The Impact of Land Use on Water Quality: Evidence from California Wells

Abstract

Nitrate pollution threatens human health and ecosystems in many regions of the world. Although scientists agree that nitrogen compounds from human activity, notably agriculture, enter groundwater systems, empirical estimates of the impacts of land use on nitrate concentrations in well water are still lacking. We provide evidence on such impacts by combining nitrate measurements from 6,016 groundwater wells with remotely sensed California land use data from 2007–2023. We categorize agricultural land uses according to crops' propensities to leach nitrogen and further consider urban development, in addition to undeveloped land—the default land use. Results show that a 10 percentage point increase in the share of land used to grow high-nitrogen crops within 500 meters of a well is associated with a 11.6% increase in nitrate concentrations a decade later, while the same increase in urban developments contributes about a 10% increase. When conditioning on initial nitrate measurements, the impact of nearby land use attenuates while initial concentrations explain a large share of future variation in concentrations, demonstrating the persistent nature of nitrates in groundwater. A calculation based on our regression estimates implies that replacing high-nitrogen with low-nitrogen crops around sample wells would achieve a 4.6% reduction in nitrate concentrations, saving municipal water systems $25 million annually. We evaluate the opportunity cost of such crop substitution to be large; however, targeting only the crops with the highest propensity to leach nitrates easily passes a cost-benefit test.

1 Introduction

Water pollution from human activity threatens drinking water supplies and ecosystems in many world regions (Rabotyagov et al., 2014; Van Meter, Van Cappellen, and Basu, 2018; Rahman, Mondal, and Tiwari, 2021; Abascal et al., 2022; Tozer, 2023; Jones et al., 2023).

In the United States (U.S.), water contamination has been a lingering cause of concern among the general public and, since the early 1970s, the object of much federal regulatory action following the adoption of the Clean Water Act and the Safe Drinking Water Act (Keiser and Shapiro, 2019b). By several measures, these laws have been successful at improving the quality of U.S. waterways (Keiser and Shapiro, 2019a). However, contaminants, such as nitrates, that enter water systems through non-point sources are excluded from the Clean Water Act because they are hard to directly regulate; yet they increasingly contribute to water quality impairment (Olmstead, 2010; DeSimone, McMahon, and Rosen, 2014; Van Metre et al., 2016). For instance, Pennino, Compton, and Leibowitz (2017) estimate that in 2016, about 1.5 million people in the U.S. were supplied water from public systems in violation of the U.S. Environmental Protection Agency maximum contaminant level (MCL) for nitrates of 10 mg/L of nitrate-nitrogen. For households outside of public water system boundaries, a 2014 study of 3,621 randomly sampled private groundwater wells found that 4.1% exceeded the nitrate MCL (DeSimone, McMahon, and Rosen, 2014).

Nitrate contamination of U.S. groundwater resources poses large social costs, largely through damages to public health and drinking water treatment (Keeler et al., 2016; Mosheim and Ribaudo, 2017). The regulatory MCL for nitrates in public water systems was established to mitigate the risk of infant methemoglobinemia, commonly known as "blue baby syndrome" (U.S. EPA, 1977). The limit was set based on public health studies conducted during the 1950s (Walton, 1951; Fewtrell, 2004) and did not comprehensively reflect other potential health hazards (Ward et al., 2018). Reviews of the epidemiological literature reveal that, beyond methemoglobinemia, nitrate-contaminated drinking water has been most strongly associated with gastric cancer (Picetti et al., 2022) along with colorectal cancer, thyroid disease, and neural tube defects (Ward et al., 2018). Importantly, these health conditions exhibit positive correlations with nitrate concentrations even below regulatory thresholds.

Nitrates in water systems originate from numerous sources, both anthropogenic such as urban runoff, gardens, wastewater treatment, or septic systems, and natural such as nitrogen fixation or atmospheric deposition (Wakida and Lerner, 2005; Lockhart, King, and Harter, 2013). However, studies point to nitrogen leaching from farmland as a leading cause of increasing ambient nitrate concentrations not only in surface water systems (Isbell et al., 2013; Hendricks et al., 2014; Paudel and Crago, 2021) but also in groundwater (Lockhart, King, and Harter, 2013; Rosenstock et al., 2014; Ransom et al., 2018), a primary source of drinking water for over 130 million U.S. residents (DeSimone, McMahon, and Rosen, 2014). Nitrogen leaching from agricultural fields into groundwater occurs under the combined effects of residual synthetic or organic fertilizers not absorbed by crops, decomposition of crop residue after harvest, and seepage of water—whether rainfall or irrigation—into soils. Because manure is costly to transport and typically used as fertilizer, local cattle populations may also contribute to groundwater nitrate contamination. Nitrate leaching from topsoil into groundwater can take many years or even decades, thus current nitrate contamination is likely to be the result of past agricultural practices (Boyle et al., 2012; Lockhart, King, and Harter, 2013). In addition, once they reach the water table, nitrates may persist in groundwater for long periods of time, a phenomenon consistent with the empirical findings of this study. The lag between source and destination and the legacy nature of nitrates in groundwater have historically posed a challenge for the measurement of this agricultural externality and the evaluation of its potential policy remedies.

Groundwater nitrate pollution has received increased research attention in recent years. According to Abascal et al. (2022), the annual number of peer-reviewed studies on the topic increased from 20 in 1990 to 280 in 2021. Existing studies, most of them in the environmental science literature, tend to employ highly mechanistic (Kourakos et al., 2012) or non-parametric (Ransom et al., 2017) models of nitrate emissions, attenuation, and transport through soils and aquifers. Even economic studies of water contamination from agriculture tend to resort to mechanistic biophysical models to represent leaching from fields once farmer behavior has been accounted for (Mérel et al., 2014; Lark et al., 2022; Weng et al., 2024).

Our paper complements this literature by providing reduced-form evidence on the response of groundwater nitrate concentrations to local land use decisions based on observational data. To this end, we combine water-quality measurements from approximately 6,000 California wells over 17 years with cattle inventories and remotely sensed land use data. Our main econometric model identifies groundwater quality impacts from spatial variation in land use shares and cattle populations that are plausibly exogenous to groundwater nitrate concentrations. Specifically, informed by the groundwater hydrology literature on plausible leaching times, we regress mean nitrate concentrations measured from wells in recent years (2019–2023) on local cattle populations as well as mean land use shares measured twelve years prior (2007–2011) in the vicinity of each well, conditional on a suite of biophysical and regional controls. In an alternate set of regressions, we also control for initial nitrate concentrations, which allows us to assess the persistent nature of groundwater nitrates.

Interestingly, initial nitrates alone explain over 76% of the variation in later nitrate concentrations, and in models that control for initial nitrates, coefficients on initial nitrate concentrations are statistically indistinguishable from one while land uses and cattle populations generally have small and statistically insignificant effects. These empirical results are consistent with both the legacy nature of nitrates in groundwater and the fact that land uses, even if they determine nutrient leaching and ultimate groundwater contamination, evolve very slowly over time. Indeed, our data show that over the period 2007–2023, land uses around sample wells changed very little in comparison to cross-sectional differences across wells. As a result, initial concentration levels are likely correlated with both past and subsequent land use patterns, rendering identification of incremental contamination empirically challenging. Yet, to the extent that land use shares can be considered stationary, a regression that omits initial conditions captures long-run nitrate pollution effects from persistent land use patterns, an interpretation we follow in the remainder of our analysis.

Regressions without initial nitrates indicate that a 10 percentage point increase in the share of land used to grow high-nitrogen crops—such as tree nuts or corn—within 500 meters of a well relative to undeveloped land is associated with an 11.6–19.7% increase in nitrate concentrations, while a 10 percentage point increase in the share of land used to grow low-nitrogen crops—such as rice and alfalfa—is associated with a 6.3–8.3% increase.[1] By comparison, a 10 percentage point increase in the share of land used for low-intensity (resp., high-intensity) urban development is linked to a 10.1–15% (resp., 10.5–16.2%) increase in nitrate concentrations. Similar to Meyer and Raff (2025), we find that an additional 1,000 dairy cows, which falls short of the average dairy herd size in California, within one kilometer of a well increases nitrate concentrations by 16–20%.[2] Overall, these effects document the critical role of land development and human activities on groundwater quality.

We use our regression estimates and a revealed-preference model of crop choice adapted from Costinot, Donaldson, and Smith (2016) to provide insights into the economic magnitude of land use externalities from cropping systems on drinking water quality. Specifically, we find that replacing high-nitrogen with low-nitrogen crops around our sample of wells could achieve a 4.6% reduction in nitrate concentrations, saving California drinking water systems approximately $25 million annually in treatment costs. We evaluate the opportunity cost of such crop substitution to be about $36 million, exceeding the anticipated water quality benefits. However, we also show that a more targeted land use policy that only replaces crops with the highest nitrate-leaching potential (a subset of high-nitrogen crops), while delivering a lower reduction in nitrate concentrations (1.02%), easily passes the cost-benefit test. Taken together, these findings suggest that land use incentives could be part of an

[1] Classification of crops into high-nitrogen and low-nitrogen categories is based on the "Nitrogen Hazard Index," which measures the propensity to leach nitrogen compounds under common cultural practices and a crop's typical nitrogen demands. Whether the effects of high-nitrogen crops are statistically different from those of low-nitrogen crops in our analysis depends on the choice of controls.

[2] As of 2019, California had about 1.7 million dairy cows, 1,330 dairy farms, and an average of 1,278 milking age cows per dairy (Marklein et al., 2021) The average number of dairy cattle within one kilometer of a well in our sample is only 10, as many wells have no dairy operations in their vicinity.

efficient portfolio of nitrate management actions in our setting alongside other incentives such as reductions in fertilizer intensity, provided that they target the set of crops with the most severe propensity to leach nitrates given current fertilization practices.[3]

The intersection of heavy reliance on groundwater, urban development pressure, and proximity of wells to input-intensive and highly diversified agriculture makes California a compelling setting to measure pollution externalities from human activity. California has suffered from groundwater nitrate problems for decades (Harter et al., 2012) and studies indicate that the issue has gotten worse in recent times (Burow et al., 2013). Indeed, Figure 1 shows a rising trend in the number of California public water systems violating the nitrate MCL since the 1990s.[4] This trend is largely driven by increasing violations in small, rural public water systems, in contrast to the violations among larger systems that occurred in the 1980s. Nitrate contamination is central to many ongoing public policy deliberations regarding the competing interests of agricultural and residential groundwater users (Lubell, Blomquist, and Beutler, 2020) amidst efforts by California regulators to deter agricultural practices believed to most significantly contribute to nitrate leaching. Notably, the Irrigated Lands Regulatory Program requires growers to implement nutrient management plans to prevent nitrogen fertilization in excess of crop uptake (California Water Boards, 2024b; California Water Boards, State Water Resources Control Board, 2025).[5]

Groundwater nitrate concentrations depend on the interplay of human, chemical, biological, and hydrological actions responsible for the nitrate emissions below the plant root zone and the subsequent transport of nitrates through subterranean systems (McMahon et al.,

[3]Nutrient management planning requirements for commercial agriculture started in 2003 in California's Central Valley (California Water Boards, Central Valley Regional Water Quality Control Board, 2023) and were thus already in place for the better part of our study period. Further reductions in fertilizer application could be incentivized, but there is no guarantee that they would deliver nitrate abatement at a lower marginal cost than agricultural land use changes.

[4]The California Health and Safety Code §116275 (2024) defines a public water system as delivering water for human consumption to at least 15 service connections used by yearlong residents or at least 25 people daily for 60 or more days per year.

[5]In addition, between 2000 and 2010, the Central Valley Regional Water Board implemented the Waste Discharge Requirements General Order for Existing Milk Cow Dairies and the Central Valley Salinity Alternatives for Long-Term Sustainability program, which require land managers to engage in nitrate monitoring and reporting and adopt nutrient management plans (Harter, 2015).

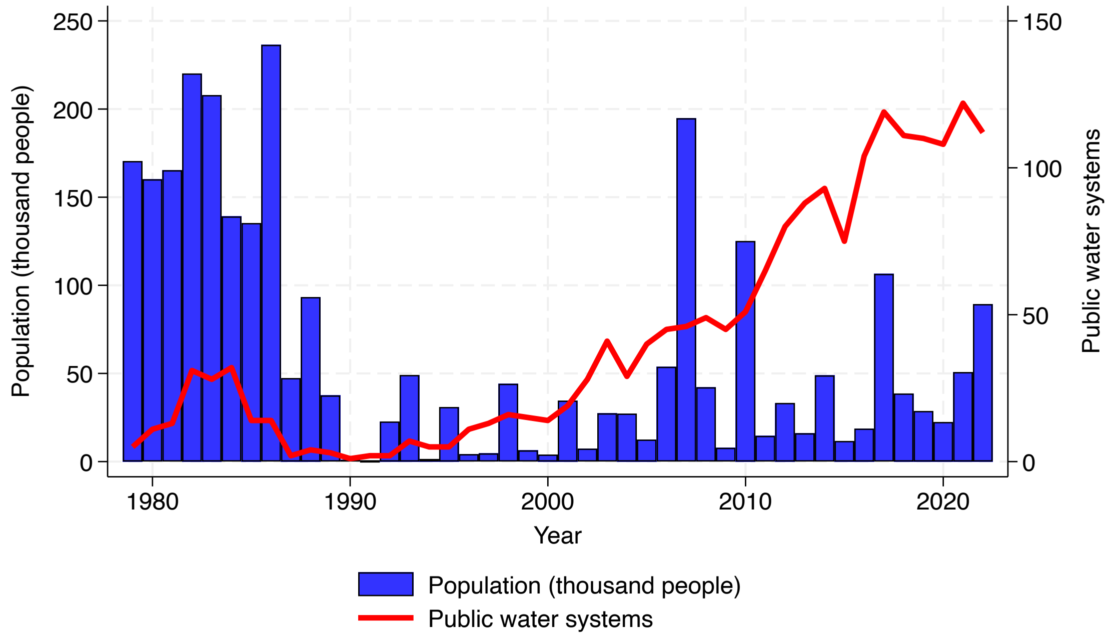

Figure 1: Count of California public water systems in violation of the nitrate maximum contaminant level, and affected population

Source: U.S. Environmental Protection Agency (2023).

2008). The primary empirical challenge is controlling for the many features that determine the path—over both time and space—of nitrate molecules from the point at which they appear on the land surface. We address this challenge with the following strategies. First, we focus on land use within a 500-meter radius of the well, encompassing a region where nitrates accumulate within our effective lag length of twelve years (California Department of Health Services, 2000; Harter, 2002; Boyle et al., 2012; DeSimone, McMahon, and Rosen, 2014). Second, we confine our analysis to variations within sub-basins—geographical areas of interconnected groundwater with shared characteristics influencing nitrate movement—and include additional controls for site-specific variables, such as soil composition, groundwater depth, and proximity to rivers, previously shown to be important factors in determining the fate of nitrates (Ransom et al., 2017). Third, we harness comprehensive land use data sets, such as the Cropland Data Layer, which have been underutilized in existing literature. The spatially detailed land use data allows for precise groupings that reveal the relative importance of different land uses around wells, information that may be missed when relying on more coarsely aggregated data (Lichtenberg and Shapiro, 1997; Ransom et al., 2017). Lastly, given that the primary sources of variation in nitrate concentrations and land use allocations occur across space, our cross-sectional model offers the advantage of leveraging substantial variation for identification, in a context where variables evolve only gradually over time. Because aquifer contamination occurs primarily through the leaching of contaminants deposited near the land surface, and we control for a variety of biophysical factors affecting their flow towards the water table, the scope for omitted variable bias remains limited in our setting.

Our paper contributes to the understanding of critical questions surrounding the fate of nutrient emissions from land management (Galloway et al., 2008). We take a decadal view of the association between land use patterns and the concentration of nitrates in groundwater wells, where contamination can potentially cause the most harm. Our empirical methodology relies on observational data, distinguishing it from approaches that integrate estimates derived from simulation models. Some recent observational studies have linked historical water quality data to crop and livestock land use decisions (Paudel and Crago, 2021; Raff and Meyer, 2022; Metaxoglou and Smith, 2025) and conservation efforts (Liu, Wang, and Zhang, 2023; Karwowski and Skidmore, 2024). These empirical studies, however, focus on surface water quality impacts, and analogous evidence for groundwater quality is needed to inform land use policy, given the distinct uses and valuations of groundwater. Regarding the primary explanatory variables, we adopt an innovative approach for categorizing land uses according to their propensity to emit nitrogen below the root zone (Wu et al., 2005).

The remainder of the paper is structured as follows. In the next section, we present our main econometric model. Next, we explain the construction of our data set and provide summary statistics. Subsequently, we present our main findings, supported by several sensitivity checks. We then use our empirical estimates to assess the costs and benefits of replacing high-nitrogen crops by low-nitrogen crops around sample wells. The last section concludes.

2 Empirical Methods

Our research design leverages cross-sectional variation in nitrate concentrations and land use surrounding well i in sub-basin b by regressing mean nitrate concentrations in recent years on mean land use shares measured in a prior period. Nitrate concentrations and land use shares are calculated as five-year averages and measured twelve years apart to account for the diffusion process. Our preferred regression equation takes the following form:

$$\ln N_{ibT_1} = \mathbf{L}_{ibT_0}{}'\boldsymbol{\beta} + \kappa C_{ib} + \mathbf{X}_{ib}{}'\boldsymbol{\gamma} + \lambda_b + \alpha \ln N_{ibT_0} + \varepsilon_{ibT_1} \tag{1}$$

where T_0 represents the period 2007–2011, T_1 the period 2019–2023, N_{ibT_0} and N_{ibT_1} are mean nitrate concentrations during periods T_0 and T_1, respectively, and ln is the natural logarithm. The column vector $\mathbf{L}_{ibT_0}$ denotes land use shares and C_{ib} denotes local dairy cattle population. Note that this latter covariate is not indexed by a time period as we only observe one year of dairy cattle population data. We discuss this issue further in Section 3. The vector $\mathbf{X}_{ib}$ includes control variables for soil characteristics, the share of land with subsurface drains, distance to the nearest river, depth to groundwater, precipitation, and surface water deliveries. The fixed effects λ_b control non parametrically for unobserved characteristics of the aquifer and deep soils common to wells located within sub-basin b. In some regressions, we include lagged nitrate concentrations to reflect the fact that nitrates may remain in groundwater for extended periods of time, so initial conditions matter.

We estimate Equation (1) using Ordinary Least Squares. The vector $\boldsymbol{\beta}$ captures land use impacts, with each element β^k representing an $(e^{\beta^k} - 1) \times 100$ percent change in groundwater nitrate concentrations associated with a one unit increase in the share of land dedicated to activity k. If we measure the land use share using an index from zero to one, then the effect is that of a change from a zero to one share. When discussing our results, we consider instead the effect of a 10 percentage point increase in the share, which is obtained by computing $(e^{\beta^k \times 0.1} - 1) \times 100$. Since land use shares sum up to one, we omit undeveloped land (i.e., natural lands such as forests, wetlands, and deserts), so the effect of an increase in land use k is to be understood as arising from replacing undeveloped land by activity k. In Section 4.3, we discuss the implications of disaggregating the undeveloped land category and using forested land as the omitted land use. The coefficient κ captures the relative impact of an additional one thousand dairy cattle located within a specific distance of well i.

In our main cross-sectional specifications, temporal averages in the recent and past periods are calculated over a five-year window, and we allow for a 12-year lag between the midpoints of recent and past periods.[6] This lag, as well as the averaging of land shares over multiple years, are meant to capture the fact that nutrient leaching into groundwater is generally a gradual, multi-year process. For deep wells (>70 ft), in particular, hydrology models predict that leaching may take a decade or longer (Boyle et al., 2012; Lockhart, King, and Harter, 2013). Given that the average depth to groundwater across our sample of wells is 31 meters (99 ft), it is unlikely that land use changes could have a direct contemporaneous (or even short-run) effect on groundwater concentrations (Boyle et al., 2012).[7]

The vector $\mathbf{X}_{ib}$ includes, among others, controls for depth to groundwater, precipitation, and surface water deliveries. Because these variables typically vary over time and their values plausibly affect the ultimate nitrate concentrations cumulatively, we define the depth to groundwater as the mean depth to groundwater over the length of our panel (2007 through 2023), precipitation as the cumulative precipitation from 2007 through 2023, and surface water deliveries as the sum of acre-feet of surface water delivered per acre of agricultural land in the water region in which well i is located from 2007 through 2021.[8]

Identification of the impacts of land use on nitrate concentrations requires adequate controls for biophysical and well characteristics, as these may also partially affect land uses.

[6]Ideally, we would observe land uses around wells over multiple decades, which would allow us to better measure historic land use around wells. However, this 12-year lag is the longest afforded by the remotely sensed Cropland Data Layer.

[7]For completeness, we estimate contemporaneous regressions of mean 2019–2023 nitrate concentrations on mean 2019–2023 land use shares. See Appendix Table C.2 and the discussion in Section 4.3.

[8]Water regions are Detailed Analysis Unit by County regions as defined by California's Department of Water Resources (California Department of Water Resources, 2019).

Our long list of controls includes variables highlighted in previous literature as meaningfully impacting nitrate concentrations in groundwater (Ransom et al., 2017). However, data limitations mean that we cannot control for every characteristic of the aquifers, wells, and deep soils; thus, we adopt the common econometric approach of controlling for unobserved potential confounders using fixed effects, here at the sub-basin level.[9]

The California Department of Water Resources defines 515 sub-basins that underlie approximately 42% of the state's land area, 82% of its population, and 97% of its agricultural land (California Department of Water Resources, 2019, 2021). The average sub-basin underlays 480 square kilometers of land area. The sub-basin delineation of California groundwater systems divides the large San Joaquin and Sacramento Valley basins—both within the Central Valley, the heartland of California agriculture and the region where about half of the wells in our sample reside—into 35 regions based on geological features that slow, but might not entirely prevent, water from mixing over time.[10] The California Department of Water Resources subdivides 28 smaller basins into 86 sub-basins. The remainder of the state's basins are not divided into sub-basins and are treated as their own sub-basin in our analysis.

Sub-basin fixed effects capture local unobserved biophysical characteristics that might vary greatly throughout the large Central Valley basins, such as reduction/oxidation conditions—the chemical environment that determines the rate at which nitrates convert to other nitrogen compounds—and groundwater age (Ransom et al., 2017). To the extent that these characteristics correlate with local land use patterns, using basin instead of sub-basin fixed effects would cause bias. The inclusion of sub-basin fixed effects is not costless, however. First, it removes a source of potentially useful cross-sectional variation, namely that present within basins. Second, our data include 29 sub-basins with only one well, so using

[9]Cross-sectional regressions with spatial data are particularly susceptible to omitted variable bias as geographic proximity may affect the outcome variable through a variety of channels that are difficult to control for. A common practice in such contexts is to include fixed effects that capture spatial proximity. Many studies use administrative delineations such as zip codes, counties, agricultural districts, or state boundaries (Schlenker, Hanemann, and Fisher, 2006; Ortiz-Bobea, 2020; Gammans, Mérel, and Ortiz-Bobea, 2024). In the present case, where the outcome of interest, groundwater contamination, likely varies according to hydrology, we find it appropriate to use sub-basin fixed effects.

[10]In contrast, basins map hydrologically isolated groundwater bodies.

sub-basin fixed effects reduces the effective sample size. Fortunately, these 29 observations represent a small share of the 6,016 wells and 230 sub-basins present in the sample.

3 Data

We use publicly available data from several government and academic institutions. In what follows, we describe our data sources, explain our approach to data cleaning and aggregation, and provide detailed descriptions and summary statistics of our variables.

3.1 Data Set Construction

3.1.1 Nitrate Concentrations

We obtain data on nitrate concentrations from the State Water Resources Control Board's Groundwater Ambient Monitoring and Assessment (GAMA) Program, readily available from their online portal (California Water Boards, 2024a). GAMA staff compiled these data from multiple government, research, and local sources that sample from private, public, irrigation, and monitoring wells throughout California. We exclude monitoring wells from our sample as many are close to locations of unauthorized releases of pollutants into the environment, such as leaking underground storage tanks on industrial sites. In addition, monitoring wells have a different set of design, construction, and management standards compared to irrigation and drinking water wells, leading to water samples not representative of water extracted for human use.[11] Public drinking water wells make up the majority of our final data, comprising above 99% of the wells in our sample.

The groundwater quality data include measurements of nitrate-nitrogen and nitrite-nitrogen. Nitrate-nitrogen refers to the weight of the nitrogen atom in the nitrate molecule.[12] For brevity, we refer to nitrate-nitrogen as nitrates. Nitrite, the other nitrogen molecule re-

[11] These well standards are described on the California Department of Water Resources (2024) website.

[12] Laboratories typically measure and report nitrate-nitrogen concentrations in water samples, and by convention, scholarly works focus on nitrate-nitrogen. We follow this convention in this paper.

ported in the data, is an unstable molecule that readily oxidizes to nitrate and occurs in much smaller quantities in groundwater (Burkart and Stoner, 2008). For drinking water quality purposes, nitrate plus nitrite concentrations represent nitrate concentrations (California Water Boards, Central Coast Regional Water Quality Control Board, 2013). Therefore, we sum nitrate-nitrogen and nitrite-nitrogen concentrations and report this measure as nitrate.

The GAMA data includes geographic coordinates, sample collection date, and the laboratory minimum nitrogen concentration detection limit. Minimum detection limits range from 0.02 mg/L to 1 mg/L, depending on the laboratory. To deal with censored observations, we follow Keiser and Shapiro (2019a) and let concentrations below the minimum detection threshold equal the detection limit.[13]

Lastly, the month and frequency of water sampling vary over wells. Thus, we calculate the annual average nitrate concentration within the calendar year. This decision is supported by the fact that we find no evidence of seasonality in nitrate concentrations in the data. This lack of seasonal variation is not surprising given that California groundwater experiences low annual recharge and because of groundwater mixing (Lockhart, King, and Harter, 2013).

3.1.2 Land Use

We use land use data from the Cropland Data Layer (CDL), a satellite data product of the U.S. Department of Agriculture National Agricultural Statistics Service available online. The CDL is an annual raster image of the U.S., with each cell classified into a land use or crop type based on remotely sensed data and verified by U.S. Department of Agriculture personnel by ground truth sampling to ensure accuracy. The first California CDL image was taken in 2007, with cells measuring 56 square meters. Subsequent images have cells measuring 30 square meters.

We focus on land use within a 500-meter radius of a well. Using a circular buffer zone is a standard approach in the existing literature and a good approximation to the land that

[13]As a sensitivity check, we let the censored concentration equal half the detection limit. See Section 4.3.

contributes to groundwater recharge to a well (Johnson and Belitz, 2009). Kolpin (1997) used a range of buffers from 200 meters to 2 kilometers and showed that 500 meters provide the best correlation between land use and nitrate concentrations, while Koterba (1998) reviewed six articles focusing on nitrate and pesticide pollution and recommended a 500-meter buffer for empirical studies. More recently, Johnson and Belitz (2009) show that a 500-meter buffer is a robust proxy for the well supply area in the Central Valley of California.[14] We use well location coordinates from the groundwater quality data and extract land use data from the CDL using geospatial methods in R.

There are about 160 land use and crop types within 500 meters of our sample of wells. To create a parsimonious regression model, we aggregate crops based on the Nitrogen Hazard Index (NHI), a protocol that uses expert opinion and data to assign a value of 1 through 4 to crops based on five natural and management factors that contribute to nitrate leaching propensity, namely: 1) rooting depth, 2) ratio of nitrogen in the crop tops to recommended nitrogen application, 3) fraction of crop nitrogen removed from the field with the marketed product, 4) magnitude of the peak nitrogen uptake rate, and 5) whether the crop is harvested at a time when nitrogen uptake rate is high (Wu et al., 2005). The NHI, therefore, provides a richer metric than a crop's nitrogen demand alone, because it incorporates agronomic factors associated with how crops absorb nitrogen in the soil.[15] To date, researchers have used the NHI to aggregate crops in a handful of research and extension publications (e.g., Dzurella et al. (2015) and Beaudette and O'Geen (2009)). Furthermore, the NHI has been verified by the U.S. Geological Survey to capture realized leaching patterns across crops in case studies across California (Wu et al., 2005). A list of the crops and non-agricultural land uses found within 500 meters of sample wells and their assigned category is provided in Appendix Table A.1. Crops with an NHI equal to 1 are assigned to the "Low-NHI crops" group, while crops with an NHI equal to 2, 3, or 4 are assigned to the "High-NHI crops" group. This

[14] In Section 4.3, we show results based on an alternative one-kilometer buffer.

[15] The primary downside of using this metric is that we do not directly observe nitrogen amounts, as the NHI is developed based on *recommended* rates. Nevertheless, in the absence of data on field-level fertilizer rates, it provides the best measure of crop-specific nitrate leaching potential available.

categorization results in crop groups with average land shares of similar magnitude, as crops with an NHI of 3 or 4 tend to occupy a very small area in our sample. For supplemental analyses, we also divide crops into three groups (NHI-1, NHI-2, and NHI-3/NHI-4).

3.1.3 Soils

Data on soil characteristics come from the U.S. Department of Agriculture (2014) as a raster file, with each pixel representing an area of 90 square meters. The soil data represent an area and depth weighted average of soil attributes within the raster cell measured from the land surface to a depth of about 1.5 meters.[16] Sand, silt, and clay percentages characterize the soil texture, and the percentages sum up to one. Organic matter, also called humus, refers to the percentage of decomposed plant and animal residues in the soil's dry weight. Organic matter, sand, silt, and clay constitute the major components of soil (Hillel, 2008).

Similar to the procedure for land use data, we extract soil data within 500 meters of the well and then calculate average sand, silt, clay, and organic matter percentages using weighted averages across pixels, where weights are based on the share of pixel area contained within the buffer.

3.1.4 Tile Drains

Subsurface tile drainage is often installed in poorly drained soil to divert water away from fields and into distant waterways. Therefore, the presence of tile drainage may meaningfully affect nitrate leaching into groundwater. We use a raster data set of subsurface tile drainage in the U.S. from Valayamkunnath et al. (2020) with cells measuring 30 square meters. This data set contains a variable indicating the presence of subsurface drains within a raster cell. Like land use and soil data, we extract drainage raster cells within 500 meters of the well and then calculate the share of land with drains using weighted averages.

[16] Wieczorek (2014) offers a useful overview of the soil data.

3.1.5 Precipitation

Precipitation data come from Oregon State University PRISM Climate Group (2024). The PRISM data set provides a model-based estimate of precipitation for the U.S. at a resolution of 4 km. For each sample well, we extract cumulative precipitation amounts from 2007 to 2023 from the grid cell containing the well. In supplemental analysis, we also aggregate precipitation by season to investigate how precipitation timing affects nitrate leaching.

3.1.6 Rivers

We use the Major Rivers and Creeks maps from the U.S. Geological Survey's National Hydrology data set available online (California Department of Water Resources, 2023). We compute the distance from a well to the nearest river using geospatial techniques in R.

3.1.7 Surface Water Deliveries

California agriculture heavily relies on irrigation via surface water storage and distribution networks, since California's agricultural regions receive very little rainfall during the growing season. Surface water irrigation allotments, therefore, may affect both land use patterns and nitrate leaching, making it an important control variable. We use a data set of surface water deliveries compiled by Hagerty (2022) and available online. The dataset contains reported surface water deliveries to agricultural users in California regions from 1993 to 2021 and acres of agricultural land in each region. The regions, called Detailed Analysis Unit by County (DAUCO), divide California's hydrological regions and planning areas into smaller geographic areas for agricultural land use and water balance analysis by California's Department of Water Resources.

3.1.8 Dairy Cattle Inventories

As part of the Waste Discharge Reports and Requirements Order, livestock enterprises are required to submit a Report of Waste Discharge that includes livestock inventories, and the

California State Water Resources Control Board publishes an online database that includes the geographic coordinates of the facility and the livestock populations (California State Water Resources Control Board, 2022). The inventories are self-reported and periodically updated. Therefore, the available data represent the latest livestock inventories reported by farmers. Unfortunately, it is not possible to recover historical inventories throughout the sample period. We focus on dairy cattle because dairies are responsible for most of the nitrogen-rich manure produced by livestock species and most dairies are located in the Central Valley where a large share of our sample wells are located.

3.2 Data Aggregation

In our preferred model specification, we group annual well-level observations of nitrate concentrations and land use shares into five-year windows at the endpoints of the sample period and calculate the mean of the respective variables. The following considerations inform our decision to construct averages over time. First, many wells have nitrate measurements in some years but not in others. Therefore, using a single year for determining nitrate concentrations would severely limit the number of observations that enter the regression, especially when we include a lagged dependent variable to capture initial conditions. Averaging over the available annual observations within a five-year window results in a larger sample size. In doing so, we implicitly assume that nitrate concentration data are missing at random. Second, we find that nitrate concentrations and land use shares evolve gradually over time; therefore, we do not believe that we lose meaningful information by averaging over a five-year window. Third, nitrate concentrations at a point in time are the result of cumulative nutrient leaching from past years, excluding perhaps the most recent years, as it takes time for nutrients to reach the groundwater table. Using a five-year average of land use over prior years partially captures the cumulative nature of the leaching process.

3.3 Data Summary

Figure 2 shows the relative size, shape, and location of California's 515 groundwater sub-basins and the spatial distribution of our effective sample of 6,016 wells across 230 sub-basins scattered across the state. Most wells are located in the Central Valley and coastal and southern regions.[17] The figure shows that ten large Central Valley sub-basins contain 90–455 sample wells and a further thirteen sub-basins contain more than 30 wells. Consequently, about 50% of observations lie within the 35 Central Valley sub-basins. In comparison, basins in the Northeast and along the North Coast are smaller and have fewer observations. On average, the observed sub-basins outside the Central Valley contain 17 wells. We do not observe nitrate concentrations in many of the basins in southeast California, a mostly desert and mountainous region with little agriculture and far from major population centers. White regions in Figure 2 represent non-basin regions, for instance the Sierra Nevada mountain range east of the Central Valley.

Table 1 provides variable descriptions and Table 2 reports summary statistics for the sample of 6,016 wells used in the analysis. The sample includes observations from 5,998 municipal wells, 3 domestic wells, 5 irrigation wells, and 10 other water supply wells. The summary statistics reveal that mean nitrate concentrations increased from 2.7 mg/L in 2007–2011 to 2.9 mg/L in 2019–2023, an increase of 7.4% that points to worsening water quality. This positive trend is consistent with earlier studies of nitrate concentrations in public well water supply (Burow, Shelton, and Dubrovsky, 2008; Pennino, Compton, and Leibowitz, 2017). Scientists have linked nitrate concentrations above 2 mg/L to contamination from anthropogenic sources such as agriculture and urban development (Mueller and Helsel, 1996; Harter, 2009; Lockhart, King, and Harter, 2013). Moreover, epidemiological studies reveal an increased risk of thyroid (Ward et al., 2010) and ovarian (Inoue-Choi et al., 2015) cancer from drinking water containing 2–3 mg of nitrates per liter relative to water with less than

[17]The Central Valley is a 700-kilometer-long region of flat land running north to south along the spine of California and is the top agricultural area in the state.

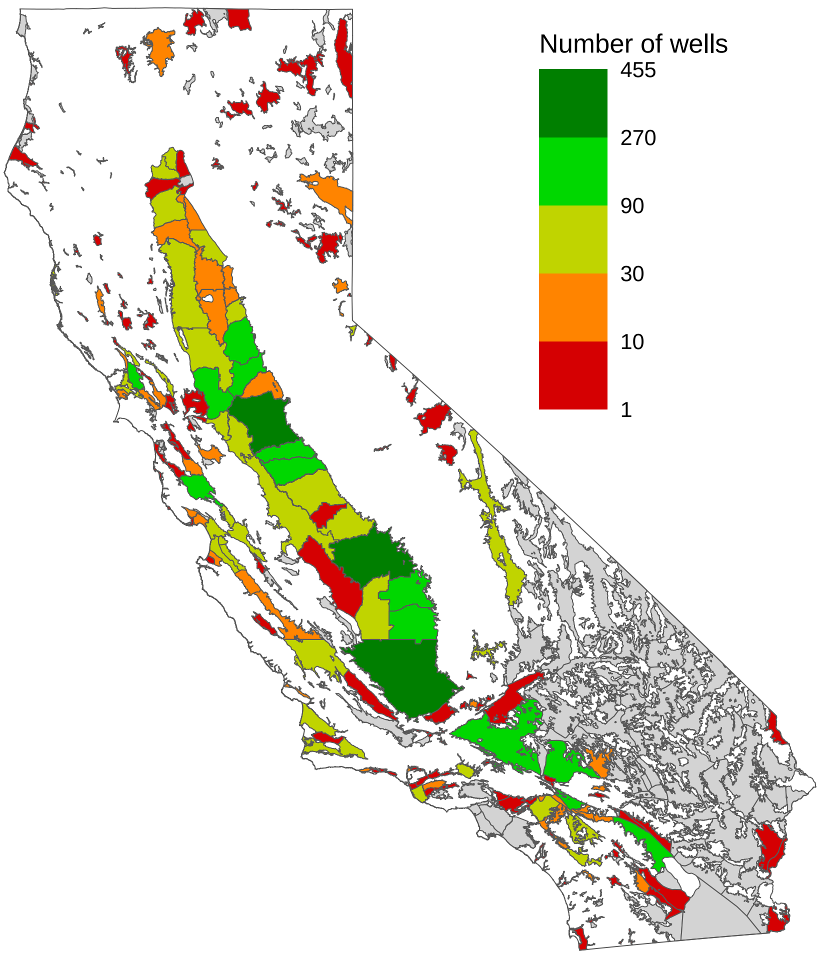

Figure 2: Number of wells observed in each sub-basin

Note: The figure maps the 515 sub-basins and shows the distribution of the 6,016 wells in our sample. Grey regions indicate sub-basins with no well data, and white regions represent non-basin areas.

0.5 mg/L. Out of our 6,016 sample wells, 45.2% have 2007–2011 nitrate concentrations above 2 mg/L, and 2.7% have baseline concentrations above the federal MCL of 10 mg/L. These shares rise to 45.4% and 3.6%, respectively, for the period 2019–2023.

Table 2 reveals that low- and high-NHI crops account for 5% and 9% of total land use, respectively. Fallow agricultural land has the smallest share (3%) among the land use categories defined in our analysis. Pasture, which includes grazing grasslands and pasture harvested for hay, makes up the largest share of agricultural land surrounding wells (17%).

Urban developments represent the largest share of land use, with low- and high-intensity developments occupying 30% and 23% of land around wells, respectively. Low-intensity developments are areas with less than 50% of the land covered in impervious surfaces like concrete and asphalt. Examples include urban open spaces like parks and golf courses and areas with a mixture of constructed materials and vegetation, like housing units with gardens. In high-intensity developments, impervious surfaces account for more than 50% of the land cover, and examples include apartment, commercial, and industrial complexes. The dominance of urban land use in our sample is not surprising, considering that many of the wells are used to extract water for urban uses, particularly municipal wells.

Undeveloped land comprises, on average, 13% of total land use, and encompasses forests, herbaceous scrubland, and barren regions with little vegetation, such as rocky mountains and deserts. Undeveloped land serves as the base land use category in our regressions, reflecting land that remains unaffected by any form of agricultural, urban, or industrial activity.

Table 2 reveals that the sample has, on average, 10 dairy cattle within 1 km of wells and 380 cattle within 1–5 km. We find that 73% of wells with a dairy within 1 km lie inside the Central Valley, with most in Stanislaus, Tulare, and Kings counties. Similarly, Central Valley wells account for 81% of wells with a dairy within 1–5 km, with wells in Stanislaus and Tulare accounting for the largest share.[18] Outside of the Central Valley, we observe wells with a dairy located less than 5 km away in the North Coast region, particularly Sonoma and

[18] Figure A.1 shows a map of California counties.

Table 1: Variable Descriptions

Variable	Description
Nitrate concentration	Milligrams of nitrate-nitrogen plus nitrite-nitrogen per liter of untreated water
Low-NHI crops	Share of land within buffer zone used to grow crops with a Nitrogen Hazard Index 1
High-NHI crops	Share of land within buffer zone used to grow crops with a Nitrogen Hazard Index 2, 3 and 4
Fallow	Share of cropland within buffer zone fallowed or idle
Pasture	Share of land within buffer zone used to grow pasture or grassland
Low-intensity development	Share of land within buffer zone with a mixture of vegetation, such as gardens and parks, and constructed materials where impervious surfaces account for less than 50% of the land cover, typically single-family housing
High-intensity development	Share of land within buffer zone where impervious surfaces account for more than 50% of land cover such as apartment, commercial, and industrial complexes
Undeveloped land	Share of land within buffer zone used for forest, wetland, and other natural land cover
Cattle within 1km	Inventory of lactating and dry cows and heifers on dairies located within 1 kilometer of the well (thousand)
Cattle within 1–5km	Inventory of lactating and dry cows and heifers on dairies located between 1 and 5 kilometers of the well (thousand)
Surface water deliveries	Cumulative acre-feet of surface water delivered to a DAUCO region per acre of agricultural land in 2007–2021 in one hundred feet increments
Precipitation	Cumulative precipitation in 2007–2023 in ten meter increments
Depth to groundwater	Distance from land surface to groundwater in ten meter increments
Distance to river	Distance from well to nearest river in ten kilometer increments
Sand, silt & clay	Mean share of soil textural fraction composed of sand, silt and clay, respectively, within buffer zone
Organic matter	Mean share of organic matter in soil within buffer zone
Drainage	Share of land within buffer zone with subsurface drains

Table 2: Summary Statistics

	Mean	Std. Dev.	Min.	Max.
Nitrate concentration in 2019–2023	2.90	3.61	0.004	67.28
Nitrate concentration in 2007–2011	2.70	3.06	0.02	56.44
Low-NHI crops	0.05	0.11	0	0.90
High-NHI crops	0.09	0.15	0	0.94
Fallow	0.03	0.06	0	0.69
Pasture	0.17	0.20	0	0.96
Low-intensity development	0.30	0.19	0	0.95
High-intensity development	0.23	0.25	0	0.99
Undeveloped land	0.13	0.21	0	1
Cattle within 1km	0.01	0.17	0	8.69
Cattle within 1–5km	0.38	1.67	0	23.03
Surface water deliveries	0.06	0.85	0	20.21
Precipitation	0.65	0.35	0.10	2.50
Depth to groundwater	3.10	2.87	0.05	20.97
Distance to river	0.15	0.19	0	1.92
Sand	0.55	0.20	0.04	0.98
Silt	0.26	0.11	0.01	0.70
Clay	0.19	0.11	0.01	0.65
Organic matter	0.01	0.02	0.00005	0.37
Drainage	0.01	0.05	0	0.82

Note: Sample size is 6,016 wells. Low-NHI crops, high-NHI crops, pasture, fallow, developed, and undeveloped land represent mean land use shares from 2007 through 2011.

Marin counties, and a handful in the Southern California and Central Coast regions, both minor dairy-producing areas. The predominance of Central Valley wells in the set of wells with nearby dairies is unsurprising considering that approximately 90% of milk cows reside in Central Valley dairies, with Tulare county containing 28% of the state herd, followed by Merced and Stanislaus (U.S. Department of Agriculture, 2022).

4 Results and Discussion

Table 3 shows estimates from a regression of mean 2019–2023 nitrate concentrations on mean 2007–2011 land use shares within 500 meters of the well and various controls, based on Equation (1). The table contains six columns of results. Columns (1) and (2) display the results of regressions without initial nitrate concentrations, while the regressions in columns (3) and (4) control for mean 2007–2011 nitrate concentrations. Therefore, the land use coefficients in columns (3) and (4) represent incremental impacts on nitrates approximately twelve years later. Columns (2) and (4) show results of regressions that include sub-basin fixed effects. Columns (5) and (6) are equivalent to columns (2) and (4), respectively, except that the high-NHI crop category is split into NHI-2 crops and NHI-3/NHI-4 crops. In all regressions, we estimate coefficients for land use relative to undeveloped land, and for sand and silt relative to clay. We cluster standard errors by sub-basin.

Model fit comparisons indicate that sub-basin fixed effects explain a large share of the variation in nitrate concentrations across wells. In models excluding initial concentrations, the R-squared rises from 0.14 to 0.32 upon the inclusion of sub-basin fixed effects. The model fit improves markedly when including initial concentrations, with the R-squared increasing to 0.77 in column (3) and further to 0.79 when sub-basin fixed effects are added in column (4).[19] Splitting high-NHI crops into two sub-categories only improves the model fit marginally.

4.1 Land Use and Cattle Effects

We begin the discussion by focusing on estimates of regressions without initial nitrate concentrations reported in columns (1) and (2) of Table 3. Estimates reveal positive and significant relationships between nitrate concentrations and the share of land used for agriculture and urban development relative to undeveloped land. The inclusion of sub-basin fixed effects leads to a marked decrease in the magnitude of land use coefficients and a reduction in significance for cattle population within 1 km. The coefficients on fallow and cattle population within 1–5 km change signs, but they are not statistically significant in columns (1) or (2).

The coefficients on high-NHI crops are the largest point estimates among the land use shares in specifications without initial nitrates, equaling 1.8 without sub-basin fixed effects (column (1)) and 1.1 when controlling for sub-basin fixed effects (column (2)). The coeffi-

[19] In fact, initial nitrates alone explain 76% of the variation in later nitrate concentrations.

Table 3: Impacts of Mean 2007–2011 Land Use Shares Within 500 meters of Wells on Mean 2019–2023 Nitrate Concentrations

	Dependent variable: Log nitrate concentration 2019–2023					
	(1)	(2)	(3)	(4)	(5)	(6)
Low-NHI crops	0.80***	0.61**	-0.23**	-0.01	—	—
	(0.26)	(0.31)	(0.10)	(0.13)		
High-NHI crops	1.8***	1.1***	0.21	0.14	—	—
	(0.34)	(0.31)	(0.14)	(0.14)		
NHI-1 crops	—	—	—	—	0.61*	-0.01
					(0.31)	(0.13)
NHI-2 crops	—	—	—	—	1.0***	0.09
					(0.34)	(0.16)
NHI-3/NHI-4 crops	—	—	—	—	2.7**	0.85*
					(1.2)	(0.47)
Fallow	-0.38	0.88	0.02	0.48*	0.89	0.48*
	(0.60)	(0.74)	(0.16)	(0.26)	(0.74)	(0.26)
Pasture	1.3***	0.73***	0.11	0.07	0.74***	0.07
	(0.17)	(0.25)	(0.07)	(0.10)	(0.25)	(0.10)
Low-intensity development	1.4***	0.96***	0.11	0.10	0.97***	0.10
	(0.19)	(0.16)	(0.07)	(0.07)	(0.16)	(0.07)
High-intensity development	1.5***	1.0***	0.08	0.13	1.0***	0.13
	(0.23)	(0.22)	(0.07)	(0.09)	(0.22)	(0.09)
Cattle within 1km	0.18**	0.15*	0.02	0.009	0.15*	0.01
	(0.07)	(0.08)	(0.07)	(0.07)	(0.08)	(0.07)
Cattle within 1–5km	0.01	-0.01	0.004	0.003	-0.008	0.004
	(0.02)	(0.02)	(0.009)	(0.01)	(0.02)	(0.01)
Surface water deliveries	0.05*	0.05***	-0.001	-0.0003	0.05***	-0.0003
	(0.03)	(0.003)	(0.003)	(0.001)	(0.003)	(0.001)
Precipitation	-0.57***	-0.11	-0.19***	0.03	-0.11	0.03
	(0.14)	(0.38)	(0.05)	(0.12)	(0.38)	(0.12)
Depth to groundwater	0.006	0.002	0.002	0.007	0.001	0.007
	(0.01)	(0.02)	(0.004)	(0.005)	(0.02)	(0.005)
Drainage	-1.6***	-0.85	-0.33*	-0.30**	-0.89	-0.33**
	(0.35)	(0.58)	(0.18)	(0.13)	(0.62)	(0.13)
Sand	0.35	-0.27	-0.16	-0.38**	-0.25	-0.38**
	(0.33)	(0.31)	(0.16)	(0.17)	(0.31)	(0.17)
Silt	-0.17	-0.68	-0.45*	-0.74**	-0.71	-0.76**
	(0.55)	(0.56)	(0.27)	(0.30)	(0.56)	(0.30)
Organic matter	-5.1***	-4.2**	-0.43	-0.42	-4.2**	-0.40
	(1.7)	(1.9)	(0.62)	(0.66)	(1.9)	(0.65)
Distance to river	0.24	0.51	0.16**	0.16*	0.51	0.16*
	(0.28)	(0.34)	(0.07)	(0.09)	(0.34)	(0.09)
Initial nitrate concentration	—	—	1.0***	0.98***	—	0.98***
			(0.02)	(0.02)		(0.02)
Sub-basin FE	No	Yes	No	Yes	Yes	Yes
Observations	6,016	6,016	6,016	6,016	6,016	6,016
R^2	0.13855	0.32333	0.77203	0.79430	0.32392	0.79442

Note: Undeveloped land is the default land use and clay is the default soil textural fraction. Initial nitrate concentration equals log nitrate concentration 2007–2011. Standard errors are clustered by sub-basin; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

cients from columns (1) and (2) imply that a 10 percentage point increase in the share of land used for high-NHI crops is associated with a 19.7% and 11.6% increase in nitrate concentrations, respectively, relative to undeveloped land. For example, using the sample means reported in Table 2 and the coefficient from high-NHI crops from column (2), increasing the mean share of land dedicated to high-NHI crops from 9% to 19% would increase nitrate concentrations from 2.9 mg/L to 3.2 mg/L, all else constant. Column (5) further differentiates the contributions of NHI-2 crops and NHI-3/NHI-4 crops. Crops in the NHI-3/NHI-4 category comprise less than 1% of land uses around wells, but they indeed contribute the highest marginal effect on groundwater nitrates, as expected.

The coefficients on low-NHI crops from columns (1) and (2) imply that a 10 percentage point increase in the share of land used for low-NHI crops is associated with nitrate concentrations 8.3% and 6.3% higher, respectively, than undeveloped land. Results of a Wald test for equality of the coefficients reveal that without sub-basin fixed effects (in column (1)), the coefficient on high-NHI crops is statistically larger than that on low-NHI crops at the 5% significance level, while the two coefficients are not statistically different in the regression with fixed effects (in column (2)). The finding that the coefficients on low-NHI crops are smaller than the coefficients on high-NHI crops is consistent with the crop categories' propensity for leaching nitrates below the root zone (Wu et al., 2005).[20]

The coefficient on pasture in column (1) equals 1.3, meaning that a 10 percentage point increase in the share of pasture is linked with a 13.9% rise in nitrate concentrations relative to undeveloped land. From column (2), a 10% increase in the share of pasture is linked with a 7.6% rise in nitrates. The large coefficients on pasture may be due to the inclusion of grass harvested for hay and silage in the CDL's pasture and grasslands category. Growers typically fertilize harvested grasslands with synthetic fertilizer and manure if the field is

[20]This finding also aligns with past hydrology literature (Ransom et al., 2018), which estimates that emissions of nitrate-nitrogen into California Central Valley groundwater from rice and alfalfa fields (low-NHI crops) total about 4 kg of nitrogen per hectare per year (kg N/ha/yr), while emissions from high-NHI crops like citrus (resp. vegetables and berries, resp. tree nuts) equal 65 kg N/ha/yr (resp. 49 kg N/ha/yr, resp. 25 kg N/ha/yr).

located close to a dairy (Ransom et al., 2018). Consequently, excess nitrogen compounds can leach below the shallow root zone and into groundwater if they surpass the grass crop's nutrient requirements. Indeed, Ransom et al. (2018) find that nitrate emissions from manure-fertilized forage crops in the Central Valley equal 46 kg N/ha/yr, roughly equivalent to emissions from some high-NHI crops like vegetables and berries.

Increasing the cattle population within 1 km of a well by 1,000, which falls short of the average dairy herd size in California, is associated with a 16–20% increase in nitrate concentrations. As dairy operations became increasingly concentrated in California, especially through the 1990s, manure production in Central Valley counties has exceeded the acreage available for application (Kellogg et al., 2000). Thus, dairy managers face a choice between applying excess nutrients to suitable crops or costly processing, such as drying manure, to transport it to other areas.[21] We find no meaningful effect of dairies located further (1–5 km) from wells. The evidence from prior literature on the extent to which cattle populations contribute to nitrate contamination of groundwater is inconclusive. On the one hand, Ransom et al. (2018) find that nitrate emissions from manure-fertilized forage are twice as large as emissions from equivalent fields treated with synthetic fertilizer, and Harter et al. (2002) show that cattle housing and manure lagoons act as point sources of nitrates. In Wisconsin, Meyer and Raff (2025) find that an additional dairy confined animal feeding operation within 1 mile of a well increases nitrate concentrations by 6%, but these effects are limited to privately owned wells. On the other hand, using a sample of Central Valley wells, Lockhart, King, and Harter (2013) find no clear correlation between the presence of a dairy farm within 2.4 km of wells and nitrate concentrations. However, Lockhart, King, and Harter (2013) focus on correlations and do not control for biophysical features like depth to water or soils. Using regression models that include hydrological characteristics and land uses at the county level in Maryland, Lichtenberg and Shapiro (1997) find no statistically

[21] Since 2013, the Irrigated Lands Regulatory Program (ILRP) has required dairies to submit an annual nutrient management plan to the Central Valley Water Control Board. The ILRP technical standards for nutrient management stipulate that dairies should not apply nitrogen in excess of 1.4 times the nitrogen removed from the field in the harvested portion of the crop.

significant association between dairy cattle and nitrate concentrations. However, typical dairy production in Maryland in the early 1990s involved small, pasture-based herds rather than the concentrated feeding operations prevalent in California (Somerville et al., 2020).

The positive coefficient on fallow in column (2) might be explained by the fact that without a crop to absorb residual nutrients left from previous crop years, nitrates leach deeper into the soil and below the root zone. Results of field experiments by Bauder, Sinclair, and Lund (1993), Campbell et al. (2006), and John et al. (2017) reveal positive associations between fallow cropland and nitrate emissions into groundwater. However, the coefficient on fallow is not statistically significant.

Urban developments are positively and significantly associated with nitrate concentrations in columns (1), (2), and (5), although the differences in the estimated effect between the two intensities considered are modest. The coefficients from column (2) imply that a 10 percentage point increase in low-intensity (resp., high-intensity) development is associated with a 10.1% (resp., 10.5%) increase in nitrate concentrations. Some key nitrate sources in urban landscapes include septic and sewage systems, gardens, and parklands (Lichtenberg and Shapiro, 1997; Pennino, Compton, and Leibowitz, 2017; Ransom et al., 2018).

Nitrate contamination of groundwater through leaching is a cumulative process, characterized by potentially long time lags between the absorption of nutrients in the topsoil and their reaching of the water table as well as the persistence of contaminants in groundwater over time. To understand the extent to which land use may affect nitrate concentrations over a twelve-year period, we include initial concentrations in our analysis and present the regression estimates in columns (3), (4), and (6) of Table 3. In general, these specifications show that the land use coefficients are an order of magnitude smaller compared to columns (1), (2), and (5) and generally insignificant, indicating that land use has little relationship to nitrate concentrations twelve years later once initial concentrations are included. Point estimates for low-NHI crops, fallow, and NHI-3/NHI-4 crops are exceptions. In column (3), the coefficient on low-NHI crops is -0.23; however, the estimate decreases in magnitude and loses significance when controlling for sub-basin fixed effects. Columns (4) and (6) reveal a relatively large coefficient on fallow (0.48), but this estimate is only significant at the 10% level. Results of a Wald test reveal that in column (3), the coefficient on high-NHI crops is significantly larger than the coefficient on low-NHI crops at the 5% level, while the coefficients on low- and high-NHI crops in column (4) are not statistically different.

4.2 Initial Nitrates

The coefficient on initial nitrate concentrations in column (3) of Table 3 is estimated to be one, indicating that a 1% increase in mean 2007–2011 nitrate concentrations is associated with a 1% increase in 2019–2023 concentrations, conditional on land use and biophysical factors. Introducing sub-basin fixed effects in column (4), the coefficient slightly decreases to 0.98, with a 95% confidence interval that includes one, and similarly for column (6). Another striking feature of the regressions reported in columns (3), (4), and (6) of Table 3 is their relatively large R-squared.

Given that our model involves the logarithm of nitrate concentration, as opposed to the concentration level, a coefficient on initial nitrates equal to one, controlling for features that determine the flow of nitrate pollutants, could be consistent with constant nitrate concentrations within the time frame considered, as depicted in panel (a) of Figure 3 for two wells, A and B, whose concentrations are observed at two time periods, T_0 and T_1. Constant nitrate concentrations over time could be obtained if the twelve-year period considered was too short for nitrates leached during the initial period to reach the water table (which would explain why the coefficients on land use are not statistically significant) and if there were negligible attenuation of the stock of nitrates initially present in groundwater over a decade. The absence of attenuation would align with research by Landon et al. (2011) showing that denitrification—the process by which natural processes convert nitrates to nitrogen gas—has minimal impact on nitrate concentrations in the San Joaquin Valley. Similarly, other attenuation mechanisms, such as the assimilation of nitrates into microbial biomass, appear

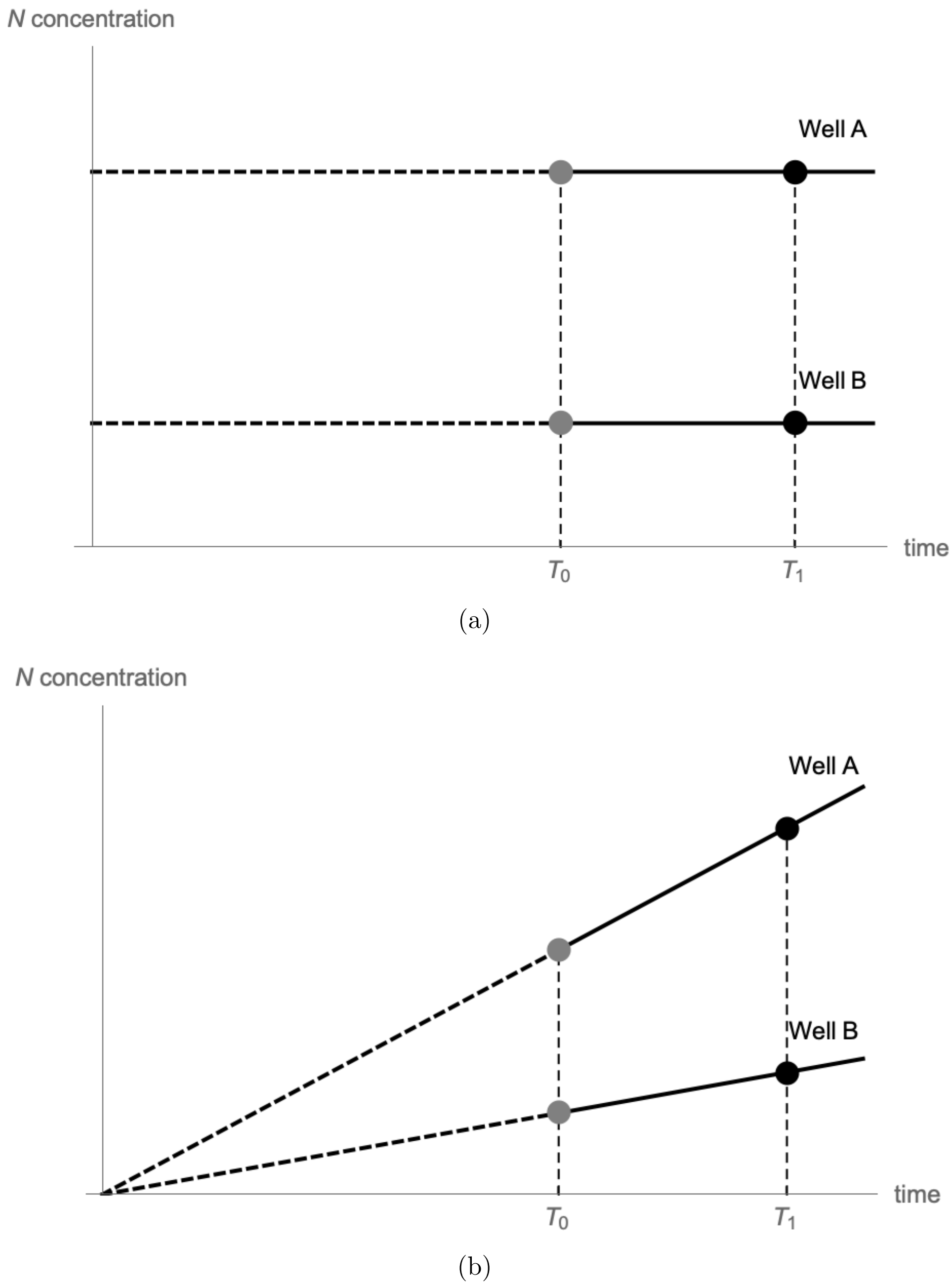

Figure 3: Possible Evolution of Nitrate Concentrations Over Time

to have a limited effect in reducing nitrate levels in this context (Rivett et al., 2008).

However, Table 2 suggests that, on average, nitrate pollution has worsened during the period. Panel (b) of Figure 3 depicts nitrate accumulation pathways for two wells that are driven by stationary nitrate emissions, resulting in linear trajectories, where the slope of the trajectory is a direct function of land use and biophysical characteristics at each well.

Because the *relative* difference in concentrations between wells is constant over time and our cross-sectional approach essentially compares wells subject to different conditions, the process depicted in panel (b) of Figure 3 is consistent with our findings that (i) nitrate concentrations have increased during the period of investigation, (ii) the coefficient on initial concentrations in a regression in logarithms is close to one, (iii) land use and biophysical factors have little explanatory power once initial concentrations are controlled for, and (iv) the model fit of the regression with initial concentrations is large. The fact that variation in recent nitrate concentrations is explained by initial conditions, rather than covariates describing subsequent land uses, also points to the legacy nature of groundwater nitrates.

Table 4: Land Use Shares Regressed on Well Fixed Effects

	Dependent variable:						
	Low-NHI crops	High-NHI crops	Fallow	Pasture	Low-int. devel.	High-int. devel.	Undevel.
Obs.	12,032	12,032	12,032	12,032	12,032	12,032	12,032
R^2	0.92196	0.94098	0.82213	0.88985	0.94807	0.98056	0.93987
$\lvert\hat{\varepsilon}_{it}\rvert > 0.10$	2.74%	5.09%	0.81%	10.14%	3.01%	2.79%	7.75%
$\sigma_{\varepsilon}^{\text{within}}$	0.03	0.04	0.02	0.06	0.04	0.04	0.06
σ_{ε}	0.12	0.17	0.05	0.18	0.18	0.26	0.23

Note: Row 2 shows the R^2 of a two-period panel of land use shares regressed on well fixed effects using mean land use shares in 2007–2011 and 2019–2023. Row 3 displays the percent of observations with absolute residuals greater than 0.1 (10 pp.) from the regression. Row 4 reports the standard deviation of the residuals from the regression. Row 5 reports the overall standard deviation in the two-period panel.

Of course, linear accumulation of nitrates in groundwater over time would require the leaching process to be stationary, but our data suggest that this assumption may be plausible. Table 4 assesses the temporal variation in land use shares between the endpoints of our study period based on a panel regression of land use shares on well fixed effects. Observations represent 5-year averages of land uses during the recent and initial periods, therefore there are two time periods per panel. The R-squared, reported in the second row, measures the proportion of variation in land use shares that is due to cross-sectional differences, the rest being attributable to variations over time. The third row reports the percentage of residuals from each model that exceed 10 percentage points in absolute value, connoting a change in the land use share by a magnitude larger than 20 percentage points over the period. The fourth row reports the within-well standard deviations, which are generally much smaller than the overall standard deviations reported in the last row. We provide additional graphical evidence of the limited variation in land uses over time in Appendix Figure B.1, which plots the histogram of the residuals from regressing land uses on well fixed effects using annual data from 2007 to 2023. The limited temporal variation suggested by these various measures indicates that the assumption of stationarity may be justified in our context.[22] If land use around wells does not vary much over time, initial nitrate concentrations may plausibly act as a sufficient statistic for subsequent land use patterns, resulting in small and insignificant effects of land use variables in the regression based on Equation (1).

Regressing untransformed nitrate concentrations on land use shares and controls provides further insights into the trajectory of nitrate concentrations over time. In regressions where nitrate concentrations are expressed in levels rather than logarithms, a coefficient on initial nitrate concentrations exceeding one implies divergent trends across wells consistent with panel (b) of Figure 3, whereas a coefficient equal to one indicates parallel trends. Appendix Table C.1 presents results of such regressions, with coefficients on initial nitrate concentrations estimated at 0.99 and 0.97 in columns (3) and (4), respectively—values that are not statistically different from one. When combined with the unitary coefficient on initial nitrates in the regressions in logarithms, these results provide support for near-constant concentrations, as illustrated in panel (a) of Figure 3. However, they do not preclude the interpretation of panel (b) as a valid representation of nitrate evolution over long periods of time. Specifically, the effective lag of 12 years may simply be insufficient to capture nitrate accumulation (or decomposition) despite the observed increase in mean nitrate concentrations (see Table 2). In this context, panel (a) may more accurately characterize the dynamics of groundwater contamination over the study period, whereas panel (b) could be applicable for longer durations. An alternative explanation is that nitrate decomposition offsets the

[22] We cannot test for stationarity of cattle populations as we observe them in a single year.

addition of new nitrates, resulting in relatively stable concentrations over time.

These considerations point to a critical trade-off inherent in observational studies seeking to identify the contributions of land use to groundwater contamination. On the one hand, clean identification of land use impacts requires controlling for initial concentrations. On the other hand, because land uses tend to change slowly over time, land use determinants of incremental contamination may be highly correlated with those that explain initial concentrations, resulting in *de facto* collinearity and the impossibility of identifying land use contributions conditional on initial conditions, particularly if nitrates emitted in the past remain in the environment for extended periods of time. Under that interpretation, regressions that omit initial concentrations, such as those reported in columns (1), (2), and (5) of Table 3, indicate long-run land use impacts, provided that the land use shares used as explanatory variables proxy for long-run patterns.

4.3 Sensitivity Analysis

In this section, we assess the sensitivity of the results to assumptions regarding the nitrate accumulation process over space and time, data measurement issues, sample definition, and model specification. We also investigate the heterogeneity of effects along key environmental characteristics of wells.

An immediate concern is that our preferred 500-meter buffer is too narrow. We thus construct a 1 km buffer and recalculate the mean land use shares, soil characteristics, and drainage share using similar spatial methods as those described in the data section. Summary statistics are provided in Appendix Table A.2 and reveal slightly higher mean 2007–2011 land use shares within 1 km of wells used for low- and high-NHI crops, fallow, and undeveloped land, and a lower share of land used for urban development. The results obtained with the 1 km buffer are reported in Table 5, which has the same structure as the first four columns of Table 3. Estimates are similar in magnitude and significance to those in Table 3, with some exceptions. Column (3) reveals significant coefficients on high-NHI crops, pasture,

Table 5: Impacts of Mean 2007–2011 Land Use Shares Within 1 km of Wells on Mean 2019–2023 Nitrate Concentrations

	Dependent variable: Log nitrate concentration 2019–2023			
	(1)	(2)	(3)	(4)
Low-NHI crops	0.61**	0.52*	-0.19*	0.05
	(0.26)	(0.32)	(0.10)	(0.14)
High-NHI crops	2.0***	1.5***	0.31**	0.24
	(0.31)	(0.29)	(0.13)	(0.15)
Fallow	-0.88	0.84	-0.13	0.38
	(0.64)	(0.83)	(0.18)	(0.34)
Pasture	1.3***	0.80***	0.14**	0.11
	(0.18)	(0.26)	(0.07)	(0.10)
Low-intensity development	1.5***	1.1***	0.18**	0.15*
	(0.24)	(0.18)	(0.09)	(0.09)
High-intensity development	1.4***	1.0***	0.07	0.15
	(0.26)	(0.27)	(0.07)	(0.11)
Cattle within 1km	0.17**	0.15**	0.02	0.010
	(0.07)	(0.08)	(0.07)	(0.07)
Cattle within 1–5km	0.001	-0.01	0.002	0.001
	(0.02)	(0.02)	(0.009)	(0.01)
Surface water deliveries	0.05*	0.05***	-0.0006	-9.7×10^{-5}
	(0.03)	(0.004)	(0.003)	(0.001)
Precipitation	-0.53***	-0.05	-0.19***	0.04
	(0.14)	(0.38)	(0.05)	(0.13)
Depth to groundwater	0.001	-0.004	0.0008	0.006
	(0.01)	(0.02)	(0.004)	(0.005)
Drainage	-2.0***	-1.5*	-0.40*	-0.50***
	(0.48)	(0.86)	(0.21)	(0.17)
Sand	0.40	-0.19	-0.12	-0.38*
	(0.35)	(0.40)	(0.18)	(0.23)
Silt	-0.25	-0.70	-0.46	-0.82**
	(0.64)	(0.77)	(0.32)	(0.41)
Organic matter	-6.7***	-6.7***	-0.74	-0.64
	(2.1)	(2.5)	(0.74)	(0.66)
Distance to river	0.25	0.51	0.17**	0.16*
	(0.27)	(0.34)	(0.07)	(0.09)
Initial nitrate concentration	—	—	1.0***	0.98***
			(0.02)	(0.02)
Sub-basin FE	No	Yes	No	Yes
Observations	6,016	6,016	6,016	6,016
R^2	0.14928	0.32807	0.77251	0.79431

Note: Undeveloped land is the default land use and clay is the default soil textural fraction. Initial nitrate concentration equals log nitrate concentration 2007–2011. Standard errors are clustered by sub-basin; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

and low-intensity urban development at the 5% level, providing some evidence that these land use shares are associated with increased nitrate concentrations twelve years later. By including sub-basin fixed effects, as in column (4), we find a positive coefficient on low-intensity development that is significant at the 10% level.

In Appendix Table C.2, we regress nitrate concentrations on contemporaneous (2019–2023) land use shares. Although it is not possible to know with certainty how long the leaching process from topsoil down to groundwater actually takes, based on prior literature, contemporaneous land use is less likely to influence current groundwater nitrates than land use measured in prior years. Consistent with this expectation, we find that the land use coefficients in columns (1)–(2) of Table C.2 are smaller in magnitude compared to those in Table 3, with a corresponding loss in statistical significance on the low-NHI crop coefficients. Controlling for initial nitrates, as in columns (3)–(4), we also find a decrease in the magnitude of most coefficients. The coefficients on low-NHI crops in columns (3) and (4) and fallow in column (3) are exceptions. Compared to Table 3, the coefficients on the control variables in Table C.2 do not change much, and the R-squared values are very similar.

In another sensitivity test, we follow Keiser and Shapiro (2019a) and halve nitrate concentrations previously set at the detection limit for concentrations below the laboratory detection limit. Summary statistics of these data are provided in Appendix Table A.3 and show small decreases in mean nitrate concentrations compared to Table 2. Results of the regressions using these revised data are provided in Appendix Table C.3. The results reveal no notable changes in the magnitude or significance of the regression coefficients compared to the estimates shown in the first four columns of Table 3.

The CDL, like other remotely sensed datasets, contains classification errors. Our methodology aggregates land uses into seven distinct categories, thereby combining crops that the CDL may have difficulty differentiating. For instance, vegetable crops are incorporated into the high-NHI crop group. However, fallow and pasture land do not have an associated NHI value, rendering them unsuitable for classification into either low- or high-NHI crops; they also belong to the least accurate land covers in the CDL (Lark, Schelly, and Gibbs, 2021). Therefore, in another sensitivity test, we aggregate fallow and pasture land use shares into one category and present the results in Appendix Table C.4. The coefficient on pasture and fallow across model specifications is close to the coefficient on pasture in Table 3. This is not surprising, considering that 17% of land within 500 meters of wells is used for pasture, compared to only 3% for fallow. Coefficients on the other regressors do not change much as a result of aggregating pasture and fallow into a single land use category.

Given that our baseline category of undeveloped land comprises diverse environmental characteristics, we investigate whether disaggregating this category into distinct forests, deserts, wetlands, and other undeveloped land influences other land use coefficients. Results from these specifications are reported in Appendix Table C.5, where forested land serves as the base category. This change has little influence on our estimates, likely due to the fact that forested land comprised a large share of the aggregated undeveloped land category.

We explore whether our results are sensitive to potential outlier wells through a sub-sample analysis of only municipal wells and excluding wells in sub-basins with fewer than 10 reporting wells. Results from these specifications are included in columns (1) and (2), respectively, of Appendix Table C.6, and mirror those of Table 3. We also test whether the results are sensitive to choices regarding the definition of our outcome variable. Column (3) of Appendix Table C.6 reports results using a 3-year window to average land uses and nitrate concentrations instead of a 5-year window. Columns (4) and (5) use the difference between 2019–2023 and 2007–2011 nitrate concentrations as the dependent variable, and the results are comparable to those that instead control for initial concentrations. Finally, Appendix Table C.7 uses annual nitrate concentrations in the years between 2019 and 2023 (instead of taking a 5-year average), which provides more observations; this change does not meaningfully influence the coefficients. In summary, our main empirical results hold across alternative sample definition and model specification choices.

Our primary results underscore the *average* long-run effects of land uses on groundwater nitrate concentrations. Yet, nitrates accumulate into groundwater differentially according to environmental conditions (Skidmore, Andarge, and Foltz, 2023; Metaxoglou and Smith, 2025). Thus, in Appendix Table C.8 we test for heterogeneous treatment effects along three dimensions: precipitation, soil type, and well depth. All columns decompose total precipitation into three seasons. The seasons are defined as groupings of four consecutive months, with breaks chosen to distinguish different precipitation regimes throughout the year. Appendix Figure A.2 shows average precipitation by month across sample wells over the period 2007–2023. It clearly identifies the dry summer season as comprising the months of June–September, which forms the basis for our groupings. Column (1) indicates that seasonal precipitation variables are not statistically significant. This result is not surprising as sub-basin fixed effects already capture much of the cross-sectional variation in climate. Column (2) interacts the high-NHI crop share with a dummy variable indicating whether a well received higher annual precipitation than the sample median (over the years 2007–2011) and shows that precipitation does not significantly amplify leaching. Similarly, column (3) shows that springtime precipitation does not amplify leaching from high-NHI crops. These patterns could be expected as fertilization in California usually happens through irrigation during summer months, a period with very little precipitation. As a result, fertilizer application is largely disconnected from rainfall events.[23] Column (4) interacts the sand fraction of soil with the high-NHI crop share and shows that crops grown in sandy soils drive the average effect. Finally, column (5) interacts the high-NHI crop share with an indicator for whether the well depth is below the median. While this coefficient indicates that shallower wells accumulate more nitrates from high-NHI crops, it is not statistically significant.

[23]Although not reported in Table C.8, a regression interacting the high-NHI crop share with a high summer precipitation dummy shows no significant interaction.

5 Costs and benefits of land use change

This section uses our regression estimates to contrast the costs and benefits of changing land-use patterns to reduce nitrate leaching. Specifically, since our findings suggest that high-NHI crops contribute more than low-NHI crops to groundwater contamination, we study the economic impacts of replacing high-NHI crops with low-NHI crops across our sample of wells. Our measure of opportunity costs is elicited from a simple positive model of crop allocation borrowed from Costinot, Donaldson, and Smith (2016) that assumes farmers allocate cropland based on highest returns. We measure benefits by combining our estimates of land use contributions to nitrate concentrations and the predictions of our crop allocation model with municipal treatment cost estimates from the literature, the idea being that lower emissions at the source reduce the need for drinking water treatment. Because we wish to study a policy that targets the highest-NHI crops, we use the coefficient estimates in column (5) of Table 3 that distinguish between low- (NHI index equal to 1), medium- (NHI index equal to 2), and high-NHI crops (NHI index equal to 3 or 4).

5.1 Opportunity costs of altering cropping patterns

Denote by L the land area occupied by low-, medium-, and high-NHI crops across our sample of wells, and by I the set of crops that may be grown. This set may be further divided into the set I_- of low-NHI crops, the set I_+ of medium-NHI crops, and the set I_{++} of high-NHI crops. As in Costinot, Donaldson, and Smith (2016), we assume that the returns $R_i(\omega)$ to growing crops $i \in I$ are random across a continuum of parcels $\omega \in [0, 1]$ making up the land area L. These returns are given by the following joint Fréchet distribution:

$$\Pr\left[R_i(\omega) \leq r_i,\ i \in I\right] = \exp\left[-\gamma \sum_{i \in I} \left(\frac{r_i}{R_i}\right)^{-\theta}\right] ,$$

where $\theta > 1$ is a parameter reflecting the degree of parcel heterogeneity and γ can be chosen so that $\mathbb{E}\left[R_i(\omega)\right] = R_i$ for all $i \in I$, that is, R_i represents the unconditional return to growing crop i.[24] Values of θ close to one connote high heterogeneity in returns across parcels, whereas larger values connote parcel homogeneity and, given a set of unconditional returns R_i, lead to more pronounced crop specialization.

Standard Fréchet algebra implies that, if farmers grow the highest-return crop on each parcel $\omega \in [0,1]$, the share of cropland grown in crop i is given by

$$\pi_i = \Pr\left[R_i(\omega) = \max_{j\in I} R_j(\omega)\right] = \frac{R_i^\theta}{\sum_{j\in I} R_j^\theta} \tag{2}$$

and the expected return per unit land conditional on growing crop i is

$$\mathbb{E}\left[R_i(\omega)\middle| R_i(\omega) = \max_{j\in I} R_j(\omega)\right] = \left(\sum_{j\in I} R_j^\theta\right)^{\frac{1}{\theta}} .$$

Thus, the average return per unit land once land has been allocated is identical across crops and the total land rent is

$$\mathrm{LR} = L\left(\sum_{j\in I} R_j^\theta\right)^{\frac{1}{\theta}} .$$

Suppose that we observe the average land rent $\bar{R} \equiv \frac{\mathrm{LR}}{L}$. Conditional on a value of the land heterogeneity parameter θ, one can deduce from Equation (2) the unconditional crop returns that rationalize the observed cropping pattern:

$$R_i = \bar{R}\pi_i^{\frac{1}{\theta}} . \tag{3}$$

Now, suppose that high-NHI crops are eliminated from the set of eligible crops so that cropland is allocated to the set of medium- and low-NHI crops according to the highest return on each parcel. The new land shares for crops $i \in \{I_-, I_+\}$ are given by

$$\pi_i' = \frac{R_i^\theta}{\sum_{j\in\{I_-,I_+\}} R_j^\theta}$$

[24] Specifically, $\gamma = \Gamma\left(\frac{\theta-1}{\theta}\right)^{-\theta}$, where $\Gamma(t) = \int_0^{+\infty} u^{t-1}e^{-u}du$ for $t > 0$.

and the new total land rent is

$$\mathrm{LR}' = L\left(\sum_{j\in\{I_-,I_+\}} R_j^\theta\right)^{\frac{1}{\theta}} = L\bar{R}\left(\sum_{j\in\{I_-,I_+\}} \pi_j\right)^{\frac{1}{\theta}}, \tag{4}$$

where we have made use of Equation (3) in the second equality. Since $\sum_{j\in\{I_-,I_+\}} \pi_j < 1$, $\mathrm{LR}' < \mathrm{LR}$ and the reduction in the total land rent represents the opportunity cost of replacing high-NHI crops with either medium- or low-NHI crops. The only information needed to compute this opportunity cost is the cropland area L, the average land rent $\bar{R}$, the area share $\sum_{j\in\{I_-,I_+\}} \pi_j$, and an estimate of the heterogeneity parameter θ.

The total area occupied by low-, medium-, and high-NHI crops in our sample is equal to $L = 161,958$ acres, representing 13.9% of the total area surrounding sample wells. The average rent for irrigated cropland in California across the years 2007–2011 was \$350/acre (in 2010 dollars) based on rent data from USDA/NASS and CPI data from the Bureau of Labor Statistics. We take this value to be representative of the land rent for cropland located around sample wells. In their study of the impact of climate change on crop production and trade, Gouel and Laborde (2021) use a value for the land heterogeneity parameter θ equal to 1.1 and investigate sensitivity to values of 1.05 and 1.2. These values apply to a 1-degree of latitude/longitude grid cell for farmland located anywhere across the globe. Since our sample wells are scattered throughout California, California includes hundreds of such cells, and it has a diverse agricultural landscape in terms of soils and climates, a higher degree of heterogeneity in crop returns should be expected. We thus set $\theta = 1.01$.[25]

In addition to the scenario described above, we investigate a more ambitious program that would eliminate both high- and medium-NHI crops, leaving crops within the set I_- as the only available choices around sample wells. Equation (4) is readily adapted to compute opportunity costs in that scenario.

The resulting opportunity costs are shown in Panel A of Table 6. In scenario (1), which

[25] Costinot, Donaldson, and Smith (2016) estimate θ to be equal to 2.46, but this value applies to 5-arc-minute grid cells, that is, much smaller areas for which heterogeneity in crop returns is arguably smaller.

Table 6: Opportunity Costs and Anticipated Benefits from Crop Switching Around Wells

	Scenario (1)	Scenario (2)
Panel A: Opportunity costs		
Type of crops being eliminated	NHI-3/NHI-4	NHI-2/NHI-3/NHI-4
Initial cropland share of remaining crops (%)	96.0	36.6
Opportunity cost of crop reallocation ($1,000)	2,245	35,731
Panel B: Benefits		
Initial land share of crops being eliminated (%)	0.55	8.80
Reduction in nitrate concentration, r (%)	1.02	4.60
Treatment cost savings, small systems ($1,000)	5,340	24,080
Treatment cost savings, large systems ($1,000)	110	498
Total cost savings ($1,000)	5,450	24,578

Note: Estimates of benefits are based on coefficient estimates in column (5) of Table 3.

targets high-NHI crops, only 4% of the initial cropland is affected by the crop ban and is converted to medium- and low-NHI crops at an opportunity cost of $2,245,000. In contrast, scenario (2) bans both high- and medium-NHI crops, which occupy 63.4% of initial cropland. As a result, opportunity costs reach $35,731,000. Note that since $\theta > 1$, an upper bound to the opportunity cost of crop switching is obtained by letting $\theta \to 1$, which yields a value of $35,939,000 in scenario (2). With $\theta = 1.2$, the largest value considered in the study by Gouel and Laborde (2021), the opportunity cost decreases to $32,155,000.

5.2 Anticipated benefits from lowering nitrate concentrations

The scenarios described above—replacing higher-NHI crops surrounding sample groundwater wells with lower-NHI crops—will yield social benefits to users of the groundwater resource. These benefits may manifest through a variety of channels, including improved human health outcomes, increased property values, and reduced drinking water treatment costs. (The vast majority of our sample wells are municipal wells.) Due to drinking water regulations in the U.S., it is likely that the costs and benefits of perturbations in nitrate contamination in drinking water are primarily borne by the municipal water provider (Mosheim and Ribaudo, 2017; Cullmann et al., 2024), and are only realized by the consumer in the most extreme cases that result in violations (Hadachek, 2024). Therefore, this exercise focuses on the drinking water treatment cost savings arising from changes in nitrate concentration.

To translate these changes into monetary values, we rely on treatment costs elasticities with respect to changes in water source nitrate levels from Mosheim and Ribaudo (2017). Importantly, these authors show that drinking water treatment exhibits scale economies, as small systems incur higher marginal costs than larger ones. They predict that treatment costs increase by 0.03% ($2,280 annually) for small public water systems and by 0.004% ($304 annually) for larger public water systems for a 1% increase in nitrate concentration.[26] The groundwater wells in our California sample belong to 2,296 small public water systems ($\leq 3,300$ people as defined by the EPA) and 356 larger public water systems.

We scale these treatment cost savings to the state level and to reflect the change in nitrate concentrations from the two land use scenarios. For a r% reduction in nitrate concentration, small public water systems in California would save $\$2,280 \times 2,296 \times r$ annually, while larger water systems would save $\$304 \times 356 \times r$. We use baseline land shares, the predictions from the land allocation model, and the coefficient estimates from column (5) of Table 3 to compute the reduction in nitrate concentrations, r, for each scenario.

The results are reported in Panel B of Table 6. For scenario (1), which focuses on the highest-NHI crops occupying only 4% of the cropland around wells, total water treatment benefits exceed opportunity costs by a factor of more than two, indicating that banning these crops around wells would be economically justified. However, this land use change only achieves a 1.02% reduction in nitrate contamination. In contrast, a policy targeting medium-NHI in addition to high-NHI crops would achieve a 4.60% reduction in nitrates and bring anticipated benefits of $24,578,000. While these benefits do not exceed opportunity costs, they demonstrate the large magnitude of external benefits that may accrue to other users of groundwater. In our context, where high-value agriculture and groundwater-

[26]The 1996 American Water Works Association survey reports that annual variable costs are $5.5 million on average per water system (Mosheim and Ribaudo, 2017). We inflate these values to 2010 dollars using the CPI and assign an average variable cost of $7.6 million.

dependent communities are in close proximity, external benefits are about 69% of the private opportunity costs of the alternative land use in scenario (2). In other contexts, where agricultural rental rates are lower, land use policy may represent an economically beneficial abatement strategy for nitrogen contamination even at more ambitious abatement targets.

6 Conclusion

This study examines the relationship between land use and groundwater nitrate concentrations using a sample of 6,016 groundwater wells in California. Our findings indicate significant associations between agricultural and urban land use shares and nitrate concentrations. The most pronounced effects are observed for high-NHI (Nitrogen Hazard Index) crops, which occupy 9% of the area surrounding wells. Specifically, a 10 percentage point increase in the high-NHI land share is associated with an 11.6% rise in nitrate concentrations relative to undeveloped land. Similarly, urban land uses, whether high- or low-intensity development, contribute about a 10% increase in nitrate concentrations for every 10 percentage point increase in land use share. These significant associations underscore the importance of directing groundwater quality programs toward emissions from both agricultural and urban land uses in regions where wells exhibit poor or deteriorating water quality. Focusing solely on agricultural emissions could overlook cost-effective opportunities to improve well water quality through better management of urban developments.

A key challenge uncovered by our analysis is the difficulty to identify the incremental impact of land use on nitrate concentrations using observational data. Our results demonstrate that initial nitrate concentrations almost entirely explain the observed nitrate concentrations a decade or so later, likely due to the legacy nature of agricultural nitrogen in groundwater and the limited temporal variation in land use surrounding wells over time. That is, land use patterns that explain nitrate concentrations at the beginning of our period are likely close to those we use to explain subsequent contamination, so that conditioning on initial concentrations renders our land use variables redundant, explaining the overall decrease in size and statistical significance for their estimated effects, as well as the near-unit coefficient estimate on initial concentrations. Addressing this empirical challenge may require a multi-decade study relating long-term variation in land use on nitrate concentrations, or a focus on shallow wells, although current data constraints prevent such analyses. Studies focusing on other groundwater regions may face similar challenges, especially if cropping alternatives are more limited and urban development less rapid than in the California context.

Interpreting our land use variables as capturing a stationary source of nitrates, that is, not conditioning on initial concentrations, we are able to document meaningfully smaller coefficients on low-NHI crops compared to high-NHI crops, consistent with the definition of the NHI. To our knowledge, this is the first study to apply the NHI within a regression analysis, offering a novel approach to aggregating crops based on characteristics that influence nitrate emissions below the root zone. The NHI provides a parsimonious method to relate land use to nitrogen pollution, although further research is needed to compare the performance of NHI-based estimates against other crop aggregation methods commonly used in economics, such as those based on fertilizer application rates or traditional crop classifications (e.g., tree nuts, vegetables, row crops, etc.). Our regression analysis also confirms the role of dairy cattle as a meaningful determinant of nitrate concentrations.

Our analysis underscores the critical policy challenge of remediating nitrate contamination in groundwater through present-day land use changes. Indeed, our findings indicate that there is significant persistence in groundwater nitrate levels even at a decadal scale. As a result, regulatory attempts to rectify the anthropogenic contribution to groundwater nitrates may not have identifiable impacts for several decades. More generally, the valuation of groundwater quality degradation (or improvements) must account for the discounted value of land use externalities many years into the future.

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Appendix

A Variable Descriptions and Summary Statistics

Table A.1: Land Use Categories

Categories	Land uses
Low-NHI crops; Nitrogen Hazard Index 1	Rice, alfalfa, peas, dry beans, vetch, apricots, grapes, olives, soybeans, lentils, chickpeas, and Christmas trees.
High-NHI crops; Nitrogen Hazard Index 2	Barley, canola, corn, sugar beets, oats, rye, cotton, safflower, sorghum, sunflower, winter wheat, spring wheat, durum wheat, buckwheat, almonds, apples, avocados, cherries, citrus, nectarines, oranges, peaches, pears, pecans, pistachios, plums, pomegranates, prunes, walnuts, carrots, sweet potatoes, triticale, millet, other small grains, other tree crops, camelina, sod grass seed, other hay non-alfalfa, other crops, sugarcane. In addition, the Cropland Data Layer defines the following double-cropped combinations: Winter wheat and corn, triticale and corn, winter wheat and sorghum, oats and corn, barley and corn, winter wheat and cotton, lettuce and cotton, barley and sorghum, and durum wheat and sorghum.
High-NHI crops; Nitrogen Hazard Index 3	Asparagus, cantaloupes, sweetcorn, cucumbers, eggplant, garlic, honeydew melons, mint, potatoes, pumpkins, radishes, squash, tomatoes, turnips, watermelons, popcorn, and ornamental corn.
High-NHI crops; Nitrogen Hazard Index 4	Broccoli, cabbage, cauliflower, celery, lettuce, onions, mustard, herbs, peppers, greens, strawberries, cranberries, blueberries, cane berries, miscellaneous fruits and vegetables, and the following double-cropped crops: lettuce and cantaloupe, lettuce and barley, and lettuce and durum wheat.
Low-intensity development	Developed open space and developed low intensity.
High-intensity development	Developed high intensity, developed medium intensity, and aquaculture.
Undeveloped land	Clover wildflowers, barren, shrubland, evergreen forest, woody wetlands, herbaceous wetlands, deciduous forest, mixed forest, forest, perennial ice and snow, and wetlands.
Fallow	Fallow and idle cropland.
Pasture	Pasture and grassland.

Note: The table includes land uses that appear within 500 meters of sample wells.

Table A.2: Summary Statistics of Land Use Shares, Soil Characteristics, and Drainage Within One Kilometer of Wells

	Mean	Std. Dev.	Min.	Max.
Low-NHI crops	0.06	0.11	0	0.90
High-NHI crops	0.11	0.17	0	0.84
Fallow	0.03	0.05	0	0.59
Pasture	0.18	0.20	0	0.97
Low-intensity development	0.27	0.17	0	0.91
High-intensity development	0.20	0.24	0	0.95
Undeveloped land	0.15	0.22	0	1.00
Sand	0.55	0.19	0.06	0.97
Silt	0.26	0.10	0.01	0.69
Clay	0.19	0.10	0.01	0.60
Organic matter	0.01	0.01	0	0.31
Drainage	0.01	0.04	0	0.74

Note: Effective sample size is 6,016 wells. Mean land use shares in 2007 through 2011.

Table A.3: Summary Statistics Using Nitrate Concentrations Equal to Half the Detection Limit for Concentrations Below the Detection Limit

	Mean	Std. Dev.	Min.	Max.
Nitrate concentration in 2019–2023	2.80	3.64	0.002	67.28
Nitrate concentration in 2007–2011	2.60	3.10	0.01	56.44

Note: Effective sample size is 6,016 wells.

Figure A.1: California Counties

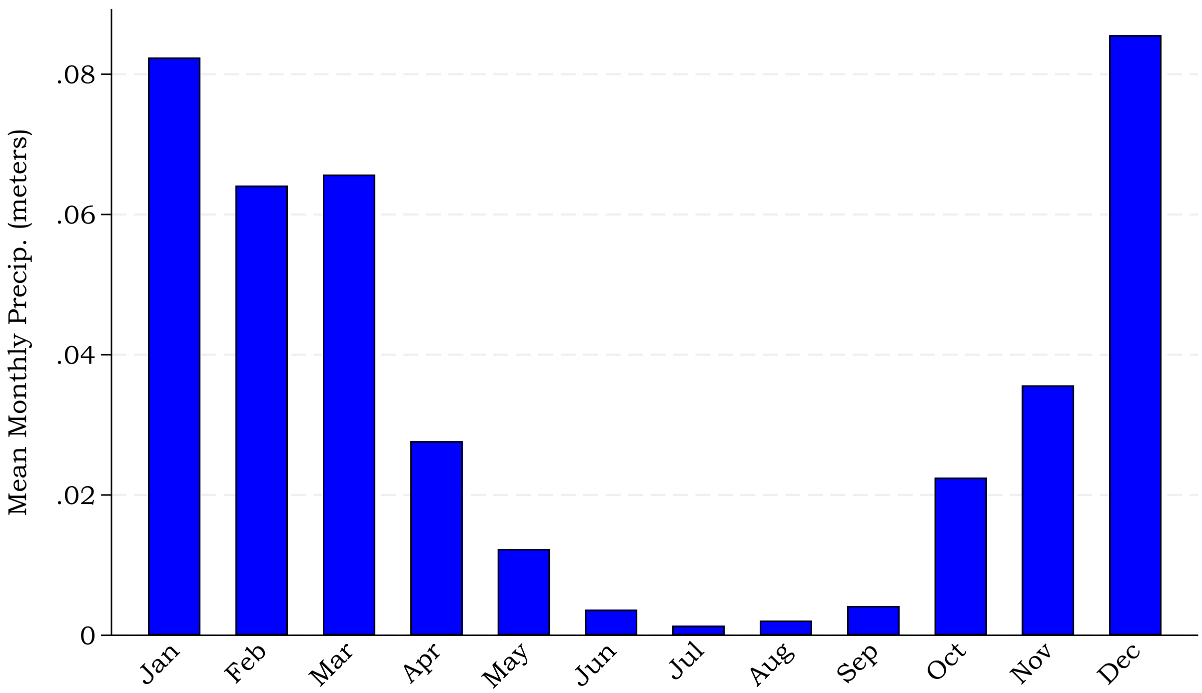
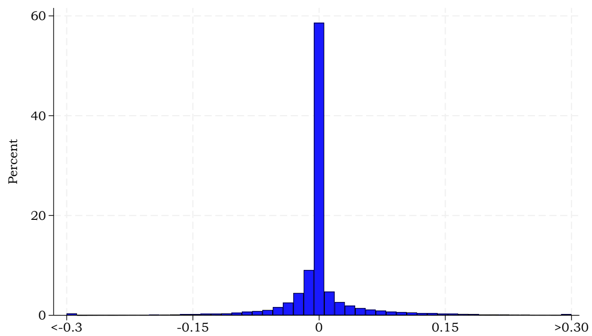
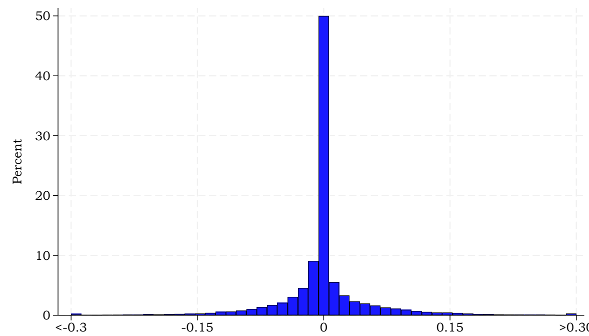


Figure A.2: Mean Monthly Precipitation around Wells, 2007–2023

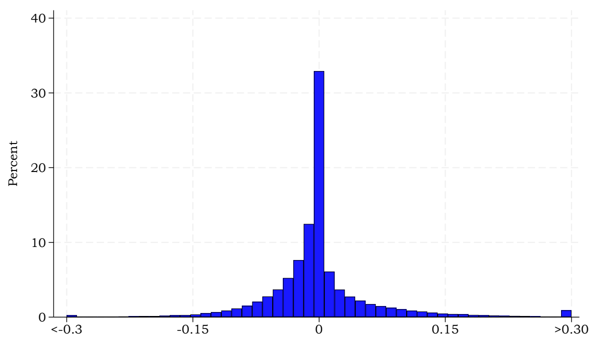
B Residuals from regression of land uses on well fixed effects



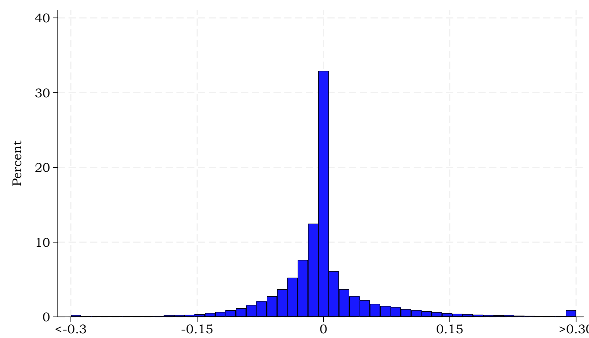
(a) Low-NHI Crops



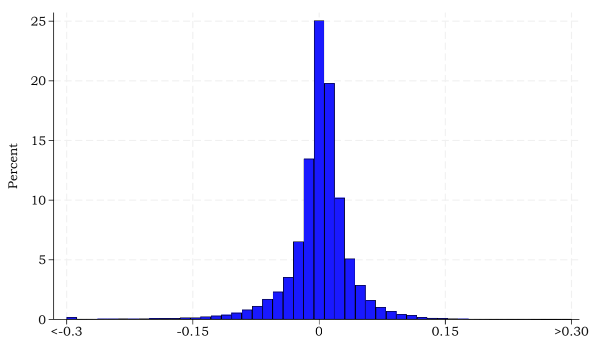
(b) High-NHI Crops



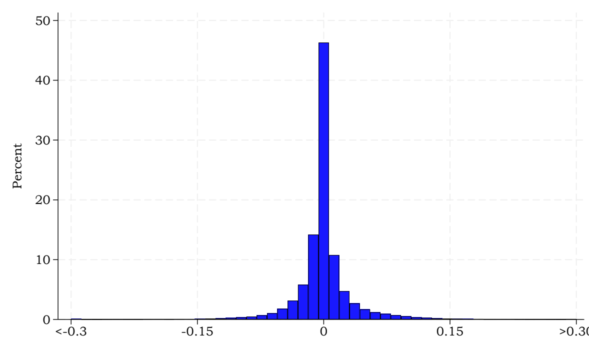
(c) Fallow



(d) Pasture



(e) Low-int. Devel.



(f) High-int. Devel.

Figure B.1: Histograms of Residual Variation in Land Use Shares about Well Fixed Effects

Note: Residuals are from panel regressions of a particular land use share on well fixed effects using annual observations from 2007 to 2023.

C Robustness checks

Table C.1: Impacts of Mean 2007–2011 Land Use Shares Within 500 meters of Wells on Mean 2019–2023 Nitrate Concentrations: Estimated Using Nitrate Concentrations in Levels

	Dependent variable: Nitrate concentration 2019–2023			
	(1)	(2)	(3)	(4)
Low-NHI crops	2.0***	2.4***	-0.40	-0.17
	(0.60)	(0.77)	(0.29)	(0.31)
High-NHI crops	5.9***	4.8***	1.1***	0.93***
	(0.92)	(0.84)	(0.38)	(0.35)
Fallow	-1.5	2.1	0.06	1.0***
	(1.7)	(1.7)	(0.56)	(0.38)
Pasture	2.9***	1.7**	0.18	-0.04
	(0.56)	(0.75)	(0.21)	(0.26)
Low-intensity development	3.4***	2.4***	0.39	0.26
	(0.57)	(0.45)	(0.27)	(0.22)
High-intensity development	2.8***	2.1***	-0.03	-0.05
	(0.59)	(0.55)	(0.22)	(0.22)
Cattle within 1km	0.50**	0.41**	0.18	0.17
	(0.20)	(0.20)	(0.23)	(0.23)
Cattle within 1–5km	0.02	-0.03	0.02	0.02
	(0.04)	(0.04)	(0.03)	(0.03)
Surface water deliveries	0.29*	0.30***	-0.010	0.003
	(0.15)	(0.08)	(0.01)	(0.01)
Precipitation	-1.1***	-1.1	-0.19**	-0.13
	(0.30)	(1.1)	(0.09)	(0.34)
Depth to groundwater	-0.006	-0.05	0.008	0.02
	(0.04)	(0.06)	(0.02)	(0.02)
Drainage	-1.9**	-1.6	0.27	0.05
	(0.92)	(1.3)	(0.61)	(0.54)
Sand	0.65	-1.3	-0.18	-0.55
	(0.82)	(0.90)	(0.39)	(0.34)
Silt	-1.1	-2.1	-0.70	-0.83
	(1.3)	(1.6)	(0.57)	(0.65)
Organic matter	-6.2**	-8.4**	-0.35	-0.90
	(2.6)	(4.0)	(0.98)	(1.3)
Distance to river	1.3	1.9*	0.63**	0.59*
	(0.85)	(0.98)	(0.29)	(0.34)
Initial nitrate concentration	—	—	0.99***	0.97***
			(0.04)	(0.04)
Sub-basin FE	No	Yes	No	Yes
Observations	6,016	6,016	6,016	6,016
R^2	0.08296	0.22382	0.72275	0.73981

Note: Undeveloped land is the default land use, and clay is the default soil textural fraction. Initial nitrate concentration equals mean nitrate concentration 2007–2011. Standard errors are clustered by sub-basin; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C.2: Impacts of Mean 2019–2023 Land Use Shares Within 500 meters of Wells on Mean 2019–2023 Nitrate Concentrations

	Dependent variable: Log nitrate concentration 2019–2023			
	(1)	(2)	(3)	(4)
Low-NHI crops	0.32	0.37	-0.32***	-0.16
	(0.24)	(0.27)	(0.08)	(0.10)
High-NHI crops	1.4***	1.0***	0.18**	0.13
	(0.24)	(0.21)	(0.09)	(0.10)
Fallow	-0.98	0.04	-0.11	0.27
	(0.70)	(0.78)	(0.24)	(0.33)
Pasture	1.1***	0.63***	0.07	-0.04
	(0.19)	(0.21)	(0.08)	(0.09)
Low-intensity development	0.98***	0.81***	0.06	0.05
	(0.19)	(0.14)	(0.07)	(0.06)
High-intensity development	1.2***	0.83***	0.06	0.07
	(0.20)	(0.16)	(0.06)	(0.07)
Cattle within 1km	0.19***	0.16**	0.02	0.01
	(0.07)	(0.07)	(0.07)	(0.07)
Cattle within 1–5km	0.006	-0.01	0.002	0.001
	(0.02)	(0.02)	(0.01)	(0.01)
Surface water deliveries	0.04	0.05***	-0.002	-0.0003
	(0.03)	(0.004)	(0.003)	(0.001)
Precipitation	-0.48***	-0.18	-0.17***	0.010
	(0.15)	(0.38)	(0.05)	(0.12)
Depth to groundwater	0.010	0.003	0.002	0.008
	(0.02)	(0.02)	(0.004)	(0.005)
Drainage	-1.3***	-0.71	-0.18	-0.25*
	(0.38)	(0.55)	(0.16)	(0.13)
Sand	0.27	-0.29	-0.17	-0.40**
	(0.36)	(0.31)	(0.16)	(0.17)
Silt	-0.25	-0.72	-0.47*	-0.76***
	(0.55)	(0.57)	(0.26)	(0.29)
Organic matter	-4.9***	-4.3**	-0.31	-0.51
	(1.6)	(1.9)	(0.64)	(0.69)
Distance to river	0.19	0.47	0.16**	0.15*
	(0.28)	(0.35)	(0.06)	(0.09)
Initial nitrate concentration	—	—	1.0***	0.98***
			(0.02)	(0.02)
Sub-basin FE	No	Yes	No	Yes
Observations	6,016	6,016	6,016	6,016
R^2	0.12841	0.32444	0.77276	0.79448

Note: Undeveloped land is the default land use and clay is the default soil textural fraction. Initial nitrate concentration equals log nitrate concentration 2007–2011. Standard errors are clustered by sub-basin; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C.3: Impacts of Mean 2007–2011 Land Use Shares Within 500 meters of Wells on Mean 2019–2023 Nitrate Concentrations Using Nitrate Concentrations Equal to Half the Detection Limit for Concentrations Below the Detection Limit

	Dependent variable: Log nitrate concentration 2019–2023			
	(1)	(2)	(3)	(4)
Low-NHI crops	0.93***	0.72**	-0.31***	-0.03
	(0.30)	(0.34)	(0.11)	(0.14)
High-NHI crops	2.0***	1.2***	0.20	0.16
	(0.40)	(0.37)	(0.15)	(0.16)
Fallow	-0.58	0.92	-0.01	0.53*
	(0.79)	(0.91)	(0.21)	(0.32)
Pasture	1.6***	0.92***	0.09	0.09
	(0.20)	(0.29)	(0.08)	(0.11)
Low-intensity development	1.7***	1.2***	0.14	0.14*
	(0.22)	(0.18)	(0.08)	(0.08)
High-intensity development	1.7***	1.2***	0.06	0.16*
	(0.26)	(0.26)	(0.08)	(0.09)
Cattle within 1km	0.21**	0.17*	0.01	0.007
	(0.09)	(0.10)	(0.07)	(0.07)
Cattle within 1–5km	0.006	-0.01	0.001	-0.0002
	(0.02)	(0.02)	(0.01)	(0.01)
Surface water deliveries	0.05*	0.06***	0.003	0.004
	(0.03)	(0.007)	(0.004)	(0.004)
Precipitation	-0.71***	-0.03	-0.25***	0.03
	(0.16)	(0.46)	(0.06)	(0.15)
Depth to groundwater	0.010	0.005	0.002	0.007
	(0.02)	(0.02)	(0.005)	(0.006)
Drainage	-2.1***	-1.1	-0.40	-0.37*
	(0.42)	(0.69)	(0.25)	(0.21)
Sand	0.53	-0.23	-0.13	-0.39**
	(0.40)	(0.37)	(0.18)	(0.19)
Silt	-0.005	-0.68	-0.43	-0.78**
	(0.66)	(0.68)	(0.30)	(0.33)
Organic matter	-6.9***	-5.4**	-0.06	-0.13
	(1.9)	(2.3)	(0.55)	(0.64)
Distance to river	0.27	0.57	0.20***	0.20**
	(0.31)	(0.38)	(0.07)	(0.09)
Initial nitrate concentration	—	—	0.97***	0.96***
			(0.02)	(0.02)
Sub-basin FE	No	Yes	No	Yes
Observations	6,016	6,016	6,016	6,016
R^2	0.14863	0.33352	0.78150	0.80274

Note: Undeveloped land is the default land use and clay is the default soil textural fraction. Initial nitrate concentration equals log nitrate concentration 2007–2011. Standard errors are clustered by sub-basin; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C.4: Impacts of Mean 2007–2011 Land Use Shares Within 500 meters of Wells on Mean 2019–2023 Nitrate Concentrations: Aggregated Share of Land Used for Pasture and Fallow

	Dependent variable: Log nitrate concentration 2019–2023			
	(1)	(2)	(3)	(4)
Low-NHI crops	0.70***	0.60**	-0.23**	-0.02
	(0.27)	(0.30)	(0.10)	(0.13)
High-NHI crops	1.6***	1.1***	0.20	0.14
	(0.35)	(0.31)	(0.14)	(0.15)
Pasture and fallow	1.2***	0.75***	0.10	0.10
	(0.17)	(0.24)	(0.07)	(0.09)
Low-intensity development	1.4***	0.96***	0.11	0.09
	(0.20)	(0.16)	(0.07)	(0.07)
High-intensity development	1.4***	1.0***	0.08	0.11
	(0.23)	(0.23)	(0.07)	(0.09)
Cattle within 1km	0.19**	0.15*	0.02	0.009
	(0.08)	(0.08)	(0.07)	(0.07)
Cattle within 1–5km	0.01	-0.01	0.004	0.003
	(0.02)	(0.02)	(0.009)	(0.01)
Surface water deliveries	0.05*	0.05***	-0.001	-0.000028
	(0.03)	(0.004)	(0.003)	(0.001)
Precipitation	-0.51***	-0.12	-0.19***	0.001
	(0.13)	(0.39)	(0.05)	(0.12)
Depth to groundwater	0.006	0.001	0.002	0.007
	(0.01)	(0.02)	(0.004)	(0.005)
Drainage	-1.6***	-0.84	-0.33*	-0.29**
	(0.36)	(0.58)	(0.18)	(0.13)
Sand	0.39	-0.27	-0.16	-0.39**
	(0.35)	(0.30)	(0.16)	(0.17)
Silt	-0.16	-0.68	-0.45*	-0.74**
	(0.56)	(0.57)	(0.27)	(0.30)
Organic matter	-5.1***	-4.2**	-0.43	-0.47
	(1.6)	(1.9)	(0.61)	(0.67)
Distance to river	0.25	0.51	0.16**	0.16*
	(0.27)	(0.34)	(0.07)	(0.09)
Initial nitrate concentration	—	—	1.0***	0.98***
			(0.02)	(0.02)
Sub-basin FE	No	Yes	No	Yes
Observations	6,016	6,016	6,016	6,016
R^2	0.13329	0.32331	0.77202	0.79412

Note: The regressor fallow and pasture equals the sum of the mean share of land used for fallow and pasture. Undeveloped land is the default land use and clay is the default soil textural fraction. Initial nitrate concentration equals log nitrate concentration 2007–2011. Standard errors are clustered by sub-basin; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C.5: Impacts of Mean 2007–2011 Land Use Shares Within 500 meters of Wells on Mean 2019–2023 Nitrate Concentrations: Disaggregated Undeveloped Category

	Dependent variable: Log nitrate concentration 2019–2023			
	(1)	(2)	(3)	(4)
Low-NHI crops	0.74***	0.41	-0.23**	-0.02
	(0.26)	(0.32)	(0.10)	(0.13)
High-NHI crops	1.8***	0.98***	0.21	0.14
	(0.34)	(0.30)	(0.14)	(0.14)
Fallow	-0.43	0.74	0.007	0.48*
	(0.62)	(0.74)	(0.17)	(0.26)
Pasture	1.3***	0.58**	0.11	0.06
	(0.18)	(0.24)	(0.07)	(0.10)
Low-intensity development	1.4***	0.80***	0.12	0.09
	(0.20)	(0.16)	(0.07)	(0.07)
High-intensity development	1.4***	0.83***	0.08	0.13
	(0.23)	(0.23)	(0.07)	(0.09)
Wetlands	-0.79	-1.2*	0.07	0.03
	(0.70)	(0.62)	(0.28)	(0.28)
Deserts	-3.0	-2.2*	-1.1	-0.73
	(2.3)	(1.2)	(1.4)	(1.1)
Other undeveloped	2.6	1.1	1.1	0.58
	(2.3)	(1.2)	(1.4)	(1.1)
Cattle within 1km	0.19**	0.16**	0.02	0.010
	(0.07)	(0.08)	(0.07)	(0.07)
Cattle within 1–5km	0.009	-0.01	0.004	0.002
	(0.02)	(0.02)	(0.009)	(0.01)
Initial nitrate concentration	—	—	1.0***	0.98***
			(0.02)	(0.02)
Sub-basin FE	No	Yes	No	Yes
Observations	6,016	6,016	6,016	6,016
R^2	0.14001	0.32535	0.77215	0.79434

Note: Forested land is the default land use. All regressions include the same environmental controls as the primary specifications in Table 3, but they are omitted here since the respective coefficients are approximately the same. Initial nitrate concentration equals log nitrate concentration 2007–2011. Standard errors are clustered by sub-basin; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C.6: Impacts of Mean Land Use Shares Within 500 meters of Wells on Mean Nitrate Concentrations: Different Sample and Outcome Definitions

	Dependent variable:				
	Log nitrate concentration			Δ Log concentration	
Model:	(1) Municip. only	(2) $\geq$ 10 wells	(3) 3-year avg.	(4)	(5)
Low-NHI crops	0.82***	0.69**	0.65**	-0.23**	-0.02
	(0.24)	(0.33)	(0.26)	(0.10)	(0.13)
High-NHI crops	1.1***	1.2***	1.1***	0.21	0.12
	(0.31)	(0.33)	(0.31)	(0.13)	(0.14)
Fallow	0.85	0.93	0.84	0.02	0.47*
	(0.75)	(0.77)	(0.75)	(0.16)	(0.25)
Pasture	0.75***	0.84***	0.75***	0.11*	0.06
	(0.25)	(0.27)	(0.24)	(0.07)	(0.10)
Low-intensity development	0.96***	1.1***	0.96***	0.12*	0.08
	(0.16)	(0.18)	(0.17)	(0.06)	(0.07)
High-intensity development	1.0***	1.1***	1.0***	0.08	0.12
	(0.22)	(0.24)	(0.21)	(0.06)	(0.09)
Cattle within 1km	0.15*	0.15*	0.15*	0.02	0.007
	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)
Cattle within 1–5km	-0.01	-0.009	-0.010	0.004	0.003
	(0.02)	(0.02)	(0.02)	(0.009)	(0.01)
Surface water deliveries	0.05***	0.06***	0.05***	-0.001	-0.001
	(0.004)	(0.004)	(0.003)	(0.003)	(0.0009)
Precipitation	-0.06	-0.05	-0.10	-0.19***	0.03
	(0.39)	(0.40)	(0.38)	(0.05)	(0.12)
Depth to groundwater	0.001	0.0003	0.002	0.002	0.007
	(0.02)	(0.02)	(0.02)	(0.004)	(0.005)
Drainage	-0.83	-0.94	-0.88	-0.33*	-0.30**
	(0.56)	(0.63)	(0.58)	(0.17)	(0.13)
Sand	-0.37	-0.27	-0.28	-0.16	-0.39**
	(0.30)	(0.31)	(0.31)	(0.16)	(0.17)
Silt	-0.83	-0.68	-0.69	-0.45*	-0.75**
	(0.56)	(0.58)	(0.56)	(0.27)	(0.30)
Organic matter	-4.4**	-4.4**	-4.2**	-0.43	-0.36
	(2.0)	(2.1)	(1.9)	(0.62)	(0.66)
Distance to river	0.51	0.49	0.51	0.16**	0.15*
	(0.34)	(0.35)	(0.34)	(0.06)	(0.08)
Sub-basin FE	Yes	Yes	Yes	No	Yes
Observations	5,998	5,492	6,016	6,016	6,016
R^2	0.32387	0.28396	0.32357	0.03211	0.12611

Note: Undeveloped land is the default land use and clay is the default soil textural fraction. Column (1) excludes non-municipal wells. Column (2) excludes sub-basins with fewer than 10 wells. Column (3) takes three-year averages (2007-2009 and 2021-2023) of the variables, instead of 5. The dependent variables in columns (4) and (5) are the differences in log nitrate concentration. Standard errors are clustered by sub-basin; $^{*}(p < 0.10)$, $^{**}(p < 0.05)$, $^{***}(p < 0.01)$.

Table C.7: Impacts of Mean 2007–2011 Land Use Shares Within 500 meters of Wells on Annual Nitrate Concentrations, 2019-2023

	Dependent variable: Log nitrate concentration			
	(1)	(2)	(3)	(4)
Low-NHI crops	0.51**	0.66***	-0.30***	-0.13
	(0.24)	(0.25)	(0.08)	(0.11)
High-NHI crops	1.4***	1.0***	0.17*	0.12
	(0.25)	(0.23)	(0.10)	(0.10)
Fallow	-0.29	0.41	0.04	0.34*
	(0.51)	(0.49)	(0.19)	(0.17)
Pasture	1.2***	0.69***	0.003	-0.05
	(0.20)	(0.22)	(0.10)	(0.10)
Low-intensity development	1.0***	0.88***	0.02	0.07
	(0.19)	(0.14)	(0.07)	(0.06)
High-intensity development	1.3***	0.95***	0.08	0.10
	(0.21)	(0.17)	(0.07)	(0.07)
Cattle within 1km	0.14*	0.09	0.02	0.005
	(0.07)	(0.07)	(0.06)	(0.06)
Cattle within 1–5km	0.01	-0.01	0.006	0.002
	(0.02)	(0.02)	(0.008)	(0.010)
Surface water deliveries	0.04	0.05***	-0.003	-0.002
	(0.03)	(0.006)	(0.003)	(0.003)
Precipitation	-0.47***	-0.17	-0.20***	-0.11
	(0.16)	(0.39)	(0.06)	(0.12)
Depth to groundwater	0.01	0.005	0.005	0.006
	(0.02)	(0.02)	(0.005)	(0.006)
Drainage	-1.6***	-0.86*	-0.34	-0.27
	(0.36)	(0.50)	(0.21)	(0.17)
Sand	0.25	-0.33	-0.27	-0.40**
	(0.39)	(0.31)	(0.20)	(0.20)
Silt	-0.31	-0.73	-0.68**	-0.78**
	(0.62)	(0.57)	(0.32)	(0.31)
Organic matter	-5.6***	-4.7**	-0.64	-0.63
	(2.0)	(2.2)	(0.93)	(0.82)
Distance to river	0.24	0.49	0.18***	0.14*
	(0.28)	(0.35)	(0.06)	(0.08)
Initial nitrate concentration	—	—	1.1***	1.0***
			(0.02)	(0.02)
Sub-basin FE	No	Yes	No	Yes
Observations	15,444	15,444	15,444	15,444
R^2	0.12439	0.31535	0.71554	0.74110

Note: Undeveloped land is the default land use and clay is the default soil textural fraction. Initial nitrate concentration equals log nitrate concentration 2007–2011. Standard errors are clustered by sub-basin; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C.8: Impacts of Mean 2007–2011 Land Use Shares Within 500 meters of Wells on Mean 2019–2023 Nitrate Concentrations: Heterogeneity Based on Biophysical Conditions

	Dependent variable: Log nitrate concentration 2019–2023				
	(1)	(2)	(3)	(4)	(5)
Low-NHI crops	0.63**	0.60**	0.61**	0.57*	0.62**
	(0.31)	(0.30)	(0.31)	(0.30)	(0.30)
High-NHI crops	1.1***	1.2***	1.3***	0.42	1.1***
	(0.30)	(0.34)	(0.35)	(0.52)	(0.30)
High-NHI crops × High precip	—	-0.34	—	—	—
		(0.45)			
High-NHI crops × High Feb.–May precip	—	—	-0.32	—	—
			(0.38)		
High-NHI crops × Sand	—	—	—	1.5**	—
				(0.78)	
High-NHI crops × Shallow well	—	—	—	—	0.18
					(0.31)
Cumulative Feb.–May precip.	3.1	4.0	4.3	2.9	3.1
	(4.7)	(4.7)	(4.9)	(4.7)	(4.7)
Cumulative June–Sept. precip.	0.44	-1.3	-1.6	0.69	0.42
	(11.5)	(11.2)	(11.7)	(11.5)	(11.5)
Cumulative Oct.–Jan. precip.	-1.3	-0.77	-1.2	-1.2	-1.3
	(1.3)	(1.3)	(1.3)	(1.3)	(1.3)
High precip.	—	-0.14	—	—	—
		(0.11)			
High Feb.–May precip.	—	—	-0.19*	—	—
			(0.11)		
Sand	-0.28	-0.28	-0.27	-0.47	-0.28
	(0.31)	(0.32)	(0.31)	(0.31)	(0.31)
Silt	-0.70	-0.66	-0.66	-0.72	-0.70
	(0.57)	(0.60)	(0.58)	(0.56)	(0.57)
Sub-basin FE	Yes	Yes	Yes	Yes	Yes
Observations	6,016	6,016	6,016	6,016	6,016
R^2	0.32368	0.32639	0.32502	0.32472	0.32383

Note: Undeveloped land is the default land use and clay is the default soil textural fraction. High precipitation variables are indicators for above-median precipitation over the years 2007–2011. Cumulative precipitation variables are computed over the years 2007–2023. Shallow well is an indicator variable for below-median depth to groundwater. All regressions include controls for cattle populations, cumulative surface water deliveries, depth to groundwater, drainage, organic matter, and distance to river. Standard errors are clustered by sub-basin; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.