Causal effects of urbanization and winter weather on salinity in the Delaware River Basin

Gabriel R. Lara[1], Daniel A. Brent[1], Allison Lassiter[2] and Hui Tan[2]

[1]Pennsylvania State University
[2]University of Pennsylvania

March 2025

Abstract

Salinity is increasing in freshwater reaches of rivers around the globe, including in the Delaware River Basin, located in the mid-Atlantic region of the United States. This study estimates the causal effect of land use changes on in-stream salinity concentrations in the Delaware River Basin. A 1% increase in urbanized areas increases salinity by 5.9 mg/L, or about 16.7%. Freezing precipitation, which leads to salt from deicing applications, also increases salinity, particularly in watersheds with developed land uses. Simulating salinity levels based on land use and climate projections indicates that, even in a warming climate with reduced deicing, more development increases in-stream salinity.

1 Introduction

Salt levels are increasing globally in non-tidal reaches of rivers, a phenomenon known as the freshwater salinization syndrome (Kaushal et al., 2018, 2021). Increasing salt can have various direct effects, like ecosystem degradation (Cañedo-Argüelles et al., 2013), decreased drinking water quality (Cruz et al., 2022; Kelly et al., 2018), and infrastructure corrosion (Stets et al., 2018). It can also lead to secondary effects associated with salt-mobilized chemical cocktails (Kaushal et al., 2019). Furthermore, in coastal rivers, upstream salinization has the potential to compound with rising sea levels, shifting the salinity profile of the tidal-fresh zone [Kaushal et al. 2025, in press].

Increasing salinity is due to both natural and anthropogenic causes. Two significant anthropogenic factors are urbanization and, in colder regions, road de-icing applications (Venkatesan et al., 2011; Mazumder et al., 2021; Utz et al., 2022; Beibei et al., 2025). Several studies evaluate relationships between salinity, urbanization, and road deicing. Lax et al. (2017) find that, though agricultural land contributes salts to nearby rivers through fertilizer runoff, agriculture to urban land use changes lead to an increase in salinity (Lax et al., 2017). Focusing on exurban and suburban watersheds, Rossi et al. (2022) examine impervious surface coverage and road deicing with a mass balance transfer model, finding that even small changes in imperviousness can lead to large changes in in-stream salt concentrations. Beibei et al. (2025) model future salinity for 18 river monitoring sites throughout the United States, finding population density and imperviousness are the most important predictors of salinity, yet Corsi et al. (2015) find that in-stream salinity increases faster than the rate of urban growth, attributing the increase to deicing practices. Mazumder et al. (2021) distinguish between the salinity levels observed in rivers in summer versus winter, finding that the effects of increased urbanization are especially notable during summer months.

Additional key factors associated with increasing freshwater salinity are precipitation and temperature. Drought has the potential to concentrate salts in rivers, while heavy rains have the potential to dilute salts (Van Vliet et al., 2023). Cold weather (and associated deicing) can increase salt exposure, while warmer weather (with less deicing) may decrease salt exposure. Rossi et al. (2022) find that warmer winters and reduced deicing in the northeastern US decrease salt exposure. However, in urbanizing watersheds and a warming climate, it is not yet fully established how future salinity levels can be expected to change.

While there is some possibility of removing salt with desalination technology, this approach does not protect against all primary and secondary effects of salinity. There have been attempts to capture and mitigate high salinity runoff with green stormwater infrastructure, but this approach has not yet proven to be effective. Instead, using green stormwater infrastructure can simply delay the release of salt or divert salt to groundwater (Barbier et al., 2018; Snodgrass et al., 2017; Burgis et al., 2020). Even if salt applications are reduced, salt may be retained in watershed soils for decades after initial exposure, continuing to salinize downstream waterways (Kelly et al., 2019).

Some scholars suggest salt regulations are needed to protect freshwater ecosystems. Schuler et al. (2019) discuss the need for ion-specific regulations. Hintz et al. (2022) specifically discuss the need to weigh the benefits and costs of road salt applications.

In a policy or regulatory environment, causal attribution of the source of salt can help establish management targets. This study contributes to the growing knowledge on salt in watersheds by using econometric methods to develop causal relationships between in-stream salinity concentrations, land use, and climate. While econometric methods are less common in water sciences, some notable precedents exist in using causal models to develop relationships between land use and water quantity or quality (Efroymson et al., 2016). For example, econometric methods have been used to establish causal relationships between impervious coverage and flood (Blum et al., 2020) and between land use and in-stream habitat conditions (Emmons et al., 2024).

This study investigates three questions. What is the causal relationship between in-stream chloride concentrations and upstream urbanization? How does weather, particularly precipitation in freezing conditions, affect in-stream chloride concentrations? Under future urbanization and climate scenarios, how much is in-stream chloride projected to increase?

We implement a panel data model comparing sub-watersheds within the Delaware River Basin (DRB), a watershed with a sixty-year history of managing salinity in the mid-Atlantic United States. Within the DRB, we find that a 1% increase in urbanized land increases salinity by 5.9 mg/L, or about 16.7%. Precipitation during freezing temperatures (snow, sleet, frozen rain), which is associated with de-icing applications, also increases salinity. Models that interact weather conditions with land use change show that freezing precipitation primarily increases chloride in urbanizing watersheds. Simulating salinity levels based on land use and climate projections shows mixed results. More development increases salinity, even though warmer temperatures mitigate this increase. Overall development patterns dominate warming effects, and overall salinity is predicted to increase in scenarios that show increased development.

Our primary contribution is to estimate a causal relationship between land use and salinity. Our panel data model includes watershed fixed effects that control for all static factors in a given watershed. This is important if the share of developed land is correlated with other factors that affect salinity, such as point source pollution. The model relies on changes in land use over time, which better reflects how increases in urbanization will affect water quality. This research complements work such as Rossi et al. (2022), which studies specific watersheds in the same region, but does not isolate a causal relationship. We focus on a reduced form model and do not develop a biophysical mass balance model as in Rossi et al. (2022). Mazumder et al. (2021) perform a similar analysis in Ontario, but does not generate aggregate parameters across an entire watershed. Our parameters from the Delaware Basin as a whole allow for out-of-sample predictions to simulate changes in climate and development patterns. This work highlights that increases in developed land increase chloride concentrations for an entire river basin spanning four states. Increases in warming does mitigate the salinity increases from urbanization, but without action, our models indicate that salinity will still increase in a warmer, more urban environment.

We begin by providing an overview of the study area and data in Section 2. We present the fixed effects panel data model in Section 3 and the findings in Section 4. In Section 5, we simulate chloride levels based on land use and climate scenarios. Finally, we discuss limitations and conclude in Sections 6 and 7.

2 Study area and data

2.1 Delaware River Basin

The Delaware River Basin is the drinking water source for 13 million people and exhibits significant salinization trends. From 1998 to 2018, specific conductance levels rose across the DRB, particularly during low flow conditions, indicating persistent subsurface contamination (Rumsey et al., 2023). The lower basin, characterized by higher impervious surfaces and greater land disturbance, experiences notable increases in specific conductance during the winter, consistent with deicing contributing to salinity in the water (Rumsey et al., 2023).

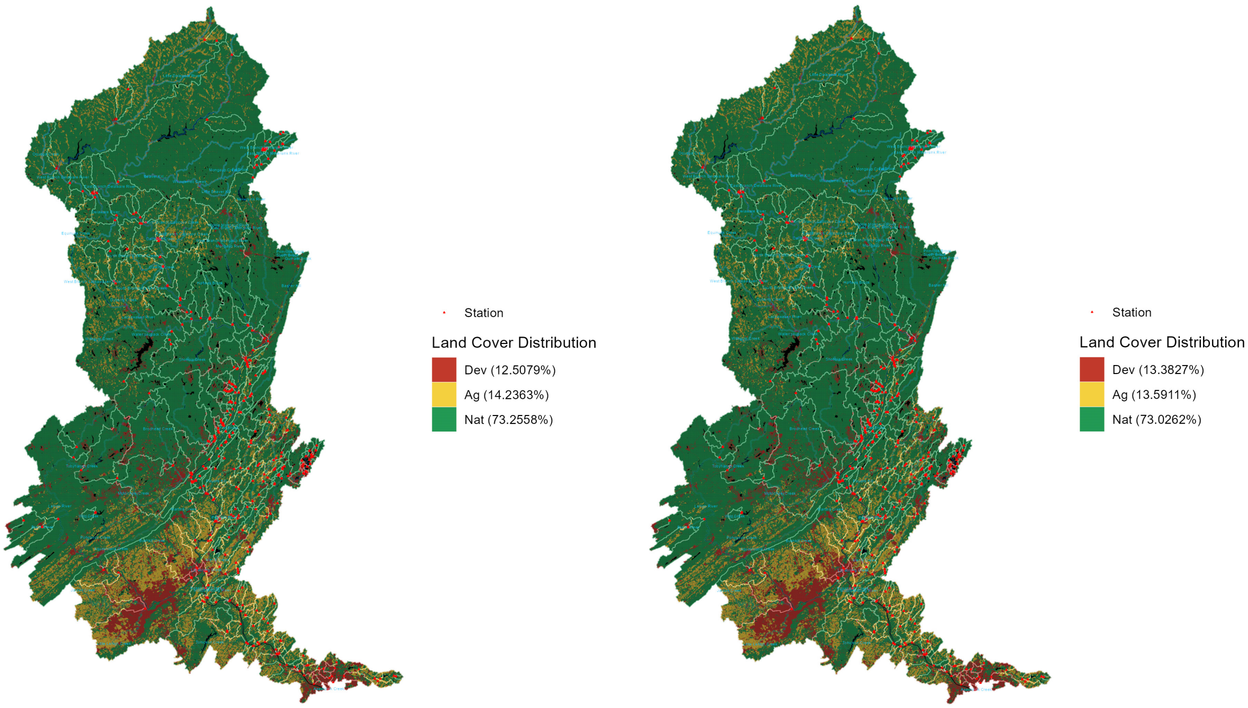
Since the 1960s, the Delaware River Basin Commission has prioritized salinity management to benefit of downstream water users located closer to the mouth of the river's estuary. Particularly vulnerable are the primary drinking water intake for Philadelphia (surface water) and Camden's groundwater supplies, which are adjacent to the Delaware River. There is an appointed River Master that coordinates upstream freshwater dam releases to maintain the location of the "salt front," where chloride concentration is 250 mg/L, at 67 to 76 miles from the river's mouth. However, maintaining this position will become increasingly difficult as sea levels rise, projecting an upriver shift of the salt front even if downstream flow volumes remain constant (Crosby et al., 2016).

In addition to sea levels, the salinity of the freshwater flowing downstream also influences the location of the salt line. The DRB's rising salinity trend could undermine the effectiveness of flow management strategies. The DRBC attributes observed salinity increases to road de-icing practices and the expansion of impervious surfaces. They note significantly higher winter chloride concentrations and emphasize the need for further monitoring, source investigation, and the development of de-icing alternatives (DRBC, 2020).

Figures 1 present the land use distribution in the study region for 2001 and 2019, respectively. Over the 18 years, significant changes in land utilization are observed, particularly in the expansion of urban areas. Figure 2 further illustrates these changes, emphasizing the areas where land use has shifted from natural or agricultural lands to urban developments. These changes are crucial for understanding how different land uses contribute to salinity levels in the Delaware River Basin. The figures highlight the complexity of land use dynamics and the need for comprehensive research to determine their impact on water quality, particularly salinity.

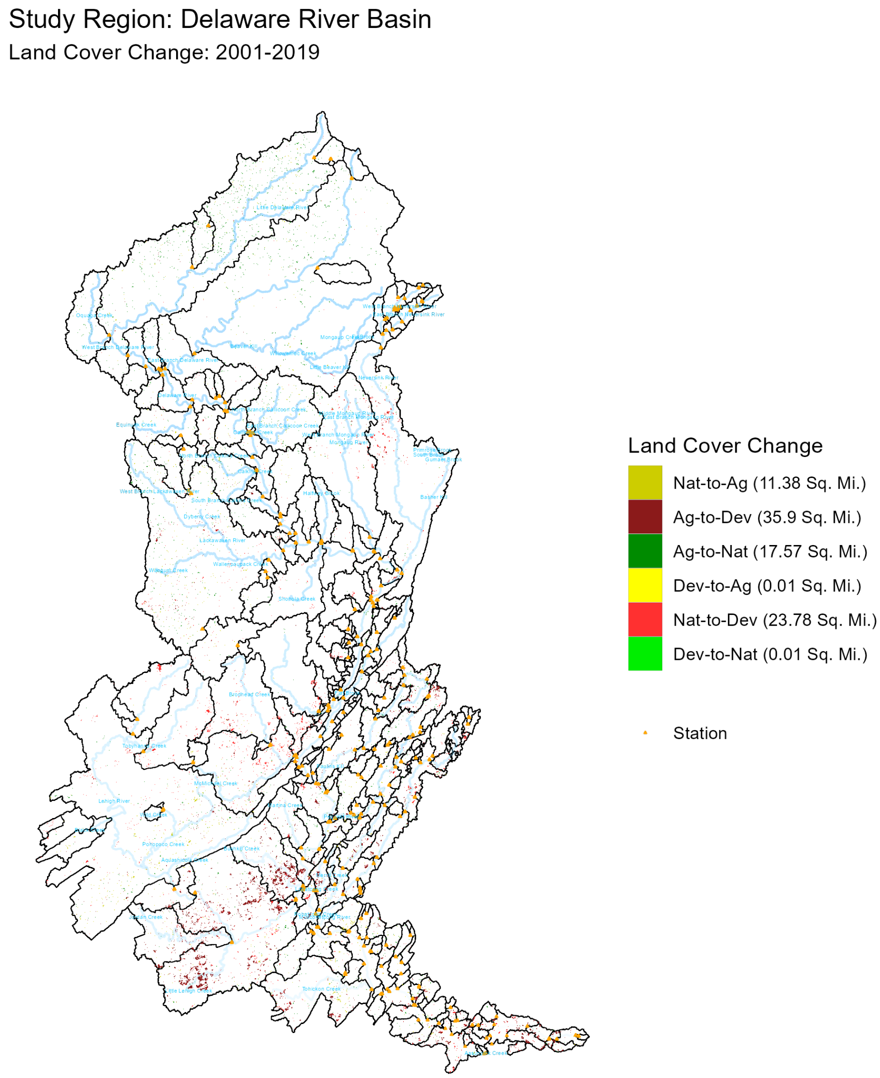
Figure 1: Land Use Distribution Comparison

Land Use Distribution in 2001 **Land Use Distribution in 2019**



Note: These figures show the land use distribution within the study region for the years 2001 and 2019, illustrating significant changes in land utilization over the 18-year period.

Figure 2: Land Use Change from 2001 to 2019



Note: This figure illustrates the land use changes in the study region between 2001 and 2019, highlighting areas of urban expansion and other land use transformations.

2.2 Data sources

We construct a panel dataset to analyze the effect of land use change on salinity in the Delaware River Basin. The dataset spans from 2001 to 2019 and integrates hydrological, land use, and weather variables. This section describes the data sources used and the methods to combine the data to link land use and weather to water quality at observed monitoring stations.

The primary source of water quality data was the Water Quality Portal, managed collaboratively by the United States Geological Survey (USGS) and the United States Environmental Protection Agency (EPA). This dataset includes measures of chloride measured in milligrams per liter (mg/L), also referred to as parts per million (ppm). Geographical data, including elevation and watershed boundaries, were sourced from the National Map's 10-meter DEM and Hydrosheds' 90-meter void-filled digital elevation models.

Land cover data were obtained from the National Land Cover Database (NLCD).[1] These data were processed to categorize land cover into natural, agricultural, and developed. Meteorological data, including daily precipitation and temperature records, were acquired from NOAA's nClimGrid-Daily dataset, providing detailed climatic profiles at the river gauge locations.[2]

2.3 Data preparation

The preparation of watershed polygons involved loading Delaware Basin Watershed geospatial data and transforming the data into a standard coordinate reference. Raster files from the National Land Cover Database (NLCD) were processed by cropping and masking them according to the watershed polygons. A reclassification scheme consolidated land cover types into broader categories, such as "Agriculture" for all planted and cultivated classes.

Frequency values of NLCD class pixels within each watershed were calculated and converted into square miles for a more intuitive measure of land cover extent. The proportions of each land cover class within the watersheds were calculated by determining the percentage of each land cover type relative to the total watershed area.

The processed data, including land cover proportions and changes, were then merged into a panel dataset. This dataset was structured to align temporal and spatial dimensions. The NLCD data are only available every two or three years.[3] When we have a water quality monitoring reading during a year without NLCD data, we assign the most recent NLCD data year. For example, we do not have NLCD data in 2017 so a water quality reading in 2017 will be assigned land use from the 2016 NLCD data. The final datasets links each water quality record with a unique spatial watershed and the land use in that watershed during that year.

Next, we merge in weather data for the watershed linked to the time of the water quality sample. We consider a range of weather variables and timeframes that could impact water quality. Our primary weather variables focus on the 30 days preceding the water quality sample. We construct the average minimum temperature, the maximum amount of precipitation, and the number of days below freezing that had precipitation. These variables can impact salinity based on flushing pollutants toward water bodies and the application of de-icing materials that contain salt. We consider different times from the water quality sample, including the past 7 days and the past 365 days.

Additional processing included cleaning and pre-processing raw data from the Water Quality Portal, focusing on key water quality measures, and utilizing Digital Elevation Models (DEM) from the USGS to accurately delineate watershed boundaries. River gauges with data spanning at least

[1] Data retrieved from the Multi-Resolution Land Characteristics Consortium, https://www.mrlc.gov/data, accessed August 2023

[2] Data retrieved from the NOAA National Centers for Environmental Information. https://www.ncei.noaa.gov/pub/data/daily-grids/, accessed October 2023

[3] The years where we observe NLCD data are 2001, 2004, 2006, 2008, 2011, 2013, 2016, and 2019.

three years were selected, reducing the number from 470 to 366 after quality assessments. The spatial analysis determined that the flow direction and land cover data were spatially joined with the delineated watersheds, categorizing land into natural, agricultural, and developed categories.

Two specific issues were addressed during the data preparation process: neighboring and clustered stations. Neighboring stations were identified when monitoring stations were located close to each other, leading to slightly different watershed areas due to the flow-accumulation pixel to which they were snapped during the watershed creation. This discrepancy often resulted in one watershed being inaccurately small. To address this, a 20-meter buffer was created around each station point to identify stations within proximity (up to 40 meters). Overlapping areas were differentiated from non-overlapping areas by calculating their geometry. Stations within the defined proximity were consolidated by selecting one representative station, typically the closest to the flowline or most downstream. This process was iterated with a 50-meter buffer to ensure stations within 100 meters were accurately consolidated, thus reducing redundancy and ensuring the watershed areas were correctly represented. Figure A.1 an example of a neighboring station issue.

The clustered stations issue occurred when there were dense clusters of water quality monitoring stations within the study area, creating tiny, hydrologically nonsensical watersheds. This issue was addressed by creating buffers around clustered stations to identify and merge closely located stations. The most representative station was selected based on its proximity to the flowline and hydrological relevance. This selection was performed manually to ensure accuracy. Additionally, corrections were made to the watershed delineation to ensure it made hydrological sense by using digital elevation models (DEMs) and verifying the stations' snapping to hydrologic features. These methods ensured that the resulting datasets were hydrologically accurate and representative of the true watershed areas, facilitating reliable water quality and environmental analysis. Figure A.2 shows an example neighboring station issue.

2.4 Summary statistics

Table 1 shows the summary statistics for the final panel dataset from 2001 to 2019 for 266 watersheds within the Delaware River Basin. Each watershed, on average, encompasses an area of 457 square miles, exhibiting substantial variation. This variance highlights the diverse sizes and scales of the watersheds analyzed.

The three rows representing the land cover highlight the spatial and temporal variation in the watersheds draining to the sample locations. Most of the land is natural (73%), followed by developed (13%) and agriculture (13%). Some watersheds are fulling natural or developed, as evidenced by the maximum value equaling one.

The final four rows describe the sampling data. There are 20,325 recorded measures of chloride in the sample. The average chloride concentration was 12.09 mg/L, compared to a Pennsylvania threshold of 250 mg/L for drinking water. There is a wide range of weather conditions with an average minimum temperature of 6 degrees Celsius. The average maximum rainfall in the previous 30 days was 185 millimeters, and on average, there were three days with freezing rain or snow in the 30 days preceding a water quality reading.

Table 1: Summary Statistics: 2001 - 2019

	Mean	SD	Min	Max	N
Watershed					
Area (Sq. Mi.)	456.53	1272.96	0.00	6783.80	266
NLCD					
Developed %	0.13	0.16	0.00	1.00	1,707
Natural %	0.73	0.22	0.00	1.00	1,707
Agriculture %	0.13	0.15	0.00	0.61	1,707
Water quality					
Chloride (mg/L)	12.09	25.01	0.02	1620.00	20,325
Weather					
Min. Temp	6.16	8.96	-25.77	24.71	20,325
Max. Rain	185.40	372.94	0.00	3325.45	20,325
Freezing Precip.	3.27	8.76	0.00	30.00	20,325

Note: The minimum watershed area is 0.0044 and is rounded to 0.00. The sample size (N) for the NLCD data represents unique watershed-years, or every year that there was a unique water quality reading in a given year. The sample sizes for weather and chloride represents the number of individual water quality readings. The weather variables are the rolling average of the most recent 30 days from the water quality reading. Min Temp is in degrees Celsius, Max. Rain is in millimeters, and Freeze Precip. is the count of days below freezing that had positive precipitation.

3 Methods

3.1 Water quality methodology

In our primary empirical approach, we model water quality as a function of land use transformation. The model is the following:

$$WQ_{it} = \beta_1 LU(\%)_{it} + \theta W_{it} + \alpha_i + \text{month}_t + \text{year}_t + \epsilon_{it} \tag{1}$$

where WQ_{it} represents the chloride concentrations at location i and time t. We also run specifications where we take the natural log of chloride concentrations, where the coefficients can be interpreted as the marginal effect of the independent variable on the approximate percentage change in chloride concentrations. Our primary variables of interest are the land use in the watershed draining to the monitoring site ($LU(\%)_{it} = ag, dev$). Since all three land use categories sum to one, they are perfectly collinear with the constant term, so we have to drop one land use from the regression. We drop the natural land use, so the estimated land use coefficients are interpreted as the impact of an additional percentage of either developed or agricultural land relative to natural land use.

The model incorporates weather variables (θW_{it}) for the previous 30 days prior to a reading. Our weather variables are average minimum temperature, maximum rainfall, and the number of freezing rain days. This selection is predicated on the typical contaminant flushing cycles observed, particularly road salt during winter and subsequent dry periods (Haq et al., 2018; Kaushal et al., 2023; Novotny et al., 2008). Similar models estimating the effect of impervious surfaces on flooding provide a causal interpretation, which has seen increasing attention in water resources studies linking land use to river flow (Blum et al., 2020; De Niel and Willems, 2019; Levy et al., 2018) and flood frequency (Ferreira and Ghimire, 2012).

The model includes month, year, and watershed fixed effects. The month and year fixed effects capture all seasonal and annual shocks to water quality that are common across all sampling locations. The watershed fixed effect captures all common unobserved factors that affect water quality in a watershed that do not change over time. For example, watersheds with more developed land may tend to have large point sources that affect water quality. This will be subsumed in the watershed fixed effect. This also makes the interpretation of the coefficients on land use as the impact of *changes* in land use conditional on the average land use throughout the sample. This is a similar approach that Blum et al. (2020) employ to estimate the causal effect of impervious cover on flooding. To account for serial correlation within watersheds over time, we cluster the standard errors at the watershed level. We estimate various model specifications to test for the robustness of our core findings.

We also estimate a model that allows for interactions between land use and weather variables. This may be important if weather has a different impact on chloride concentrations depending on the land use. The main motivation of this model is that de-icing application occurs primarily in developed areas. Therefore, the days of freezing precipitation may primarily affect water quality in developed areas. This model also feeds into our simulation results, where we observe both urbanization and warming temperatures. Less de-icing due to warmer weather may mitigate the effect of increased developed land use.

$$WQ_{it} = \beta_1 LU(\%)_{it} + \beta_2 LU(\%)_{it} * W_{it} + \theta W_{it} + \alpha_i + \text{month}_t + \text{year}_t + \epsilon_{it} \tag{2}$$

Lastly, we run seasonal models to account for potential different effects during the winter season compared to months where there is minimal or no de-icing application following the approach by Rumsey et al. (2023).

3.2 Simulation methodology

Estimating the causal effect of land use on salinity enables us to generate out-of-sample predictions, providing insight into the potential impact of land use change on salinity. The basic methodology for our simulation is based on equation 3.

$$\widehat{WQ_{it}} = \widehat{\beta}\widehat{LU_{it}} + \hat{\theta}\widehat{W_{it}} + \hat{\alpha}_i \tag{3}$$

The terms with hats ($\widehat{}$) denote predicted variables or estimated parameters, indicating that $\widehat{X_{it}}$ is the prediction or estimate of X_{it} as opposed to observed data. The results shown above use observed data and generate estimates of the parameters $(\widehat{\beta}, \widehat{\theta})$. We use these estimated parameters along with projected data of land use $(\widehat{LU_{it}})$ and climate $(\widehat{W_{it}})$ in the year 2100. We also perform a simulation for the interaction model in Equation 2.

The projected land use data $(\widehat{LU_{it}})$ employs the USGS Conterminous US Land Cover Projections, derived using the FORE-SCE model, which predicts annual land use through 2100. These projections, originally part of the "LandCarbon" project, use the 1992-2005 period as a historical baseline and forecast future land use from 2006 to 2100. The projections are based on four major IPCC Special Report on Emissions Scenarios (SRES): A1B, A2, B1, and B2, and are downscaled to ecoregions within the conterminous United States.[4] The projections, characterized by a 250-meter spatial resolution and 17 land-cover classes similar to NLCD, provide annual land cover maps and a "forest stand age" layer marking years since the last land-use change or disturbance for forest pixels. The same systematic reclassification scheme applied to the historical NLCD data was used for the projected NLCD, consolidating classes such as "Hay/Pasture Land" into an "Agriculture" class to ensure consistency across the dataset. The descriptions of the climate scenarios are provided in Section B in the Appendix and Figure A.3 shows the projected land uses for the study region for all four climate scenarios.

In addition to land use projections, we incorporate projected weather variables for 2100 using the CMIP6 CESM2 model. Two sets of shared socio-economic pathways (SSP) were conducted: SSP 1-2.6 and SSP 5-8.5.[5] Temperature and precipitation data were downscaled using bias-correcting techniques for the Delaware River Basin, ensuring precise integration with our salinity model. The projected weather data provide mean, maximum, and minimum temperatures and precipitation in 2100. This comprehensive dataset allows us to capture both land use and climatic impacts on salinity levels.

We incorporate climate impacts on land use-induced salinity in two key ways. First, the land use projections inherently account for emission scenarios, reflecting how climate change might directly influence land use patterns. By focusing on the salinity model in Equation 2, we can predict salinity changes based on the effect of climate change on land use. This approach allows us to isolate how different projected values for $\widehat{LU_{it}}$ will generate varying water quality predictions. Second, climate change may alter the relationship between land use and salinity. For instance, warmer

[4] Data retrieved from the Conterminous United States Land Cover Projections - 1992 to 2100, https://catalog.data.gov/dataset/conterminous-united-states-land-cover-projections-1992-to-2100, accessed March 2024.

[5] Data retrieved from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP-CMIP6), https://www.nccs.nasa.gov/services/data-collections/land-based-products/nex-gddp-cmip6, accessed March 2024.

weather conditions might reduce the need for deicers, thus decreasing the contribution of developed land to salinity. By adjusting the interaction terms between land use and weather variables in our extended model, we account for these potential changes in the relationship dynamics, enabling a comprehensive simulation of future salinity levels under varying climate and land use scenarios.

4 Results and discussion

4.1 Water quality model

Results from our primary model (equation 1) are presented in columns (1) and (2) in Table 2. A one percentage increase in developed land use increases chloride concentrations by a little less than 6 mg/L, which is not statistically significant. The only weather variable that impacts salinity is the number of days with precipitation below freezing. There is a positive and statistically insignificant effect of changes in agricultural land use. More days with ice and/or snow increase chloride concentrations, potentially due to more salt from de-icing. The same basic results hold in the column (2) where the dependent variable is the natural log of chloride concentrations. This model shows an approximately 16.7% increase in chloride concentrations for a one percentage increase in developed land use.[6]

Columns (3) and (4) present the results from the interaction model. In column (3), the base effects of developed land are similar. The base effect of freezing rain actually switches signs and is statistically significant. Two statistically significant interactions between land use and weather are: developed land use interacting with days of minimum temperature, and developed land use interacting with days of freezing rain. The interpretation is that freezing rain only increases salinity in watersheds with developed land. This provides additional evidence that one mechanism for urbanization's effect on salinity is through road de-icing. Similar results hold for the model using logged chloride concentrations.

[6] The actual percentage change for a logged dependent variable is e^{β}, which in our case results in a 18.15% marginal effect.

Table 2: Regression of salinity on land use

	(1) mg/L	(2) log	(3) mg/L	(4) log
Dev (%)	5.90	0.167**	5.96*	0.166**
	(3.41)	(0.064)	(3.16)	(0.063)
Ag (%)	1.34	0.087	1.53	0.087
	(1.56)	(0.067)	(1.50)	(0.067)
Min. Temp	-0.095	-0.003	0.058*	-0.003
	(0.053)	(0.002)	(0.030)	(0.002)
Max. Rain	0.0001	-0.0001***	-0.0003	-0.0001***
	(0.0005)	(2.38×10^{-5})	(0.0005)	(3.32×10^{-5})
# Days w/ Freezing Precip.	0.086***	0.002***	-0.100***	0.0004
	(0.027)	(0.0006)	(0.023)	(0.0006)
Dev (%) × Min. Temp			-0.020*	1×10^{-5}
			(0.010)	(0.0001)
Dev (%) × Max. Rain			3.92×10^{-5}	-4.69×10^{-6}
			(0.0003)	(3.92×10^{-6})
Dev (%) × # Days w/ Freezing Precip.			0.046***	0.0003***
			(0.014)	(4.25×10^{-5})
Ag (%) × Min. Temp			0.0005	7.84×10^{-5}**
			(0.001)	(3.49×10^{-5})
Ag (%) × Max. Rain			-3.03×10^{-5}	6.62×10^{-7}
			(7.5×10^{-5})	(1.74×10^{-6})
Ag (%) × # Days w/ Freezing Precip.			-0.003	4.51×10^{-5}
			(0.007)	(3.42×10^{-5})
Mean Chloride	12.1	12.1	12.1	12.1
Fixed-effects				
Month (12)	Yes	Yes	Yes	Yes
Year (19)	Yes	Yes	Yes	Yes
Watershed (266)	Yes	Yes	Yes	Yes
Observations	20,325	20,325	20,325	20,325
Adjusted R^2	0.597	0.923	0.636	0.923
Within Adjusted R^2	0.009	0.012	0.104	0.015

Table 3 shows the results for our seasonal models. We differentiate summer and winter based on whether a month has any days below freezing with precipitation. In our data, October through April all have some days with freezing precipitation, which we define as "Winter". May through September is defined as "Summer". The summer model is presented in column (1), which states that increases in both developed and agricultural land increase chloride concentrations in the summer months relative to natural land. Developed land use has roughly three times the magnitude of agricultural land and is statistically significant at the 1% level, whereas agricultural land is not statistically significant. In the winter months, presented in column (2), developed land has a much larger impact on salinity — the effect is approximately four times greater than in the summer months — however, the effect is not statistically significant. Agriculture has a larger effect in the winter, but it is not significant. The presence of a significant effect of developed land use on salinity in the summer months, when no de-icing occurs, suggests that even though de-icing may be a contributing factor to salinity increases due to urbanization, it is not the only factor.

Table 3: Regression of salinity on land use: seasonal models

	(1) Summer	(2) Winter
Dev (%)	3.34***	13.7
	(0.402)	(10.1)
Ag (%)	0.841	3.84
	(0.423)	(3.79)
Min. Temp	0.009	-0.151
	(0.012)	(0.082)
Max. Rain	-0.0008***	0.001
	(0.0001)	(0.0007)
# Days w/ Freezing Precip.		0.091**
		(0.030)
Mean Chloride	12.8	11.2
Fixed-effects		
Month	Yes	Yes
Year (19)	Yes	Yes
Watershed	Yes	Yes
# Month	5	7
# Watershed	265	216
Observations	11,243	9,082
Adjusted R^2	0.878	0.539
Within Adjusted R^2	0.017	0.018

4.2 Robustness

In this section we estimate additional models to test for the sensitivity of our results to modeling specifications. The first test is the impact of NLCD data availability. Our primary models use all chloride concentrations samples between 2001-2019 in our sample area. However, we do not observe land use in the same year as many of these water quality measures. This introduces measurement error into our primary independent variable. If this is classical measurement error, our coefficient estimates should be bias towards zero. If this is not classical measurement error, then the coefficient estimates in Tables 2 and 3 may be biased upwards or downwards. Table A.1 replicated Table 2 while restricting the sample to years where we observe NLCD land use data.

The results are qualitatively similar yet significant. Developed land use has a positive and significant impact on chloride concentrations. The effects are larger in all the models, consistent with classical measurement error biasing the primary results towards zero. Even though the sample is reduced by more than 50% the results are still statistically significant. In fact, in the restricted model, agricultural land use also has a positive and statistically significant effect on salinity in all the models at the 10% level. The effect is roughly one-third the magnitude on developed land use in using actual chloride concentrations and 25% smaller in logs. The interaction models show similar results with significant impacts of developed land and freezing precipitation primarily affecting salinity in developed areas.

We also test the impact of our preferred weather specification of using the weather from the most recent 30 days prior to the water quality reading. It's possible that weather closer to the time of the water quality measurement date is more influential on salinity measures, or that longer-term weather trends cause chloride accumulations in water bodies. In addition to measuring weather variables 30 days from the water quality measure we also create variables for weather one week (7 days) and one year (365) prior to the measurement date. Tables A.2 and A.3 replicate Table 2 but replace the temporal measurement of the weather variables. The results on land use are mostly unchanged, and although the magnitudes of the weather coefficients change, the sign and significance levels are similar.

5 Simulation results

The summary statistics for the simulated change in salinity for the SSP 1-2.6 scenario and the A1B NLCD scenario are shown in Table 4. On average, salinity goes up by about 16.74 mg/L in the base model and 15.40 in the interaction model. The lower increase in the interaction model may be due to the fact that developed areas will face higher temperatures and fewer days with freezing precipitation.

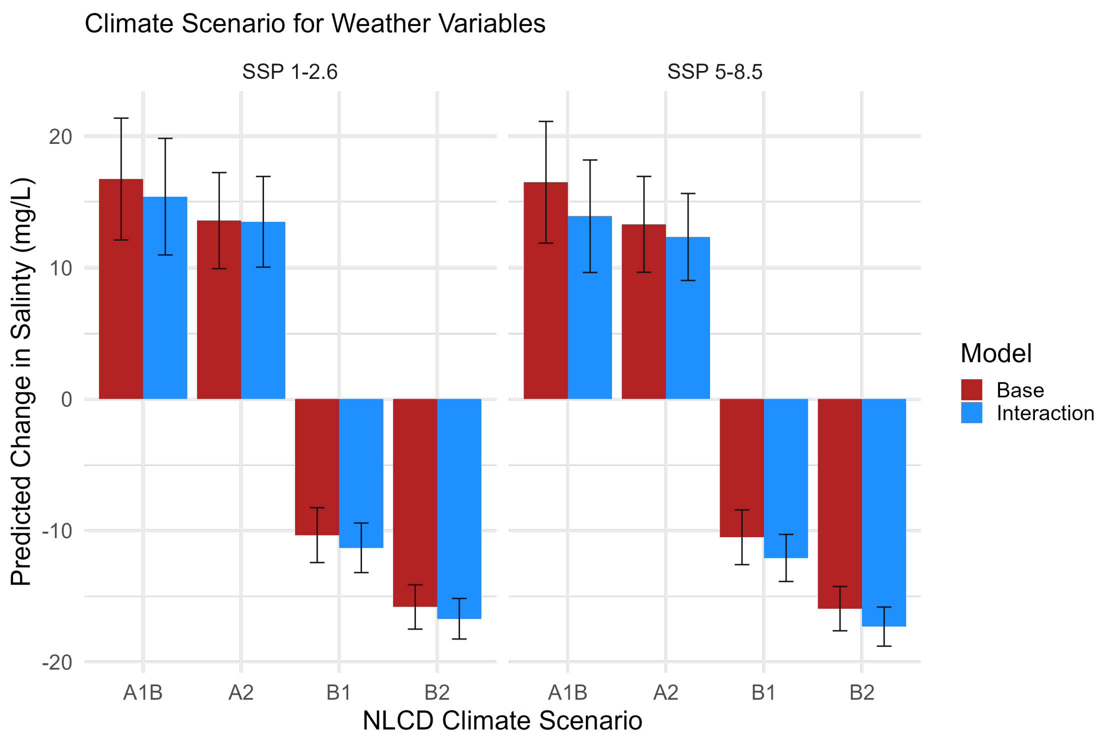
We show the results for the simulated change in salinity for all scenarios (four NLCD projections and two climate projections) in Figure 3. The left panel shows the more conservative SSP 1-2.6 and the right panel shows the more extreme SSP 5-8.5 climate scenario. The x-axis shows the different NLCD scenarios used to project land use. The bars represent the average predicted change

Table 4: **Simulation Chloride in 2100: SSP 1-2.6: A1B**

	Mean	SD	Min	Max	N
Current Chloride	28.08	37.76	0.39	389.25	266
Predicted Chloride (Base)	43.46	91.42	0.00	447.21	265
Predicted Chloride (Int.)	42.12	87.58	0.00	438.03	265
Pred. Chloride Change (Base)	16.74	75.58	-59.98	394.76	265
Pred. Chloride Change (Int.)	15.40	72.32	-56.13	385.58	265

in salinity concentrations along with standard errors of the mean. In the A1B and A2 NLCD scenarios, salinity increases on average and it decreases in the B1 and B2 scenarios. The A1B and A2 scenarios are described in the Appendix in more detail and project more robust economic and population growth leading to an increase in developed land use. The B1 and B2 scenarios actually project less developed land than is observed in the sample, and are therefore considered less likely. Within our sample frame, we see very little land area switching out of developed use. There are not large differences across the socio-economic pathways used to project the weather data (SSP 1-2.26 vs. SSP 6-8.5). The interaction model consistently simulates lower levels of chloride concentrations compared to the base model.

Figure 3: Simulated change in chloride for all scenarios and models

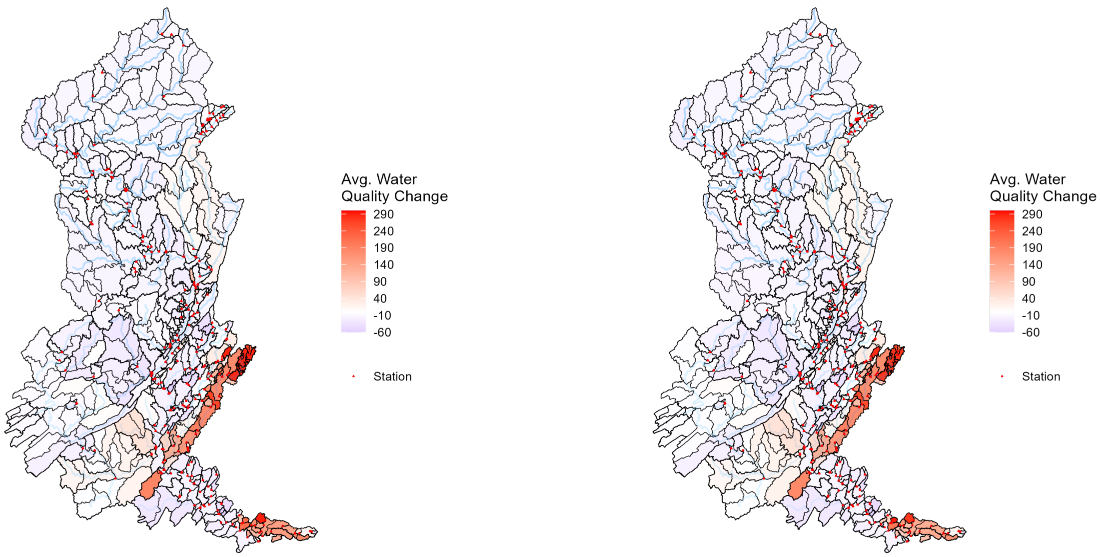


Note:

Next, we plot the spatial distribution of the changes in salinity to describe where increases and decreases are likely to occur. To do this, we spatially merge monitoring stations to HUC12 watersheds in the Delaware Basin. Most of the increase in salinity is in the lower portion of the watershed where urban sprawl from the Philadelphia metro area is projected to increase urbanization.

Figure 4: Projected Water Quality in 2100:- SSP 1-2.6, A1B

Base Model **Interaction model**



Note: The figures show the predicted changes in average water quality in the USGS HUC 12 watersheds within the Delaware River Basin for the Climate Pathway SSP 1-2.6 using the A1B NLCD land use projections in 2100.

6 Limitations

The study has several significant limitations. Accurate identification of main stem and tributary stations within the Delaware River presents substantial challenges, particularly in resolving overlapping area removal issues. Land use data are not available every year, although the findings are robust to restricting the sample to years with NLCD data. Although the fixed effects model controls for all static features of the drainage area for each monitoring location, there is no natural experiment that randomly shifts urbanization in some watersheds but not others. Additionally, while we argue that road salt applications likely play a role, we lack specific data on applications to more precisely identify this mechanism. Lastly, the land use simulations were conducted in 2005, and are likely outdated given that development patterns have already outpaced the low-development scenarios.

7 Conclusion

Increasing salinity levels is a growing concern in water bodies around the world. The Delaware River Basin is likely to experience increased urbanization combined with the stress of sea level rise pushing the salt front upstream (Lassiter, 2021). This has profound impacts for ecology and drinking water sourced from salinizing water bodies. This paper shows that increased urban land use increases salinity at the watershed scale. The number of days with freezing rain also increases salinity. The effect is more pronounced in urbanizing regions, which corroborates other studies showing how road salt application contributes to salinity. In a warmer urbanized world, these two factors have opposite impacts on salinity, but our simulations show that the land use change is the dominant factor. Future studies showing how low-impact development and changes in addressing winter weather can mitigate predicted increases in salinity.

References

Barbier, Lucie, Rémi Suaire, Ivana Durickovic, Julien Laurent, and Marie-Odile Simonnot, "Is a road stormwater retention pond able to intercept deicing salt?," *Water, Air, & Soil Pollution*, 2018, *229*, 1–12.

Beibei, E, Shuang Zhang, Elizabeth Carter, Tasmeem Jahan Meem, and Tao Wen, "Predicting salinity and alkalinity fluxes of US freshwater in a changing climate: Integrating anthropogenic and natural influences using data-driven models," *Applied Geochemistry*, 2025, *180*, 106285.

Blum, Annalise G., Paul J. Ferraro, Stacey A. Archfield, and Karen R. Ryberg, "Causal Effect of Impervious Cover on Annual Flood Magnitude for the United States," *Geophysical Research Letters*, March 2020, *47* (5), e2019GL086480.

Burgis, Charles R, Gail M Hayes, Derek A Henderson, Wuhuan Zhang, and James A Smith, "Green stormwater infrastructure redirects deicing salt from surface water to groundwater," *Science of the Total Environment*, 2020, *729*, 138736.

Cañedo-Argüelles, Miguel, Ben J Kefford, Christophe Piscart, Narcís Prat, Ralf B Schäfer, and Claus-Jürgen Schulz, "Salinisation of rivers: an urgent ecological issue," *Environmental pollution*, 2013, *173*, 157–167.

Corsi, S. R., L. A. De Cicco, M. A. Lutz, and R. M. Hirsch, "River chloride trends in snow-affected urban watersheds: increasing concentrations outpace urban growth rate and are common among all seasons," *Science of the Total Environment*, 2015, *508*, 488–497.

Crosby, Sarah C., Dov F. Sax, Megan E. Palmer, Harriet S. Booth, Linda A. Deegan, Mark D. Bertness, and Heather M. Leslie, "Salt marsh persistence is threatened by predicted sea-level rise," *Estuarine, Coastal and Shelf Science*, November 2016, *181*, 93–99.

Cruz, Yuliza D, Marissa L Rossi, and Steven T Goldsmith, "Impacts of road deicing application on sodium and chloride concentrations in Philadelphia region drinking water," *GeoHealth*, 2022, *6* (2), e2021GH000538.

Efroymson, Rebecca A., Keith L. Kline, Arild Angelsen, Peter H. Verburg, Virginia H. Dale, Johannes W.A. Langeveld, and Allen McBride, "A causal analysis framework for land-use change and the potential role of bioenergy policy," *Land Use Policy*, December 2016, *59*, 516–527.

Emmons, Sean, Taylor Woods, Matthew Cashman, Olivia Devereux, Greg Noe, John Young, Scott Stranko, Jay Kilian, Katherine Hanna, and Kelly Maloney, "Causal inference approaches reveal both positive and negative unintended effects of agricultural and urban management practices on instream biological condition," *Journal of Environmental Management*, 2024, *361*, 121234.

Ferreira, Susana and Ramesh Ghimire, "Forest cover, socioeconomics, and reported flood frequency in developing countries," *Water Resources Research*, August 2012, *48* (8), 2011WR011701.

Haq, Shahan, Sujay S. Kaushal, and Shuiwang Duan, "Episodic salinization and freshwater salinization syndrome mobilize base cations, carbon, and nutrients to streams across urban regions," *Biogeochemistry*, December 2018, *141* (3), 463–486.

Hintz, William D, Laura Fay, and Rick A Relyea, "Road salts, human safety, and the rising salinity of our fresh waters," *Frontiers in Ecology and the Environment*, February 2022, *20* (1), 22–30.

Kaushal, Sujay S, Gene E Likens, Michael L Pace, Jenna E Reimer, Carly M Maas, Joseph G Galella, Ryan M Utz, Shuiwang Duan, Julia R Kryger, Alexis M Yaculak et al., "Freshwater salinization syndrome: from emerging global problem to managing risks," *Biogeochemistry*, 2021, *154*, 255–292.

Kaushal, Sujay S., Gene E. Likens, Michael L. Pace, Ryan M. Utz, Shahan Haq, Julia Gorman, and Melissa Grese, "Freshwater salinization syndrome on a continental scale," *Proceedings of the National Academy of Sciences*, January 2018, *115* (4).

Kaushal, Sujay S, Gene E Likens, Michael L Pace, Shahan Haq, Kelsey L Wood, Joseph G Galella, Carol Morel, Thomas R Doody, Barret Wessel, Pirkko Kortelainen et al., "Novel 'chemical cocktails' in inland waters are a consequence of the freshwater salinization syndrome," *Philosophical Transactions of the Royal Society B*, 2019, *374* (1764), 20180017.

Kaushal, Sujay S., Paul M. Mayer, Gene E. Likens, Jenna E. Reimer, Carly M. Maas, Megan A. Rippy, Stanley B. Grant, Ian Hart, Ryan M. Utz, Ruth R. Shatkay, Barret M. Wessel, Christine E. Maietta, Michael L. Pace, Shuiwang Duan, Walter L. Boger, Alexis M. Yaculak, Joseph G. Galella, Kelsey L. Wood, Carol J. Morel, William Nguyen, Shane Elizabeth C. Querubin, Rebecca A. Sukert, Anna Lowien, Alyssa Wellman Houde, Anaïs Roussel, Andrew J. Houston, Ari Cacopardo, Cristy Ho, Haley Talbot-Wendlandt, Jacob M. Widmer, Jairus Slagle, James A. Bader,

Jeng Hann Chong, Jenna Wollney, Jordan Kim, Lauren Shepherd, Matthew T. Wilfong, Megan Houlihan, Nathan Sedghi, Rebecca Butcher, Sona Chaudhary, and William D. Becker, "Five state factors control progressive stages of freshwater salinization syndrome," *Limnology and Oceanography Letters*, February 2023, *8* (1), 190–211.

Kelly, Victoria R, Mary Ann Cunningham, Neil Curri, Stuart E Findlay, and Sean M Carroll, "The distribution of road salt in private drinking water wells in a southeastern New York suburban township," *Journal of environmental quality*, 2018, *47* (3), 445–451.

_, Stuart E Findlay, Stephen K Hamilton, Gary M Lovett, and Kathleen C Weathers, "Seasonal and long-term dynamics in stream water sodium chloride concentrations and the effectiveness of road salt best management practices," *Water, Air, & Soil Pollution*, 2019, *230*, 1–9.

Lassiter, Allison, "Rising seas, changing salt lines, and drinking water salinization," *Current Opinion in Environmental Sustainability*, 2021, *50*, 208–214.

Lax, Samanta Manon, Eric Wade Peterson, and Stephen J Van der Hoven, "Stream chloride concentrations as a function of land use: a comparison of an agricultural watershed to an urban agricultural watershed," *Environmental Earth Sciences*, 2017, *76*, 1–12.

Levy, M. C., A. V. Lopes, A. Cohn, L. G. Larsen, and S. E. Thompson, "Land Use Change Increases Streamflow Across the Arc of Deforestation in Brazil," *Geophysical Research Letters*, April 2018, *45* (8), 3520–3530.

Mazumder, Bhaswati, Christopher Wellen, Georgina Kaltenecker, Ryan J Sorichetti, and Claire J Oswald, "Trends and legacy of freshwater salinization: untangling over 50 years of stream chloride monitoring," *Environmental Research Letters*, 2021, *16* (9), 095001.

Niel, Jan De and Patrick Willems, "Climate or land cover variations: what is driving observed changes in river peak flows? A data-based attribution study," *Hydrology and Earth System Sciences*, February 2019, *23* (2), 871–882.

Novotny, Eric V., Dan Murphy, and Heinz G. Stefan, "Increase of urban lake salinity by road deicing salt," *Science of The Total Environment*, November 2008, *406* (1-2), 131–144.

Rossi, Marissa L, Peleg Kremer, Charles A Cravotta, Krista E Scheirer, and Steven T Goldsmith, "Long-term impacts of impervious surface cover change and roadway deicing agent application on chloride concentrations in exurban and suburban watersheds," *Science of the total environment*, 2022, *851*, 157933.

Rumsey, Christine A, John C Hammond, Jennifer Murphy, Megan Shoda, and Alexander Soroka, "Spatial patterns and seasonal timing of increasing riverine specific conductance from 1998 to 2018 suggest legacy contamination in the Delaware River Basin," *Science of the Total Environment*, 2023, *858*, 159691.

Schuler, Matthew S, Miguel Cañedo-Argüelles, William D Hintz, Brenda Dyack, Sebastian Birk, and Rick A Relyea, "Regulations are needed to protect freshwater ecosystems from salinization," *Philosophical Transactions of the Royal Society B*, 2019, *374* (1764), 20180019.

Snodgrass, Joel W, Joel Moore, Steven M Lev, Ryan E Casey, David R Ownby, Robert F Flora, and Grant Izzo, "Influence of modern stormwater management practices on transport of road salt to surface waters," *Environmental Science & Technology*, 2017, *51* (8), 4165–4172.

Stets, E.G., C.J. Lee, D.A. Lytle, and M.R. Schock, "Increasing chloride in rivers of the conterminous U.S. and linkages to potential corrosivity and lead action level exceedances in drinking water," *Science of The Total Environment*, February 2018, *613-614*, 1498–1509.

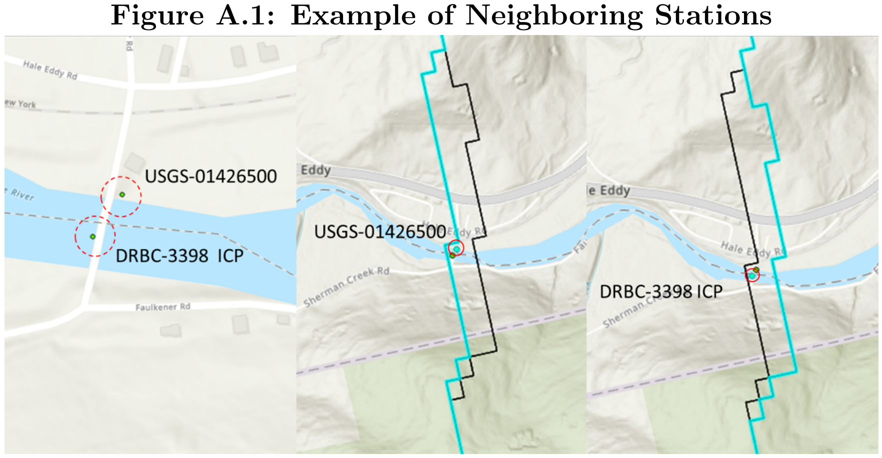
Utz, Ryan, Samantha Bidlack, Burch Fisher, and Sujay Kaushal, "Urbanization drives geographically heterogeneous freshwater salinization in the northeastern United States," Technical Report, Wiley Online Library 2022.

Venkatesan, Arjun K, Sajjad Ahmad, Walter Johnson, and Jacimaria R Batista, "Systems dynamic model to forecast salinity load to the Colorado River due to urbanization within the Las Vegas Valley," *Science of the Total Environment*, 2011, *409* (13), 2616–2625.

Vliet, Michelle TH Van, Josefin Thorslund, Maryna Strokal, Nynke Hofstra, Martina Flörke, Heloisa Ehalt Macedo, Albert Nkwasa, Ting Tang, Sujay S Kaushal, Rohini Kumar et al., "Global river water quality under climate change and hydroclimatic extremes," *Nature Reviews Earth & Environment*, 2023, *4* (10), 687–702.

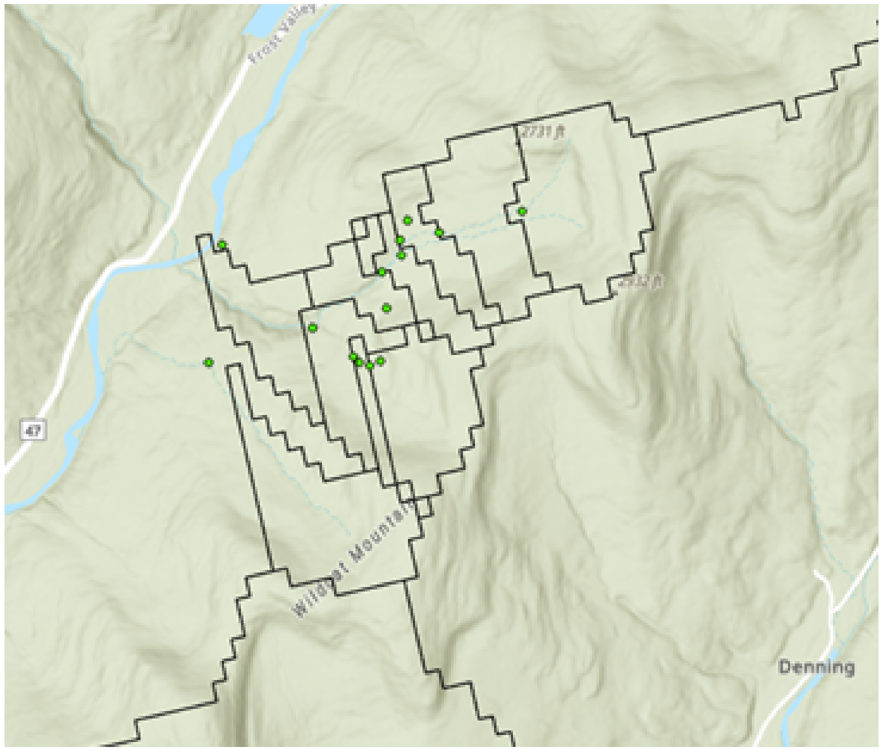
Appendix

Figure A.1: Example of Neighboring Stations



Note: Stations DRBC-3398 ICP & USGS-01426500 are both located on the main stem of the west branch Delaware River, but they have slightly different watershed areas.

Figure A.2: Example of Clustering Stations



Note: Clustered stations near west of the branch Neversink River.

A Robustness to NLCD data and weather definition

Table A.1: Regression of salinity on land use restricted to NLCD years

	(1) mg/L	(2) log	(3) mg/L	(4) log
Dev (%)	7.45**	0.205**	6.24**	0.200**
	(3.27)	(0.077)	(2.61)	(0.076)
Ag (%)	2.71*	0.155*	2.50*	0.156*
	(1.51)	(0.082)	(1.30)	(0.080)
Min. Temp	-0.065	-0.004*	0.016	-0.005**
	(0.037)	(0.002)	(0.038)	(0.002)
Max. Rain	-0.0004*	-0.0001***	0.0003	-0.0001**
	(0.0002)	(3.67×10^{-5})	(0.0002)	(4.44×10^{-5})
# Days w/ Freezing Precip.	0.072**	0.002**	-0.056**	0.0005
	(0.027)	(0.001)	(0.020)	(0.0010)
Dev (%) × Min. Temp			-0.005	7.62×10^{-5}
			(0.008)	(0.0001)
Dev (%) × Max. Rain			-0.0002	-9.19×10^{-6}*
			(0.0001)	(5.03×10^{-6})
Dev (%) × # Days w/ Freezing Precip.			0.037***	0.0003***
			(0.011)	(9.66×10^{-5})
Ag (%) × Min. Temp			-0.003	0.0001
			(0.002)	(7.71×10^{-5})
Ag (%) × Max. Rain			-1.73×10^{-5}	1.89×10^{-6}
			(4.45×10^{-5})	(2.2×10^{-6})
Ag (%) × # Days w/ Freezing Precip.			-0.007**	4.21×10^{-5}
			(0.003)	(5.4×10^{-5})
Mean Chloride	12.1	12.1	12.1	12.1
Fixed-effects				
Month (12)	Yes	Yes	Yes	Yes
Year (8)	Yes	Yes	Yes	Yes
Watershed (264)	Yes	Yes	Yes	Yes
Observations	8,507	8,507	8,507	8,507
Adjusted R^2	0.713	0.900	0.736	0.900
Within Adjusted R^2	0.018	0.013	0.098	0.016

Table A.2: Regression of salinity on land use: 7 days

	(1) mg/L	(2) log	(3) mg/L	(4) log
Dev (%)	5.92	0.167**	6.31*	0.170**
	(3.42)	(0.064)	(3.33)	(0.063)
Ag (%)	1.35	0.086	1.47	0.088
	(1.56)	(0.068)	(1.48)	(0.067)
Min. Temp	-0.093	-0.002	0.084**	-0.002
	(0.052)	(0.002)	(0.027)	(0.002)
Max. Rain	0.0002	-0.0005***	0.0005	-0.0005**
	(0.002)	(0.0001)	(0.002)	(0.0001)
# Days w/ Freezing Precip.	0.184	0.009**	-0.225	0.003
	(0.110)	(0.003)	(0.129)	(0.003)
Dev (%) × Min. Temp			-0.027*	-5.93×10^{-6}
			(0.013)	(7.93×10^{-5})
Dev (%) × Max. Rain			-0.001	-2.71×10^{-5}
			(0.0009)	(1.99×10^{-5})
Dev (%) × # Days w/ Freezing Precip.			0.123*	0.001***
			(0.062)	(0.0004)
Ag (%) × Min. Temp			0.002	7.36×10^{-5}*
			(0.004)	(4.06×10^{-5})
Ag (%) × Max. Rain			0.0002	2.72×10^{-6}
			(0.0003)	(7.93×10^{-6})
Ag (%) × # Days w/ Freezing Precip.			-2.72×10^{-5}	7.23×10^{-5}
			(0.021)	(0.0001)
Mean Chloride	12.1	12.1	12.1	12.1
Fixed-effects				
Month (12)	Yes	Yes	Yes	Yes
Year (19)	Yes	Yes	Yes	Yes
Watershed (266)	Yes	Yes	Yes	Yes
Observations	20,325	20,325	20,325	20,325
Adjusted R^2	0.597	0.923	0.623	0.924
Within Adjusted R^2	0.008	0.013	0.073	0.016

Table A.3: Regression of salinity on land use: 365 days

	(1) mg/L	(2) log	(3) mg/L	(4) log
Dev (%)	5.95	0.171**	6.02*	0.171**
	(3.41)	(0.063)	(3.14)	(0.063)
Ag (%)	1.38	0.090	1.34	0.090
	(1.57)	(0.066)	(1.48)	(0.067)
Min. Temp	-0.114*	-0.004	0.023	-0.005*
	(0.062)	(0.002)	(0.033)	(0.002)
Max. Rain	-2.78×10^{-5}	$-1.38 \times 10^{-5***}$	3.37×10^{-5}	$-1.32 \times 10^{-5***}$
	(5.04×10^{-5})	(3.52×10^{-6})	(3.56×10^{-5})	(3.81×10^{-6})
# Days w/ Freezing Precip.	0.011**	0.0002**	-0.009***	2.99×10^{-5}
	(0.004)	(8.79×10^{-5})	(0.002)	(9.71×10^{-5})
Dev (%) × Min. Temp			-0.019*	5.91×10^{-6}
			(0.010)	(0.0001)
Dev (%) × Max. Rain			-3.05×10^{-5}	-2.72×10^{-7}
			(2.27×10^{-5})	(2.23×10^{-7})
Dev (%) × # Days w/ Freezing Precip.			0.004**	$2.53 \times 10^{-5***}$
			(0.002)	(7.55×10^{-6})
Ag (%) × Min. Temp			-9.07×10^{-5}	$9.77 \times 10^{-5**}$
			(0.002)	(4.13×10^{-5})
Ag (%) × Max. Rain			3.63×10^{-6}	6.5×10^{-8}
			(7.29×10^{-6})	(2.13×10^{-7})
Ag (%) × # Days w/ Freezing Precip.			-0.0002	9.19×10^{-6}
			(0.0006)	(7.11×10^{-6})
Mean Chloride	12.1	12.1	12.1	12.1
Fixed-effects				
Month (12)	Yes	Yes	Yes	Yes
Year (19)	Yes	Yes	Yes	Yes
Watershed (266)	Yes	Yes	Yes	Yes
Observations	20,325	20,325	20,325	20,325
Adjusted R^2	0.597	0.923	0.629	0.923
Within Adjusted R^2	0.009	0.011	0.088	0.013

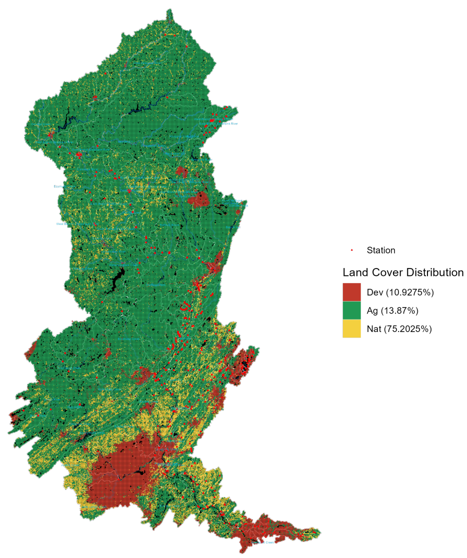
B Simulation

Climate Scenarios:

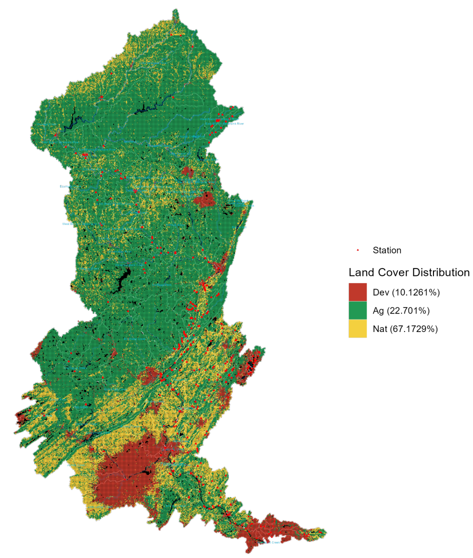
- **A1B Scenario:** Emphasizes economic growth with moderate population growth peaking at 9 billion by 2050. High global cooperation leads to rapid technological innovation and increased energy efficiency, with a balanced use of fossil fuels and cleaner energy sources. Environmental management is active, allowing for moderate protections in some regions.
- **A2 Scenario:** Focuses on economic growth with extremely high population growth, reaching 15 billion by 2100. Lower international cooperation and regional self-reliance result in slow technological innovation and high energy demands. Environmental concerns are low, with high stress on natural ecosystems.
- **B1 Scenario:** Prioritizes environmental conservation with moderate population growth peaking at 9 billion by 2050. High global cooperation drives sustainable development, reducing resource use and increasing renewable energy sources. The human footprint is lessened despite similar population growth to A1B.
- **B2 Scenario:** It also emphasizes environmental conservation but with fragmented socio-economic conditions. Population growth is slower, reaching 10 billion by 2100. Localized approaches to energy use and environmental protection result in modest economic growth and a focus on regional solutions.

Figure A.3: Land Use Distribution Comparison by Model in 2100

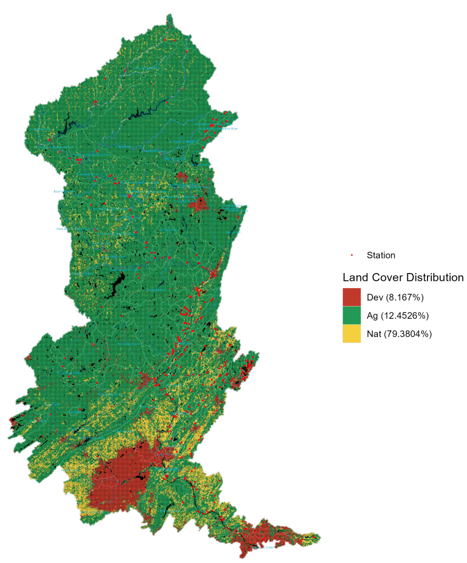
Model AB



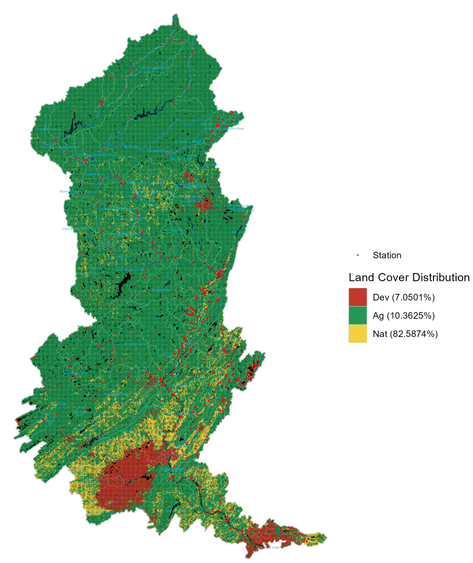
Model A2



Model B1



Model B2



Note: These figures show the land use distribution within the study region in 2100, illustrating significant changes in land utilization over the projected period. The projections are based on four major IPCC Special Report on Emissions Scenarios (SRES): A1B, A2, B1, and B2, using a systematic reclassification scheme to ensure consistency across the dataset.