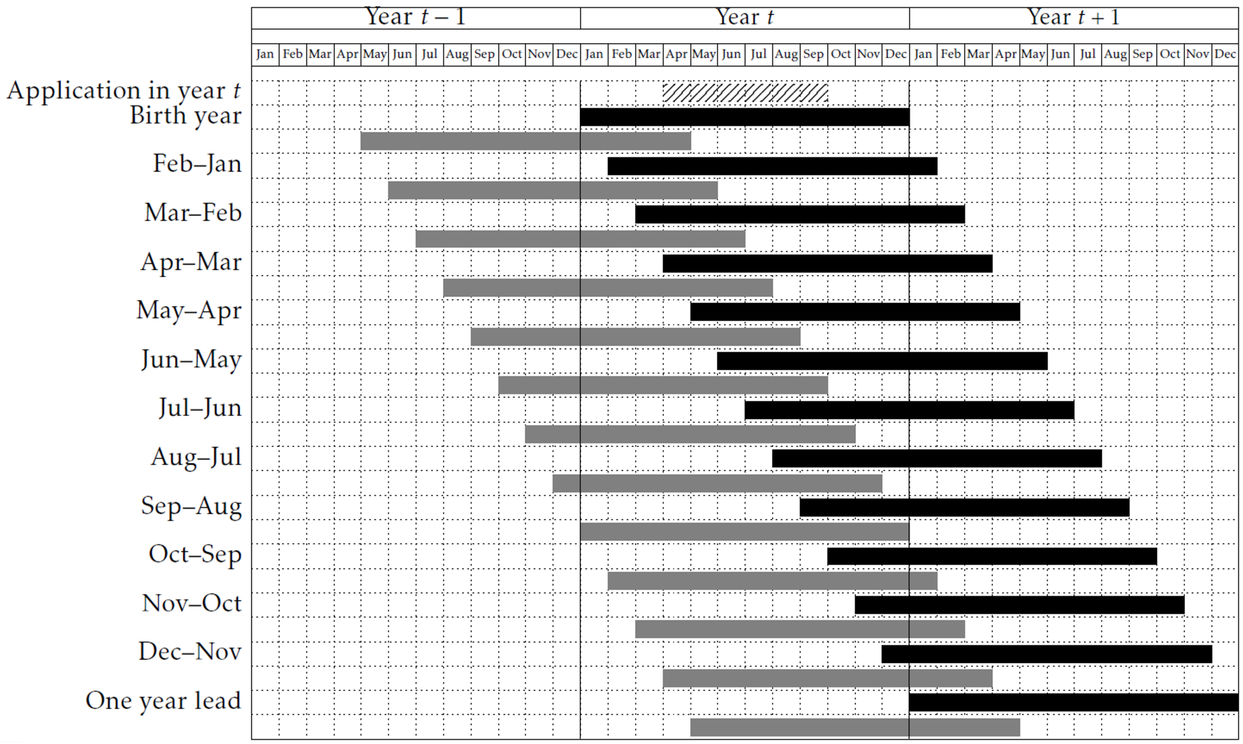

Figure G8: Timeline of glyphosate exposure and birth months. Black bars indicate the birth months of the sample, while gray bars represent the corresponding conception months, assuming a 9-month gestational period. The diagonally hatched bar denotes the glyphosate application period in year t. Using birth year includes some neonates born before the glyphosate application in year t, as well as many who were conceived prior to the application and thus more exposed to glyphosate from the previous year. In contrast, using conception year (September–August) better aligns neonatal exposure with glyphosate applications in year t.

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