Journal of Environmental Management 359 (2024) 120983

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Research article

A new perspective on water quality: Exploring spatial and temporal patterns of impaired waters

Mallory A. Jordan, Stephanie R. Rogers *

Department of Geosciences, Auburn University, 2050 Beard Eaves Court, 36849, Auburn, AL, USA

ARTICLE INFO

Keywords:
Water quality trend
Space time cube
Clean water act
Alabama rivers
Section 303(d)
GIS

ABSTRACT

Managing surface water quality is a global challenge, and understanding spatial and temporal patterns of water quality is a key component to effective management. However, analysis of spatiotemporal patterns of impaired waters over broad areas is sparse due to disparate water quality data and variable water quality standards. Thus, here we leverage the Alabama 303(d) List of impaired waters to present a new perspective for investigating spatiotemporal water quality patterns. Every two years, each state in the United States is required to assess its surface water quality and compile a list of impaired waterbodies, meaning waters that do not meet water quality standards for their designated usage – referred to as the 303(d) List. The purpose of the 303(d) List is to identify impaired waters so that corrective action can be taken to reduce pollutant loads and, ultimately, improve water quality. Using GIS, a space time cube was created to analyze and visualize spatiotemporal patterns of the impaired rivers added to the Alabama 303(d) Lists from 1996 to 2022. For this analysis, the percentage of river length impaired out of the total river length, and number of times each impairment cause was listed, were summarized within Alabama sub-basins (Hydrologic Unit Code 8) (n = 51). Trend and hot spot analyses were conducted on the river impairment and causes. There was an up trend in river impairment for eight sub-basins across the state and a downtrend in one sub-basin. Over half of the sub-basins with an up trend in impairment also had an up trend in the number of times pathogens was listed as a cause of impairment. Additionally, coastal sub-basins were found to be a hot spot for river impairment. Interestingly, there was a down trend in the number of times nutrients, ammonia, and siltation were listed as a cause of impairment at the state and sub-basin scales of analysis. Altogether, these findings show the use of spatiotemporal pattern analysis of impaired waters and can indicate where, both spatially and by pollutant, management should prioritize water quality improvement efforts.

1. Introduction

1.1. Background

Maintaining surface water quality for the health of humans and ecosystems is a ubiquitous challenge – 40 percent of global waterbodies (44,937 out of 75,458 assessed in 89 countries) do not have good ambient water quality, per national and/or subnational water quality standards (WQSs) (United Nations-Water, 2021). Regular monitoring and assessment is imperative for maintaining water quality and measuring progress towards water quality goals, like Sustainable Development Goal (SDG) 6 – Clean Water and Sanitation – set by the United Nations (United Nations-Water, 2021). To measure progress towards these goals, the ideal water quality dataset would reflect the dynamic nature of water with even spatial distribution and high frequency of samples across time, while obtaining an understanding of the unique parameters that make up each water body, necessitating the laboratory analysis of a multitude of water quality properties (e.g., pathogens, chlorophyll, pH, turbidity). Unfortunately, ideal water quality datasets are sparse as they are costly to create and maintain, leading to difficulties in the evaluation of water quality and the determination of overall water 'health'. Additionally, multiple methods exist to synthesize data and evaluate water quality – parameter measurements could be compared to relevant standards or used to calculate a water quality index (and there are many indices) (Brown et al., 1970). Furthermore, WQSs differ across management entities. For example, pathogens can be measured using different indicators, such as *Escherichia coli* (*E. coli*), Enterococci, or fecal coliform, and the threshold which

* Corresponding author.
E-mail addresses: maj0062@auburn.edu (M.A. Jordan), s.rogers@auburn.edu (S.R. Rogers).

https://doi.org/10.1016/j.jenvman.2024.120983
Received 29 January 2024; Received in revised form 22 March 2024; Accepted 20 April 2024
Available online 3 May 2024
0301-4797/

the water is classified as impaired differs by management entity (e.g., different states across the United States (U.S.) have different thresholds). The evaluation of water quality parameters and their associated spatiotemporal variability is critical for effective management. However, the variability of water quality is rarely assessed at broad scales (e.g., regional or national) due to the complexities associated with holistic data collection and analyses for the multitude of individual water bodies. Thus, here we present a new perspective on water quality analysis using accessible impaired water data to spatiotemporally analyze water quality variability through a water quality management lens.

Water quality evaluation and determination of impairment is based on WQSs, which act as a guide for surface water management. In the U.S., the Clean Water Act (CWA) governs surface water management and sought to "restore and maintain the chemical, physical, and biological integrity of the Nation's waters" (Clean Water Act, 2018, p.328). States, territories, and authorized tribes—collectively referred to as 'states' in the act—are responsible for creating WQSs and monitoring surface water quality with oversight from the federal government, specifically the U.S. Environmental Protection Agency (EPA). State WQSs are the foundation of water assessment, and measured parameters are 'interpreted' through these standards to classify waters as impaired or not. WQSs are required to include use designations (e.g., drinking water, recreation, etc.) and water quality criteria sufficient to protect those designated uses (Clean Water Act, 2018). The standards may be more stringent than the minimum standards set by the EPA and may change by state. Additionally, Section 303(d) of the CWA is a prominent component of U.S. water quality management. Section 303(d) requires of states to (1) identify impaired waters, meaning waters not meeting WQSs for its designated use and (2) establish total maximum daily loads (TMDLs), essentially a pollution 'budget' that specifies the maximum amount of pollution a waterbody can receive and meet WQSs (Clean Water Act, 2018). TMDLs are used to transform the WQSs into enforcement tools. States must produce and submit the 303(d) List of impaired waters every two years to the EPA. Through this required monitoring, data exist which represent the location, cause, and source of impaired waters for all states since the late 1990s, when Section 303(d) was enforced by the federal government.

Variability in water quality is frequently assessed using water quality trend analyses. Trend analyses look for statistically significant changes in water quality over time, often utilizing the Mann-Kendall statistical procedure. For example, water quality trends in U.S. rivers have been evaluated using concentrations of multiple parameters (Oelsner et al., 2017; Smith et al., 1987). Though trend analyses of parameter concentrations effectively assess the statistical significance of water quality trends, they may neglect to determine if the trend is environmentally significant, meaning pollutant concentrations are such that the water is not suitable for its use. To address this concern, some studies have used alternative water quality parameters to evaluate trends, such as water quality indices (Khan et al., 2003; Sun et al., 2016), levels of concern (Shoda et al., 2019), or water quality ladder thresholds (Kuwayama et al., 2020). These studies provide further insight into temporal water quality trends, but do not provide a spatially explicit analysis of water quality patterns. Here it is important to note that examples of trend analysis presented above may display the results in a spatial context (i.e., on a map), but the statistical analyses are not spatially explicit. A handful of studies have used spatial analysis to analyze water quality, such as Chang (2008), but it is not the standard method of analysis. As water quality is often a reflection of its surrounding environment, spatial analyses, along with temporal trend analyses, provide new insights into water quality patterns – meaning the degree to which water quality data are spatially related, or autocorrelated.

Comprehensive assessment of water quality patterns over large geographic areas is necessary to monitor and effectively manage water quality. The U.S. government—specifically the U.S. EPA—assesses national water quality regularly in the *National Water Quality Inventory: Report to Congress* (U.S. Environmental Protection Agency, 2017). However, peer-reviewed literature on assessing water quality trends on a national scale (Keiser and Shapiro, 2019; Smith et al., 1987) or state scale (Kuwayama et al., 2020) are sparse. Understanding water quality trends at broader scales (i.e., political boundaries) is critical as these scales often align with water quality management. For example, water quality is managed at both the national and state scales in the U.S. Without an understanding of water quality patterns at broader management scales, it is difficult to evaluate management practices (historically and currently), identify persistent pollutant causes, or identify where water quality remediation efforts should be prioritized.

1.2. Objective

Understanding spatial and temporal variability in water quality impairment can be challenging due to the need for robust water quality data collected consistently over time and across a broad spatial extent and differing WQSs. To date, water quality data on the 303(d) List has yet to be used in a broad scale water quality analysis that aligns with management entities, and no studies have looked at these data from a spatiotemporal analysis perspective. This study aims to fill these knowledge gaps by presenting a flexible framework for streamlining water quality pattern assessment over various spatial and temporal scales using impaired waters data, with the state of Alabama as a case study. Specifically, the objective of this study was to spatiotemporally evaluate surface water quality with water quality impairment data, and given this analysis was exploratory in nature, we also aimed to show the usefulness of spatiotemporal analysis of water quality. This objective was addressed by the following research question: What are the spatial and temporal patterns of river impairment and river impairment causes? To the authors' knowledge, this is the first spatiotemporal analysis of impaired waters data. Addressing this research question could allow for broader conclusions on water quality changes and the causes of water quality impairment.

2. Methodology

2.1. Area of study

This analysis was focused in Alabama, U.S., and the sub-basins within the state at hydrologic unit code (HUC) 8. Fig. 1 shows the sub-basins included in the analysis, and descriptive statistics for each sub-basin are provided in Table 1. Alabama was selected as the study area due to the availability of spatial impairment data between 1996 and 2022 and importance of the state's freshwaters within the national context—Alabama has over 132,000 miles of streams and rivers and it is estimated that 10% of the freshwater resources for the entire continental U.S. originates in or flows the state (Geological Survey of Alabama, 2023). Also, Alabama waters provide critical aquatic habitat as Alabama has the highest aquatic biodiversity of any U.S. state, gaining the nickname of 'America's Amazon' (Alabama Water Watch, 2023). Sub-basin boundaries were sourced from the national hydrography dataset (NHD) (U.S. Geological Survey, 2023). Two sub-basins that overlap with Alabama (Upper Elk and Lower Chickasawhay sub-basins) were excluded from the analysis because less than one percent of the river flowlines were within Alabama and there were no impaired rivers included in the Alabama 303(d) Lists.

2.2. Water quality trends

2.2.1. Summary of water quality trend methods

To address the research question, we analyzed spatial patterns of river impairment from 1996 to 2022 in Alabama sub-basins using a space time cube (STC). Impairment data were sourced from the Alabama 303(d) List, a list of waters that do not meet Alabama's WQSs (Alabama Department of Environmental Management, 2022). An overview of the

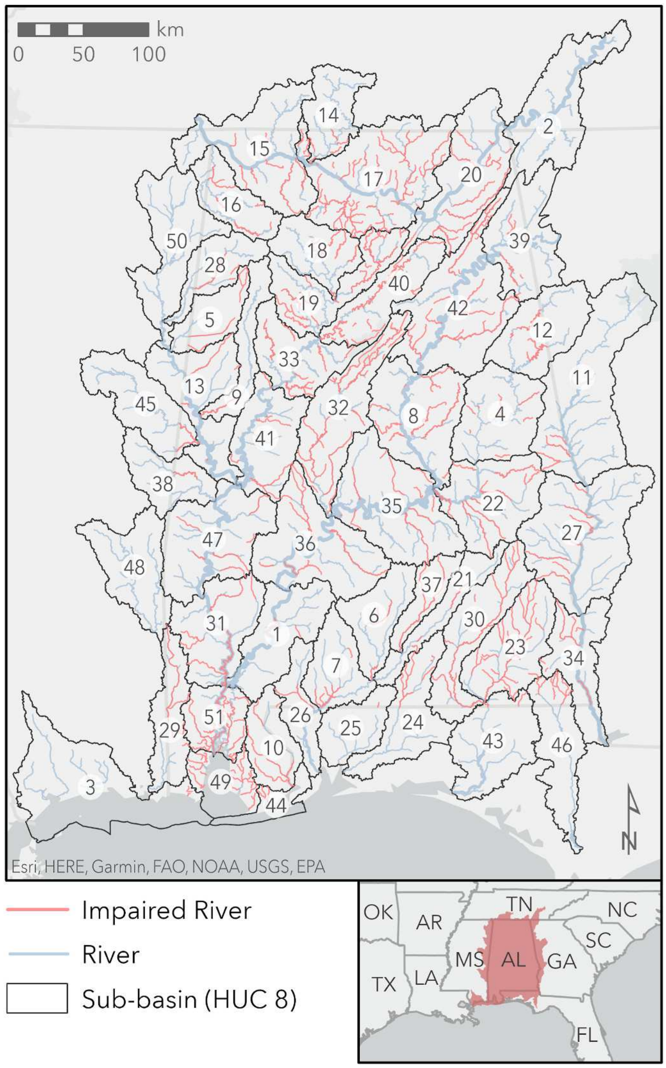

Fig. 1. All rivers that have been 303(d) listed (from 1996 to 2022) in Alabama are shown in red. Rivers may be listed multiple years. The sub-basins hydrologic unit code (HUC) 8 that intersect Alabama state boundaries included in the analysis are also shown. Sub-basin labels correspond to sub-basin IDs in Table 1. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

methods is provided in Fig. 2. First, impairment data were sourced, cleaned, and formatted for creation of a STC (described in Section 2.2.2; Fig. 2A). Then, a STC was created (described in Section 2.2.3; Fig. 2B) and pattern analyses were conducted (described in Section 2.2.4; Fig. 2C) to understand the spatiotemporal changes in Alabama river impairment. All analyses were completed in ArcGIS Pro 3.0 and Python 3.9. Spatial analyses were conducted in the Universal Transverse Mercator (UTM) 16N projection to preserve angles and shapes.

2.2.2. *Input data and data preparation*

Input data included Alabama 303(d) Lists from 1996 to 2022 (n = 14), produced and provided by the Alabama Department of Environmental Management (ADEM). ADEM manages surface water quality and has produced the 303(d) List for the state of Alabama on all even years since 1996. Data from ADEM included shapefiles that denoted the spatial extent of impaired waters (lines for rivers and polygons for lakes or estuaries). Shapefiles were available for assessment years from 1998 to 2022. The shapefile attribute data usually included the assessment unit ID, waterbody name, river basin, county, the cause of impairment, source of impairment, designated use for the water, size of impaired

Table 1
Descriptive statistics for Alabama sub-basins, including the sub-basin identification number (ID), name, hydrologic unit code (HUC) 8, states the sub-basin overlaps, area, and length of rivers in the sub-basin.

ID	Sub-basin Name	HUC 8	States	Sub-basin Area (km^2)	River Length (km)
1	Lower Alabama	3,150,204	AL	3766.23	3942.87
2	Middle Tennessee-Chickamauga	6,020,001	AL, GA, TN	4827.14	142.33
3	Mississippi Coastal	3,170,009	AL, LA, MS	7371.28	179.97
4	Middle Tallapoosa	3,150,109	AL	4117.58	4428.75
5	Luxapallila	3,160,105	AL, MS	2069.63	1931.29
6	Sepulga	3,140,303	AL	2717.81	3081.56
7	Lower Conecuh	3,140,304	AL, FL	2626.45	2713.32
8	Lower Coosa	3,150,107	AL	5082.53	5326.64
9	Sipsey	3,160,107	AL	2039.90	2310.93
10	Perdido	3,140,106	AL, FL	2383.72	1201.87
11	Middle Chattahoochee-Lake Harding	3,130,002	AL, GA	7875.21	1491.12
12	Upper Tallapoosa	3,150,108	AL, GA	3611.62	2175.21
13	Middle Tombigbee-Lubbub	3,160,106	AL, MS	4224.17	3773.27
14	Lower Elk	6,030,004	AL, TN	2496.93	756.65
15	Pickwick Lake	6,030,005	AL, MS, TN	5911.47	4045.79
16	Bear	6,030,006	AL, MS	2444.41	2286.95
17	Wheeler Lake	6,030,002	AL, TN	7493.18	6986.35
18	Sipsey Fork	3,160,110	AL	2581.43	2944.04
19	Mulberry	3,160,109	AL	3554.06	3937.60
20	Guntersville Lake	6,030,001	AL, GA, TN	5173.62	4375.04
21	Upper Conecuh	3,140,301	AL	2129.22	2391.40
22	Lower Tallapoosa	3,150,110	AL	4411.37	5234.79
23	Upper Choctawhatchee	3,140,201	AL	3997.36	4074.67
24	Yellow	3,140,103	AL, FL	3559.78	1217.23
25	Blackwater	3,140,104	AL, FL	2239.23	272.74
26	Escambia	3,140,305	AL, FL	1966.89	713.40
27	Middle Chattahoochee-Walter F	3,130,003	AL, GA	7347.50	4655.99
28	Buttahatchee	3,160,103	AL, MS	2239.52	1851.17
29	Escatawpa	3,170,008	AL, MS	2704.75	1735.28
30	Pea	3,140,202	AL, FL	4027.83	4431.26
31	Lower Tombigbee	3,160,203	AL	4175.47	4903.20
32	Cahaba	3,150,202	AL	4723.87	4716.77
33	Upper Black Warrior	3,160,112	AL	3226.44	3270.84
34	Lower Chattahoochee	3,130,004	AL, FL, GA	3222.47	1204.79
35	Upper Alabama	3,150,201	AL	6193.16	8183.34
36	Middle Alabama	3,150,203	AL	5774.78	6876.74
37	Patsaliga	3,140,302	AL	1554.46	1647.70
38	Sucarnoochee	3,160,202	AL, MS	2522.31	1072.66
39	Upper Coosa	3,150,105	AL, GA	4141.99	2415.77
40	Locust	3,160,111	AL	3134.83	3290.73
41	Lower Black Warrior	3,160,113	AL	3763.43	4161.90
42	Middle Coosa	3,150,106	AL	6692.11	6875.98
43	Lower Choctawhatchee	3,140,203	AL, FL	4026.78	315.01
44	Perdido Bay	3,140,107	AL, FL	1167.28	128.44
45	Noxubee	3,160,108	AL, MS	3673.40	407.80
46	Chipola	3,130,012	AL, FL	3347.38	428.27
47	Middle Tombigbee-Chickasaw	3,160,201	AL, MS	5388.83	6285.68
48	Upper Chickasawhay	3,170,002	AL, MS	3745.75	144.03
49	Mobile Bay	3,160,205	AL	2261.09	618.15
50	Upper Tombigbee	3,160,101	AL, MS	4654.27	363.67
51	Mobile-Tensaw	3,160,204	AL	2364.75	2057.49

waters, and the year listed, but the attributes varied by year. Additionally, the 303(d) Lists (available for assessment years from 1996 to 2022) and 303(d) Fact Sheets (available for assessment years from 2000 to 2022) were sourced from ADEM's website (Alabama Department of

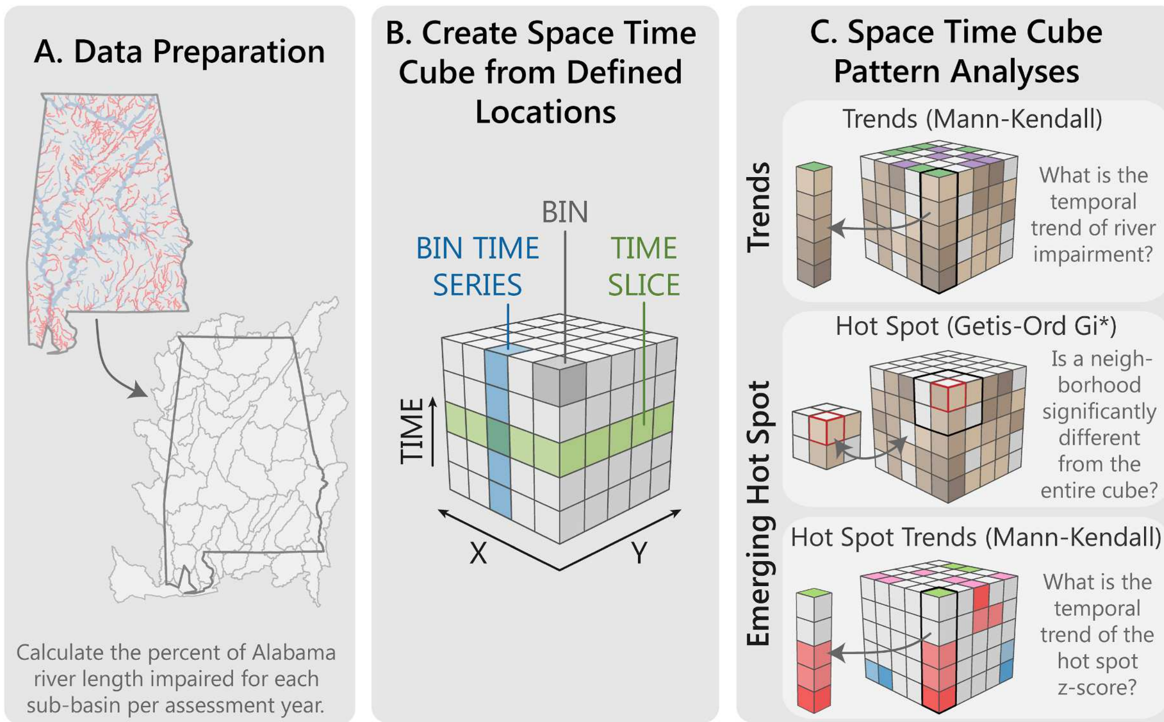

Fig. 2. Methodological workflow to assess the spatiotemporal patterns of river impairment in Alabama. First, impaired river data were sourced from all available Alabama 303(d) Lists, and the percent of Alabama river length impaired was calculated for each sub-basin (HUC 8) and assessment year (even years from 1996 to 2022) using python (A). A space time cube was created (B), and trends and hot spot analyses were completed to examine spatiotemporal patterns in river impairment data (C) using ArcGIS Pro.

Environmental Management, 2023a) as supplemental data. The 303(d) List was table-based data of impaired waters and often included additional attributes not included in the shapefiles. The 303(d) Fact Sheet summarized the waters added and removed from the 303(d) List for the assessment year. For this dataset, we assumed that if a river is not on the 303(d) List of impaired waters it is not impaired, but all waters are not assessed every year for all possible pollutants. There were not data on which rivers were assessed for all assessment years, thus we could not normalize the data to assessed waters. However, for the purposes of this study, available data are sufficient to assess the spatiotemporal trends of river water quality in Alabama.

There were several steps taken to expand and control the quality of the dataset. First, a shapefile was not available for the 1996 List, thus the 1998 shapefile was used to derive a shapefile for the rivers impaired in 1996. The 2004, 2006, and 2008 impairment data (both the List and the shapefile) did not include the year the waterbody was listed impaired. The Fact Sheets for 2004, 2006, and 2008 were used to create a list of waterbodies added to the List for each assessment year. Several quality control steps were taken to find and correct erroneous data included in the shapefiles and tables: (1) duplicate assessment unit IDs were aggregated to a single value or checked for mislabeling and (2) checked that all assessment unit IDs matched in the shapefile and table for each assessment year. Corrections to the input data are documented in SI Table S1.

All data were collated, formatted, and summarized in each sub-basin. Only rivers added to the 303(d) List each assessment year were included in the analysis because the 303(d) is a 'running' list of impaired waters and the delisting process and criteria are different than the listing process. Then, the length of rivers was summarized in Alabama sub-basins (HUC 8) for each assessment year, and the percentage of river length impaired was calculated using Equation (1):

$$\textit{Percent of Rivers Impaired} = \frac{\textit{Impaired Rivers}\ (km)}{\textit{Total Rivers}\ (km)} \qquad \text{Equation 1}$$

where *Impaired Rivers* is the length of rivers (km) impaired added to the 303(d) List per assessment year (calculated from the impaired waters shapefiles), *Total Rivers* is the total length of rivers in Alabama (km) with visibility less than or equal to 1:100,000 calculated from the NHD, and *Percent of Rivers Impaired* is the percent of Alabama rivers impaired for each sub-basin and assessment year. The number of times each impairment cause was also calculated for each sub-basin per assessment year. There were 18 different causes of impairment identified across the data: *ammonia*, *biology*, *chlorides*, *color*, *flow alteration*, *metals*, *nonpriority organics*, *nutrients*, *organic enrichment/dissolved oxygen (OE/DO)*, *other habitat alteration*, *pathogens*, *pesticides*, pH, *priority organics*, *siltation*, *total dissolved solids (TDS)*, *turbidity*, and *unknown*. Table S2 provides types and additional impairment descriptions that were included on the 303 (d) List for select causes of impairment; however, there could be additional types used for monitoring that were not specified. To capture the variation in the number of impairment causes, an additional field called *unique causes* was created and calculated by counting the number of unique impairment causes for each sub-basin per assessment year. All variables of interest (the percentage of rivers impaired, count of each impairment cause, and number of unique causes) were calculated for each sub-basin and assessment year for a total of 714 observations (51 sub-basins x 14 time-steps).

2.2.3. *Space time cube creation*

STCs are a data structure where a variable is measured across space and time. The data structure can be illustrated as a cube made of space-time bins where the x and y directions represent planar space, and the z direction represents time (Fig. 2B). Bins associated with the same time interval represent a time slice, and bins associated with the same physical location represent a bin time series (Fig. 2B). The concepts that underpin the STC were introduced by Hägerstrand (1970) and have been used to understand spatial and temporal patterns of various phenomena such as COVID-19 (Mo et al., 2020) and crime clusters (Nakaya and Yano, 2010). However, to the authors' knowledge these methods have not been applied to understand impaired water quality patterns. Standard water quality data collection procedures include collection of location and time data allowing for input into a STC. Also, the dynamic nature of water quality data where quality can (and likely does) vary by location and time lends itself well to spatiotemporal analysis. For this analysis, the percentage of rivers impaired, count of each impairment cause, and number of unique causes were spatiotemporally aggregated in a STC using the *Create Space Time Cube From Defined Locations* tool in ArcGIS Pro (Esri, 2024a). Each location was a sub-basin and each time-step was 2-years where each time slice represents one assessment year. Thus, each bin is representative of one sub-basin and assessment year (Fig. 2B).

2.2.4. Space time cube pattern analysis

2.2.4.1. Trends: river impairment and impairment causes. The Mann-Kendall statistic was used to assess the trend in the percentage of rivers impaired and the number of impairment causes from 1996 to 2022 (Kendall, 1948; Mann, 1945). The Mann-Kendall statistic is a rank correlation analysis for the bin value and their time sequence (Esri, 2023a). The Mann-Kendall test statistically assesses if there is a monotonic upward or downward trend of the variable of interest over time. A monotonic upward (downward) trend means that the variable consistently increases (decreases) through time, but the trend may or may not be linear. This test was performed on every location (sub-basin) as an independent bin time series test and indicated whether there was an up trend, down trend, or no trend in the values of the bin time series (Fig. 2C). Results were reported at the sub-basin scale and state scale, where all sub-basins in each time-step are analyzed together as a time series.

2.2.4.2. Emerging Hot Spot Analysis. The *Emerging Hot Spot Analysis* tool (Esri, 2024b) was used to identify patterns in the clustering of values over space and time (Esri, 2023b). First, this tool calculates the Getis Ord Gi* statistic (similar to the *Hot Spot Analysis* tool) for each location. Simply, the Getis Ord Gi* statistic is a measure of spatial autocorrelation and, in this case, describes the intensity of river impairment clustering. The greater the magnitude of the statistic, the more intense the clustering, meaning there are spatial groups of sub-basins with similar values of river impairment. A statistic value of zero indicates no spatial clustering, or there is a random spatial distribution of river impairment. When the local sum is statistically different from the expected local sum the feature had a statistically significant z-score (Esri, 2023c), meaning that impairment was higher in that particular neighborhood of sub-basins versus all others. Local, neighborhood, values are calculated within the spatiotemporal neighborhood, which are defined by the user. Spatial neighborhoods were defined as sub-basins that shared an edge or node (i.e., contiguity edges and corners), and temporal neighborhoods were defined as one time-step (two years). Each spatiotemporal neighborhood value was compared to the percentage of impaired rivers for all sub-basins and assessment years (i.e., the global window was defined as the entire cube). A statistically significant hot spot is a sub-basin that had a relatively high percentage of impaired rivers and was surrounded (spatially and temporally) by sub-basins that also had a relatively high percentage of impaired rivers. Then, the Mann-Kendall statistic was used to analyze the trend in clustering over time; the statistic was applied to the z-scores from the hot spot analysis. Finally, the *Emerging Hot Spot Analysis* tool categories each bin by the resulting z-score and z-score trend into one of 17 categories (Esri, 2023b).

3. Results and discussion

3.1. Impairment trends

There was no trend in river impairment at the state scale, indicating that overall, Alabama's river impairment has not increased or decreased from 1996 to 2022. This demonstrates that Alabama's river quality has remained relatively stable, neither deteriorating nor improving, when investigated at the state scale. However, at the sub-basin scale, significant trends in river impairment were discovered. Eight sub-basins across Alabama had a significant up trend (i.e., an increase in river impairment): Chipola (46), Lower Alabama (1), Lower Coosa (8), Luxapallila (5), Middle Chattahoochee-Walter F (27), Middle Tombigbee-Chickasaw (47), Patsaliga (37), Upper Choctawhatchee (23) (Fig. 3). The Middle Tombigbee-Chickasaw (47) and Patsaliga (37) sub-basins were significant at $\alpha = 0.05$, and all other basins with an up trend were significant at $\alpha = 0.1$. There was one sub-basin with a down trend: the Perdido (10) sub-basin ($\alpha = 0.1$) (Fig. 3). Sub-basins with increasing river impairment should be prioritized for water quality improvement efforts (i.e., TMDL development and implementation) and may warrant further investigation as to why water quality was degrading over time (e.g., increase in pollution sources, unmanaged pollution sources, etc.). Additionally, sub-basins with decreasing river impairment could represent where water quality improvement efforts (e.g., TMDL implementation) were

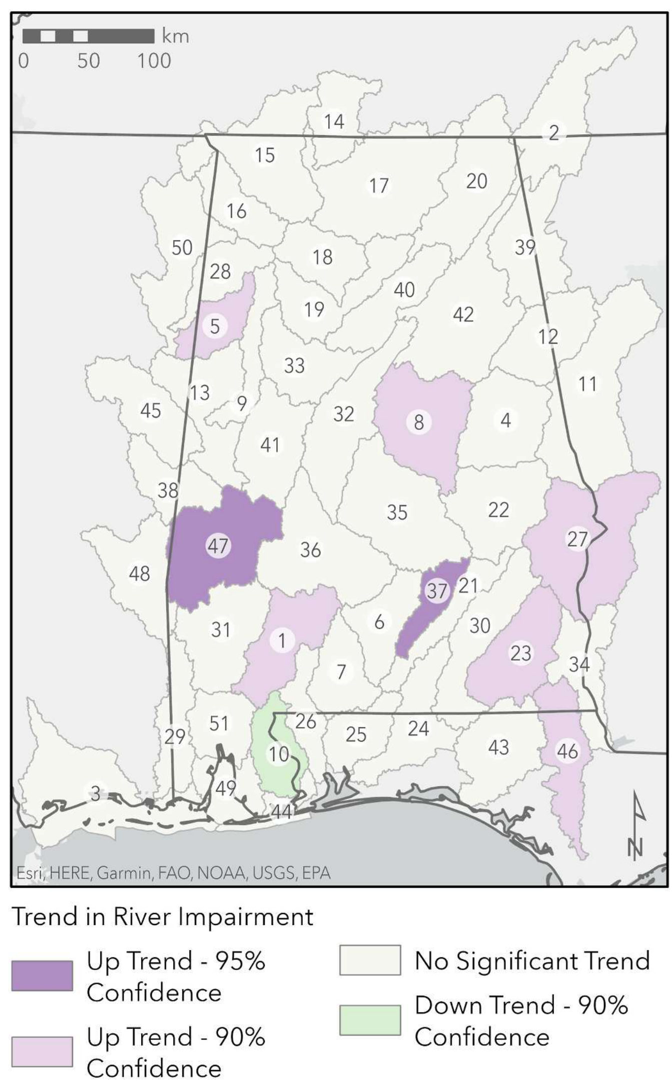

Fig. 3. Trends in the percentage of river length impaired analyzed using the Mann-Kendall trend test for sub-basins hydrologic unit code (HUC) 8 in Alabama. Sub-basins with an up trend are shown in purple and sub-basins with a down trend are shown in green. Darker colors indicate a higher confidence interval in the observed trend. Sub-basin labels correspond to sub-basin IDs in Table 1. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

most effective and could be used as a model of effective water quality improvement strategies. Understanding the cause of these observed trends could be useful to evaluate management efforts.

3.2. Emerging hot spots of impairment

Results of the *Emerging Hot Spot Analysis* revealed that six sub-basins were statistically significant hot spots of river impairment (where impairment was higher than expected), and there were no cold spots of river impairment (where impairment was lower than expected) (Fig. 4). Four sub-basins (Mississippi Coastal (3), Perdido (10), Escambia (26), and Perdido Bay (10)) were consecutive hot spots, meaning sub-basins with a single uninterrupted run of at least two statistically significant hot spot bins in the final time-step intervals (2022 and 2020). Also, these consecutive hot spots were never a statistically significant hot spot prior to the final hot spot run, and less than 90 percent of all bins were statistically significant hot spots. One sub-basin (Escatawpa, 29) was a new hot spot, where impairment was higher in 2022 compared to impairment in all sub-basins and time-steps (i.e., the entire STC). One sub-basin (Mobile Bay, 49) was a sporadic hot spot, meaning impairment was higher than expected in 2022 and periodically a hot spot in the past (less than 90 percent of the time-steps), and none of the time-step intervals were statistically significant cold spots. Hot spots were only found in the coastal region of the state for reasons we can only speculate—this could be due to the rapid development of this area over period of analysis, more sampling in the coastal area, the aggregation of pollutants in the these downstream sub-basins from headwaters (Alexander et al., 2007), or a combination of factors. Insight to the driving cause of the pattern could better equip management entities tailor regulations or remediation efforts.

The *Emerging Hot Spot Analysis* categorizes patterns in a way that emphasizes the presence of a significant hot (or cold) spot in the final time-step; for a location to have a detected pattern from the *Emerging Hot Spot Analysis* and not have a significant hot (or cold) spot in the final time-step, 90 percent or more of the previous hot spots must have been a significant hot (or cold) spot. Therefore, the *Emerging Hot Spot Analysis* results were visualized by the percentage of time-steps with significant hot spots (Fig. 5) to show sub-basins that were hot spots in the past but were not in the final time-step (Fig. 4). Approximately one-third (18/51) of the sub-basins were a hot spot for at least one year. Lower Chattahoochee (34), Chipola (46), and Mobile Bay (49) sub-basins were the

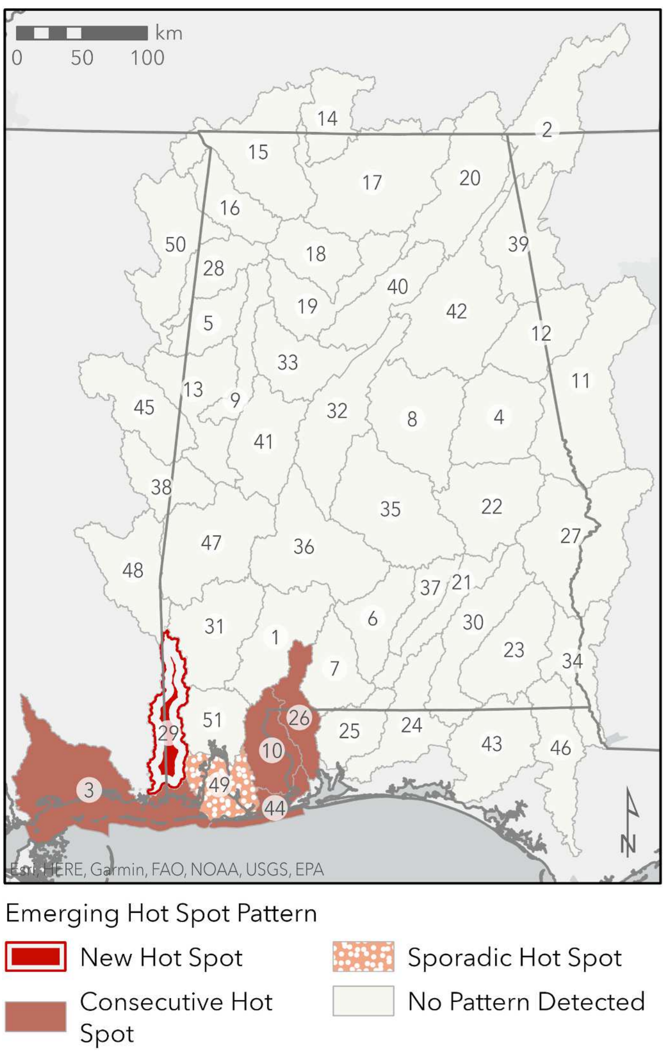

Fig. 4. Emerging hot spots of the percentage of river length impaired for sub-basins, hydrologic unit code (HUC) 8, in Alabama. Consecutive hot spot denotes a sub-basin with a single uninterrupted run of at least two statistically significant hot spot bins in the final time-step intervals (2022 and 2020). A new hot spot indicates where impairment was higher in 2022 compared to impairment in all sub-basins and time-steps (i.e., the entire STC). A sporadic hot spot denotes impairment was higher than expected in 2022 and periodically a hot spot in the past. Sub-basin labels correspond to sub-basin IDs in Table 1.

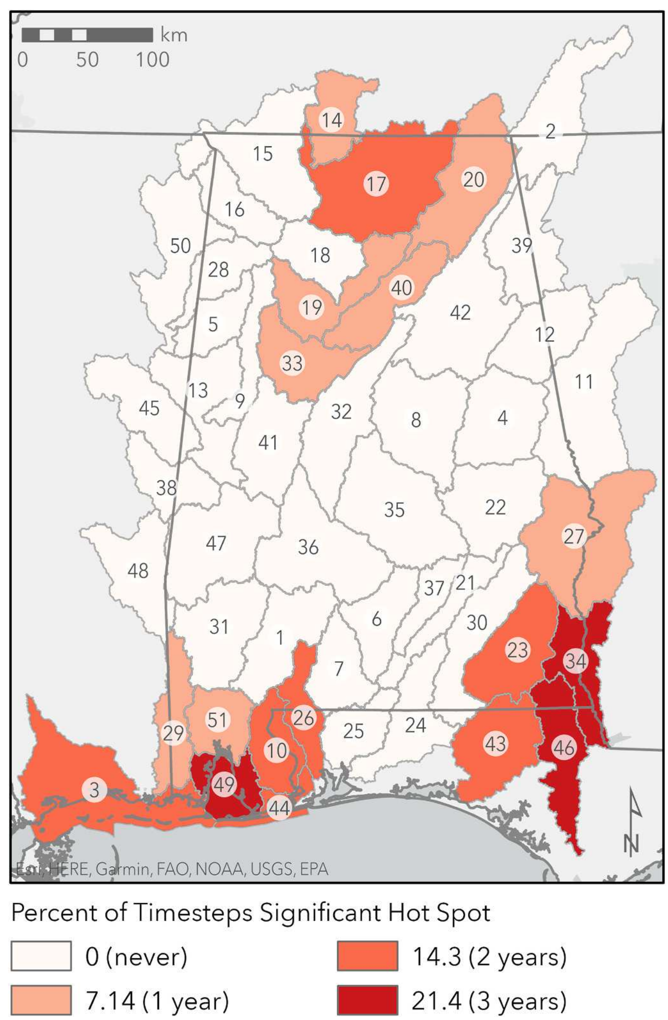

Fig. 5. Percent of the space time cube (STC) generated timesteps that each Alabama sub-basin, hydrologic unit code (HUC) 8, was a significant hot spot of river impairment. Darker red denotes a more frequent hot spot. Sub-basin labels correspond to sub-basin IDs in Table 1. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

most frequent hot spots for 3 time-steps (21.4% of the time-steps) (Fig. 5). There were three groups of hot spots across all time periods: the coast, the central north, and the southeast part of the state. The coastal sub-basins were visible hot spots in Figs. 4 and 5 because they were hot spots in the most recent time-steps. However, the other sub-basins were hot spots in the past and not the most recent time-step, and thus were not classified as a pattern with the *Emerging Hot Spot Analysis* in Fig. 4. This highlights the importance of visualizing spatio-temporal analysis results using different classification schemes, especially if historical patterns are of importance.

The *Emerging Hot Spot Analysis* results also provided the trend in hot spot changes (calculated from the z-score of the Getis Ord Gi* statistic). Fig. 6 shows the trends in the z-score of hot and cold spots (using the Mann-Kendall statistic) for river impairment. No sub-basins had a decreasing trend in the hot spot z-score, indicating a decrease in the hot spot intensity. Twelve sub-basins had an increasing trend in the hot spot analysis z-score, meaning those sub-basins had an increasing hot spot intensity—increasingly deviating from the average global value. In other words, over time, the percentage of impaired rivers has increasingly diverged from the average percentage of river impairment across the state. Interestingly, many sub-basins with a hot spot z-score up trend overlap with the state of Georgia and/or Florida, indicating that

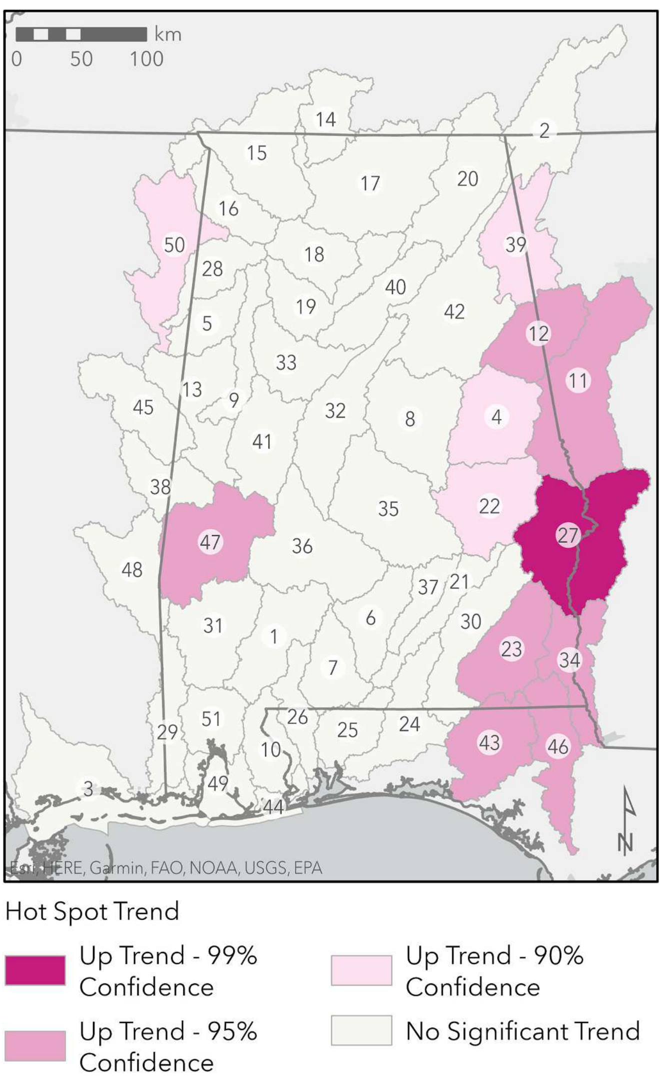

Fig. 6. Trends in hot and cold spots analyzed using the Mann-Kendall trend test on percentage of river length impaired hot spot analysis z-scores for sub-basins hydrologic unit code (HUC) 8 in Alabama. Sub-basin labels correspond to sub-basin IDs in Table 1.

impairment may not be occurring locally, and further solidifying the complexities in water quality management. If the observed trends were to continue, these sub-basins may become hot spots of river impairment, and thus areas of potential concern for water quality managers.

3.3. Causes of impairment trends

3.3.1. State scale

There were 18 unique causes of river impairment on Alabama 303(d) Lists (from 1996 to 2022), and the number of times each impairment cause was listed is presented in Fig. 7. Fig. 7A shows the count of impairment causes to display the magnitude of impairment causes, and Fig. 7B shows the percent of each impairment cause to display the relative proportion of each impairment cause by year more clearly. There are a few observations that can be made from these graphs.

First, 1996 and 1998 had the greatest number of causes of impairment listed (Fig. 7A)because 1996 and 1998 had the highest number of impaired rivers. This initial surge in rivers added to the 303(d) List is because the EPA added many waterbodies to the 303(d) List, which the state is attempting to delist. This stems from the 303(d) assessment being mandated by the EPA in 1998 (Birkeland, 2001), and the data used to list impaired river covers a longer timespan than subsequent assessment years. It is important to the note there is not a one-to-one relationship between the count of impairment causes and count of rivers as one river could have multiple causes of impairment.

Second, there was a decrease in the variation of impairment causes from 1996 to 2022. There was a statistically significant down trend in the count of unique impairment causes.

Third, *metals* was the only cause of impairment that was listed every year, suggesting that metals have been a persistent pollutant to Alabama's rivers. There was not a statistically significant statewide temporal trend for the number of times *metals* was listed as a cause of river impairment, suggesting that there has been consistent metal pollution and no effective remediation.

Fourth, from 2016 to 2022, *pathogens* was the major cause of impairment for Alabama rivers (Fig. 7B; impairment from p*athogens* was greater than 80% of total causes in 2016, 2018, and 2022; and 67% of total causes in 2020). However, this could also be reflective of changes to pathogen WQSs in 2018, where the single grab standard for *E. coli* decreased from 487 cfu/100 mL in 2016 (Alabama Department of Environmental Management, 2016) to 298 cfu/100 mL in 2018 (Alabama Department of Environmental Management, 2018) in waters designated for public water supply and fish and wildlife usage. Though prior to this change in standards, in 2016 most impairment in rivers was caused by *pathogens*.

Lastly, there was a statistically significant down trend in the number of times *ammonia*, *flow alteration*, *nutrients*, *pesticides*, *siltation*, and *unknown* were reported as causes of impairment at the state scale which can be seen in Fig. 7. However, there was no impairment cause with a statistically significant increase in the number of times reported at the state scale indicating that is not an impairment cause(s) that should be focused on statewide.

3.3.2. Sub-basin scale

A trend analysis for the number of impairment causes at the sub-basin scale was completed to understand patterns at a more local scale. Impairment causes with significant trends at the sub-basin scale are shown in Fig. 8. At the sub-basin scale there was a down trend in the number of times *ammonia*, *nutrients*, *siltation*, *OE/DO*, and pH were listed as a cause of impairment (Fig. 8A–D, F). There was an up trend in *pathogens* and *unique causes* (Fig. 8E–G). Comparing the results of the impairment trends (Fig. 3) to trends in the impairment causes (Fig. 8), 5/8 (62.5%) of the sub-basins with an up trend in river impairment also had an up trend in the number of times *pathogens* was reported as a cause of impairment. This suggests that pollution from pathogens was driving trends in impairment but noting that changes to pathogen WQSs in 2018

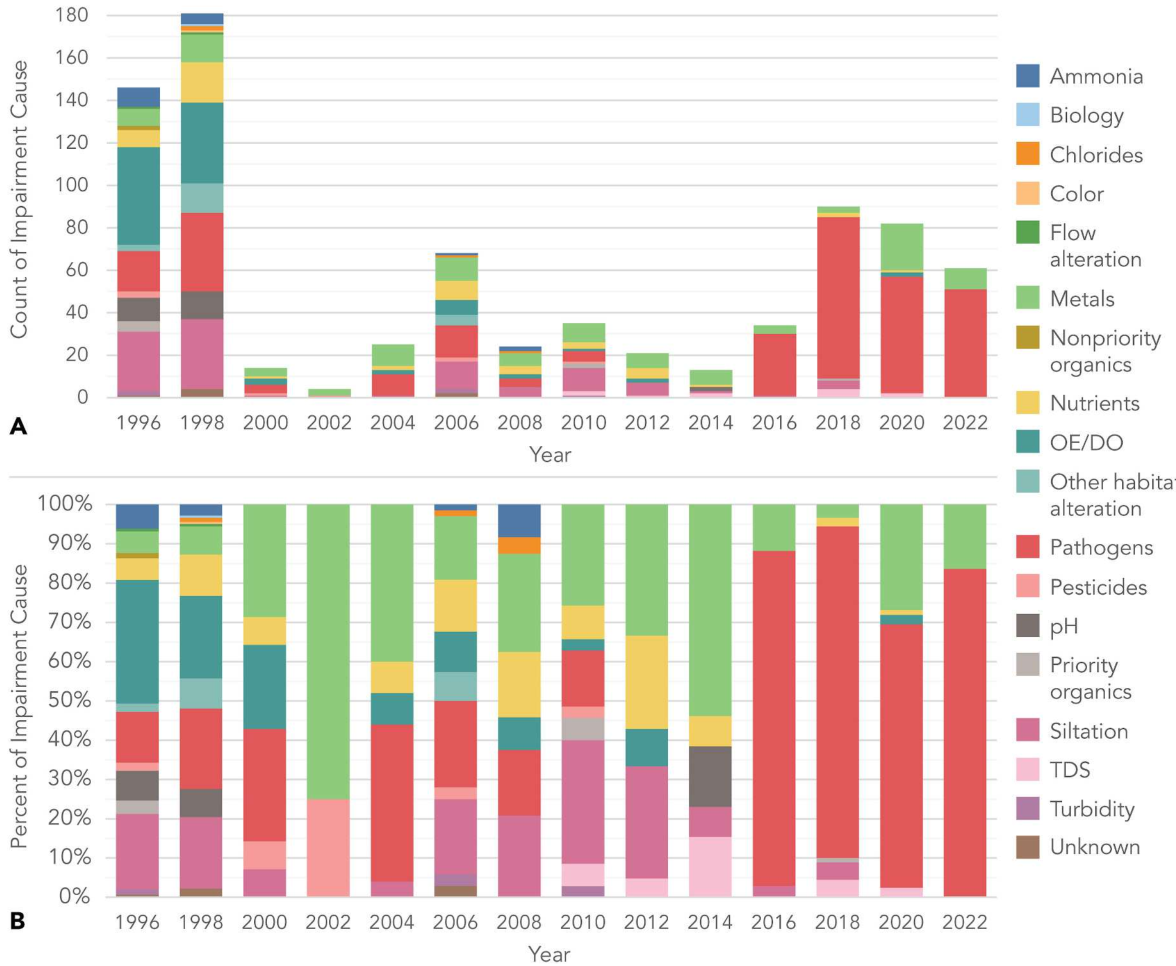

Fig. 7. The number of times each river impairment cause was listed (A) and the percentage each river impairment cause was listed relative to all causes of impairment listed for each assessment year (B) in Alabama. Note: Organic enrichment/dissolved oxygen (OE/DO); total dissolved solids (TDS).

may have affected this observation. Of the sub-basins with an up trend in river impairment, 6/8 (75%) also had an up trend in the number of *unique causes* of impairment. This indicates that where there was an up trend in impairment there was an increase in impairment cause variation.

3.4. Alabama water quality trends in a broader context

Observed water quality trends were similar to trends found in other studies across the U.S. For example, Kuwayama et al. (2020) analyzed the percentage of waters that did not meet water quality ladder thresholds (a commonly-used scale for determining whether waterbodies meet established thresholds for human uses) across the state of Texas and found that from 1990 to 2018 the share of waters that did not meet the thresholds remained constant. Similarly, Keiser and Shapiro (2019) found that nationally in the U.S., the share of waters that were not swimmable or not fishable has remained relatively constant from 1990 to 2001. Here, we found that at the state scale, river impairment remained constant from 1996 to 2022. A decrease in both *ammonia* and *nutrients* was found at the state scale and a decrease in *OE/DO* was found at the sub-basin scale, consistent with nationwide trends in declining point source industrial pollution and improved wastewater treatment plants which may be attributed to the CWA (Keiser and Shapiro, 2019); the CWA largely targeted point sources of pollution such as wastewater treatment plants and industrial pollution sources to improve water quality known to produce ammonia, nutrients, and organic enriched material. Consequently, we surmised that the down trend in *nutrients*, *siltation*, *ammonia*, *OE/DO*, and pH could have occurred as a result of increased regulations on point sources of these pollutants (e.g., improved wastewater treatment plant technology) which, compared to nonpoint sources, are easier to are easier to regulate. However, dissimilar to our results Kuwayama et al. (2020) found that fecal coliform was never a driver of Texas waterbodies' failure to attain designated uses. This does not necessarily indicate that pathogens were not a pollutant of concern in Texas but trends may have been masked by changed in WQSs; Texas WQSs changed from using *E. coli* to *Enterococci* as the fecal indicator (Kuwayama et al., 2020). This highlights the limitations of understanding water quality changes due to changing WQSs. However, elucidating how these changes in WQSs may affect our understanding of water quality is important for effective management.

3.5. Considerations for leveraging impaired waters data to understand water quality variability

To better understand if the trends elucidated in this study are representative of water quality changes, not sampling or reporting changes, the authors discussed the results with ADEM, the state agency responsible for setting WQSs and creating the Alabama 303(d) List. Here we provide further context to the data analyzed. Water quality sampling is generally completed during the growing season, April through October. There is a three-year monitoring rotation, where ADEM focuses on a particular area for that assessment period (Alabama Department of Environmental Management, 2023b). However, monitoring is also completed outside of the targeted monitoring areas. Data from

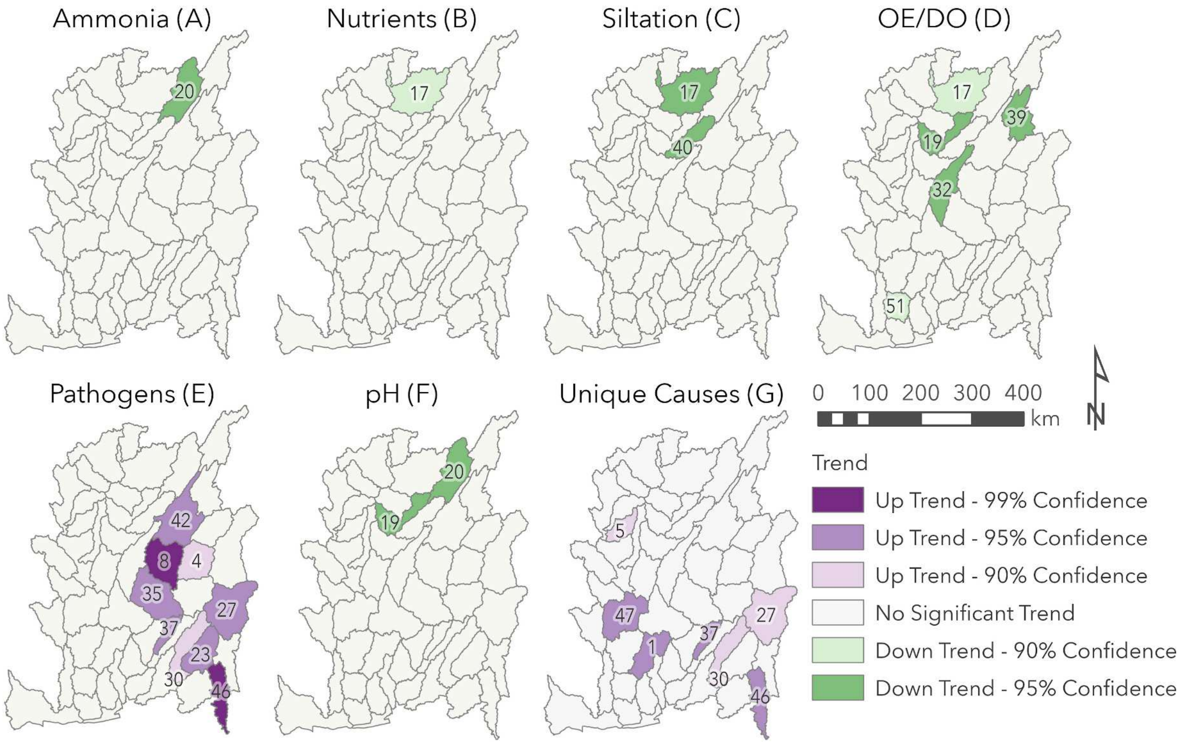

Fig. 8. Significant trends in the count of impairment causes within Alabama sub-basins hydrologic unit code (HUC) 8 using the Mann-Kendall trend test. Sub-basins with an up trend are shown in purple and sub-basins with a down trend are shown in green. A darker color indicates a higher confidence in the observed trend. Sub-basin labels correspond to sub-basin IDs in Table 1. Note: Organic enrichment/dissolved oxygen (OE/DO). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

independent water quality campaigns (e.g., Alabama Water Watch) are used to identify where ADEM needs to conduct additional sampling for the next assessment period, but those data are not directly used to list waters as impaired. ADEM confirmed that all impairment causes—except for *biology*, *color*, *non-priority organics*, and *unknown*—have been used to define impaired waters throughout the analysis period. Thus, the authors maintain that patterns revealed by this analysis are reflective of water quality changes but acknowledge that this method of assessing water quality patterns is subject to bias from changes in monitoring and impairment listing protocol. In future analyses, data on assessed water could be used to increase the accuracy of percentage of rivers impaired, and this data could be used to further explore if there is a sampling bias. Aside from gleaning water quality patterns from the analysis, assessing patterns of river impairment through the lens of the management entity (i.e., ADEM) allows for review of the state's monitoring efforts. For this analysis, Alabama was used as a case study to develop the framework, but it could be utilized by other states or management entities.

3.6. Environmental management applications: case study

To illustrate how these analyses can come together to tell a story of water quality changes over time we will highlight the Perdido sub-basin (10), an area that has been the focus of restoration and preservation efforts (Specker, 2022) and showed statistical significant results in many of the statistical tests conducted (Figs. 3–5). The Perdido sub-basin is in southeast coastal Alabama and the western panhandle of Florida, situated between Baldwin County, Alabama and Pensacola, Florida which are quickly growing. Government agencies at the state and federal levels and non-profits came together to acquire land along the Perdido River and its tributaries for conservation (RESTORE Council, 2022). As a result of this nearly 20 year effort, the Perdido River is a rare coastal waterway where preservation has outpaced development (Specker, 2022). These conservation efforts were reflected in the finding that Perdido had a down trend in river impairment. However, it was also a consecutive hot spot (i.e., had higher impairment in 2022 and 2020 compared to all sub-basins and assessment years). This reveals that the percentage of rivers impaired decreased over time, but river impairment in Perdido was still relatively higher in 2020 and 2022 compared to the average amount of river impairment for the analysis period. Although, there were no trends for impairment causes in the Perdido sub-basin (Fig. 8). However, after discussion of the results with ADEM they suggested splitting the *metals* impairment cause into the individual metals monitored and test for a trend in mercury as an impairment cause. There was a down trend in the number of times mercury was listed as a cause of impairment from 2000 to 2022 in the Perdido sub-basin—the analysis only extended to 2000 because the 1996 and 1998 lists did not specify the type of metal that caused the impairment for all rivers impaired by metals. No other sub-basins had a trend in the number of times mercury was listed as a cause of impairment. Altogether, this highlights how spatiotemporal analysis provides a new perspective on existing data, and helps to generate new questions to understand how, when, and where water quality changes.

4. Conclusions

The spatiotemporal analysis of water quality is complex due to the dynamic nature of water and water quality data, but here we presented a new perspective to analyze water quality trends by compiling Alabama impaired rivers data from 1996 to 2022 using spatiotemporal and statistical methods. Specifically, this framework is useful for uncovering obscured patterns that can inform water quality management decisions. We have summarized several main takeaways from this analysis that can be used to inform water quality management.

1. Generally, river water quality in Alabama has remained relatively static from 1996 to 2022. However, water quality patterns change with the scale of analysis. Also, an increase in river impairment often coincided with an increase in river impaired by pathogens or an increase in the variation of pollutants causing impairment.
2. Coastal sub-basins have more impaired rivers compared to the rest of the state. Considering the importance of recreational activity and the population increase in this area, mitigating and remediating river impairment in coastal rivers should be prioritized. As evidenced by the decrease in river impairment in the Perdido sub-basin, concerted efforts to manage pollution can produce improved water quality.
3. Ammonia, nutrients, and siltation river impairment causes have effectively been reduced at both scales of analysis. Further investigation as to how and why the state has achieved this reduction would be valuable as curbing nutrient pollution is a priority for many waters.
4. *Metals* is a persistent cause of river impairment from 1996 to 2022. State mitigation and remediation efforts should be prioritized for *metals.*

Future research that compares water quality trends using alterative metrics (i.e., water quality indices or selected water quality parameters) to impaired water patterns would be valuable to understand how using different water datasets effects our understanding of water quality patterns or where there may be potential limitations in impaired waters data. Furthermore, the use of a STC to spatiotemporally assess water quality changes could be utilized by other research to better integrate a spatial component of assessing water quality patterns. It could be insightful to investigate how impairment patterns compare between states (or other management entities) to elucidate how specific water management practices may affect water quality. Ultimately, the framework presented here could aid management entities in uncovering water quality patterns to evaluate historical and current management practices.

CRediT authorship contribution statement

Mallory A. Jordan: Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Stephanie R. Rogers:** Writing – review & editing, Supervision, Software, Resources, Project administration, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Mallory Jordan reports financial support was provided by US Department of Agriculture (USDA). If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

The authors wish to acknowledge the Alabama Department of Environmental Management (ADEM), specifically Jennifer Halsbauer, for providing context to the results of this study. We acknowledge partial funding support from the USDA (TAT-RWTS 00–69526) and Auburn University's Presidential Graduate Research Fellowship.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2024.120983.

References

Alabama Department of Environmental Management, 2023a. Alabama department of environmental management, 303(d) Information and Map [WWW Document]. https://adem.alabama.gov/programs/water/303d.cnt, 12.7.23.
Alabama Department of Environmental Management, 2023b. Surface water quality monitoring program [WWW Document]. URL. https://adem.alabama.gov/programs/water/wqsurvey/SWQMP.pdf, 10.30.23.
Alabama Department of Environmental Management, 2022. Alabama's water quality assessment and listing methodology [WWW Document]. URL. https://adem.alabama.gov/programs/water/wquality/2022WAM.pdf.
Alabama Department of Environmental Management, 2018. Alabama's water quality assessment and listing methodology [WWW Document]. URL. https://adem.alabama.gov/programs/water/wquality/2018WAM.pdf.
Alabama Department of Environmental Management, 2016. Alabama's water quality assessment and listing methodology [WWW Document]. URL. https://adem.alabama.gov/programs/water/wquality/2016WAM.pdf.
Alabama Water Watch, 2023. America's Amazon poster – 2023 update [WWW Document]. URL. https://awwblog.auburn.edu/2023/01/27/americasamazonposter/. (Accessed 12 December 2023).
Alexander, R.B., Boyer, E.W., Smith, R.A., Schwarz, G.E., Moore, R.B., 2007. The role of headwater streams in downstream water quality. J. Am. Water Resour. Assoc. 43, 41–59. https://doi.org/10.1111/j.1752-1688.2007.00005.x.
Birkeland, S., 2001. EPA's TMDL Program. Ecol. Law Q. 28, 297–325. https://www.jstor.org/stable/24114128.
Brown, R.M., McClelland, N.I., Deininger, R.A., Tozer, R.G., 1970. A water quality index-do we dare. Water and Sewage Works 117.
Chang, H., 2008. Spatial analysis of water quality trends in the Han River basin, South Korea. Water Res. 42, 3285–3304. https://doi.org/10.1016/j.watres.2008.04.006.
Clean Water Act, 2018. 33 U.S.C. § 1251 et. seq.,, pp. 328–425.
Esri, 2024a. Create space time cube from defined locations (space time pattern mining)—ArcGIS Pro | documentation [WWW Document]. URL. https://pro.arcgis.com/en/pro-app/3.1/tool-reference/space-time-pattern-mining/createcubefromdefinedlocations.htm, 3.22.24.
Esri, 2024b. Emerging hot spot analysis (space time pattern mining)—ArcGIS Pro | documentation [WWW Document]. URL. https://pro.arcgis.com/en/pro-app/3.1/tool-reference/space-time-pattern-mining/emerginghotspots.htm, 3.22.24.
Esri, 2023a. How create space time cube works—ArcGIS Pro | documentation [WWW Document]. URL. https://pro.arcgis.com/en/pro-app/latest/tool-reference/space-time-pattern-mining/learnmorecreatecube.htm.
Esri, 2023b. How emerging hot spot analysis works—ArcGIS Pro | documentation [WWW Document]. URL. https://pro.arcgis.com/en/pro-app/latest/tool-reference/space-time-pattern-mining/learnmoreemerging.htm, 9.29.23.
Esri, 2023c. How hot spot analysis (Getis-Ord Gi*) works—ArcGIS Pro | documentation [WWW Document]. URL. https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-statistics/h-how-hot-spot-analysis-getis-ord-gi-spatial-stati.htm.
Geological Survey of Alabama, 2023. Ecosystems Investigations Program [WWW Document]. Geological Survey of Alabama. URL. https://www.gsa.state.al.us/gsa/ecosystems, 10.25.23.
Hägerstrand, T., 1970. What about people in regional science? Pap. Reg. Sci. Assoc. Reg. Sci. Assoc. Meet. 24, 6–21. https://doi.org/10.1007/BF01936872.
Keiser, D.A., Shapiro, J.S., 2019. Consequences of the clean water act and the demand for water quality. Q. J. Econ. 134, 349–396. https://doi.org/10.1093/qje/qjy019.
Kendall, M.G., 1948. Rank correlation methods. Rank Correlation Methods. Griffin, Oxford, England.
Khan, F., Husain, T., Lumb, A., 2003. Water quality evaluation and trend analysis in selected watersheds of the atlantic region of Canada. Environ. Monit. Assess. 88, 221–248. https://doi.org/10.1023/A:1025573108513.
Kuwayama, Y., Olmstead, S.M., Wietelman, D.C., Zheng, J., 2020. Trends in nutrient-related pollution as a source of potential water quality damages: a case study of Texas, USA. Sci. Total Environ. 724, 137962 https://doi.org/10.1016/j.scitotenv.2020.137962.
Mann, H.B., 1945. Nonparametric tests against trend. Econometrica 13, 245–259. https://doi.org/10.2307/1907187.
Mo, C., Tan, D., Mai, T., Bei, C., Qin, J., Pang, W., Zhang, Z., 2020. An analysis of spatiotemporal pattern for COIVD-19 in China based on space-time cube. J. Med. Virol. 92, 1587–1595. https://doi.org/10.1002/jmv.25834.
Nakaya, T., Yano, K., 2010. Visualising crime clusters in a space-time cube: an exploratory data-analysis approach using space-time kernel density estimation and scan statistics. Trans. GIS 14, 223–239. https://doi.org/10.1111/j.1467-9671.2010.01194.x.
Oelsner, G.P., Sprague, L.A., Murphy, J.C., Zuellig, R.E., Johnson, H.M., Ryberg, K.R., Falcone, J.A., Stets, E.G., Vecchia, A.V., Riskin, M.L., 2017. Water-quality Trends in the Nation's Rivers and Streams, 1972–2012—Data Preparation, Statistical Methods, and Trend Results.
RESTORE Council, 2022. RESTORE Council visits ADCNR land acquisition as the Council prepares to update its comprehensive plan for restoration | restore the gulf [WWW Document]. URL. https://www.restorethegulf.gov/release/2022/05/31/restore-council-visits-adcnr-land-acquisition-council-prepares-update-its, 1.12.24.

Shoda, M.E., Sprague, L.A., Murphy, J.C., Riskin, M.L., 2019. Water-quality trends in U.S. rivers, 2002 to 2012: relations to levels of concern. Sci. Total Environ. 650, 2314–2324. https://doi.org/10.1016/j.scitotenv.2018.09.377.
Smith, R.A., Alexander, R.B., Wolman, M.G., 1987. Water-quality trends in the Nation's rivers. Science 235, 1607–1615. https://doi.org/10.1126/science.235.4796.1607.
Specker, L., 2022. 'Lost' and found: the saving of the Perdido River [WWW Document]. al. URL. https://www.al.com/life/2022/01/lost-and-found-the-saving-of-the-perdido-river.html, 10.30.23.
Sun, W., Xia, C., Xu, M., Guo, J., Sun, G., 2016. Application of modified water quality indices as indicators to assess the spatial and temporal trends of water quality in the Dongjiang River. Ecol. Indicat. 66, 306–312. https://doi.org/10.1016/j.ecolind.2016.01.054.
United Nations-Water, 2021. Summary Progress Update 2021: SDG 6 — water and sanitation for all [WWW Document]. UN-Water. URL. https://www.unwater.org/publications/summary-progress-update-2021-sdg-6-water-and-sanitation-all, 10.25.23.
U.S. Environmental Protection Agency, 2017. National water quality inventory: report to congress [WWW Document]. URL. https://www.epa.gov/waterdata/2017-national-water-quality-inventory-report-congress.
U.S. Geological Survey, 2023. USGS national hydrography dataset best resolution (NHD) - Alabama (published 20230109). FileGDB.