Water Quality and Price under Land Use Pressure: Economic and Institutional Perspectives

Mehdi Guelmamen [*] Youba Ndiaye [†]

Working Paper
March 2026

Abstract

Recent drought episodes have underscored growing tensions in water resource management. These supply pressures coincide with mounting concerns over water quality, as both climate change and land use practices contribute to the degradation of surface and groundwater. Agriculture, in particular, has been singled out for its role in nitrate and pesticide contamination. This article investigates the economic and institutional determinants of raw water quality in France, with a specific focus on agricultural land use. Using spatial econometric models and a panel dataset covering the Rhin-Meuse basin from 2008 to 2023, we assess the extent to which agricultural activity influences nitrate and pesticide concentrations in water catchments. We also examine how social, geographic, and governance factors interact with land use patterns to shape pollution outcomes, explicitly accounting for spatial spillover effects. Our findings show that agricultural land use is a strong and robust determinant of nitrate pollution, while pesticide contamination reflects more heterogeneous pressures. Significant spatial spillovers confirm that pollution processes extend beyond administrative boundaries. However, we do not find evidence of a direct cost pass-through from predicted chemical pollution to drinking water prices. Instead, pricing outcomes are more strongly associated with land-use composition and institutional arrangements, suggesting a partial decoupling between environmental degradation and tariff formation.

[*]University of Lorraine, University of Strasbourg, AgroParisTech, CNRS, INRAE, BETA.
[†]University of Lorraine, University of Strasbourg, AgroParisTech, CNRS, INRAE, BETA.
Corresponding author: mehdi.guelmamen@univ-lorraine.fr

JEL Classification: C21; Q25; R11; R52

Keywords: Water management; public services; land uses; spatial spillovers

1 Introduction

The sustainable management of drinking water has become an increasingly urgent challenge in the context of accelerating climate change and mounting pressure on natural resources. Rising temperatures, prolonged droughts, and changing precipitation patterns are intensifying stress on freshwater systems, raising fundamental questions about how water services are organized, governed, and financed. In France, the summer of 2023 provided a stark illustration of these vulnerabilities: 343 municipalities required emergency water deliveries, and 90% of the country was subjected to water restrictions. At the same time, approximately one billion cubic meters of drinking water are lost annually through leaks in public distribution networks—equivalent to the yearly consumption of 20 million people.

Beyond issues of infrastructure efficiency, a more structural concern lies upstream: the degradation of raw water quality due to land-use pressures. Before treatment, drinking water is extracted from surface or groundwater bodies whose ecological status increasingly reflects surrounding land-use patterns. In 2024, 2,700 French catchment areas were classified as priority sites due to chronic contamination by phytosanitary products and nitrates. These figures highlight that the pressure exerted by agricultural and urban land uses is not peripheral but central to understanding the sustainability of drinking water services. Land-use competition shapes pollutant mobility, alters hydrological cycles, and directly affects treatment costs borne by local governments and consumers.

This paper is built around the following central research question: *How does land-use pressure—particularly agricultural land use—interact with local governance structures to influence raw water quality and, ultimately, drinking water prices?* By explicitly linking environmental externalities to institutional arrangements and economic outcomes, the analysis places land-use pressure at the core of drinking water governance rather than treating it as a background condition.

Municipalities are the primary authorities responsible for drinking water provision in France. In accordance with the principle of local public service autonomy, they may choose to manage the service directly or delegate it to private operators via contractual arrangements. However, the extreme fragmentation of the French municipal landscape—comprising over 34,000 municipalities—raises significant challenges in terms of economies of scale, technical expertise, and regulatory compliance. From a neo-institutionalist perspective, such fragmentation increases transaction costs, limits institutional capacity, and exacerbates coordination failures across jurisdictions (Oliver, 1991; North, 1990). When pollution externalities are spatially diffuse—as is the case with nitrate leaching—administrative boundaries rarely coincide with ecological ones, creating a misalignment between environmental processes and governance structures.

Intermunicipal cooperation (IMC) has emerged as a key institutional response to these challenges. By pooling resources and coordinating investments, IMCs may internalize externalities and better align governance scales with hydrological realities (Ostrom, 1990; Williamson, 1985). Yet the extent to which such governance arrangements mitigate the economic consequences of land-use pressure remains insufficiently understood. In particular, little empirical evidence connects land-use composition, spatial spillovers in pollution, and drinking water pricing within a unified analytical framework.

Among land cover types, agriculture constitutes the primary source of diffuse pollution due to the widespread use of nitrogen-based fertilizers and phytosanitary products (Tong and Chen, 2002; Lerner and Harris, 2009). These inputs leach into aquifers and surface waters, especially under conditions of soil compaction and limited vegetative buffers (Veron, 2024; Feuillet and Michon, 2016). Forested areas, by contrast, provide protective ecosystem services by enhancing infiltration, reducing runoff, and filtering pollutants (Fiquepron et al., 2013; Ernst et al., 2004; Abildtrup et al., 2013; Binkley and Brown, 1993). Consequently, land-use composition is not merely an environmental descriptor but a determinant of treatment costs, regulatory compliance, and consumer prices.

This paper adopts a three-step empirical strategy using an original panel dataset for the Rhin-Meuse basin[1] (2008–2023). First, we examine the determinants of agricultural land share to address potential endogeneity in land-use allocation. Second, we estimate

[1] The Rhin-Meuse basin (Bassin Rhin-Meuse) is one of the six major hydrographic districts defined under the European Water Framework Directive. Located in northeastern France, it covers approximately 31,000 km^2 and includes parts of the Grand Est region.

spatial autoregressive models to assess how land-use patterns affect nitrate and pesticide concentrations in raw water. Third, we evaluate how predicted water quality influences drinking water prices, incorporating governance variables and spatial spillovers.

Our results indicate that agricultural land use is a strong and robust determinant of nitrate pollution, while its effect on pesticide contamination is positive but less pronounced. Forest areas are generally associated with lower levels of pollution, and spatial dependence plays a significant role, confirming that diffuse contamination processes extend beyond administrative boundaries. However, we do not find evidence of a direct cost pass-through from predicted chemical pollution to drinking water prices. Instead, pricing outcomes appear to be driven primarily by land-use composition and institutional characteristics.

By integrating land-use competition, spatial econometrics, and institutional analysis, this paper contributes to a more comprehensive understanding of how environmental externalities and governance structures jointly shape the economic performance of essential public services.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature. Section 3 outlines the institutional context in France. Sections 4 and 5 present the data and empirical strategy. Section 6 discusses the results and section 7 concludes.

2 Literature review

A growing literature has investigated the determinants of water quality, highlighting its dependence on a combination of economic, spatial, and institutional factors. The provision of water services, as a local public good, involves both technical efficiency considerations and complex externalities related to resource quality and environmental protection. In this context, the quality of raw and treated water has emerged as a key outcome variable in the analysis of public utility performance and regulatory effectiveness.

While water services in France operate within a relatively robust institutional and regulatory framework - defined at both national and European levels - empirical evidence points to persistent disparities in water quality across territories. These variations reflect the differentiated capacity of local actors to address pollution pressures, implement protection measures, and manage infrastructural constraints. They also raise important questions about the alignment between ecological challenges and governance structures. A growing body of empirical and theoretical work seeks to understand how local institutions, land use patterns, and interjurisdictional coordination jointly shape environmental outcomes and the cost of public service provision.

2.1 Technical and institutional factors

Drinking water services supply drinking water to the population by extracting raw water from the ground. During this process, the water flows through pipelines and undergoes treatment. To maintain water quality, the distance it travels through the distribution network should be minimized as much as possible. Therefore, in most countries, municipalities are tasked with overseeing the management and regulation of water quality. Ensuring efficient production and distribution requires them to possess adequate technical capabilities.

First, network length is a key determinant of water quality, as resource quality deteriorates with the distance traveled. Destandau and Garcia (2014) highlights the critical issue of heterogeneity among water utilities. Water quality can vary significantly depending on the specific characteristics of each utility, as network length and infrastructure renewal differ across local governments. Beyond the distance traveled by the resource, interconnections between services matter too. Interconnections involve the reciprocal linking of distinct distribution units to ensure supply continuity and to enhance both the qualitative and quantitative security of drinking water provision for each interconnected unit. Kiliç (2021) empirically shows that they are negatively correlated with water quality.

The treatment processes applied to raw water to make it drinkable are, unsurprisingly, key determinants of water quality. However, the volume of water circulated through the distribution network also plays a significant role. Research on water utilities showed that maintaining high water quality depends on an optimal network design and appropriate water turnover rates. A study by Carabeț et al. (2011) indicates that factors such as flow dynamics and volumes introduced in the network play a significant role in contamination risks, disinfection effectiveness, and the overall quality of drinking water. Finally, the age and deterioration of the drinking water distribution network are crucial factors influencing drinking water quality: the older the distribution network, the more likely the quality of drinking water is to deteriorate (Denis and Florentin, 2024).

The management model (public or private) is a key variable in previous studies assessing both drinking water quality and the technical efficiency of the sector. The findings consistently indicate a significant impact of private management on water quality. While Fu et al. (2020) show that publicly managed water services tend to be less compliant with microbiological quality thresholds, Le Lannier and Porcher (2014) and Maziotis and Molinos-Senante (2024) highlight that publicly managed services demonstrate greater environmental responsibility and adopt more sustainable water management practices in accordance with quality standards. However, these results must be interpreted in light of population density, as noted by Benito et al. (2019), who finds that higher population density positively influences both environmental efficiency of the sector and the quality of the resource. More specifically, higher population density tends to degrade water resource quality, as it necessitates more extensive and complex water treatment facilities. Consequently, services may face challenges in maintaining consistent quality standards under high demand.

2.2 Climate change and soil management influence

Land uses and water quality are closely related since nitrate levels are low under forest cover. Nitrates are among the most closely monitored pollutants in drinking water, and the European Directive of November 3, 1998, on the quality of water intended for human consumption set the maximum allowable nitrate concentration at 50 mg/L. In an empirical study, Fiquepron et al. (2013) assess a positive relationship between land use, forest presence, and water quality. Their analysis goes further, showing that afforestation can lead to a reduction in the average household drinking water bill by €22 per year.

These findings align with the conclusions of Hascic and Wu (2006); Langpap et al.

(2008); Phiri et al. (2020), who identify a significant relationship between raw/drinking water quality and land use. According to Feuillet and Michon (2016), between 1997 and 2013, a total of 7,716 water catchments were decommissioned in France, primarily due to pollution. In these affected catchments, pollutant concentrations exceeded the drinking water standards established by the French Ministry of Health. Lerner and Harris (2009) found that inappropriate land use and particularly poor land management lead to chronic groundwater quality problems.

Tong and Chen (2002) build on this by arguing that runoff, which is closely linked to land use patterns, is a major source of nonpoint source pollution. The agricultural sector, in particular, is considered the largest contributor to water pollution through runoff and the leakage of nutrients, sediments, pesticides, and other contaminants. Hascic and Wu (2006) support this finding, observing that runoff from agricultural land is the primary cause of water pollution. Moreover, Abildtrup and Strange (2000) showed that forest land use is generally associated with the protection of water resources from contamination and with lower drinking water supply costs. Similar conclusions were reached by Ernst et al. (2004), who highlighted the crucial role of forests in maintaining raw water quality.

Binkley and Brown (1993) argue that cultivated lands release more than five times as much sediment into waterways as forested areas, which, in turn, tend to occupy the most integral parts of the watershed. More recently, Veron (2024) showed that French public policies regarding the protection of water catchment areas lack coherence, which may have negative consequences for resource quality. Consequently, estimating drinking water quality without accounting for land uses and catchment areas may lead to biased results.

More broadly, the impact of climate change is becoming a central factor in the analysis of drinking water quality. An extensive literature review by Delpla et al. (2009) highlights that climate change can directly affect water quality through various mechanisms. First, rising temperatures lead to an increased frequency of drought events. Van Vliet and Zwolsman (2008); Van Vliet et al. (2023) establish a significant relationship between temperature rise and the physico-chemical quality of drinking water, showing that higher temperatures contribute to quality deterioration. The same pattern is observed for nutrient levels (Wilhelm and Adrian, 2008) and microbiological quality (Charron et al., 2004). Finally, Hamid et al. (2020) expand on this analysis by identifying local determinants of drinking water quality. According to their findings, temperature and land use must be incorporated into water quality assessments, as they play a crucial role in driving its spatio-temporal variations.

Despite a rich body of research on land use and water pollution, and a growing literature on drinking water governance and pricing, three main gaps remain. First, few studies jointly model land-use determinants and water quality outcomes while explicitly addressing endogeneity in land allocation. Second, spatial spillovers in pollution are often acknowledged but insufficiently integrated into pricing analyses. Third, the economic transmission channel from land-use pressure to consumer water prices—through treatment costs and regulatory compliance—remains underexplored in the literature. This paper contributes to filling these gaps by combining a control-function approach for land-use endogeneity, spatial econometric models for pollution dynamics, and a price equation incorporating predicted water quality. In doing so, it provides an integrated assessment of how environmental and institutional factors jointly determine both ecological and economic outcomes in the drinking water sector.

3 The French institutional context

3.1 Overview of the French water sector

The management of raw and drinking water is governed by a strict institutional and regulatory framework operating at multiple scales. In Europe, key directives have been adopted to standardize and systematize water quality monitoring. The Water Framework Directive[2] established a comprehensive framework for water policy across the European Union, aiming to protect and enhance the status of aquatic ecosystems while promoting the sustainable use of water resources. It introduced a paradigm shift from a purely sectoral or administrative management of water toward an integrated, river basin–based approach. One of its core innovations is the requirement to achieve "good status" for all surface and groundwater bodies, both in terms of ecological and chemical

[2]Directive 2000/60/EC of the European Parliament and of the Council of 23 October 2000.

quality, by explicitly linking environmental objectives with economic instruments such as cost recovery and the "polluter pays" principle (Kaika, 2003).

In France, municipalities are administratively responsible for the provision of drinking water. In other words, water supply and sanitation services (including wastewater collection and treatment) are public services managed at the municipal level, under the authority of the mayor.

In France, the Water and Aquatic Environments Act[3] (LEMA) was enacted to align domestic water policy with the EU Water Framework Directive and strengthen integrated basin-scale governance. Notably, LEMA introduced the concept of Organismes Uniques de Gestion Collective (OUGC) for irrigation in aquifers under structural water deficits—especially in areas dominated by agriculture—to regulate water allocations among users more effectively. It mandated the creation of protection perimeters around drinking water catchments and enabled the sequencing of land-use regulations—such as compulsory buffer strips, nutrient management plans, and phytosanitary product tracking—to curb nitrate and pesticide leaching. Despite such provisions, challenges persist due to fragmented land ownership, varying enforcement levels, and the political sensitivity of regulating agricultural practices, as observed by national water agencies (Figureau et al., 2014).

In practice, some local authorities delegate the development and operation of these public services to private companies. Public service delegation involves the transfer of operational responsibility to a private operator, who assumes the financial risk and retains the revenue generated by the service. This arrangement typically entails a comprehensive transfer of service management or infrastructure operations, while core public authority responsibilities remain with the municipality. A municipality's decision to delegate its water service is rarely random and can be influenced by several factors. Financial considerations are often decisive: when facing high levels of debt and lacking the means to maintain the water system, a municipality may opt for delegated management. In addition, increasingly strict regulations governing equipment standards, personnel management, safety, and legal liability may encourage local authorities to outsource the service in order to navigate complex legal requirements.

[3] Law No. 2006-1772 of 30 December 2006.

Moreover, the technical complexity of water service provision and the expertise required—both of which can entail substantial costs—may lead municipalities to delegate the service to benefit from the efficiency, infrastructure quality, and technical competence offered by private operators. However, delegation also involves various risks, including commercial risk and uncertainties related to construction and operational performance, which must be factored into the decision.

Because drinking water is sourced from natural resources, it is essential to protect these resources to prevent pollution and to avoid the need for complex and costly water treatment processes. In this context, public authorities have established procedures for declaring water catchments to be of public interest, which includes the creation of legally protected zones around water abstraction points. These procedures are now mandatory for all public water sources intended for human consumption.

Each catchment area has a specific "recharge zone", referring to the territory from which infiltrated or runoff water feeds the source. This zone is the priority area for protecting the water resource from diffuse pollution. Protected zones are a key tool for preventing and reducing contamination that could compromise the quality of water extracted. Responsibility for establishing and managing these protected areas lies with the local authorities that own the water abstraction points.

In France, drinking water is managed through water supply services. To ensure effective management, municipalities can form inter-municipal associations or joint bodies, such as water syndicates or municipal communities. These groupings may manage the service directly with their own staff—this is referred to as direct public management. Alternatively, they may enter into delegation contracts with specialized private companies. Although France has relatively abundant water resources, delivering potable water to every household remains a complex and costly undertaking. Drinking water treatment increasingly relies on advanced technologies. The water bill paid by French consumers covers not only the treatment and distribution of drinking water but also wastewater treatment and environmental protection efforts.

3.2 Needs and limitations of the French agricultural sector

Freshwater consumption in France—defined as the share of water withdrawn but not returned to aquatic ecosystems—is unevenly distributed across economic sectors. According to national water accounting data, agriculture is by far the largest consumer, accounting for 58% of total freshwater use between 2010 and 2019. This is followed by domestic water production (26%), energy generation—primarily for cooling in thermal power plants (12%)—and industrial uses, including tourism and agri-food processing (4%) (ONEMA, 2016; Eaufrance, 2023).

The agricultural sector's dominance in water use is consistent with its macroeconomic weight in France. A 2024 report from the French National Institute of Statistics and Economic Studies (INSEE) confirmed that France remains the leading agricultural producer in the European Union. In 2022, French farms generated €88.2 billion in agricultural output, with €56.9 billion from crop production and €31.4 billion from animal production. France alone accounted for 17.9% of the EU's total agricultural value. Since 1980, the structure of French agricultural production has shifted markedly, with crop production increasing from 54% to 61% of total output, while the share of livestock has declined from 42% to 33%. Meanwhile, agricultural services—such as landscape management and on-farm processing—have doubled, albeit from a low base (from 3% to 6%).

This structural evolution raises pressing environmental concerns, particularly in the context of increasingly frequent droughts and mounting water scarcity. Intensive agricultural practices are among the primary sources of nonpoint pollution in surface and groundwater bodies (Tong and Chen, 2002; Lerner and Harris, 2009). The widespread use of pesticides and synthetic fertilizers contributes to elevated levels of nitrates and phytosanitary residues, which often infiltrate water catchments and necessitate more advanced and costly treatment processes by drinking water utilities (Fiquepron et al., 2013; Honey-Rosés et al., 2014). These additional treatment costs may ultimately be passed on to consumers through higher water tariffs, creating a spatially and socially uneven burden of environmental degradation.

In recent years, a growing number of farmers have adopted more environmentally friendly practices. As of January 2023, more than 36,000 farms in France were certified under the High Environmental Value (HVE) label, and over 60,000 were engaged in certified organic farming—a number that has increased 2.5-fold in the last decade (Veron, 2024). While these trends are promising, they do not eliminate environmental externalities entirely. Even under organic or HVE-certified systems, nutrient runoff and pesticide residues may persist depending on crop type, soil conditions, and climatic variability. As such, the actual effectiveness of these certification schemes in protecting water quality remains an open empirical question.

3.3 Focus on the Rhin-Meuse basin

The Rhin–Meuse Water Agency's territory—i.e., its hydrographic basin—partly spans one region and eight departments, encompassing 3,230 municipalities and covering roughly 31,400 km^2 (about 6% of metropolitan France). Defined by natural drainage boundaries rather than administrative borders, this footprint offers a consistent frame for basin-scale analyses of raw-water quality dynamics. The Agency is one of France's six water agencies, a state administrative body overseen by the Water Directorate of the Environment Ministry. Its mandate is to coordinate basin-wide action through multi-annual programs prepared with the basin committee and framed by Parliament; in practice, it levies fees under the polluter-pays principle, supports aquatic-ecosystem restoration and pollution reduction, assists in developing river-basin management plans (SDAGE), contributes to water-quality data production, and implements integrated water-resources management.

Spanning the French drainages of the Rhine and the Meuse, the Rhin–Meuse basin provides a coherent hydrological setting that cuts across administrative borders and links upland Vosges headwaters to lowland agricultural and urban plains. This mosaic includes long-established industrial corridors, intensive farming areas, vineyards, forests, wetlands, and alluvial aquifers, generating diverse pressures on raw water—from diffuse nutrient and pesticide loads to legacy pollutants and morphological alterations. The basin is intrinsically transboundary, with upstream–downstream interdependencies involving Belgium, Luxembourg, and Germany, making coordination over quantity and quality a practical necessity.

The basin also benefits from dense monitoring and planning infrastructures (river-basin management plans, ecological status assessments, systematic water-quality surveillance), which provide consistent data and institutional continuity over time. Taken together, these features—hydrological connectedness, land-use heterogeneity, historical path-dependencies, and mature governance—make the Rhin–Meuse basin a particularly informative and policy-relevant context for examining how territorial organization and resource uses shape raw-water conditions and service outcomes. Figure 1 illustrates the basin outline and offers a visual guide to the spatial structure discussed here.

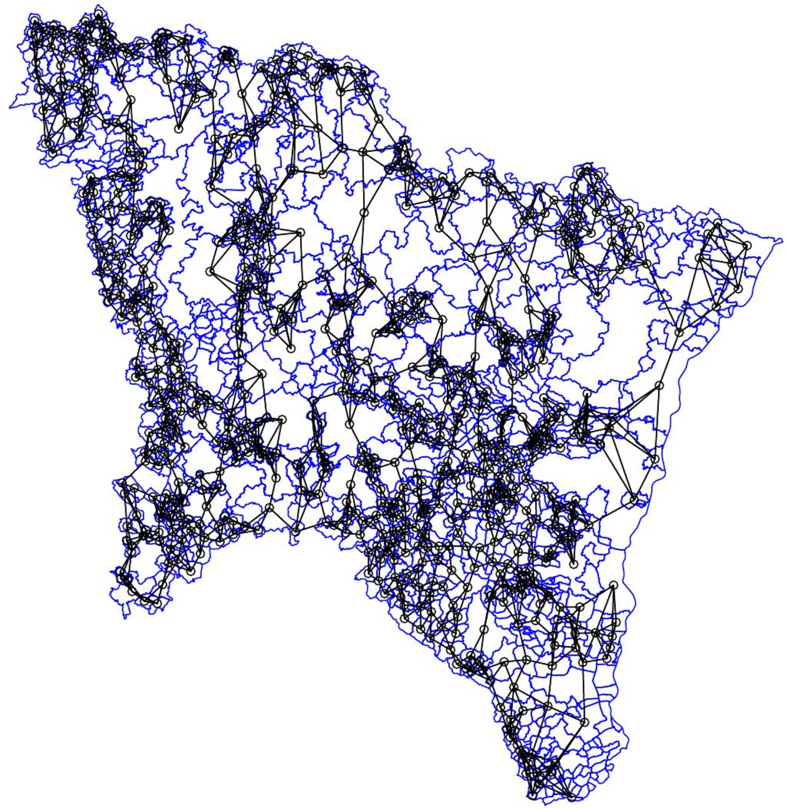
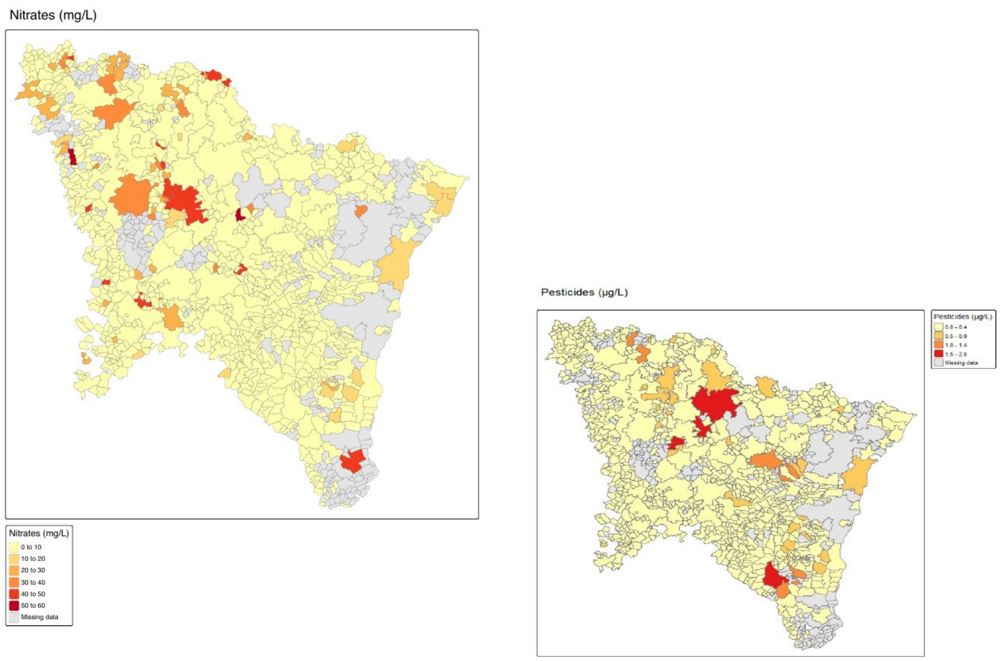


Figure 1: Water services in the Rhin–Meuse basin. *Note*: black lines represent administrative boundaries (municipalities); blue lines represent hydrological network boundaries (catchment divides).

The basin's landscape heterogeneity—from forested headwaters to intensive agricultural plains, industrial valleys, wetlands, and alluvial aquifers—drives substantial spatial variation in raw-water pollution. Land use, soil properties, topography, runoff pathways, and hydrological connectivity shape the transport of nitrates and pesticides from fields to streams and abstractions, producing upstream–downstream gradients and contamination hotspots. Figure 2 illustrates this pattern, with higher concentrations in predominantly agricultural areas and lower levels in forested or well-buffered zones.



(a) Nitrate pollution in the Rhin-Meuse basin

(b) Pesticide pollution in the Rhin-Meuse basin

Figure 2: Water pollution by nitrates and pesticides in the Rhin-Meuse basin

4 Data and sample

Price. The variable representing the price of drinking water paid by consumers was derived from the SISPEA database (Information System on Public Water and Sanitation Services). This dataset covers the period 2008–2023 and compiles information annually reported by local water utilities. In accordance with the French General Code of Local Authorities, all water services are legally required to produce and disclose an annual report on the quality and price of drinking water, thereby ensuring transparency for consumers.

The unit price per cubic meter is calculated based on an annual consumption of 120 m3. Set by local public authorities, the price reflects multiple determinants, including the nature and quality of the water resource, geographical conditions, population density, the chosen level of service, infrastructure renewal policies, and the scale and financing of investments. This price encompasses all components of the water service — production, transmission, and distribution — together with the fees levied by the Water Agencies for resource preservation and pollution control. Where applicable, it also includes the charges collected by Voies Navigables de France for surface water abstraction, as well as the value-added tax (VAT). The water price variable used in this study refers to the portion of the household bill attributable solely to drinking water services, excluding the component related to wastewater treatment.

The price, set by local authorities and public agencies, represents a descriptive indicator of the drinking water service. It results from multiple factors, some of which are context-specific, such as the quality of the raw water resource. Land-use patterns within the catchment area may exert an indirect influence on this price by affecting water quality and, consequently, the treatment costs required to ensure drinkable standards.

Quality. The data on raw water quality used in this study were obtained from the Naïades database, the national repository for surface and groundwater monitoring in France. Naïades compiles measurements produced by a wide range of public and private entities for regulatory, research, or operational purposes. Each record distinguishes between the data producer—the institution commissioning the monitoring activity—and the operators responsible for field sampling and laboratory analysis. In most cases, water agencies, regional environmental directorates (DREALs), or accredited laboratories act as producers, while sampling and analytical work may be performed either in-house or by external contractors. All measurements follow standardized national protocols for physico-chemical and hydrobiological parameters, ensuring the comparability and reliability of the dataset across sites and over time.

The Naïades database provides several types of water quality measurements, including physico-chemical, hydrobiological, and hydromorphological indicators. Among these, the physico-chemical data are the most systematically reported and cover the longest continuous time series, particularly for the Rhine-Meuse river basin. For this reason, our analysis focuses on raw water measurements of nitrates and pesticides, which are key indicators of agricultural and land-use pressures on water resources. In Naïades, pesticide contamination is recorded as the sum of quantified pesticide concentrations, expressed in micrograms per liter (g/L). Nitrate levels are measured in milligrams per liter (mg/L) using similar protocols.

An important consideration concerns the exact location of the Naïades monitoring stations within catchments. Measurements can be taken at various points along the hydrological network—within the catchment body itself, along rivers, or at groundwater abstraction points—rather than systematically at the inlet of the drinking-water treatment plant. This contrasts with certain prior studies that used quality data recorded directly at the production station entry point (Destandau and Garcia, 2014). As a consequence, our quality indicators reflect upstream environmental pressures rather than the final treated water quality at the service level. We discuss the implications of this measurement design in the conclusion.

Based on these continuous indicators, we construct binary variables identifying whether a given water sample exceeds the official quality thresholds defined by the European Drinking Water Directive (EU Directive 2020/2184) and transposed into French environmental regulation. For nitrates, the quality standard is set at 50 mg/L, above which water is considered non-compliant for human consumption. For pesticides, the limit is defined as 0.1 g/L per individual substance and 0.5 g/L for the sum of all detected pesticides. Each observation is therefore assigned a value of 1 if the concentration exceeds the corresponding regulatory threshold, and 0 otherwise. These binary indicators allow us to capture episodes of water quality deterioration and to link them empirically to local governance structures, land-uses and characteristics of water services.

4.1 Explanatory variables

Land uses. The Corine Land Cover (CLC) dataset provides a harmonized biophysical inventory of land use and land cover across Europe. It is produced through visual interpretation of satellite imagery with a spatial resolution of approximately 20 meters, following a 44-class nomenclature established at the European level. The dataset maps homogeneous land-cover units with a minimum mapping area of 25 hectares (5 hectares for detected land-cover changes). Initiated in 1985 under the Copernicus Earth Observation Programme, CLC supports the consistent monitoring of land-use changes across Member States and the development of European environmental policies.

In this study, we use CLC data to characterize the land-use composition of each catchment area. We focus on four aggregated land-use categories: (1) forests and semi-natural areas, (2) agricultural land, (3) artificial surfaces (mainly urban and industrial zones), and (4) other land uses, including wetlands and water bodies. These four shares sum to one by construction. *Other land uses* serves as the reference category in all estimations. Because wetlands, water bodies, and bare soils are generally associated with limited pollutant inputs, using this category as the baseline allows coefficients on agricultural, forest, and urban shares to be interpreted as differentials relative to this low-pollution, low-infrastructure benchmark.

These categories capture the dominant land-use patterns likely to influence raw water quality, particularly through their indirect effects on nutrient runoff, pesticide diffusion, and hydrological dynamics. Furthermore, by comparing CLC layers over successive years, we are able to analyze land-use transitions within catchment areas—most notably, the conversion of agricultural land into forested areas or into urban and industrial zones. These transitions are particularly relevant for understanding the evolving pressures on water resources and the long-term environmental impacts of land-use change.

The Registre Parcellaire Graphique (RPG) is a detailed geographical database that serves as the national reference for administering the Common Agricultural Policy (CAP) subsidies in France. It provides geospatial information on agricultural plots, including their location, crop type, and the characteristics of the farms that declare them. These data make it possible to construct indicators describing the structure and intensity of agricultural activity within each catchment area. In particular, the RPG allows us to distinguish between conventional and organic farming practices, the latter being generally associated with lower pesticide use and thus considered less harmful to raw water quality. Based on these data, we also derive a variable representing the number of agricultural holdings within each area, which serves as a proxy for the density and fragmentation of farming activity. The combination of these indicators provides a more refined understanding of how agricultural practices and structures interact with land-use patterns and environmental pressures on water resources.

It should be noted that not all agricultural uses generate equivalent pollution pressures. Permanent grasslands, for instance, receive far fewer inputs than arable crops, contributing substantially less to nitrate and pesticide contamination (Tong and Chen, 2002). This heterogeneity is partly captured by the RPG-based variables included in the analysis—notably the number of organic farms and the CAP-eligible area—which are precisely designed to capture within-agricultural variation in farming intensity and production structure across services.

Table 1: Dependent variables

Variable	**Description**	**Source**	**Unit**	**Effect on Price**	**Effect on Quality**
$Price_{it}$	Drinking water price including production, transmission and distribution (excluding wastewater).	SISPEA	€/m^3	–	–
$Nitrates_{it}$	Nitrate concentration in raw water.	Naïades	mg/L	↑ if treatment	–
$Pesticides_{it}$	Sum of pesticide concentrations in raw water.	Naïades	μg/L	↑ if treatment	–

Water services characteristics. The SISPEA database compiles detailed socioeconomic characteristics of French drinking water services, including the price paid by consumers. It provides comprehensive information on the financial, technical, and organizational features of all French water utilities over the period 2008–2024.

From this dataset, we extract two key organizational variables. The first, Private$_{it}$, indicates whether the provision of drinking water in water service i at time t is delegated to a private operator or managed directly by the public authority. The second, Intermunicipal$_{it}$, identifies whether the service is operated under a collective (intermunicipal) arrangement or managed independently by a single municipality. These variables capture the main institutional dimensions of local water governance in France. The literature has consistently highlighted the relationship between the price paid by consumers and the governance structure of water services (Carpentier et al., 2006; Guelmamen, 2025).

Regarding the technical characteristics of the water network, we include the variable Renewal$_{it}$, which measures the rate of network renewal. Specifically, this indicator represents the average annual percentage of the drinking water network that has been renewed over the previous five years, relative to the total network length. This variable reflects the level of infrastructure investment and maintenance effort undertaken by the service provider, which can directly influence the cost structure of the utility and, consequently, the price paid by consumers.

We also include variables describing the volumes of water imported (Import$_{it}$) and exported (Export$_{it}$) by each drinking water service. These indicators capture the degree of interdependence between neighboring utilities in terms of water supply. Such dependence may directly affect price formation, as services that import water from external sources often face higher tariffs due to additional transport and interconnection costs, while exporting services may benefit from economies of scale or revenue transfers from neighboring networks (Guelmamen et al., 2025). Finally, the population served by each utility (Population$_{it}$) is included as a proxy for the size of the water service. This variable captures the scale of operations and potential economies (or diseconomies) of scale that may influence both the cost structure and the pricing behavior of water utilities.

Instrument. To address the potential endogeneity of agricultural land use, we exploit spatial variation in farming systems and construct an external shifter based on neighboring organic farming. Specifically, we use the mean number of organic farms in the four nearest neighboring services, *Mean organic farms (neighbors)*$_{it}$, as an instrument for the local share of agricultural land. This construction follows the logic of shift-share instruments (?), which exploit variation in a local outcome driven by the composition of neighboring units rather than local conditions. The instrument is computed as:

$$Z_{it} = \frac{1}{|\mathcal{N}_i|} \sum_{j \in \mathcal{N}_i} \text{OrganicFarms}_{jt}, \tag{1}$$

where $\mathcal{N}_i$ denotes the set of the four nearest neighboring services of i. Areas surrounded by many organic farms are likely to exhibit more intensive and specialized agricultural activity, so this spatial measure should be positively correlated with the agricultural land share. Conditional on local land-use composition, governance covariates, and service and year fixed effects, we assume that neighboring organic farms do not directly affect water prices or raw-water quality, so that Z_{it} can be excluded from the structural equations and enters only through the control-function term (Wooldridge, 2015, 2019).

The validity of the exclusion restriction relies on the assumption that neighboring organic farming intensity does not directly affect the raw water quality of service i, conditional on local land use and fixed effects. This assumption is justified by the fact that organic farming in adjacent services typically operates on distinct hydrological catchments and is unlikely to generate direct cross-boundary externalities on water inflows. While organic farming practices may reduce pollutants locally, their impact is spatially bounded due to heterogeneous hydrographic boundaries and water service jurisdictions. As a consequence, mechanisms such as reduced nitrate leaching or pesticide use would not spill over significantly across catchment boundaries. Furthermore, we control for the full composition of local land uses (including organic share where relevant), governance, and service-level fixed factors, thereby isolating local determinants of water quality from spatially distal influences.

A further identification concern relates to the origin of raw water. In the Rhin–Meuse basin, groundwater is by far the dominant source of drinking water supply: underground aquifers provide approximately 85% of the potable water produced in the basin. This predominance has important implications for our identification strategy. Groundwater quality is partly buffered from surface land-use pressures, which could attenuate the estimated relationship between catchment land-use composition and measured pollution (Lerner and Harris, 2009). The share of surface versus groundwater abstraction varies across services and is not systematically recorded in our data. Since groundwater dominates the basin, the measured pollution indicators reflect hydrological processes operating at longer time scales than surface water, with concentration dynamics that respond more gradually to changes in land-use composition.

Table 2: Explanatory variables and instrument

Variable	**Description**	**Source**	**Unit**	**Effect on Price**	**Effect on Quality**
Land use (CLC)					
Agricultural land$_{it}$	Share of agricultural land in catchment.	CLC	%	–	↓
Forests / semi-natural$_{it}$	Share of forests and semi-natural areas.	CLC	%	–	↑
Artificial surfaces$_{it}$	Share of urban/industrial land.	CLC	%	–	↓
Other land uses$_{it}$	Wetlands and water bodies. *Reference category.*	CLC	%	–	↑
Service characteristics (SISPEA)					
Private$_{it}$	Dummy = 1 if service is delegated to a private operator.	SISPEA	0/1	↑	–
Intermunicipal$_{it}$	Dummy = 1 if service is under intermunicipal arrangement.	SISPEA	0/1	↑	–
Renewal$_{it}$	Average annual network renewal rate.	SISPEA	%	↑	–
Import$_{it}$	Volume of water imported from neighbouring services.	SISPEA	m^3	↑	–
Export$_{it}$	Volume of water exported to neighbouring services.	SISPEA	m^3	↓	–
Population$_{it}$	Population served by the water utility.	SISPEA	inhab.	↓	–
Agricultural practices (RPG)					
Eligible area$_{it}$	Agricultural surface eligible for CAP payments.	RPG	ha	↑	–
Instrument					
Organic farms (neighbors)$_{it}$	Average number of organic farms in the four nearest neighbouring services (Bartik-type).	RPG + neighbors	Mean count	–	–

Notes: SISPEA = Information System on Public Water and Sanitation Services; Naïades = national database on water quality; CLC = Corine Land Cover; RPG = Registre Parcellaire Graphique.

5 Empirical strategy

This paper examines (i) the relationship between agricultural land use and raw water quality, and (ii) the indirect effect of land use on water prices. Because agricultural land use is likely endogenous—e.g., it co-moves with unobserved determinants of water quality or reacts to local shocks—we implement a three-step control-function strategy in panel data (Wooldridge, 2015, 2019).

A central concern in our setting is that the agricultural land share, A_{it}, is likely endogenous: it may co-move with unobserved determinants of raw-water quality (e.g., local agronomic or governance factors). The CF strategy mirrors the logic of instrumental variables: we (i) obtain a reduced-form projection for the potentially endogenous regressor using excluded shifters and (ii) include the resulting residual (or generalized residual) in the outcome equation to purge endogeneity.[4]

5.1 Step 1 : Land-use competition, endogeneity, and control function

Let i index water service utilities and t years. A central explanatory variable in the subsequent environmental and price equations is the share of agricultural land, AgriShare_{it}. This variable is potentially endogenous because land-use decisions may be jointly determined with unobserved economic, institutional, or environmental factors that also affect water quality and pricing outcomes.

5.1.1 Identification strategy using RPG data

To address this concern, we exploit detailed information from the *Registre Parcellaire Graphique* (RPG), which provides parcel-level data on land use and agricultural practices. RPG variables are intrinsic to the agricultural production sector and are determined by agronomic conditions, policy eligibility rules, and farm-level structural characteristics. As such, they are plausibly exogenous to short-run shocks affecting agricultural land dynamic.

[4]Strictly speaking, all land-use shares—forest, urban, and *other land uses*—are also potentially endogenous, as local allocation decisions may reflect unobserved determinants of water quality and prices. Addressing endogeneity for all shares simultaneously would require a system-of-shares approach with multiple excluded instruments, which is beyond the scope of this paper. We focus on agricultural land as the primary driver of diffuse pollution and treat the remaining shares as predetermined conditional on the control function.

In our context, RPG-based variables (such as the number of organic farms and eligible agricultural area on CAP subsidies) are used to model competition between land uses and to isolate exogenous variation in agricultural land share. This strategy follows a growing literature (Levavasseur et al., 2016; Leonhardt et al., 2023) that leverages detailed agricultural registries to address endogeneity in land-use and environmental outcomes.

5.1.2 CRE/Mundlak specification

We estimate the agricultural land share equation using a correlated random effects (CRE) approach:

$$\text{AgriShare}_{it} = \beta_0 + \mathbf{X}_{it}'\beta + \rho_t + a_i + u_{it}, \tag{2}$$

where $\mathbf{X}_{it}$ includes forest and urban land shares as well as RPG-based agricultural variables, ρ_t are year fixed effects, and a_i captures time-invariant unobserved heterogeneity at the service level. Following the Mundlak device (Mundlak, 1978), we include the within-service means $\bar{\mathbf{X}}_i$ to allow correlation between a_i and the regressors. Specifically, the Mundlak correction amounts to projecting the individual effect on the time-means: $a_i = \bar{\mathbf{X}}_i'\boldsymbol{\theta} + v_i$, where v_i is uncorrelated with $\mathbf{X}_{it}$ and $\bar{\mathbf{X}}_i$ by assumption.[5] Substituting into (2) and absorbing v_i into the composite error delivers estimates equivalent to within (fixed-effects) estimators for the time-varying coefficients. Formally, we estimate:

$$\text{AgriShare}_{it} = \beta_0 + \mathbf{X}_{it}'\beta + \bar{\mathbf{X}}_i'\theta + \rho_t + v_i + u_{it}. \tag{3}$$

5.1.3 Control function approach

While the CRE specification accounts for correlation with time-invariant unobservables, remaining endogeneity may arise from time-varying shocks affecting agricultural land allocation. To address this issue, we implement a control function approach (Wooldridge,

[5] The Chamberlain (1982) generalization allows for a fully nonlinear projection and applies to unbalanced panels; in the linear case considered here, the Mundlak device is sufficient and numerically equivalent to within (fixed-effects) estimation for the time-varying coefficients.

2015). Specifically, we recover the residual from the agricultural land share equation:

$$\hat{u}_{it} = \text{AgriShare}_{it} - \widehat{\text{AgriShare}}_{it}, \tag{4}$$

and include $\hat{u}_{it}$ as an additional regressor in the subsequent structural equations. Under standard assumptions, the significance of $\hat{u}_{it}$ provides a test for endogeneity, while its inclusion corrects for bias due to correlation between AgriShare_{it} and the structural error term (Wooldridge, 2015; Lin and Wooldridge, 2019).

The estimated agricultural land share equation is:

$$\begin{aligned}\text{AgriShare}_{it} = {} & \beta_1 \text{ForestShare}_{it} + \beta_2 \text{UrbanShare}_{it} + \beta_3 \text{OrganicFarms}_{it} + \beta_4 \text{EligibleArea}_{it} + \\ & \theta_1 \overline{\text{ForestShare}}_i + \theta_2 \overline{\text{UrbanShare}}_i + \theta_3 \overline{\text{OrganicFarms}}_i + \theta_4 \overline{\text{EligibleArea}}_i + \rho_t + u_{it}\end{aligned} \tag{5}$$

The residual $\hat{u}_{it}$ from (5) is then carried forward as a control function in the water quality equation.

5.2 Step 2 : Spatial determinants of nitrate pollution

Diffuse environmental pollution generates hydrological and spatial externalities: nitrate loads originating upstream or in neighboring service areas can affect measured water quality downstream (and, empirically, in nearby services). To account explicitly for these interdependencies, we estimate a spatial autoregressive (SAR) panel model. This specification captures endogenous spatial spillovers in nitrate pollution across neighboring water services through a predefined spatial weights matrix W (row-standardized) defined by a k-nearest neighbours spatial weights matrix with $k = 4$, based on geographical proximity between drinking-water services. This choice reflects the fact that hydrological and diffuse pollution processes are inherently local, so that nitrate contamination is most likely to propagate across nearby service areas rather than over long distances. The weights matrix W is row-standardized so that each row sums to one, implying that the spatial lag $(Wy)_{it}$ captures the average nitrate pollution level among the closest neighbouring services of unit i at time t.

Such k-nearest-neighbours specifications are widely used in applied spatial econometric studies. They ensure connectivity of the spatial network and help avoid isolated units, especially when administrative units differ in size and shape.

The SAR framework is standard in spatial econometrics for modeling spatial dependence and interpreting direct vs. spillover effects. See LeSage and Pace (2009) and the spatial panel discussion in Elhorst et al. (2014), as summarized and used in Sheng and LeSage (2021).

Let y_{it} denote the nitrate pollution outcome for drinking-water service i in year t (e.g. a nitrate level or pesticide level). Let X_{it} include land-use drivers and agricultural practice proxies:

$$X_{it} = \big(\text{AgriShare}_{it},\ \text{ForestShare}_{it},\ \text{UrbanShare}_{it},\ \text{OrganicFarms}_{it},\ \text{EligibleArea}_{it}\big),$$

where agricultural covariates are constructed from RPG information to exploit intrinsic, sector-specific variation and mitigate endogeneity concerns in land-use measures.

SAR panel model (random effects with Mundlak correction). We start from the following SAR panel model:

$$y_{it} = \rho\,(Wy)_{it} + X_{it}'\beta + \lambda_t + \mu_i + \varepsilon_{it}, \tag{6}$$

where $(Wy)_{it} = \sum_{j\neq i} w_{ij} y_{jt}$ is the spatial lag of pollution outcomes, and ρ is the spatial autoregressive coefficient. When $\rho > 0$, higher nitrate pollution in neighboring services is associated with higher nitrate pollution in service i, consistent with diffuse pollution spillovers.

To account for potential correlation between time-invariant unobserved heterogeneity μ_i (e.g. persistent hydrogeological vulnerability, historical infrastructure, measurement intensity) and the regressors, we adopt the Mundlak correlated random effects device (Wooldridge, 2019). Specifically, we assume that:

$$\mu_i = \overline{X}_i'\theta + \xi_i,$$

where ξ_i is uncorrelated with the regressors.

Substituting this decomposition into Equation (6) yields the following estimable specification:

$$y_{it} = \rho\,(Wy)_{it} + X_{it}'\beta + \overline{X}_i'\theta + \lambda_t + \xi_i + \varepsilon_{it}, \tag{7}$$

where $\overline{X}_i$ captures the component of μ_i correlated with X_{it}, while ξ_i represents the remaining unobserved heterogeneity.

Time-varying common shocks are controlled for by year fixed effects λ_t. This CRE specification delivers robustness to correlated heterogeneity while preserving the likelihood-based framework used by spatial panel ML estimators.[6]

5.2.1 Estimation strategy

Equation (6) is estimated by maximum likelihood for spatial panels with a spatial lag and random effects (as implemented in `spml/sprem`). The inclusion of $(Wy)_{it}$ implies that marginal effects are not equal to β in general; impacts decompose into direct and indirect (spillover) components through the spatial multiplier $(I - \rho W)^{-1}$, following the standard interpretation framework in spatial econometrics.

Neighbourhood definition and spatial weights matrix. Constructing the spatial weights matrix is central to identifying "neighbours" and, hence, spatial interaction channels. We rely on a k-nearest-neighbours scheme with $k = 4$: for each water service area i, we define $w_{ij} = 1$ if j belongs to the set of the four closest services to i (according to the chosen distance metric), and $w_{ij} = 0$ otherwise, with $w_{ii} = 0$. The matrix $W = [w_{ij}]$ is then row-normalised so that $\sum_{j \neq i} w_{ij} = 1$, implying that $(Wy)_{it} = \sum_{j \neq i} w_{ij} y_{jt}$ represents the average nitrate outcome in the neighbourhood of unit i at time t. In the context of diffuse nitrate pollution in the Rhine–Meuse basin, this construction operationalises the idea that nitrate pressures and measured water qual-

[6] We estimate the SAR model without spatial lags of the explanatory variables (WX, as in a Spatial Durbin Model). Including WX terms would additionally capture the direct spillover of neighboring land-use composition on local pollution, beyond the endogenous lag (Wy). We experimented with a Spatial Durbin specification as a robustness check; results are qualitatively unchanged and are available upon request. We retain the more parsimonious SAR specification as the benchmark.

ity may propagate across nearby services through hydrological connections and spatial spillovers.[7]

Why SAR coefficients are not directly interpretable and how to obtain marginal effects. With a SAR model, the spatially lagged dependent variable creates a feedback mechanism: a change in an explanatory variable in one unit affects its own outcome, which in turn affects neighbouring outcomes through W, and these neighbours feed back to the original unit. Therefore, the coefficient β in a SAR equation cannot be interpreted as a simple ceteris paribus marginal effect. Consider the SAR panel specification (the time subscript t indexes the cross-sectional system; individual index i is retained throughout):

$$y_{it} = \rho(Wy)_{it} + X_{it}\beta + \varepsilon_{it}, \tag{8}$$

which implies the reduced form

$$y_{it} = (I - \rho W)^{-1} X_{it}\beta + (I - \rho W)^{-1}\varepsilon_{it}, \tag{9}$$

where y_{it} and X_{it} denote the $n \times 1$ and $n \times k$ cross-sectional vectors at time t, stacking all y_{it} and X_{it}. Hence, the matrix of partial derivatives of y_{it} with respect to an explanatory variable $x_{k,it}$ is:

$$\frac{\partial y_{it}}{\partial x'_{k,it}} = (I - \rho W)^{-1}\beta_k, \tag{10}$$

where β_k denotes the coefficient associated with regressor x_k (e.g. agricultural share, urban share). In practice, marginal effects are summarised into (i) *direct effects* (average of the diagonal elements of $(I - \rho W)^{-1}\beta_k$), capturing the impact on the originating unit; (ii) *indirect effects* (average of off-diagonal elements), capturing spillovers to neighbours; and (iii) *total effects* (direct + indirect). This impacts decomposition follows the standard interpretation of spatial econometric models (e.g. LeSage and Pace (2009)).

[7] As a robustness check, we also estimate alternative specifications based on other neighbourhood criteria (e.g. distance-band weights and contiguity matrices). Results are available upon request.

5.3 Step 3: Drinking water price equation with predicted pollution

To estimate the determinants of drinking water prices while accounting for water quality, we follow a two-stage strategy. In Step 2, nitrate and pesticide pollution are each modeled using a spatial autoregressive (SAR) panel specification, capturing diffusion processes consistent with diffuse pollution dynamics. We then use the fitted values from those SAR models ($\widehat{\text{Nitrates}}_{it}$ and $\widehat{\text{Pesticides}}_{it}$) as proxies for water quality in the price equation. Using predicted rather than observed pollution aims at mitigating simultaneity and measurement issues between pollution indicators, land uses, and pricing decisions: the SAR structure filters idiosyncratic noise and explicitly accounts for spatial dependence before entering the pricing stage.

In Step 3, we estimate a correlated random effects (CRE/Mundlak) panel model for the water price (measured for a standardized consumption of 120 m^3), allowing unobserved time-invariant heterogeneity to be correlated with covariates through unit-specific means. We present three specifications: (i) predicted nitrates only, (ii) predicted pesticides only, and (iii) both indicators jointly. The full empirical model reads:

$$\text{Price}_{it} = \alpha + \beta_1 \widehat{\text{Nitrates}}_{it} + \beta_2 \widehat{\text{Pesticides}}_{it} + \gamma_1 \text{ForestShare}_{it} + \gamma_2 \text{UrbanShare}_{it} + \mathbf{X}'_{it}\boldsymbol{\delta} + \overline{\mathbf{Z}}'_i\boldsymbol{\theta} + \mu_i + \varepsilon_{it}, \tag{11}$$

where Price_{it} is the drinking water price of service i at time t, $\mathbf{X}_{it}$ collects time-varying service characteristics (e.g., intermunicipal status, management mode, imports/exports, renewal rate, population served), and $\overline{\mathbf{Z}}_i$ denotes the vector of unit-specific time averages of the same (or selected) covariates as in the Mundlak correction. μ_i is an individual (water service) random effect and ε_{it} is an idiosyncratic error term.

Because land-use shares sum to one at the relevant spatial scale, one category must be omitted to avoid perfect multicollinearity (the "dummy trap"). Following the practice in the water-cost/price literature, we take *other land uses* as the overarching reference category for the land-use composition; agricultural land is further omitted from Eq. (11) to resolve the collinearity, so that coefficients on ForestShare_{it} and UrbanShare_{it} are interpreted as price differentials relative to agricultural land as the implicit omitted category (Abildtrup et al., 2013, see the discussion on choosing agriculture as the reference land use).[8]

The predicted pollution indicators $\widehat{\text{Nitrates}}_{it}$ and $\widehat{\text{Pesticides}}_{it}$ are treated as predetermined in Equation (11): because they are fitted values from the Step 2 SAR models, they are purged of idiosyncratic noise that could generate simultaneity with prices. However, we acknowledge that residual endogeneity may persist if unobserved service-level factors jointly determine pollution levels and pricing decisions beyond what the SAR structure captures.

6 Results

6.1 Step 1 : Agricultural land determinants

Table 3 reports the results of the first-step estimation explaining the share of agricultural land at the water-service level. This equation plays a key role in the empirical strategy. It characterizes land-use competition under a fixed land endowment and provides the residual used in the control-function approach applied in the subsequent water-quality equations.

The estimates reveal a very strong and highly significant substitutability between agricultural land and alternative land uses. Both forest and urban shares enter the equation with large negative coefficients (–0.960 and –0.849, respectively), significant at the 1% level. These magnitudes are close to unity. This reflects the mechanical and economic constraint that land-use shares must sum to one: increases in forested or urban areas almost one-for-one crowd out agricultural land. This result is consistent with the land-use competition framework developed in Section 5 and confirms that agricultural land allocation is largely driven by spatial trade-offs with non-agricultural uses rather than independent expansion or contraction dynamics.

The near-unity coefficients and the significance of Mundlak terms indicate that land-use allocation is highly persistent and largely determined by time-invariant geographical and structural characteristics. This near-deterministic relationship reinforces the

[8] We exclude a spatial lag of prices from Equation (11). Given the infrequent and institutionally driven tariff-setting process in France, contemporaneous strategic interactions in prices are unlikely. Moreover, introducing a spatially lagged dependent variable would generate simultaneity concerns and require strong additional exclusion restrictions, undermining identification. Finally, limitations of the SISPEA database prevent the consistent construction of spatial price measures.

importance of using the CRE/Mundlak correction and the control function to isolate time-varying endogenous shocks.

By contrast, RPG-based agricultural structure variables—the number of organic farms and the eligible agricultural area under CAP subsidies—do not exert a statistically significant direct effect on the agricultural land share in this reduced-form specification. This finding is consistent with their role in the identification strategy. Rather than directly determining land allocation, these variables primarily capture sector-specific characteristics and policy-related constraints that shape agricultural practices and incentives within a given land-use configuration. As such, they generate plausibly exogenous variation that can be exploited to isolate the endogenous component of agricultural land use in the subsequent water-quality models.

The inclusion of year fixed effects accounts for common macro trends affecting land use over time, such as changes in agricultural policy, commodity prices, or regulatory frameworks. In addition, the correlated random effects (CRE/Mundlak) specification allows unobserved, time-invariant service-level characteristics to be correlated with observed regressors. These include historical land-use patterns, soil suitability, and long-standing institutional arrangements. This is particularly important in the present context, as land-use decisions are highly persistent and embedded in local structural conditions.

6.2 Step 2 : Determinants of nitrates pollution

Table 4 reports the results of the spatial autoregressive (SAR) panel model explaining nitrate pollution at the drinking-water service level. This specification explicitly accounts for spatial spillovers in water quality and incorporates a control-function correction to address the potential endogeneity of agricultural land use identified in Step 1.

The coefficient on the agricultural land share is positive and highly significant. A higher proportion of agricultural land is associated with higher nitrate pollution, consistent with the extensive literature linking intensive agricultural activities—fertilizer application, livestock density, and diffuse runoff—to nitrate contamination of water resources. This result confirms that agricultural land use is a primary driver of nitrate pressures in the Rhine–Meuse basin.

Importantly, the residual from the first-stage agricultural land equation enters the nitrate equation with a negative and statistically significant coefficient. This finding validates the control-function approach: once the endogenous component of agricultural land allocation is isolated, the remaining residual variation captures unobserved factors that are negatively correlated with nitrate pollution, such as local agronomic constraints, soil characteristics, or institutional practices that limit pollution intensity. The significance of this residual term indicates that failing to correct for endogeneity would bias the estimated effect of agricultural land on nitrate pollution.

Beyond agriculture, land-use composition plays a differentiated role. Forest share is associated with significantly lower nitrate pollution, reflecting the well-documented buffering and filtering capacity of forested areas, which reduce nitrogen leaching and runoff. Urban share exhibits a positive effect at the 15% significance level, suggesting that urban land use may contribute to nitrate pressures through sewer overflows, stormwater runoff, or legacy infrastructure effects, although this channel appears weaker and more heterogeneous than agricultural sources. Recall that *other land uses* is the reference category in all estimations; coefficients on agriculture, forest, and urban shares are therefore interpreted as differentials relative to this baseline.

Agricultural practices also matter. The number of organic farms has a strong and negative association with nitrate pollution, indicating that areas with a higher prevalence of organic farming tend to exhibit lower nitrate concentrations. This result is consistent with reduced synthetic nitrogen inputs under organic practices and supports the view that agricultural intensity—not merely land allocation—drives water quality outcomes. Conversely, the eligible agricultural area under CAP subsidies is positively associated with nitrate pollution, suggesting that policy-defined eligible surfaces may correlate with more intensive or structurally productive agricultural zones where nitrate pressures are higher.

The spatial autoregressive parameter ρ is positive and highly significant, providing clear evidence of spatial dependence in nitrate pollution across water services. This confirms the presence of hydrological and spatial spillovers: nitrate contamination in one service area is partly driven by pollution levels in neighboring services, consistent with upstream–downstream processes and diffuse transport mechanisms within the river basin. The magnitude of ρ implies that ignoring spatial interactions would lead to an incomplete and potentially misleading assessment of nitrate dynamics.

Finally, the impact decomposition reported in Table 5 shows that estimated effects extend beyond the originating service. For all key land-use variables, indirect (spillover) effects are statistically significant and reinforce the direct impacts, resulting in larger total effects. This highlights the systemic nature of nitrate pollution: changes in land use or agricultural practices in one service area propagate to neighboring areas, amplifying their overall effect on water quality.

6.3 Step 2 : Determinants of pesticides pollution

Tables 6 and 7 report the results of the spatial autoregressive (SAR) panel model explaining pesticide pollution and the associated decomposition of marginal effects into direct, indirect, and total impacts. As for nitrates, the specification combines a SAR structure with a control-function correction to address the potential endogeneity of agricultural land use identified in Step 1.

The estimated coefficient on the agricultural land share is positive and highly significant, indicating that a higher proportion of agricultural land is associated with higher pesticide contamination in drinking-water services. This result is consistent with the diffuse nature of pesticide pollution, which primarily originates from agricultural practices such as crop treatment and chemical inputs. In contrast to nitrates, the magnitude of the coefficient is smaller, reflecting the fact that pesticide indicators capture more heterogeneous substances and application patterns, often characterized by episodic use and localized exposure.

The residual from the first-stage agricultural land equation also enters the pesticide equation with a positive and highly significant coefficient. This finding confirms the relevance of the control-function approach in this context: unobserved factors driving agricultural land allocation—such as production orientation, crop specialization, or regulatory environments—are positively correlated with pesticide pollution intensity. Ignoring this endogenous component would therefore underestimate the contribution of agriculture to pesticide contamination.

Table 3: Determinants of Agricultural Land Share

	Dependent variable: Agriculture share
Forest share	-0.960^{***}
	(0.029)
Urban share	-0.849^{***}
	(0.062)
Organic farms	0.0004
	(0.0006)
Eligible area	0.0000
	(0.0000)
Year fixed effects	Yes
Service fixed effects	No
Estimator	OLS (Mundlak CRE)
Standard errors	Clustered (ID water service)
Individuals means of time-varying regressors included	
Observations	15,944

Notes: The dependent variable is the share of agricultural land. The model includes year fixed effects. Time-averaged covariates are included following the Mundlak correlated random effects approach (Mundlak, 1978). Standard errors are clustered at the ID water service level. *Other land uses* is the reference category. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 4: Determinants of nitrate pollution: Spatial autoregressive (SAR) panel model

	Estimate	Std. Error
Agriculture share	0.0824^{***}	(0.0228)
Residual agriculture share (control function)	-0.0656^{**}	(0.0232)
Forest share	-0.0256^{*}	(0.0125)
Urban share	$0.0520^{\cdot}$	(0.0295)
Organic farms	-0.0278^{***}	(0.0070)
Eligible area	$8.44 \times 10^{-5\,**}$	(2.98×10^{-5})
Spatial autoregressive parameter (ρ)	0.0579^{***}	(0.0114)
Error variance (ϕ)	2.243^{***}	(0.104)
Individuals means of time-varying regressors included		

Notes: This table reports estimates from a spatial autoregressive (SAR) panel model of nitrate pollution. The specification includes a control function approach à la Wooldridge to address the potential endogeneity of agricultural land use. The residual from the first-stage agriculture equation is included directly in the nitrate equation. The spatial autoregressive parameter ρ captures spillover effects across neighbouring water services. Mundlak time-averaged regressors included. *Other land uses* is the reference category. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, $^{\cdot}p < 0.15$.

Land-use composition beyond agriculture exhibits clear and intuitive effects. Forest share is associated with significantly lower pesticide pollution, highlighting the buffering role of forested areas, which act as protective zones limiting pesticide runoff and leaching into water resources. Conversely, urban share has a strong positive effect on pesticide pollution. This result likely reflects the presence of non-agricultural pesticide uses (e.g. urban green spaces, infrastructure maintenance, household applications) as well as legacy contamination and stormwater runoff in urbanized areas.

Agricultural practice indicators play a more nuanced role. The number of organic farms does not have a statistically significant direct effect on pesticide pollution once land allocation and spatial dependence are controlled for. This suggests that, at the spatial scale of drinking-water services, organic farming adoption may not be sufficient in itself to generate a measurable reduction in aggregate pesticide contamination, possibly due to coexistence with conventional practices or limited spatial coverage. By contrast, the eligible agricultural area under CAP subsidies is positively and significantly associated with pesticide pollution, indicating that policy-defined eligible zones tend to coincide with more intensive or chemically reliant agricultural systems.

The spatial autoregressive parameter ρ is positive and highly significant, providing strong evidence of spatial dependence in pesticide pollution across water services. This confirms that pesticide contamination propagates across neighboring services through hydrological connectivity, atmospheric drift, and shared catchment characteristics. As a result, pesticide pollution is not a purely local phenomenon but one that exhibits spatial feedback effects within the basin.

The impact decomposition in Table 7 further emphasizes the importance of spatial spillovers. For all key land-use variables, indirect effects are statistically significant and reinforce direct effects, leading to larger total impacts. In particular, changes in agricultural or urban land use generate spillover effects on neighboring services that are non-negligible relative to the direct effects. This highlights the systemic nature of pesticide pollution and underscores the need for coordinated, basin-wide management strategies rather than purely local interventions.

Table 5: Spatial impacts of land-use determinants on nitrate pollution

	Impact measures (dy/dx)		
	Direct	Indirect	Total
Agriculture share	0.0824***	0.00506***	0.0875***
Residual agriculture share (control function)	−0.0656***	−0.00403**	−0.0696***
Forest share	−0.0256**	−0.00157*	−0.0271**
Urban share	0.0520*	0.00319*	0.0552*
Organic farms	−0.0278***	−0.00171***	−0.0295***
Eligible area	8.44×10^{-5}***	5.18×10^{-6}**	8.96×10^{-5}***
Individuals means of time-varying regressors included			

Notes: This table reports average direct, indirect (spillover), and total impacts from the spatial autoregressive (SAR) panel model with a control function approach. Impacts are computed using Monte Carlo simulations based on the spatial multiplier $(I-\rho W)^{-1}$. Indirect effects capture diffusion of nitrate pollution across neighbouring water services.
Significance levels are based on simulated p-values: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 6: Determinants of pesticide pollution: Spatial autoregressive (SAR) panel model

	Estimate	Std. Error
Agriculture share	0.00236***	(0.00051)
Residual agriculture share (control function)	0.00236***	(0.00052)
Forest share	−0.00118***	(0.00028)
Urban share	0.00406***	(0.00066)
Organic farms	5.11×10^{-5}	(0.00016)
Eligible area	2.67×10^{-6}***	(6.63×10^{-7})
Spatial autoregressive parameter (ρ)	0.0437***	(0.0123)
Error variance (ϕ)	0.122***	(0.008)
Individuals means of time-varying regressors included		

Notes: This table reports estimates from a spatial autoregressive (SAR) panel model of pesticide pollution. The specification includes a control function approach to address the potential endogeneity of agricultural land use. The residual from the first-stage agriculture equation is included directly in the pesticide pollution equation. The spatial autoregressive parameter ρ captures diffusion of pesticide pollution across neighbouring water services. *Other land uses* is the reference category. Mundlak terms included. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 7: Spatial impacts of land-use determinants on pesticide pollution

	Impact measures (dy/dx)		
	Direct	Indirect	Total
Agriculture share	0.00236***	0.00011***	0.00247***
Residual agriculture share (control function)	0.00236***	0.00011***	0.00247***
Forest share	−0.00118***	−0.00005***	−0.00124***
Urban share	0.00406***	0.00019***	0.00425***
Organic farms	5.11×10^{-5}	2.33×10^{-6}	5.34×10^{-5}
Eligible area	2.67×10^{-6}***	1.22×10^{-7}**	2.79×10^{-6}***

Notes: This table reports average direct, indirect (spillover), and total impacts from a spatial autoregressive (SAR) panel model of pesticide pollution. Impacts are computed using Monte Carlo simulations based on the spatial multiplier $(I - \rho W)^{-1}$. Indirect effects capture diffusion of pesticide contamination across neighbouring water services. The control function residual addresses endogeneity in agricultural land allocation, while Mundlak terms (group means) account for correlated unobserved heterogeneity. Significance levels are based on simulated p-values: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

6.4 Step 3 : Drinking water prices

Tables 8, 9 and 10 report the results of the three price specifications: (i) predicted nitrates only, (ii) predicted pesticides only, and (iii) both indicators jointly. All specifications are based on Equation (11) estimated over the same sample ($n = 844$ services, $N = 5{,}956$ observations). By relying on fitted values of nitrate and pesticide pollution from the Step 2 SAR models, this approach mitigates simultaneity concerns between land use, water quality, and pricing decisions, while explicitly accounting for spatial dependence in pollution processes upstream.

Across all specifications, the coefficients on predicted nitrate pollution and predicted pesticide pollution are negative but not statistically significant. This result suggests that, conditional on land-use composition and service characteristics, higher levels of diffuse chemical pollution do not translate into higher drinking water prices. This finding is consistent with institutional constraints in the water sector, where pricing is often regulated, politically sensitive, and only imperfectly responsive to marginal cost increases driven by environmental degradation.

Land-use composition exerts a much clearer and robust influence on prices. Relative to the reference land-use category (*other land uses*), forest share is associated with significantly lower water prices, while urban share has a strong and positive effect. Agricultural land is omitted from the price equation to resolve collinearity, so its effect is implicit in the reference structure. These patterns are consistent with earlier results and with the interpretation that forested areas reduce treatment complexity and protect raw water quality, whereas urbanized areas increase infrastructure, treatment, and management costs.

Institutional and organizational variables also play a central role. Intercommunal water services exhibit substantially higher prices, reflecting higher coordination, investment, and governance costs typically associated with inter-municipal management structures. Conversely, public management under a régie is associated with significantly lower prices, in line with the view that publicly managed services prioritize cost recovery and affordability over profit margins.

Operational characteristics further contribute to price heterogeneity. Water imports and exports are positively associated with prices, indicating that inter-service water transfers entail additional costs that are at least partially reflected in tariffs. Higher network renewal rates are also associated with higher prices, consistent with capital-intensive investment being passed on to users. By contrast, service size variables—such as the number of households, municipalities, or population served—do not exert strong or systematic effects once institutional and land-use factors are controlled for.

The combined specification (Table 10) confirms these conclusions. Neither pollution indicator becomes statistically significant when included jointly, while land-use, governance, and operational variables retain their magnitude and significance. This reinforces the interpretation that water pricing in the Rhine–Meuse basin responds more strongly to structural and institutional determinants than to marginal variations in chemical water quality.

Table 8: Drinking water price determinants with predicted nitrate pollution (Step 3)

	Estimate	Std. Error
Predicted nitrate pollution ($\widehat{\text{Nitrates}}$)	-0.00220	(0.00242)
Forest share	-0.00447^{*}	(0.00195)
Urban share	0.02987^{***}	(0.00335)
Intercommunal (IMC = 1)	0.1956^{***}	(0.0231)
Management mode: Public service (Régie)	-0.3106^{***}	(0.0369)
Water import	$4.05 \times 10^{-7\,***}$	(8.81×10^{-8})
Water export	$9.95 \times 10^{-8\,*}$	(4.66×10^{-8})
Renewal rate	0.00294^{**}	(0.00107)
Households served	9.30×10^{-8}	(1.47×10^{-7})
Municipalities	0.000192	(0.000172)
Population served	-2.61×10^{-6}	(1.82×10^{-6})
Constant	2.004^{***}	(0.165)
Agricultural land share	Omitted (collinearity resolution)	
Other land uses	Reference category	
Individual effects	Random effects (Swamy–Arora)	
Model	Correlated random effects (Mundlak)	
Individuals means of time-varying regressors included		
Panel structure	Unbalanced: $n = 844$, $T = 1$–16, $N = 5956$	
R^2	0.2358	
Adj. R^2	0.2330	
χ^2 (df = 22)	377.861	
p-value	$< 2.22 \times 10^{-16}$	

Notes: Predicted nitrate pollution is assumed exogenous (predetermined) as it is a fitted value from the Step 2 SAR model. Land-use shares sum to one; *other land uses* is the overall reference category; agriculture is additionally omitted to resolve collinearity. Coefficients on forest and urban shares are interpreted relative to agricultural land. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 9: Drinking water price determinants with predicted pesticide pollution (Step 3)

	Estimate	Std. Error
Predicted pesticide pollution ($\widehat{\text{Pesticides}}$)	-0.00260	(0.00279)
Forest share	-0.00447^{*}	(0.00195)
Urban share	0.02982^{***}	(0.00335)
Intermunicipal (IMC = 1)	0.1957^{***}	(0.0231)
Management mode: Public service (Régie)	-0.3109^{***}	(0.0368)
Water import	$4.05 \times 10^{-7\,***}$	(8.81×10^{-8})
Water export	$9.93 \times 10^{-8\,*}$	(4.66×10^{-8})
Renewal rate	0.00294^{**}	(0.00107)
Households served	9.21×10^{-8}	(1.47×10^{-7})
Municipalities	0.000193	(0.000172)
Population served	-2.62×10^{-6}	(1.82×10^{-6})
Constant	2.001^{***}	(0.165)
Agricultural land share	Omitted (collinearity resolution)	
Other land uses	Reference category	
Individual effects	Random effects (Swamy–Arora)	
Model	Correlated random effects (Mundlak)	
Individuals means of time-varying regressors included		
Panel structure	Unbalanced: $n = 844$, $T = 1$–16, $N = 5956$	
R^2	0.2366	
Adj. R^2	0.2337	
χ^2 (df = 22)	378.628	
p-value	$< 2.22 \times 10^{-16}$	

Notes: Predicted pesticide pollution is assumed exogenous (predetermined) as it is a fitted value from the Step 2 SAR model. *Other land uses* is the reference category. Agriculture is additionally omitted to resolve collinearity. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 10: Determinants of Drinking Water Prices with Predicted Water Quality (Joint specification)

	Estimate	Std. Error
Predicted nitrates	-9.77×10^{-4}	(4.77×10^{-3})
Predicted pesticides	-1.60×10^{-1}	(5.50×10^{-1})
Forest share	-4.54×10^{-3}**	(1.95×10^{-3})
Urban share	2.98×10^{-2}***	(3.35×10^{-3})
Intermunicipal	1.94×10^{-1}***	(2.31×10^{-2})
Public management (Régie)	-3.05×10^{-1}***	(3.67×10^{-2})
Water imports	2.58×10^{-7}***	(5.96×10^{-8})
Water exports	9.17×10^{-8}**	(4.43×10^{-8})
Network renewal rate	2.90×10^{-3}**	(1.07×10^{-3})
Households served	9.17×10^{-8}	(1.48×10^{-7})
Municipalities	1.98×10^{-4}	(1.72×10^{-4})
Population served	-2.50×10^{-6}	(1.82×10^{-6})
Constant	1.99***	(0.165)
Observations	5,956	
Number of water services	844	
Time periods	1–16	
Estimator	Random effects (Swamy–Arora)	
Individuals means of time-varying regressors included		
R^2	0.236	
χ^2	373.25	

Notes: Joint specification including both predicted nitrate and pesticide concentrations from the Step 2 SAR models. *Other land uses* is the reference category; agricultural land share is additionally omitted to resolve collinearity. Coefficients on forest and urban shares are interpreted relative to agricultural land. Standard errors in parentheses. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

7 Discussion and conclusion

The objective of this paper was to identify and quantify the links between land use, water quality, and drinking water prices, using a control-function-based econometric strategy that explicitly accounts for endogeneity and spatial dependence. The results provide consistent evidence that land-use composition plays a central role in shaping raw water quality, while pricing outcomes are primarily determined by structural and institutional characteristics of water services.

First, the control function estimates confirm the strong substitutability between agricultural land and alternative land uses under a fixed land endowment. This structural allocation mechanism provides a sound basis for identification in the subsequent quality equations. Once this structure is taken into account, agricultural land use emerges as a key driver of nitrate pollution: both the probability of exceeding regulatory thresholds and mean nitrate concentrations increase significantly with the agricultural share. The significance of the control function residual confirms that failing to address endogeneity would bias the estimated effect of agriculture on nitrate contamination. Forest land, by contrast, is associated with lower nitrate levels, although the magnitude of this protective effect remains moderate once spatial interactions are controlled for.

Results for pesticides display a more heterogeneous pattern. Agricultural land use is positively associated with pesticide contamination, but the effect is weaker and less robust than for nitrates. Urban land, however, consistently shows a strong association with pesticide exceedance and concentration levels, highlighting the importance of diffuse and non-agricultural sources. The significance of spatial parameters in both nitrate and pesticide models underscores the systemic nature of diffuse pollution: changes in land use in one service area propagate to neighboring areas, amplifying their overall impact on water quality. These findings justify the use of spatial econometric techniques and point to the limitations of purely local regulatory approaches. In a final step, we examine whether pollution levels are internalized through drinking water prices. Contrary to a simple cost-pass-through mechanism, predicted nitrate and pesticide pollution do not have a statistically significant effect on tariffs once land-use composition, governance arrangements, and service characteristics are controlled for. This suggests that water pricing in the Rhin–Meuse basin is only imperfectly responsive to marginal increases in treatment costs induced by environmental degradation. Regulatory constraints, political considerations, and cost-smoothing mechanisms likely limit the transmission of pollution-related costs to consumers. We also note that the Naïades monitoring stations capture raw water conditions at various points in the hydrological network rather than systematically at treatment plant inlets, which may attenuate the estimated relationship between measured pollution and consumer prices.

Instead, drinking water prices respond more strongly to structural and institutional determinants. Forest land is associated with lower tariffs relative to agricultural land, while urban land increases prices, reflecting differences in infrastructure intensity and service complexity. Governance variables—particularly intermunicipal organization, public management, inter-service water transfers, and network renewal investments—play a decisive role. Pricing outcomes thus appear to be shaped less by contemporaneous chemical indicators and more by long-term organizational choices and capital-related commitments. Taken together, these results point to a partial decoupling between diffuse agricultural pollution and tariff formation. While land-use patterns strongly influence raw water quality, the economic burden of pollution is not systematically internalized through prices. From an economic perspective, this finding raises questions regarding the effective implementation of the polluter-pays principle. If pollution-induced costs are not fully reflected in tariffs, incentives for preventive behavior at the source may remain weak.

These findings carry important policy implications. First, they highlight the central role of land-use regulation and agri-environmental policies in water quality protection. Because pollution processes are spatially interdependent, coordination at the basin scale is essential to avoid fragmented or ineffective interventions. Second, the limited responsiveness of tariffs to pollution suggests that relying solely on water pricing as an adjustment mechanism may be insufficient. Complementary instruments—such as targeted subsidies for land conversion, stricter nutrient management standards, or payments for ecosystem services—may be necessary to align agricultural incentives with water protection objectives. More broadly, this paper underscores that ensuring the long-term sustainability of drinking water services requires integrating environmental externalities into institutional design. Effective governance must reconcile ecological scales, land-use dynamics, and pricing frameworks to achieve both environmental resilience and economic efficiency.

References

Abildtrup, J., Garcia, S., and Stenger, A. (2013). The effect of forest land use on the cost of drinking water supply: A spatial econometric analysis. *Ecological Economics*, 92:126–136.

Abildtrup, J. and Strange, N. (2000). The option value of non-contaminated forest watersheds. *Forest Policy and Economics*, 1(2):115–125.

Benito, B., Faura, Ú., Guillamón, M.-D., and Ríos, A.-M. (2019). Empirical evidence for efficiency in provision of drinking water. *Journal of Water Resources Planning and Management*, 145(4):06019002.

Binkley, D. and Brown, T. C. (1993). Forest practices as nonpoint sources of pollution in north america 1. *JAWRA Journal of the American Water Resources Association*, 29(5):729–740.

Carabeț, A., Mirel, I., Florescu, C., Stăniloiu, C., Gîrbaciu, A., and Olaru, I. (2011). Drinking water quality in water-supply networks. *Environmental Engineering & Management Journal (EEMJ)*, 10(11).

Carpentier, A., Nauges, C., Reynaud, A., and Thomas, A. (2006). Effets de la délégation sur le prix de l'eau potable en france. *Economie & prévision*, 2006/3(174):1–19.

Charron, I., Feliers, C., Couvert, A., Laplanche, A., Patria, L., and Requieme, B. (2004). Use of hydrogen peroxide in scrubbing towers for odor removal in wastewater treatment plants. *Water Science and Technology*, 50(4):267–274.

Delpla, I., Jung, A.-V., Baures, E., Clement, M., and Thomas, O. (2009). Impacts of climate change on surface water quality in relation to drinking water production. *Environment international*, 35(8):1225–1233.

Denis, J. and Florentin, D. (2024). Urban infrastructures' maturity and the age (s) of maintenance. In *Handbook of Infrastructures and Cities*, pages 119–132. Edward Elgar Publishing.

Destandau, F. and Garcia, S. (2014). Service quality, scale economies and ownership: an econometric analysis of water supply costs. *Journal of Regulatory Economics*, 46(2):152–182.

Eaufrance (2023). Les usages de l'eau en france. Online. Portail public de l'eau en France.

Elhorst, J. P. et al. (2014). *Spatial econometrics: from cross-sectional data to spatial panels*, volume 479. Springer.

Ernst, C., Gullick, R., and Nixon, K. (2004). Opflow, protecting the source, conserving forests to protect water.

Feuillet, C. and Michon, J. (2016). *Chiffres-clés L'eau et milieux aquatiques (édition 2016).* Ministère chargé de l'environnement (MEDDE).

Figureau, A.-G., Montginoul, M., and Rinaudo, J.-D. (2014). scénarios de régulation décentralisée des prélèvements agricoles en eau souterraine. evaluation participative dans le bassin du clain. *Economie rurale*, 342(4):27–44.

Fiquepron, J., Garcia, S., and Stenger, A. (2013). Land use impact on water quality: Valuing forest services in terms of the water supply sector. *Journal of environmental management*, 126:113–121.

Fu, G., Liu, P., and Swallow, S. K. (2020). Effectiveness of public versus private ownership: violations of the safe drinking water act (sdwa). *Agricultural and Resource Economics Review*, 49(2):291–320.

Guelmamen, M. (2025). Does Intermunicipal Cooperation Affect Prices? An Economic Analysis of the French Drinking Water Sector. *Review of Industrial Organization.*

Guelmamen, M., Garcia, S., and Mayol, A. (2025). Inter-municipal cooperation in drinking water supply: Trade-offs between transaction costs, efficiency and service quality. *International Review of Law and Economics*, 84:106303.

Hamid, A., Bhat, S. U., and Jehangir, A. (2020). Local determinants influencing stream water quality. *Applied Water Science*, 10(1):1–16.

Hascic, I. and Wu, J. (2006). Land use and watershed health in the united states. *Land Economics*, 82(2):214–239.

Honey-Rosés, J., Schneider, D. W., and Brozović, N. (2014). Changing ecosystem service values following technological change. *Environmental Management*, 53:1146–1157.

Kaika, M. (2003). The water framework directive: a new directive for a changing social, political and economic european framework. *European planning studies*, 11(3):299–316.

Kiliç, R. (2021). The strategic development for water loss prevention. *Applied Water Science*, 11(2):28.

Langpap, C., Hascic, I., and Wu, J. (2008). Protecting watershed ecosystems through targeted local land use policies. *American Journal of Agricultural Economics*, 90(3):684–700.

Le Lannier, A. and Porcher, S. (2014). Efficiency in the public and private french water utilities: prospects for benchmarking. *Applied Economics*, 46(5):556–572.

Leonhardt, H., Hüttel, S., Lakes, T., Wesemeyer, M., and Wolff, S. (2023). Use cases of the integrated administration and control system's plot-level data: Protocol and pilot analysis for a systematic mapping review. *German Journal of Agricultural Economics (GJAE)*, 72(3/4):168–184.

Lerner, D. N. and Harris, B. (2009). The relationship between land use and groundwater resources and quality. *Land use policy*, 26:S265–S273.

LeSage, J. P. and Pace, R. K. (2009). Spatial econometric models. In *Handbook of applied spatial analysis: Software tools, methods and applications*, pages 355–376. Springer.

Levavasseur, F., Martin, P., Bouty, C., Barbottin, A., Bretagnolle, V., Thérond, O., Scheurer, O., and Piskiewicz, N. (2016). Rpg explorer: A new tool to ease the analysis of agricultural landscape dynamics with the land parcel identification system. *Computers and Electronics in Agriculture*, 127:541–552.

Lin, W. and Wooldridge, J. M. (2019). Testing and correcting for endogeneity in nonlinear unobserved effects models. In *Panel data econometrics*, pages 21–43. Elsevier.

Maziotis, A. and Molinos-Senante, M. (2024). Comparative efficiency of chilean water utilities: a bayesian stochastic frontier approach. *Urban Water Journal*, 21(8):965–975.

Mundlak, Y. (1978). On the pooling of time series and cross section data. *Econometrica: journal of the Econometric Society*, pages 69–85.

North, D. C. (1990). *Institutions, institutional change and economic performance.* Cambridge university press.

Oliver, C. (1991). Strategic responses to institutional processes. *Academy of management review*, 16(1):145–179.

ONEMA (2016). Water uses and consumption in france. Online. Rapport national.

Ostrom, E. (1990). *Governing the commons: The evolution of institutions for collective action.* Cambridge university press.

Phiri, B. J., Pita, A. B., Hayman, D. T., Biggs, P. J., Davis, M. T., Fayaz, A., Canning, A. D., French, N. P., and Death, R. G. (2020). Does land use affect pathogen presence in new zealand drinking water supplies? *Water Research*, 185:116229.

Sheng, Y. and LeSage, J. P. (2021). Interpreting spatial regression models with multiplicative interaction explanatory variables. *Journal of Geographical Systems*, 23(3):333–360.

Tong, S. T. and Chen, W. (2002). Modeling the relationship between land use and surface water quality. *Journal of environmental management*, 66(4):377–393.

Van Vliet, M. and Zwolsman, J. (2008). Impact of summer droughts on the water quality of the meuse river. *Journal of Hydrology*, 353(1-2):1–17.

Van Vliet, M. T., Thorslund, J., Strokal, M., Hofstra, N., Flörke, M., Ehalt Macedo, H., Nkwasa, A., Tang, T., Kaushal, S. S., Kumar, R., et al. (2023). Global river water quality under climate change and hydroclimatic extremes. *Nature Reviews Earth & Environment*, 4(10):687–702.

Veron, É. (2024). *Incentives and spatial heterogeneity on organic farming development.* PhD thesis, Strasbourg.

Wilhelm, S. and Adrian, R. (2008). Impact of summer warming on the thermal characteristics of a polymictic lake and consequences for oxygen, nutrients and phytoplankton. *Freshwater Biology*, 53(2):226–237.

Williamson, O. E. (1985). *The Economic Institutions of Capitalism.* The Free Press.

Wooldridge, J. M. (2015). Control function methods in applied econometrics. *Journal of Human Resources*, 50(2):420–445.

Wooldridge, J. M. (2019). Correlated random effects models with unbalanced panels. *Journal of Econometrics*, 211(1):137–150.