



A Review of Recent Water Quality Assessments in Watersheds of Southeastern United States using Continuous Time Models

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Abstract

Water quality is an indicator of the health and safety of the environment which is subjected to natural and human-induced changes. Although a considerable amount of research has been done to explain the different factors affecting water quality and the various approaches to predict spatiotemporal water quality factors, there are several challenges in the water quality modeling scenarios. The article revisits the water quality assessments conducted in the watersheds of southeastern United States using continuous time models with the aid of statistical analysis, remote sensing, theoretical models, and bigdata based approaches. The review illuminates that the need of the hour is the inclusion of novel prediction methods, quick access to updated and right water quality data, arriving at usable factors to improve prediction reliability, exploring combined conceptual methods of analysis, and collecting more field reference data that can benchmark the developed water quality models.

Keywords: Water quality; Continuous models; Remote sensing; Southeastern United States; Nutrients; Climate change; Machine learning

Abbreviations: GIS - Geographical Information System; SWIM - Surface Water Improvement and Management; SWAT - Soil and Water Assessment Tool; MIKE SHE - Integrated Hydrological Modelling System; IDW - inverse distance weight; GRACE - Gravity Recovery and Climate Experiment; MODIS - Moderate-resolution Imaging Spectroradiometer

Introduction

The natural and anthropogenic environment plays a critical role in balancing the water cycle [1]. The changes in the environment have impacted the quality [2] and quantity [3] of the water resources, leading to degraded watershed systems. Water quality is recognized as one main indicator of the health and safety of the environment which is subjected to natural and human-induced changes. Various factors have affected water quality and human health throughout many watersheds and major river basins in the southeastern United States. Many studies found that the main hydrological responses of surface runoff, streamflow, and ground

water levels that affect water quality are projected to decline over the next 30 – 50 years in river basins encompassing regions of intense agricultural activity, thus exacerbating water quality problems in the United States [4].

Factors affecting water quality

The main factors that affect the health and quality of these watersheds and basins include the presence of dissolved compounds in the water, landscapes, climate change, urbanization, agricultural activity, and laws and regulations limiting surface and ground water use. Another factor crucially contributing to varying water quality

is nutrient concentrations including nitrogen, phosphorus, carbon, and organic compounds primarily caused by irrigation. High agricultural activity deteriorates the water quality mainly using fertilizers and chemicals causing the decline of available surface and ground water resources. The southeastern United States has experienced climate change that occurred due to the increase in carbon dioxide emissions in the atmosphere resulting in the increased incidence of snow, flooding, and droughts. [5] gives an example of what a drought can do to the downstream and upstream water users throughout the region. Lake Lanier, the main source of drinking water to the Atlanta metro region, which also feeds the Chattahoochee River and supplies water to the states of Alabama and Florida has increased the rate of ground water abstraction in the past two decades which eventually reduced the water quality in the region. Additionally, climate change and land use land cover changes can simultaneously affect streamflow and baseflow in different ways resulting in declined quality of water. Studies that used process-based continuous time models such as GIS, SWIM, SWAT, FEFLOW, MODFLOW, and MIKE SHE showed that a decrease in streamflow was influenced more strongly by climate change while land use land cover changes impacted the baseflow [6]. The most negative water quality impacts were predicted by continuous time models such as SWAT and MIKE SHE under the combined effects of land use and climate change with notable increases in deforestation [7].

Spatial and temporal water quality trends

Few studies demonstrated the importance of environmental vulnerability in catalyzing the space and time-wise water quality impacts of coastal and water-bound regions in the Southeastern United States. A study put forward the patterns of hydrologic consequences of converting natural forested wetlands to pine plantations in the southern United States at different years of observation. These kinds of literature helped bring the importance of space and time wise predictions of several water quality parameters which can directly affect the freshwater demand, ground water pumping and total water use on a regional extent [8]. Numerous studies indicated a strong association between seasons of the year and variation in management practices of specific land covers which crucially affect the land cover specific water quality evaluation [9-11]. [12] found that the periods between rainy seasons are expected to alter the water lands in addition to the noticeable changes caused in vegetative and agricultural areas. In contrast, [13] showed that both summer and spring seasons were active modifiers of land covers as well as vegetation indices. Therefore, the temporal conditions of the water quality assessments are significant for improved spatial representation of the land management and vegetation scenarios for each subunit of the watersheds [14,15]. For these evaluations, various studies adopted multiple statistical approaches including the IDW method for spatial interpolation and mapping of the factors and indices affecting soil erosion loss and water quality [16,17]. Such methods are mainly employed to obtain comprehensive geospatial maps. They can generate even the spatial attributes of cloud points and null data values from the dynamic data variables in subunits of watersheds [18,19]. The

IDW method holds well for medium-sized and small watersheds if the data source that go into the modeling process have defined minimum and maximum ranges and are evenly distributed within the watershed [20-22]. These data could be used to estimate and geospatially map the water quality parameters derived from the traditional or modified time step models. On the other hand, parametric and non-parametric tests have been widely employed to detect time-series trends annually, seasonally, monthly, and daily for various constituents of water quality [23,24]. The continuous models which are based on historical data, simulated data, as well as surveyed data, have advantages and disadvantages. Hence, trend detection tests must be employed for accurate trend detection of the estimated water quality factors to check their temporal reliability.

Data needs for water quality predictions

Many shreds of studies implemented a unified approach connecting hydrogeological continuous time step models and progressively updated data from remote sensing to improve the water quality predictions directly or indirectly. [25] found a significant reduction in water storage throughout Alabama and Mississippi by using GRACE satellites. This reduction in water storage arose with an increase in ground water irrigation during this period. Such studies emphasized the gaps in the existing surface water regulations that pave way for regions to heavily rely on ground water in one or more states of the United States [26]. Similarly, studies utilized satellite data, hydrologic models, and climate projections together to determine the potential water table changes throughout various wetlands in the southeastern United States for evaluating future water demands and supplies [27]. They predicted that the future changes in precipitation and evapotranspiration would alter the wetlands and ground water quality in the study region significantly. Recently, studies have attempted to analyze spatial and temporal trends of various constituents affecting water quality for the southeastern United States by introducing bigdata based systems such as machine learning, artificial intelligence, and fuzzy logic-based methodologies in conventional modeling tools. Such study outcomes elevated the range with which water quality predictions occur [28].

By reinvestigating the existing literature in the field, this review report develops an understanding of the recent spatial and temporal water quality assessments conducted in the watersheds of the southeastern United States comprehensively using continuous time models. In addition, the review depicts the challenges associated with the current research and the changes needed in research methodology for advancing water quality predictions in watersheds that can be implemented by hydrologic modelers.

Discussions

The implementation of the dynamic and novel factors in water quality modeling including soil moisture content, atmospheric deposition, vegetation indices, and solar radiation, notably enhanced the closeness between the predicted estimates of sediment yields and nutrient loading in watersheds of the Southeast United States compared to the available true measurements through sampling and surveying [29,30]. The findings from the comprehensive review

indicated that the combined application of non-traditional water quality models and online data sources powerfully represented the sediment yield estimates both for the whole watershed and for the spatial subunits in the watersheds. This finding is corroborated by the studies of [31,32]. Hence expanding the avenues of water quality data and its implementation can elevate the water quality predictions in the conventional hydrologic models that work on continuous time steps. The results also emphasized more efficacy of soil erosion loss estimates and irrigation demand fluctuations when all the satellite remotely sensed dynamic variables are used in the continuous time model algorithms [33]. It was evidenced that some of the studies used data with different spatial and temporal resolutions to develop water quality models. Despite the different spatial resolution of the various remotely sensed variables of the studies ranging from 30 m to 2000 m in pixel wise spatial resolution (LandSat, MODIS), around 59% of the studies could demonstrate an advancement from the existing water quality predictions using continuous time models [34].

Challenges in water quality predictions

The differences between the model predictions and real measurements of various constituents of water quality in the spatial and temporal extents in the watersheds can be attributed to the modeling techniques, interpolation methods, and real hydrogeological conditions involved in the study areas. They also included the ambiguity in the space-wise trends from the IDW technique when interpreting different factors from multiple data sources, which were employed in models for watershed scales. Additionally, the dynamic modification that was subjected to the existing models of water quality is not all-inclusive. The unexplored factors affecting water quality directly or indirectly including surface-ground interactions, bacterial activity, and contaminant transport might improve the precision and reliability of their spatiotemporal estimates in watersheds [35-37].

Conclusion

As shown in the current review, several indicators can and should be used to determine water quality in watersheds of the Southeastern United States. Using one factor/one analysis method/one mode of data collection contributing to water quality to predict the real water quality of water bodies and their space and time wise trends may produce ambiguities in the watershed scale outcomes. Hence the water quality modeling process is complex which demands for a variety of interrelated indicators that will closely represent the actual conditions of the water body. The article reviews the water quality assessments conducted in the watersheds of southeastern United States using continuous time models and with the aid of statistical analysis, remote sensing, theoretical models, and bigdata based approaches. The review puts forward the following points to improve water quality assessments realistically:

- Successful inclusion of novel prediction methods to estimate water quality factors of sediments and nutrients
- Quick access to updated and right water quality data that can be fed into continuous time models

- Arrive at usable factors based on the climate, land use land cover, topography, and soil characteristics of the watershed to improve the reliability of water quality predictions
- Explore combined conceptual methods of analysis in the conventional water quality models
- Extensive collection of field and experimental reference data that can benchmark the developed water quality models

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Conflicts of Interest

The authors declare no competing interests.

References

1. Ashraf Z Al-Hamdan, Pooja P Preetha, Mohammad Z Al-Hamdan, William L Crosson, Reem N Albashaireh (2018) Reconnoitering the linkage between cardiovascular disease mortality and long-term exposures to outdoor environmental factors in the USA using remotely sensed data. *Journal of Environmental Science and Health* 53(9): 809-818.
2. Naveen Joseph, Pooja P Preetha, Balaji Narasimhan (2021) Assessment of environmental flow requirements using a coupled surface water-groundwater model and a flow health tool: A case study of Son River in the Ganga basin. *Ecological Indicators* 121.
3. Preetha PP Joseph N, Narasimhan B (2021) Quantifying Surface Water and Groundwater Interactions using a Coupled SWAT_FEM Model. Implications of Management Practices on Hydrological Processes in Irrigated River Basins. *Water Resour Manage* 35: 2781-2797.
4. Al-Hamdan AZ, Preetha PP, Albashaireh RN, Mohammad Z Al-Hamdan, William L Crosson (2018) Investigating the effects of environmental factors on autism spectrum disorder in the USA using remotely sensed data. *Environ Sci Pollut Res* 25(8): 7924-7936.
5. Manuel John (2008) Drought in the Southeast Lessons for Water Management. National Institute of Environmental Health Sciences U.S. Department of Health and Human Services.
6. Rodger Kirk (2020) An Analysis of Streamflow Trends in the Southern and Southeastern US from 1950-2015. MDPI Multidisciplinary Digital Publishing Institute.
7. Suttles Kelly M, Nitin K Singh, James M Vose, Katherine L Martin, Ryan E Emanuel, et al. (2018) Assessment of Hydrologic Vulnerability to Urbanization and Climate Change in a Rapidly Changing Watershed in the Southeast U.S. *Science of The Total Environment*, Elsevier 645: 806-816.
8. Aguilos Maricar et al(2021) Effects of Land Use Change and Drought on Decadal Evapotranspiration and Water Balance of ...” *Agricultural and Forest Meteorology*.
9. Huq N Bruns A Ribbe L (2019) Interactions between freshwater ecosystem services and land cover changes in southern Bangladesh A perspective from short-term (seasonal) and long-term (1973-2014) scale. *Sci Total Environ* 650-1:132-143.
10. Preetha PP Al-Hamdan AZ Anderson MD (2021) Assessment of climate variability and short-term land use land cover change effects on water quality of Cahaba river basin. *Int J Hydrol Sci Technol* 11: 54-75.
11. Preetha PP Shirani-bidabadi N Al-Hamdan AZ (2021)A Methodical Assessment of Floodplains in Mixed Land Covers Encompassing Bridges in Alabama State: Implications of Spatial Land Cover Characteristics on Flood Vulnerability. *Water Resour Manage* 35: 1603-1618.
12. Gaertner BA, Zegre N Warner T Fernandez R He Y Merriam ER (2019) Climate forest growing season and evap-otranspiration changes in the central Appalachian Mountains, USA. *Sci Total Environ* 650: 1371-1381.

13. Piedallu C, Chéret V, Denux JP, Perez V, Azcona JS, Seynave I, Gégou JC (2019) Soil and climate differently impact NDVI patterns according to the season and the stand type. *Sci Total Environ* 651-2: 2874-2885.
14. Chu H, Venevsky S, Wu C, Wang M (2019) NDVI-based vegetation dynamics and its response to climate changes at Amur-Heilongjiang River Basin from 1982 to 2015. *Sci Total Environ* 650: 2051-2062.
15. Preetha PP, Al-Hamdan AZ (2020) Developing Nitrate-Nitrogen Transport Models using Remotely-Sensed Geospatial Data of Soil Moisture Profiles and Wet Depositions. *J Environ Sci Health Part A* 55: 615-628.
16. Ferro V, Giordano G, Iovino M (2009) Isoerosivity and erosion risk map for Sicily. *Hydrol Sci J* 36(6): 549-564.
17. Panagos P, Ballabio C, Borrelli P (2015) Rainfall erosivity in Europe. *Sci Total Environ* 511: 801-814.
18. Xin Z, Yu X, Li Q, Lu XX (2010) Spatiotemporal variation in rainfall erosivity on the Chinese Loess Plateau during the period 1956-2008. *Reg Environ Chang* 11: 149-159.
19. Huang J, Zhang J, Zhang Z, Xu CY (2013) Spatial and temporal variations in rainfall erosivity during 1960-2005 in the Yangtze River basin. *Stoch Env Res Risk A* 27: 337-351.
20. Risal A, Rabin Bhattarai, Donghyuk Kum, Youn Shik Park, Jae E Yang, et al. (2016) Application of Web Erosivity Module (WERM) for estimation of annual and monthly R factor in Korea. *Catena* 147: 225-237.
21. Sadeghi SHR, Singh JK, Das G (2004) Efficacy of annual soil erosion models for storm-wise sediment prediction: A case study. *Int Agric Eng J* 13: 1-14.
22. Preetha PP, Al-Hamdan AZ (2022) A Union of Dynamic Hydrological Modeling and Satellite Remotely-Sensed Data for Spatiotemporal Assessment of Sediment Yields. *Remote Sens* 14: 400.
23. Onoz B, Bayazit M (2012) Block bootstrap for Mann-Kendall trend test of serially dependent data. *Hydrol Process* 26: 3552-3560.
24. Yue S, Wang C (2004) The Mann-Kendall test modified by effective sample size to detect trend in serially correlated hydrological series. *Water Resour. Manag.* 18: 201-218.
25. Engström, Johanna, et al. (2021) Decreasing Water Resources in Southeastern U.S. as Observed by the Grace Satellites. *Water Policy*, IWA Publishing.
26. Zhu, Jie, et al. (2017) Modeling the Potential Impacts of Climate Change on the Water Table ... *Dukespace*.
27. Preetha PP, Al-Hamdan AZ (2020) Integrating finite-element-model and remote-sensing data into SWAT to estimate transit times of nitrate in groundwater. *Hydrogeol J* 2(6): 2187-2205.
28. Sahoo S, Russo T, Elliott J, Foster I (2017) Machine learning algorithms for modeling groundwater level changes in agricultural regions of the US. *Water Resources Research* 53(5): 3878-3895.
29. Preetha PP, Al-Hamdan AZ (2019) Multi-level pedotransfer modification functions of the USLE-K factor for annual soil erodibility estimation of mixed landscapes. *Model Earth Syst Environ* 5: 767-779.
30. Preetha PP, Al-Hamdan AZ (2022) Synergy of remotely sensed data in spatiotemporal dynamic modeling of the crop and cover management factor. *Pedosphere* 32(3): 381-392.
31. Almagro A, Thomé TC, Colman CB, Pereira RB, Marcato Junior J, et al. (2019) Improving cover and management factor (C-factor) estimation using remote sensing approaches for tropical regions. *Int Soil Water Conserv Res* 7(4): 325-334.
32. Anache JAA, Bacchi CGV, Panachuki E, Sobrinho TA (2016) Assessment of Methods for Predicting Soil Erodibility in Soil Loss Modeling. *Geociências (São Paulo)* 34: 32-40.
33. Gitas IZ, Douros K, Minakou C, Silleos GN, Karydas CG (2007) Multi-temporal soil erosion risk assessment in N. Chalkidiki using a modified USLE raster model. *EARSeL eProc* 8: 40-52.
34. Waldhoff G, Lussem U, Bareth G (2017) Multi-data approach for remote sensing-based regional crop rotation map-ping: a case study for the Rur catchment, Germany. *Int J Appl Earth Obs* 61: 55-69.
35. Pham TG, Degener J, Kappas M (2018) Integrated universal soil loss equation (USLE) and geographical information system (GIS) for soil erosion estimation in a sap basin; Central Vietnam. *ISWCR* 6(2): 99-110.
36. James F Cruise, Ashutosh S Limaye, Nassim Al-Abed (1999) ASSESSMENT OF IMPACTS OF CLIMATE CHANGE ON WATER QUALITY IN THE SOUTHEASTERN UNITED STATES. *Wiley Online Library* 35(6): 1539-1550.
37. Suttles Kelly M, Nitin K Singh, James M Vose, Katherine L Martin, Ryan E Emanuel, et al. (2018) Assessment of Hydrologic Vulnerability to Urbanization and Climate Change in a Rapidly Changing Watershed in the Southeast U.S. *Science of The Total Environment*, Elsevier 645: 806-816.