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RESEARCH ARTICLE

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Impacts of land use changes on discharge and water quality in rivers and streams: Case study of the continental United States

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Abstract

Water quality trends in streams and rivers are impacted by several factors including land use of the watershed; however, it is unclear what influence changes in the land use of a watershed subsequently have on changes in discharge and water quality in streams and rivers. This study seeks to fill this gap by evaluating the relationship between changes in land use and changes in discharge and water quality at United States Geological Survey (USGS) stream gages over the period of 2008–2016. Using land cover data and discharge and water quality data from 60 USGS gages, regression methods were applied to determine the strength of relationship between land use changes and changes in water quality and quantity. Trends in discharge and water quality were mixed, with a majority of watersheds demonstrating a decrease in dissolved oxygen and turbidity, no overall trend for discharge, and increases in specific conductance. A regression analysis revealed that discharge, turbidity, and specific conductance were correlated with changes in individual land use types with an R^2 between 0.12 and 0.25. Combining the influences of multiple land uses in multivariate regression improved the predictions for discharge (R^2 0.58) and specific conductance (R^2 0.47), highlighting the magnitude for which land cover changes influence trends in water quality. Overall, this study demonstrates the impact that large-scale land use changes have on surface water quality.

KEYWORDS
land use change, non-stationarity, water quality trends

1 | INTRODUCTION

Land use patterns change over time due to social, economic, political, and geographical conditions of populations. This includes increasing populations and expanding economies that grow the demand for productive agricultural and developed land (Creutzig et al., 2019). The number of people who are moving to cities is increasing, with 68% (7 billion) of the global population projected to live in cities in 2050 compared to the 55% (4 billion) in 2018 (Ritchie & Roser, 2018). To meet the increased demand for housing, commercial space, infrastructure, industries, and transportation, these cities must modify previously undeveloped space for their economic growth. Furthermore, due to socioeconomic changes, agriculture land and other natural land such as forest compositions have and will continue to undergo dramatic changes (Winkler et al., 2021).

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Research Impact Statement

Land use changes of the watershed were significant predictors of changes in discharge (R^2 0.58) and specific conductance (R^2 0.47) within a river.

These land uses have a direct impact on non-point source pollution of streams and water bodies. For example, agriculture land is known to release both natural and man-made nutrients, antibiotics, pesticides, heavy metals, and sediments to downstream waterbodies, which can lead to water quality impairments (Giri & Qiu, 2016; Paudel & Crago, 2021). In addition, runoff from urbanized cities can contain chemicals such as heavy metals, micro plastics, tire wear particles, and per- and polyfluoroalkyl substances, as well as other pollutants such as road salts that are applied during winter seasons (Giri & Qiu, 2016; McGrane, 2016). These pollutants can result in impairments to water bodies that no longer meet applicable water quality standards. In the United States (U.S.) alone, 53% of the assessed rivers and streams are impaired while 70% of the assessed lakes, reservoirs, and ponds are impaired (USEPA, 2017). It is therefore imperative to understand the impact of land use changes in watersheds to downstream water bodies.

While land uses have a direct impact on non-point source pollution of streams and water bodies, defining the causal relationships between land use and downstream water quality is complex (Baker, 2006). For example, many empirical studies demonstrate that the presence of agricultural land use enhances the sediment and nutrient concentrations within receiving water bodies (de Mello et al., 2020; Delia et al., 2021; Delkash et al., 2018); however, this is not always the case. Flow normalized concentrations of NH_4, suspended solids, and total nitrogen actually decreased overall in receiving waters from agricultural land from 1982 to 2012 within the U.S. (Stets et al., 2020). Additionally, empirical studies lack a clear relationship between urban land use and downstream water quality. For example, nutrient and total suspended solids loading from urban spaces have been shown to reduce significantly across 38 urban watersheds in the U.S. (Stets et al., 2020); however, many studies have shown that urban land use has strong positive correlations to nutrient loads to streams and rivers (Ullah et al., 2018; Yao et al., 2023).

This juxtaposition in causal relationships consequently makes it a challenge to associate temporal changes in land use with observed trends in downstream water quality. This is partly because existing empirical studies that do investigate temporal associations between land use change and downstream water quality have limitations that influence the generalization of their findings. For example, many are geographically constrained to either a single watershed or smaller geographic regions (Meneses et al., 2015; Pandey et al., 2023; Risal et al., 2020; Smith et al., 2015; Wang et al., 2023; Wijesiri et al., 2018). While these geographically limited studies provide valuable insights, their applicability is constrained to their unique geomorphologic, anthropogenic, and climatic contexts.

Furthermore, most of these studies use field data to assess how water quality relates to the land use of that watershed at a defined time or times using a model form similar to *water quality = f (land use)* (Haidary et al., 2013; Li et al., 2009). While these correlations provide valuable information for understanding the impact of land use on stream water quality in ungaged basins, they are not applicable to predicting water quality based on future expected land use changes. This is because land development practices have changed over time, and many must adhere to different or stricter regulations regarding treatment of stormwater runoff due passage of the Clean Water Act, total maximum daily load (TMDL), and Non-point Discharge Elimination System (NPDES) programs, and other changing stormwater regulations. Therefore, models that treat all land uses as the same could be biased toward historical land development that does not represent the hydrologic impact of contemporary land use changes. For example, contemporary urban land development has to adhere to stricter stormwater treatment regulations that were not required for historical development (Mika et al., 2019); therefore, treating urban land use as one category fails to capture the difference in non-point source runoff between historical and contemporary land uses. Defining the impact of more recent land use changes on receiving water quality through empirical analyses is an important gap because this understanding is needed to inform watershed management plans that can reach long-term water quality goals. Therefore, there exist several gaps in our understanding of the impact of land use changes to water quality changes including (1) conflicting causal relationships between land use and pollutants in receiving water bodies; (2) existing empirical studies that are constrained to their unique geomorphologic, anthropogenic, and climatic contexts; and (3) lack of model formulations that can capture the impact of more recent land use changes on receiving water quality.

The objective of this study is to meet these gaps by quantifying the relationship between land-use changes and trends in water quality and discharge in watersheds across the contiguous U.S. To achieve this objective, this study (1) quantified changes in land use in 60 watersheds within the U.S. over 2008–2016, (2) identified trends in water quality and discharge trends in selected watersheds using Theil–Sen slope, and (3) explored the relationship between land use change and trends in water quality and discharge using robust regression and Kruskal–Wallis test. The outcomes of this study can be applied to improve our understanding of the relationship between land use and water quality, which can inform future management of land development and non-point source pollution.

2 | METHODOLOGY

2.1 | Study area

This study evaluated the watersheds from a candidate list of 72 United States Geological Survey (USGS) stream gages across the contiguous U.S. (Figure 1). In selecting gages, they had to meet the criteria of having continuous mean daily discharge and water quality data from 2008 to 2016, corresponding to the date range in which national land-use data are available. The final set of selected gages had watersheds that ranged in area between 22 and 36,927 km^2, had diverse land use characteristics, and covered most geographic regions of the U.S., as illustrated in Figure 1.

2.2 | Datasets

Mean daily discharge and water quality (turbidity, dissolved oxygen, and specific conductance) data were collected over the study period (2008–2016) from each of the selected USGS gages (USGS, 2014). Turbidity, dissolved oxygen, and specific conductance were chosen as parameters based on their availability across a wide range of USGS gages over the years of the study period. A total of 72 gages were initially selected; however, some were removed due to characteristics of the watershed that influenced their hydrologic response. Four of the gages were removed due to their location less than 3 miles downstream of a regulated dam. This is because gages affected by regulation exhibit varied flows dominated by controlled dam releases, which also affects water quality (de Necker et al., 2019; Zuo et al., 2015). In addition, eight gages were removed because the watersheds had no land use diversity or changes throughout the study period or they encompassed many of the other watersheds analyzed in the study, resulting in nested watersheds. After removing these gages, there were a total of 60 gages that fit the criteria for the final analysis.

Land use data from the National Land Cover Database (NLCD) were obtained for the contiguous from the U.S. Multi-Resolution Land Characteristics Consortium (https://www.mrlc.gov/data) for the years of 2008 and 2016. This dataset contains 16 distinct land use categories in 30 m resolution. In addition, impervious land use data were obtained in the same resolution from MRLC for the years of 2008 and 2016, which represents the impervious surfaces as a percentage of developed surface over every 30 m pixel in the U.S.

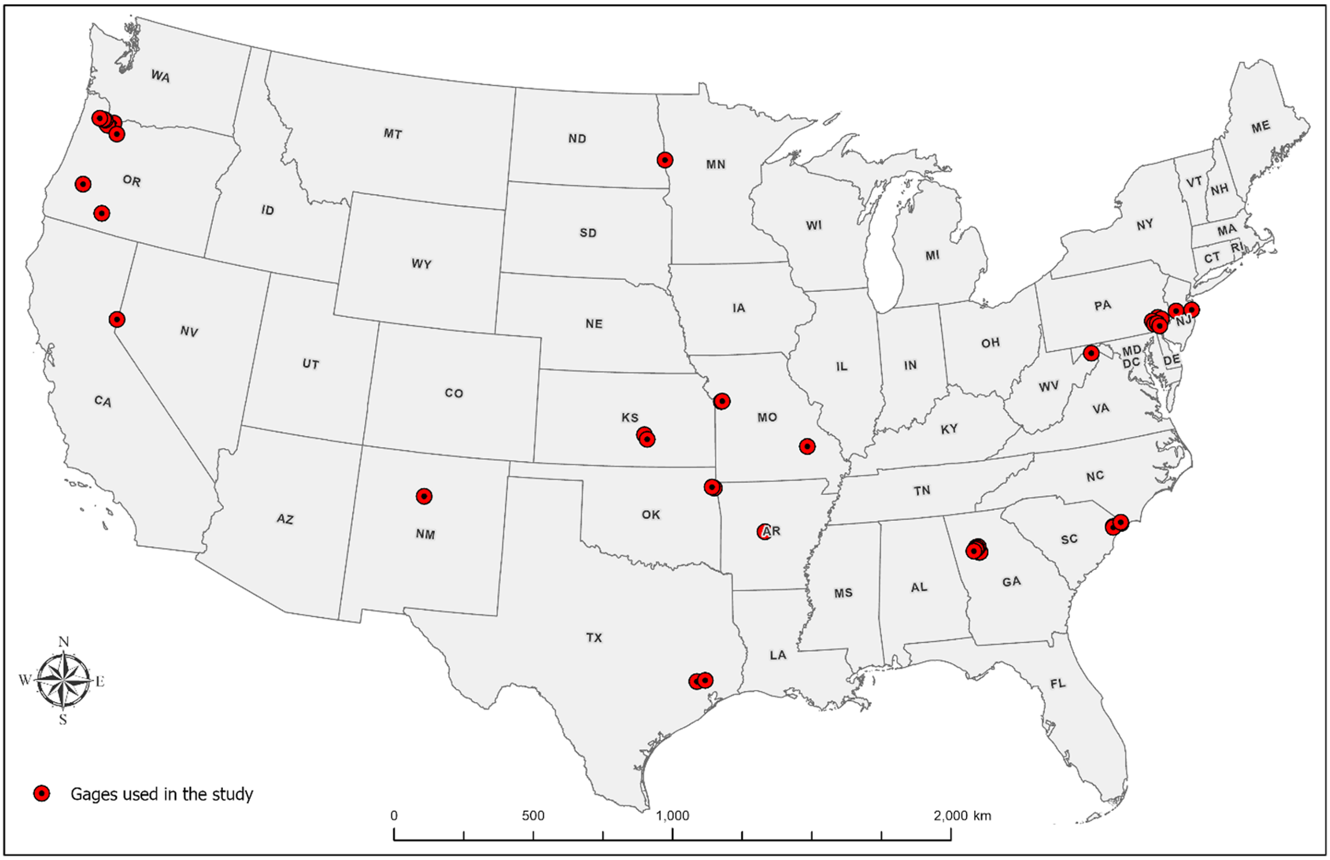

FIGURE 1 Locations of all 60 gages used in the study.

2.3 | Data preparation

2.3.1 | Water quality data

USGS datasets sometimes have periods of missing data due to environmental interference with the sensors or technical malfunctions of the gage. Therefore, to evaluate trends over a continuous dataset, we applied methods to interpolate data where there were gaps within time series of discharge and water quality (Baddoo et al., 2021; Han et al., 2023). Gages with data that had more than 40% missing data in any one category—discharge, turbidity, dissolved oxygen, and specific conductivity—were removed from the analysis. Even though missing percentages of more than 50% can be successfully imputed for trend analysis given the use of proper imputation methods (Aguilera et al., 2020; Madley-Dowd et al., 2019; Milleana Shaharudin et al., 2020), general guidance suggests limiting data imputation up to 40% if the resultant data are used for predictions (Madley-Dowd et al., 2019).

Where data gaps were observed, benchmark tests were performed over the complete dataset of each parameter to identify the most appropriate imputation method. Specifically, we used the R package "imputeTestbench" (Beck et al., 2018) and "imputeTS," which provides a wide variety of statistical methods to analyze and impute univariate datasets (Moritz & Bartz-Beielstein, 2017). The best imputation method for a specific dataset depends on the characteristics of the missing data such as percentage of missing data and gap size. Therefore, the distribution of missing data, average gap size, and percentage of missing data were computed for each dataset. This information for each gage was then summarized and the overall average gap sizes for each water quality parameter were used in testing imputation methods.

Several imputation methods were then applied to the data, including linear interpolation, spline interpolation, structural model and Kalman smoothing, simple moving average, imputation by mean, and exponential moving average, among others. To do so, first a dataset with no missing data was used to generate 30 random testing samples for each parameter (discharge, turbidity, dissolved oxygen, and specific conductivity). These samples were then imputed using each method and the methods were compared using the root mean square error (RMSE). The imputation method with the lowest RMSE was then selected to impute data for the specific parameter (Figure S2). After imputation, daily data were used to compute the monthly averages, which were then applied to evaluate trends. While the water quality and discharge data are available as a daily dataset, serial correlation of daily data increases the chance of type II error by Mann–Kendall test (von Storch, 1999) and reducing the temporal frequency to monthly data reduces the change of this error and is more suitable for long-term trend analysis (Mcleod et al., 1991).

2.3.2 | Land-use data

Watersheds for each of the 60 stream gages were delineated using ESRI's ArcGIS online and validated using watershed areas listed on the USGS stream gage site (https://waterwatch.usgs.gov/). The NLCD provides land use data in 16 categories at a 30-m resolution; however, these were condensed to seven categories for ease of analysis and included open water, developed (developed, open space; developed, low intensity; developed, medium intensity; and developed, high intensity), barren land, forest (deciduous forest, evergreen forest, and mixed forest), shrub/grassland (shrub/scrub, herbaceous, and hay/pasture), cultivated, and wetland (woody wetlands and emergent herbaceous wetlands). Using these land use categories and the delineated watersheds, land-use data for each year (2008 and 2016) were extracted from each respective watershed.

2.4 | Statistical methods

2.4.1 | Water quality and land use trends

Simple descriptive statistics were performed to visualize and evaluate the central tendency and distribution of land use, flow rate, and water quality data. Land use changes for each watershed were computed as the percent change in each land use category relative to the overall watershed area from 2008 to 2016 for each watershed. In addition, two methods were used to identify and quantify temporal trends within the water quality and quantity data: Seasonal Mann Kendall tests and Theil–Sen slope. The Seasonal Mann–Kendall test was selected to quantify temporal trends in water quality and quantity parameters over time due to seasonal autocorrelation and non-normality of residuals in the USGS gage data. This test is a nonparametric method commonly used to quantify and analyze the significance of a time-series trend (Helsel et al., 2020). Using this test, correction for serial correlation due to seasonality is done by removing the seasonal trend from the data by statistical methods introduced by Hirsch (Hirsch & Slack, 1984). While the Mann–Kendall test determines the existence or significance of a monotonic trend, the Theil–Sen slope can provide a robust estimate of the slope or magnitude of this trend (Helsel et al., 2020). Theil–Sen slope is frequently used to compute the magnitude of trends in environmental studies (He et al., 2015; Mahmoodi et al., 2021; Rozemeijer et al., 2014; Ryberg & Chanat, 2022) and represents the change in discharge or water quality parameters over time as shown in the following equation:

$$\text{Theil} - \text{Sen Slope} = \text{Median}\ \frac{X_i - X_j}{t_i - t_j},\ \text{where}\ j > i \tag{1}$$

where X_i and X_j are gage data at times t_i and t_j, respectively. Gages with significant trends based on a p-statistic of less than 0.1 ($\alpha = 10\%$) were selected for further analysis.

2.4.2 | Relationship between water quality and land use changes

Robust regression was carried out to analyze how change in water quality and quantity over time (represented by the Theil–Sen slopes) is related to the change in land use over the same period. Robust regression is a nonparametric technique that reduces the influence of extreme outliers, which are common in streamflow and other environmental data, and therefore results in better representative slope coefficients (Helsel et al., 2020).

To do so, first single variable regressions were developed to observe the direct relationships between the explanatory variables and the change in discharge and water quality. This relationship is represented by the following equation:

$$y = b_0 + b_1 x \tag{2}$$

where y is the dependent variable (discharge and water quality changes), x is the explanatory variable (land use change), b_0 is the intercept, and b_1 is the slope coefficient.

Second, multiple robust regressions were carried out to determine if multiple variables (i.e., land use changes) could provide improved predictions of discharge and water quality trends. Due to correlations between some explanatory variables, a backward elimination method coupled with variance inflation factor (VIF) was used to generate final multiple regression models. These relationships generated by robust regression are represented by the following equation:

$$y = b_0 + b_1 x_1 + b_2 x_2 + \cdots + b_n x_n \tag{3}$$

where y represents the change in water quality parameter, b_0 represents the intercept, and b_n represents the regression coefficient for n land use changes represented by x_n. The final results include explanatory variables with a VIF value less than 10.

Lastly, the slopes of water quality and quantity parameters were categorized as increasing, decreasing, or no trend for each gage based upon the Mann–Kendall test. Then, the Kruskal–Wallis test, which is a nonparametric equivalent of the one-way analysis of variance, was performed to identify whether the categorical increasing or decreasing trends were due to specific land use changes.

3 | RESULTS

3.1 | Land use characteristics of the watersheds

The land use characteristics across all 60 of the watersheds used in this study are summarized in Table 1 and their overall distribution is illustrated in Figure 2. From the table, forested land use is the most common with an average coverage of 38% that ranges between 3.5% and 93.9% of the total watershed area. This is followed by developed and cultivated land uses, with no other land use making up more than 10% of the watershed coverage on average. The variation in land uses across watersheds in this study is further illustrated in Figure 2, which shows the distribution of land cover for each individual watershed. As illustrated, there is a wide distribution in the dominant land use across each watershed, with many land uses—forest, agriculture, developed, and shrub—making up over 50% of an individual watersheds' composition. Examples of this diversity in land use composition are further illustrated in Figure 3, which provides four examples of watersheds characterized by a diversity of land cover that dominates the watershed areas.

3.2 | Land-use changes

A summary of the land-use changes from 2008 to 2016 across all watersheds in this study is shown in Figure 4. This figure shows box and whisker plots that represent the distribution of the land cover change in each watershed as a percentage of the overall watershed area. Land cover change in this figure is defined as the percent change in the land cover between two points in time: from the year 2008 to the year 2016. As illustrated, impervious land area and developed land area increased in every watershed in the study with a mean increase of 0.41% (impervious) and 0.73% (developed) relative to the overall watershed area between 2008 and 2016. Mean changes to open water, barren land, and wetlands are all under 0.03%, while shrubland declined by the largest amount of 0.62%. Forest land percentages increased on average across all watersheds; however, the median value is negative, indicating a skewed distribution.

TABLE 1 Overall land use characteristics of 60 watersheds selected for analysis for the year of 2016.

Land use type	Mean %	Median %	Standard deviation	Minimum %	Maximum %
Open water	1.21	0.39	3.00	0.02	21.89
Developed	28.36	12.05	30.49	0.68	90.40
Barren land	0.21	0.12	0.26	0.00	1.13
Forest	38.38	33.33	26.02	3.51	93.88
Shrub/grass land	8.96	2.44	13.76	0.13	62.91
Cultivated	18.08	11.07	20.96	0.00	71.80
Wetland	4.80	0.70	10.25	0.00	42.84
Imperviousness	9.65	3.03	12.45	0.07	41.03

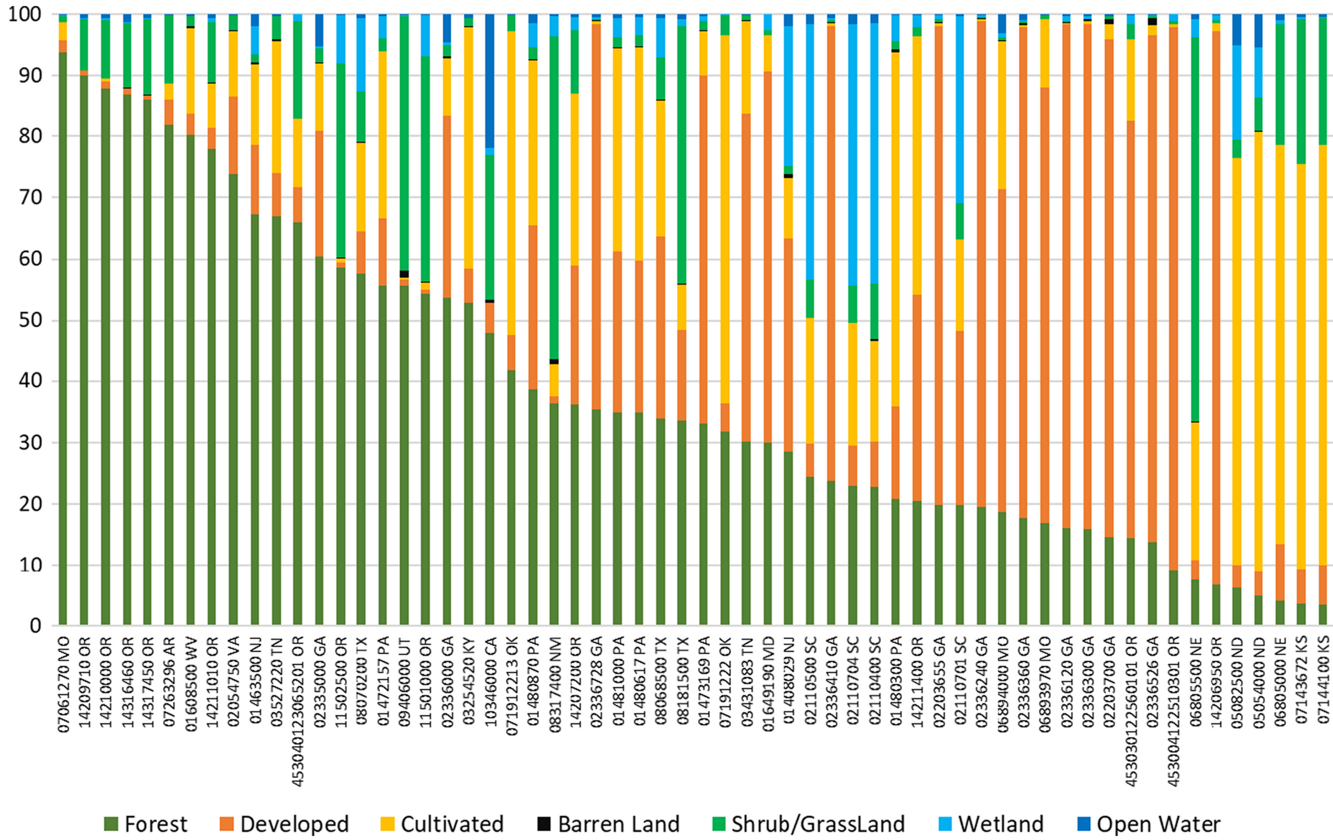

FIGURE 2 Land use composition of the 60 watersheds used for analysis for the year of 2016. Vertical axis is the percentage of the land use category within the watershed while horizontal axis is the list of gages.

3.3 | Trends in water quality

Theil–Sen slope was generated for all the gage datasets and those with statistically significant trends ($p < 0.10$) were selected for further analysis. The number of gages with significant trends included 23 gages for discharge (40%), 18 gages for dissolved oxygen (35%), 24 gages for specific conductance (44%), and 28 gages for turbidity (44%). The distribution of the Theil–Sen slope for each water quality parameter across all gages used in this study is shown in Figure 5. As illustrated, the change in discharge and specific conductance are normally distributed and while discharge is spread equally among positive and negative trends with both mean and median values near zero, specific conductance has a positive average and median trend. For dissolved oxygen, the majority of trends were negative, with the exception of three gages. In addition, for turbidity, all gages except for one indicated a decrease in turbidity.

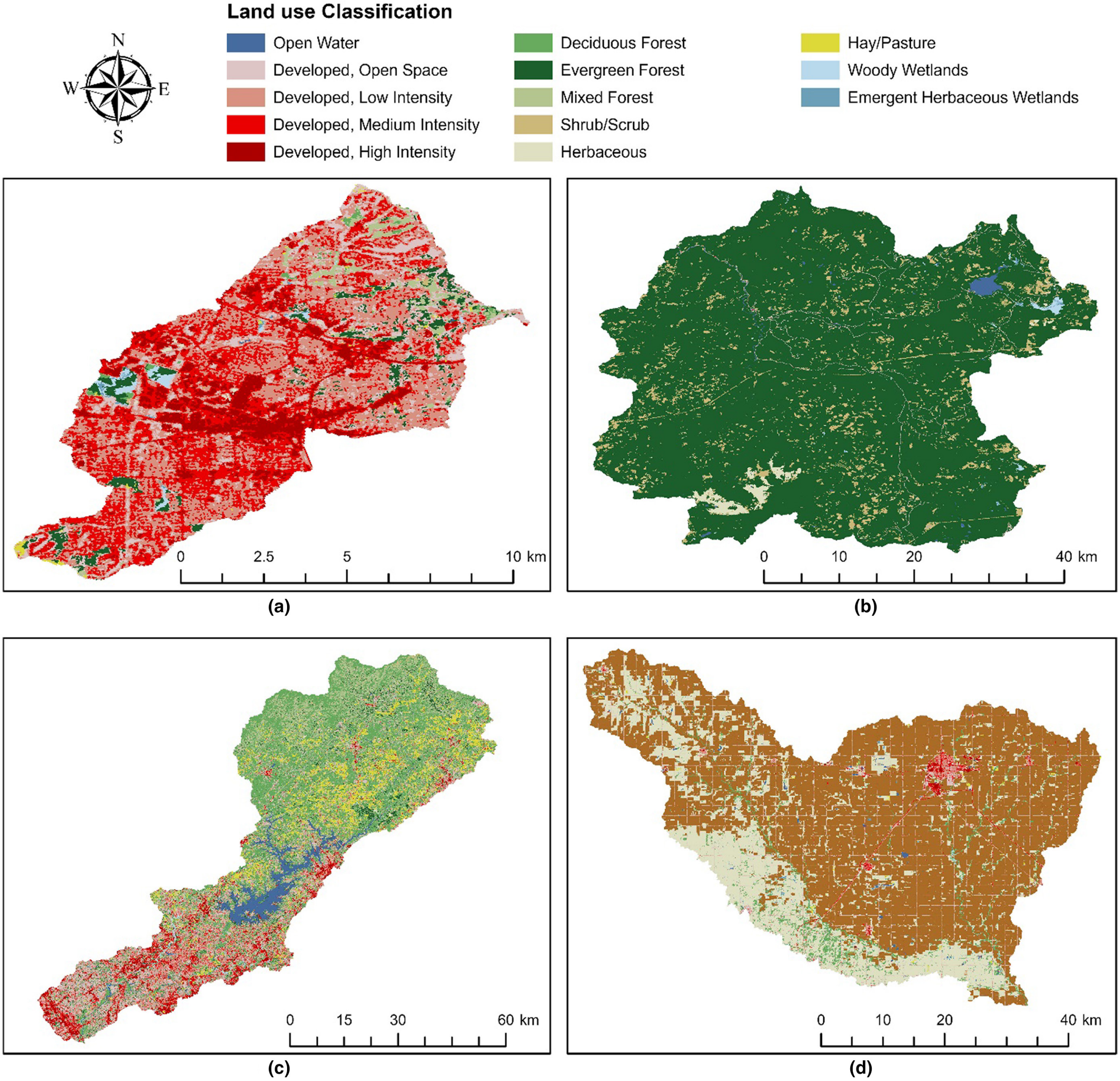

FIGURE 3 Example of the land use distribution (2008) within the watersheds of four USGS stream gages used in this study: (a) 453004122510301 OR, Latitude 45°30′04″, Longitude 122°51′03″; (b) 14209710 OR, 45°10′02″, Longitude 122°09′18″; (c) 02336000 GA, Latitude 33°51′33″, Longitude 84°27′16″; (d) 07143672 KS, 38°01′42.71″, Longitude 97°32′25.95″.

3.4 | Relationships between land-use and water quality changes

3.4.1 | Robust regression

Robust regression was performed to relate the Theil–Sen slopes of the water quality parameter (dependent variable) to the change in land use (independent variable). While this was applied to all water quality parameters and land uses, only the significant relationships ($p<0.05$) generated by robust regression are shown in Table 2. For all models, the change in land use type explains between 12% and 25% of the variance in discharge and water quality changes. All discharge and water quality variables were linearly related to a change in land use except for dissolved oxygen. Discharge is inversely related to shrub/grass land changes while directly related to changes in cultivated land area. Specific

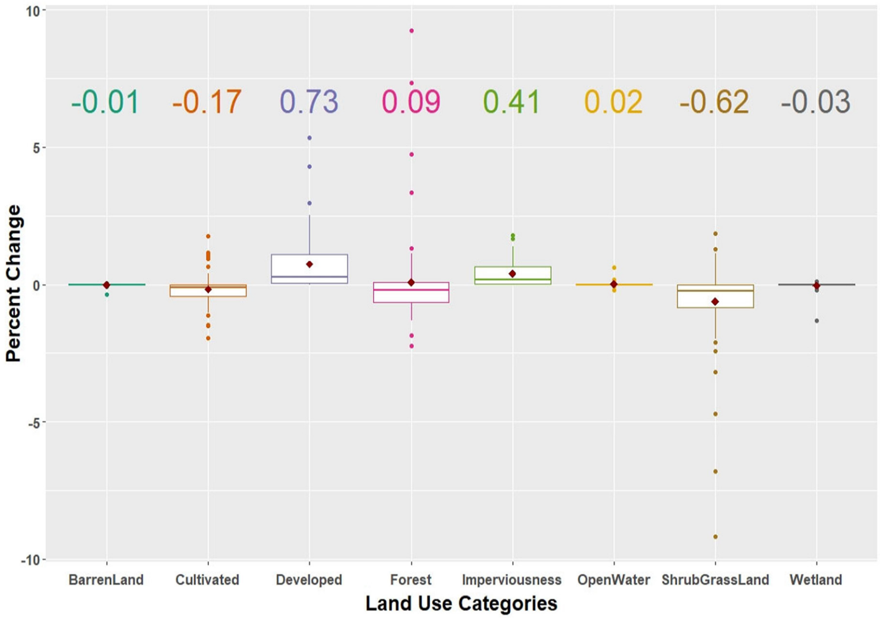

FIGURE 4 The distribution in the percent land-use change relative to the overall watershed area over the period of 2008–2016. The value above each boxplot is the mean of each distribution.

conductance on the other hand is inversely related to changes in cultivated land and open water while directly related to changes in developed land area. Turbidity is directly related to changes in developed land and impervious area while inversely related to changes in cultivated and wetlands.

To explore if a combination of these land use types could further explain the variance in water quality changes, multiple robust regression was performed as summarized in Table 3. Both discharge and specific conductivity resulted in multivariable equations that improved the goodness of fit, while also ensuring no multicollinearity among the data. According to these models, 58% of the variance in discharge trends can be explained by changes in barren, shrub/grass, and cultivated land uses, and 47% of the variance in specific conductance can be explained by open water, developed, and cultivated land uses.

Turbidity did not result in a statistically significant multivariable equation, most likely due to multicollinearity among explanatory variables. Each regression analysis was restricted to watersheds for which there were statistically significant Theil–Sen slope slopes in the water quality data. In the case of turbidity, the 28 watersheds had significant positive correlations between developed land impervious land (0.93) and negative correlations cultivated (−0.82) and wetlands (−0.46) land uses.

3.4.2 | Kruskal–Wallis test

The relationship between land cover changes and changes in discharge and water quality were further analyzed using the Kruskal–Wallis test, which is a nonparametric method of testing whether samples come from the same distribution. Figure 6 illustrates the distribution in land cover changes, which are categorized based upon whether the stream gage at that watershed had an increasing (red) or decreasing (blue) trend in discharge. A Kruskal–Wallis p-statistic of less than 0.05 means that there is a significant difference (with 95% confidence) in land use changes between watersheds with increasing and decreasing trends. Only discharge was found to have statistically significant differences between gages with increasing and decreasing trends (Figure 6). From this figure, watersheds with increasing discharge were likely to have a greater decrease in shrub/grassland ($p = 0.002$), barren land ($p = 0.045$) and wetlands ($p = 0.04$) than those that had a decreasing trend in discharge. This is consistent with the regression results that found a negative correlation between discharge and shrub/grassland and barren land. Although not significant at the 0.05 level ($p = 0.2$), increases in discharge may correspond to increases in impervious area.

4 | DISCUSSION

This study evaluated the land use and water quality changes in 60 watersheds over 2008–2016. The watersheds used represent a balanced variability in land-use types, with dominant land uses including developed, forest, agriculture, and shrub/grass across all watersheds. In

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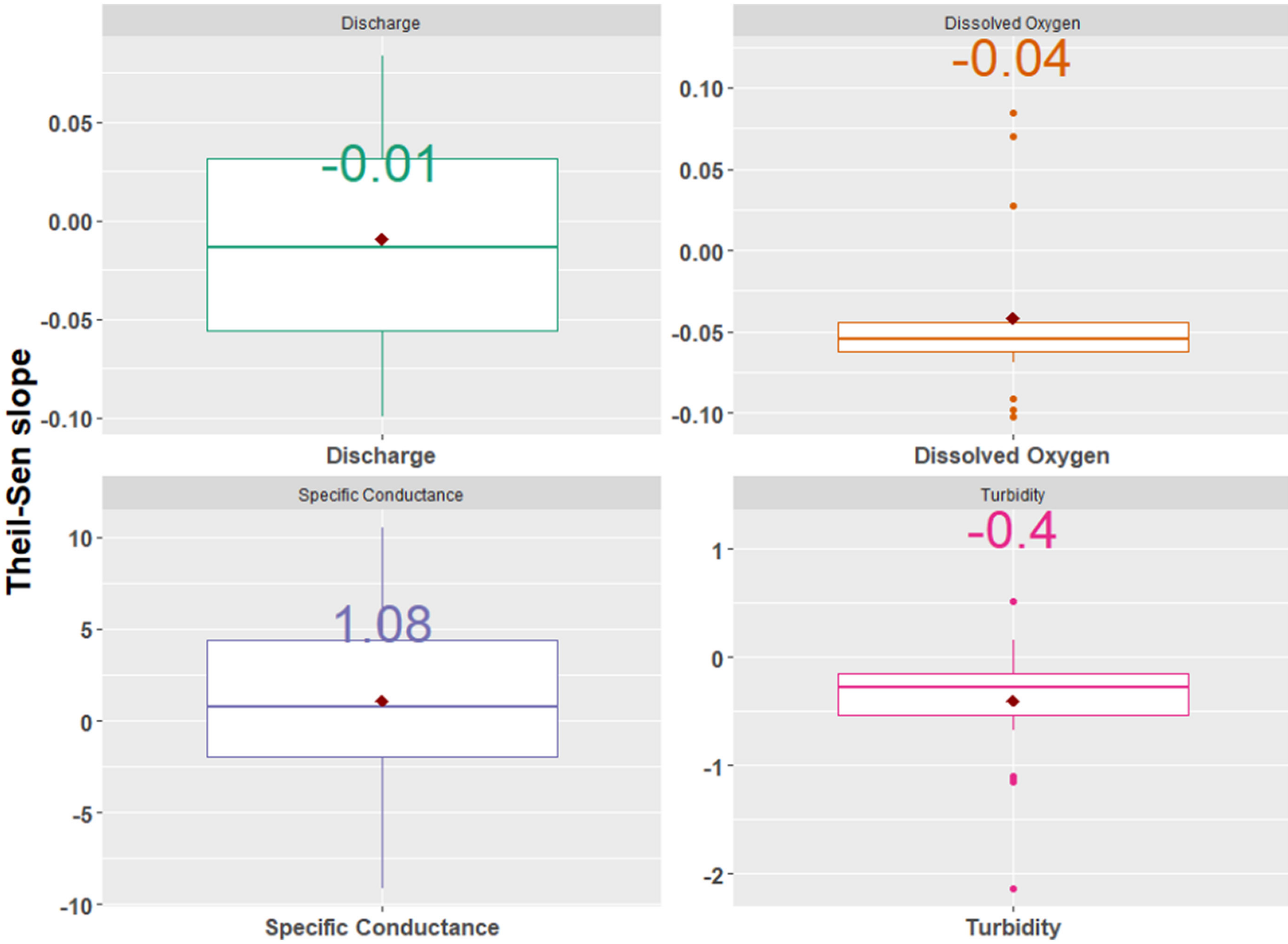

FIGURE 5 Theil–Sen slope distribution of parameters over the period of 2008–2016 with highlighted mean values.

TABLE 2 Simple robust regression coefficients with a *p* statistic less than 0.05 for yearly water parameters as dependent variables and yearly land use percentage changes as independent variables (discharge $n=23$, specific conductance $n=24$, turbidity $n=28$).

Discharge/water quality parameter	Land use type	Slope coefficient	R^2
Discharge	Shrub/grass land	−0.04	0.21
Discharge	Cultivated	0.05	0.22
Specific conductivity	Open water	−58.01	0.25
Specific conductivity	Developed	3.95	0.12
Specific conductivity	Cultivated	−5.47	0.20
Turbidity	Developed	−0.19	0.25
Turbidity	Cultivated	0.89	0.23
Turbidity	Wetland	0.64	0.14
Turbidity	Impervious	−0.52	0.23

terms of water quality, specific conductance generally increased and turbidity decreased; however, there was little to no overall trend in discharge. While almost all gages saw negative trends in dissolved oxygen, they were relatively small changes (median of −0.05%). Furthermore, in evaluating the relationship between land use changes and water quality, it was clear from the Kruskal–Wallis test that changes in barren land, shrub/grasslands and wetlands corresponded to a change in discharge. To that end, there are several implications of these results.

TABLE 3 Multiple robust regression parameters.

Water quality parameter	Land use category	Slope coefficient ($p < 0.05$)	R^2
Discharge	Cultivated	0.04	0.58
	Barren land	−0.33	
	Shrub/grass land	−0.04	
Specific conductance	Open water	−50.10	0.47
	Developed	−2.00	
	Cultivated	−13.36	
Turbidity	Developed	−0.19	0.25

4.1 | Land use changes

In this study, the watersheds on average had increases in imperviousness and developed areas, with decreases in shrub/grasslands and cultivated areas, and little to no overall trend in other land covers (<0.1% mean) This is consistent with other studies that found increasing imperviousness and developed land with decreasing cultivated areas within the U.S. (Sleeter et al., 2013; Theobald, 2005; Wilson, 2015). Over the 9 years of this study period, the overall changes are relatively small with the highest median percentage change of any land-use type of 0.45% (Figure 4). This is not surprising as the rate of change of land use has been decreasing since 2005 (Winkler et al., 2021). As a whole, these land use changes within the watersheds were found to be similar to the changes observed across the United States over the same time period (Figure S1).

4.2 | Water quality and discharge trends

Specific conductance concentrations increased in a majority of watersheds for which a significant trend was detected. This is consistent with other findings that have found mean increases in the specific conductance in rivers and streams within human-dominated landscapes across the United States (Baker et al., 2019; Stets et al., 2020). Specific conductance is representative of the amount of dissolved ions in water, and in streams is largely impacted by dissolved salts. This can come from point source pollution from industrial and residential discharges, but it is largely comprised of non-point source pollution from agricultural land use and activities such as tilling, deforestation, and fertilizer/pesticide application (Stets et al., 2020), as well as urban land uses and activities such as road de-icing (Shoda et al., 2019).

Dissolved oxygen decreased in a majority of watersheds for which a significant trend was detected. This could partly be due to the observed increase in specific conductance, as higher ionic strengths reduce oxygen solubility (Heddam, 2014). In addition, low dissolved oxygen in streams can be caused by other factors such as increases in nutrients, oxygen demand, temperature, ionic strength, and sediments, as well as reductions in aeration (Allan et al., 2021). Nutrients in U.S. streams have reduced in urban streams, with no change in agricultural streams over a 30-year time period from 1982 to 2012 (Stets et al., 2020); therefore, oxygen demand caused by increasing nutrient loads might not be the cause of reducing dissolved oxygen across watersheds. However, most streams are impounded by dams and other flow controlling infrastructure that reduces dissolved oxygen within the structures, which could impact downstream oxygen levels absent of aeration at the outlet of the structures (Zaidel, 2018). Furthermore, temperature in streams in U.S. has been rising (Kaushal et al., 2010) and increase in stream temperature reduces oxygen solubility.

Turbidity decreased in more than 85% of the watersheds with significant trends. Reduction in turbidity could be due to the management of surface runoff, as stormwater regulations in the U.S. largely focus on reductions in total suspended solids as the primary regulatory criteria (Naughton et al., 2021). This is evidence as on average total suspended solid concentrations in streams and rivers have reduced despite increases in anthropogenic disturbances (Murphy, 2020; Stets et al., 2020).

Discharge had both positive and negative trends throughout the study period. The lack of an overall trend could be due to a few reasons, including varying precipitation patterns across the dispersed watersheds in this study. For example, precipitation trends in the U.S. vary with some regions experiencing increasing trends and others decreasing trends in precipitation (Easterling et al., 2017). The reasons for this are complex but could be due to climate change, which has been shown to have a considerable impact on discharge both negatively and positively (Croitoru & Minea, 2015; Leppi et al., 2012). However, it has been further shown that increase in extreme precipitation due to climate change does not necessarily correlate with increases in stream discharges due to the complex nature of factors impacting stream volumes such as antecedent moisture conditions based on climate regions (Ivancic & Shaw, 2015). Therefore, due to the dispersed nature of the gages across regions where precipitation and other climatic factors vary, there may not be a consistent pattern in discharge trends. In addition, discharge

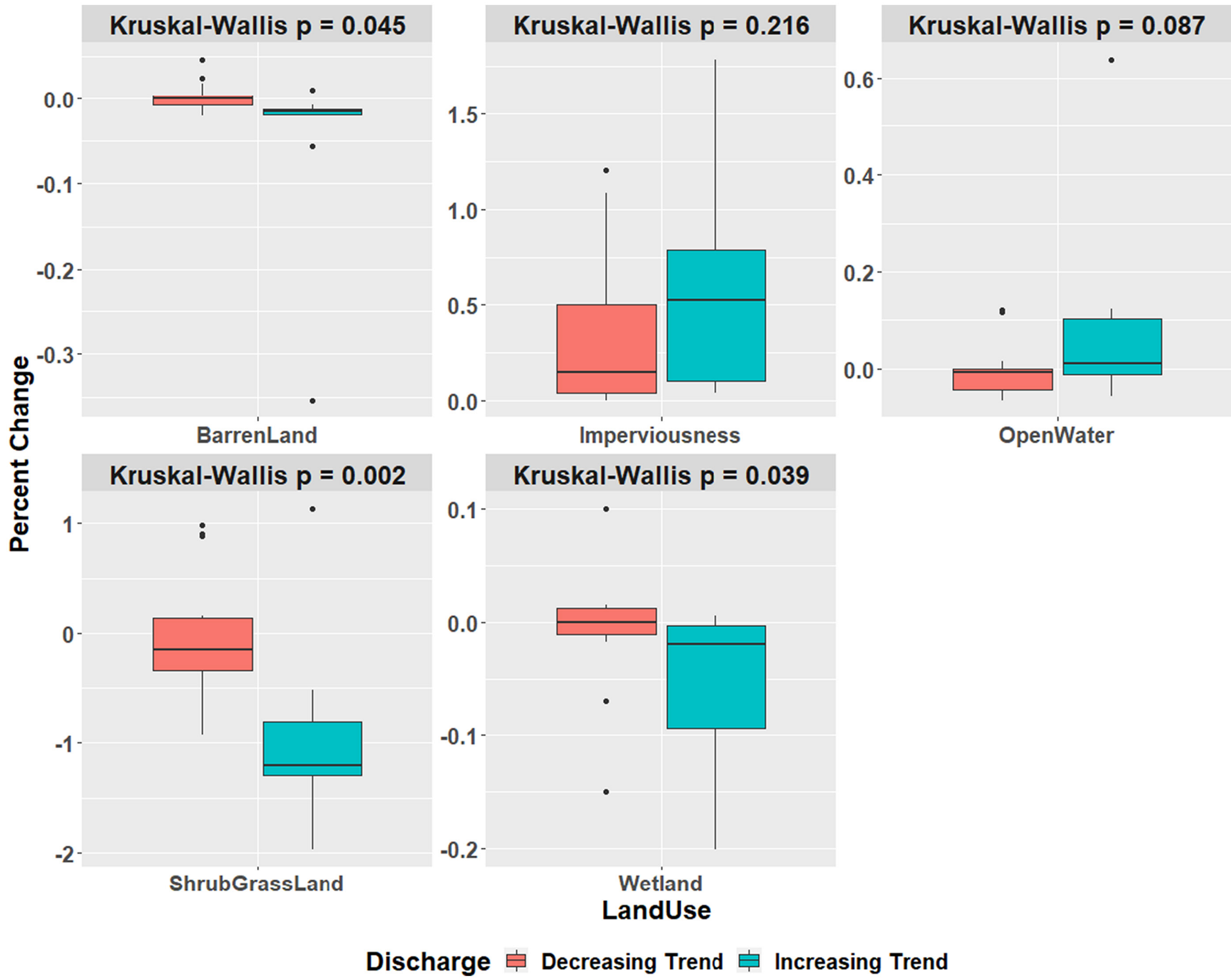

FIGURE 6 Kruskal–Wallis test on water discharge trend direction as the categorical variable and land use types as explanatory variables. *Y*-axis shows the percentage change in each land use type. Blue box and whiskers contain those gauges with a statistically significant increasing trend for that land cover and red boxes represent those with a statistically significant decreasing trend.

may influence other water quality parameters, such as high discharge that results in dilution of pollutants or the resuspension of sediments; however, there were no statistically significant relationships between discharge and other pollutants (Figure S3; Table S3).

4.3 | Impact of land use change on discharge and water quality trends

Changes in discharge were negatively correlated to changes in shrub/grassland and barren land uses and positively correlated to changes in cultivated land use. Loss of vegetated ground cover due to an increase in agricultural land has generally been found to increase groundwater recharge and reduce evapotranspiration, which leads to increases in stream baseflows (Ahiablame et al., 2017; Astuti et al., 2019; Zhang & Schilling, 2006). Conversely, an increase in cultivated land could decrease infiltration due to soil compaction from mechanized equipment, thus increasing stormwater runoff volumes (Keller et al., 2019). Similar increases in baseflows may explain the observed trends in this study, as we used average monthly area adjusted flow, encompassing both baseflow and stormflow. Increases in discharge were also moderately correlated with reductions in wetlands using the Kruskal–Wallis test ($p < 0.1$). This could be due to the higher water retention capacity of wetlands compared to the other land use types (Procházka et al., 2019).

Trends in discharge were not correlated to developed land use changes. While it is established that developed land increases peak discharge and runoff (Shi et al., 2007), this might not be seen in monthly averaged data which also encompass baseflow. The annual temporal scale these models represent, and monthly data used for trend generation, does not capture discharge differences caused by urban runoff which happens at a much smaller time scale (hours, days). While increase in imperviousness and urban land cover has shown to increase stream discharge variation at hourly and daily time scales (Simmons & Reynolds, 1982), this might not be seen in annual and monthly scales. Furthermore, many studies have found that groundwater infiltration is reduced due to imperviousness of developed land thus reducing baseflow in streams (Aboelnour et al., 2020; Chithra et al., 2015; Kauffman et al., 2009).

Turbidity was found to be positively correlated with cultivated land use and negatively correlated to developed land use. Cultivated lands often result in runoff of sediments to streams (de Mello et al., 2020), which may explain this relationship. In addition, a negative relationship of turbidity with developed land could be due to better pollution control practices within urban landscapes (Stets et al., 2020). This is because new developments and redevelopments in the U.S. are largely now subject to much more stringent stormwater control measures and regulations than those in the past (Murphy & Sprague, 2019). Therefore, even if urban land uses produce a greater pollutant runoff than their predevelopment conditions, the implementation of best management practices to capture and treat this runoff could lead to downstream pollutant reductions.

Finally, specific conductance was negatively correlated to cultivated and open water land uses and positively correlated to developed land use. Open water variation within selected watersheds is minute, with an average change of 0.008%. Thus, the impact of open water change relative to other land-use change might not be as influential. However, reduction in open water land could mean increase in ionic concentrations due to land alterations and volume reductions. The negative correlation between specific conductance and cultivated land could be due to improved management of agricultural runoff or the conversion of agricultural land to other land uses that increase the runoff of dissolved ions. The latter is supported by the positive correlation between specific conductance and developed land observed in this study. This has also been observed in regional studies (Tu, 2013) and is likely due to the influence of urban land uses and activities on salt and dissolved ions in runoff as discussed previously.

4.4 | Implications and limitations of the study

The main outcomes of this study are the correlations found between land use changes over time and water quality changes at a larger spatial scale. Understanding these relationships has implications for the development and implementation of watershed management plans. This study demonstrates that land use changes that occurred over a decade, however small, are correlated to discharge and water quality. These outcomes could be used in watershed planning to inform targeted land management practices, planning of urban best management practices, or support water conservation efforts. For example, while water quality management plans are developed and updated frequently (e.g., TMDLs need to be done every 2 years and section 303(e) of the Clean Water Act requires a continuing planning process), implementation of best management practices to reduce pollution through non-point source runoff takes decades; however, in most cases, water management plans do not project land use changes and their future impacts on water quality. For example, none of the 2017 water management plans for Wisconsin watersheds certified by the EPA have future land use projections and their impacts on water quality (Wisconsin Department of Natural Resources, 2017). This is because doing so is largely constrained to loading estimations from models that may be resource-intensive to develop and limited to prior knowledge. Incorporating predictions of land use change and their subsequent impact on the water quality changes through an empirical model, such as the one developed in this study, could improve the planning process which currently is relied upon margins of safety and current or older water quality and land use data.

One advantage of the approach presented is in the form of the model, what the data represent, and how it can be applied. The empirical model developed in this study takes the form of *water quality change = f (land use change)*. However, the majority of empirical studies evaluating the relationship between stream water quality and land use develop a model in the form of *water quality = f (land use)*, which represents a relationship at one point in time and therefore does not capture the degree to which changes in land use might influence changes in water quality. This could make the models biased toward the composition of historical land uses that may not have the same impact on discharge or water quality as contemporary land development. For example, a model that captures the impact of urban land use on water quality at one point in time might be biased by historical development within that watershed that did not have to adhere to water quality requirements derived from programs after the Clean Water Act. However, the model in this study only looks at recent changes where the implementation of best management practices and modern drainage designs are captured. Furthermore, while the form of the model *water quality = f (land use)* may be good for estimating water quality in ungaged basins, for applications where water quality is known, such as streams that are already listed as impaired in the TMDL program, there is no way to calibrate the model to current conditions. The model proposed in this study can be applied to data representing current water quality or discharge, to estimate what the subsequent change in water quality or discharge might be due to land use changes. In addition, the model proposed in this study is independent of current land use conditions and therefore can be applied based only on expected land use changes (as a percentage of the overall watershed) without having to define the existing land use composition.

While the models in this study were able to explain 11%–57% of the variance in water quality and discharge trends, there are several unobserved factors that also influence water quality and discharge in rivers. These include changes to policy, land-use patterns, stormwater control measures, and other human interventions, such as treatment plants. For example, changes to watersheds that do not modify the land use category, such as increases in population density, conversions of grazing land into crop agriculture, and improvements to waste management methods, have been shown to have a significant effect on water quality (Panthi et al., 2017; Vrebos et al., 2017; Wijesiri et al., 2018; Wilson, 2015). Furthermore, watershed management approaches, such as best management practices installed to address TMDLs, also can decrease pollutant levels in downstream water bodies by prevention and mitigation of pollutants (Murphy & Sprague, 2019; Stets et al., 2020).

This study looks at changes in land use composition; however, the pattern and scale of that land use (Chiang et al., 2021; Shehab et al., 2021; Shi et al., 2017; Wang et al., 2014), topography (Lei et al., 2021), and point sources (Pak et al., 2021) may also play a considerable role in affecting stream water quality and quantity. To this end, there are likely water quality contributions from both point and non-point sources; however, the proposed methodology is not able to distinguish between the impact that point and non-point sources have on changes in water quality. Additionally, this methodology does not incorporate what influence climate change may have on discharge or water quality; therefore, future work could evaluate how to incorporate the coupled effects of land use change climate-induced changes on discharge and water quality to project changes over a larger time scale.

5 | CONCLUSIONS

This study quantified and evaluated the relationships between changes in land-use and changes in water quality for 60 watersheds across U.S. over a 9-year period from 2008 to 2016. Developed land use had the largest increase across all watersheds with a median of 0.26% (mean of 0.73%) of the total watershed area, while shrub and grass land had the largest decrease with a median of −0.22% (mean of −0.62%). Regarding water quality, specific conductance had an increasing trend in 63% of the watersheds with significant trends, while dissolved oxygen and turbidity had a decreasing trend in 83% and 86% of the watersheds with significant trends. Discharge trends varied among watersheds and observed changes were comparatively small (less than ±0.1%). In terms of relationships between land use change and trends in hydrologic data, changes in discharge were found to be positively corelated with changes in cultivated land and negatively corelated with changes in shrub/grass and barren land. Surprisingly, changes in discharge were not corelated with changes in developed land use changes at a statistically significant level ($p < 0.05$), which could be because the discharge data are highly influenced by stream baseflow data. Turbidity trends were positively correlated with changes in cultivated land and negatively correlated with changes in developed land. This perhaps suggests that current stormwater management regulations that focus on solids removal have a positive impact on downstream water quality. Finally, specific conductance trends were negatively corelated to changes in cultivated land, perhaps due to the conversion of agricultural land to other land uses that increase the runoff of dissolved ions rather than improved management of runoff. As a whole, this case study provides broad analysis trends in land use and water quality, providing an improved our understanding of the complex relationships between human land development activity and its subsequent effect on downstream hydrology and water quality.

AUTHOR CONTRIBUTIONS

Charitha Gunawardana: Data curation; formal analysis; investigation; methodology; visualization; writing – original draft; writing – review and editing. **Walter McDonald:** Conceptualization; formal analysis; funding acquisition; project administration; resources; supervision; validation; writing – review and editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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