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Research article

Composite measures of watershed health from a water quality perspective

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ABSTRACT

Water quality data at gaging stations are typically compared with established federal, state, or local water quality standards to determine if violations (concentrations of specific constituents falling outside acceptable limits) have occurred. Based on the frequency and severity of water quality violations, risk metrics such as reliability, resilience, and vulnerability (R-R-V) are computed for assessing water quality-based watershed health. In this study, a modified methodology for computing R-R-V measures is presented, and a new composite watershed health index is proposed. Risk-based assessments for different water quality parameters are carried out using identified national sampling stations within the Upper Mississippi River Basin, the Maumee River Basin, and the Ohio River Basin. The distributional properties of risk measures with respect to water quality parameters are reported. Scaling behaviors of risk measures using stream order, specifically for the watershed health (WH) index, suggest that WH values increased with stream order for suspended sediment concentration, nitrogen, and orthophosphate in the Upper Mississippi River Basin. Spatial distribution of risk measures enable identification of locations exhibiting poor watershed health with respect to the chosen numerical standard, and the role of land use characteristics within the watershed.

1. Introduction

Clean drinking water is not only essential for human health, good water quality is important for avoiding coastal eutrophication and ocean acidification, and for maintaining healthy riverine, marine, and coastal ecosystems which is one of the 17 goals of United Nation's Sustainable Development Goals 2015–2030. Risk-based assessments have been used by water resources planners for characterizing reservoirs (Hashimoto et al., 1982; Moy et al., 1986; Vogel and Bolognese, 1995; Jain and Bhunya, 2008) and urban-water distribution networks (Mondal et al., 2010). Risk analyses have also been popularly used in water quality assessment (Maier et al., 2001; Hoque et al., 2012, 2013, 2014, 2016), evaluating the impact of climate change on water resources systems (Asefa et al., 2014; Fowler et al., 2003; Mondal and Wasimi, 2007), hydrological impact of rain water harvesting systems (Glendenning and Vervoort, 2011) and for drought characterization (Maity et al., 2012). The risk measures that are commonly computed in most risk analyses are reliability, resilience and vulnerability (R-R-V). Reliability is the probability that the system is in compliance at a given time with respect to user specified water quality standard; resilience is defined as the probability of the system to recover to a compliant state given that it was non-compliant the previous time step; and vulnerability is a measure of the average severity of damage during a non-compliant event. While reliability and resilience have probabilistic definitions, vulnerability is often used to quantify the average magnitude of damage caused during a failed (or catastrophic) event. As a result, previously used vulnerability measures have not been comparable to reliability and resilience. In this study we introduce an objective framework for computing a vulnerability metric in water quality risk assessment that is dimensionless and ranges between zero to one. Though the proposed definition is not truly a probability measure, it nevertheless has distributional properties. We also propose a composite water quality-based watershed health measure that describes the overall health of the watershed with respect to any chosen water quality constituent. By definition, the composite watershed health measure also scales between zero and one, with one indicating a very healthy watershed and vice-versa.

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Since risk measures are computed at USGS stations located along the stream network, they may follow scaling laws. Scaling laws have been a popular topic in watershed hydrology. Specifically, Horton's scaling laws (Horton, 1945) provided valuable insights into the hierarchical organizational structure of stream networks within watersheds. These laws also provided an understanding on how the physical properties of streams (e.g. flow characteristics, slope, etc.) would change as a function of spatial scale. Building on this, Strahler (1952, 1957) and Shreve (1966) popularized the concept of stream orders where numbers are assigned to stream reaches based on their hierarchies. Streams that are farthest from the watershed outlet have lowest stream orders, and those that are closest to the outlet have higher stream orders. While some researchers have highlighted the limitations of stream orders and proposed modifications (Peckham and Gupta, 1999; Gangodagamage et al., 2011), others have proposed alternative approaches to scaling analysis (Rigon et al., 1996; Betz et al., 2010; Zaliapin et al., 2010; Gangodagamage et al., 2011). Because of its simplicity, stream order continues to be used in many scaling studies (King et al., 2005; Vondracek et al., 2005; Hoque et al., 2014). For example, Hoque et al. (2014) investigated the scaling behavior of watershed risk measures over four study watersheds in the U.S. Midwest using the Soil & Water Assessment Tool (SWAT) and two scaling measures − contributing upland area and stream order. Their study focused on finding the effective stream order threshold that would yield stable risk measures; however, additional research is needed using measured streamflow data across large river basins.

In this study we investigated scaling laws using actual streamflow measurements within large river basins. Stream order and drainage density were considered as candidate scaling measures. Drainage density is defined as the ratio of total length of streams within a drainage basin divided by the total drainage area; i.e. it provides a measure of how well existing streams drain a basin. We specifically ask the following questions: What are the distributional properties of these risk measures, and are the means of these risk measures similar at stations of the same stream order or those that have the same drainage density? Do risk measures of reliability, resilience and newly-defined vulnerability increase (or decrease) as we move downstream (lower stream order to higher stream order) or how are they related to different values of drainage density, i.e. do they follow popular scaling laws within large river systems?

We further investigate the spatial distribution of risk measures over large river basins as a prelude to identifying potential source areas. We relate the spatial distribution of risk measures with dominant land use type of each drainage area. Such a comparison allows us to identify land use categories that influence risk measures for different water quality parameters. Mann-Kendall trend test and Sen's slope (Kendall, 1948; Sen, 1968; Hirsch, 1982; Hamed and Ramachandra Rao, 1998) are used to identify influences that are statistically significant. These insights can serve as a useful guide for watershed risk assessment and for implementing useful management plans.

2. Study area

The Upper Mississippi River Basin (UMRB), the Ohio River Basin (ORB), and the Maumee River Basin (MRB) were chosen as the study area. The states within the UMRB study area include Minnesota (MN), Wisconsin (WI), Iowa (IA), Illinois (IL), and parts of Missouri (MO). The UMRB has dominant agricultural land use (64%) and drains into Gulf of Mexico. The ORB is spread over states of Indiana (IN), Ohio (OH), Kentucky (KY), and parts of Illinois (IL), Tennessee (TN), Pennsylvania (PA), West Virginia (WV), and New York (NY). It has dominant forest land use (46%) followed by agricultural land use (44%) and drains into the Mississippi River and ultimately into the Gulf of Mexico. Due to intensive agricultural activities that involve application of fertilizers, both UMRB and ORB are considered to be among the primary sources of nutrients that reach the Gulf and cause eutrophication (Burkart and James, 1999; Alexander et al., 2008). The MRB is the largest Great Lakes watershed, draining all or parts of 17 Ohio (OH) counties, two Michigan (MI) counties and five Indiana (IN) counties into Maumee Bay and then to Lake Erie just east of Toledo, Ohio. The MRB is agriculturally intensive (53%) and the nutrients that get washed off from this river basin cause algal blooms in Lake Erie during the summer months (Michalak et al., 2013).

A total of 214 USGS stations (Fig. 1) - 57 stations in UMRB, 99 stations in ORB, and 58 stations in MRB with available water quality (WQ) data were identified over the study area. The U. S. Geological Survey (USGS, http://waterdata.usgs.gov/nwis/rt) daily streamflow dataset was utilized. In general, streamflow data are subjected to human interference, and therefore data contain both natural and regulated flows. Only unregulated stations were included in this study.

The U. S. Geological Survey (USGS, goo.gl/K1Th9D) daily water quality dataset and the USGS National Water Quality Assessment (NAWQA, goo.gl/Wq5dYi) data warehouse were used to collect chemical, biological and physical water quality data for the study area where available. We have a total of 151 stations with Suspended Sediment Concentration data (parameter code 80154), 70 stations with Nitrate + Nitrite data (parameter code 00631), and 49 stations with Orthophosphate data (parameter code 00671). These parameters were chosen based on the number of sampling stations with minimum 30 observations over the study period (1966 to current depending on data availability). The threshold of 30 observations was chosen to ensure a statistically robust model during reconstruction of the WQ time series.

3. Methodology

While daily continuous records of streamflow data were available over the study area, water quality data are discontinuous in time. Using the data reconstruction method proposed in Hoque et al. (2012) water quality data at all stations were reconstructed as a function of daily streamflow measurements available at those stations using relevance vector machines (RVM; Bishop, 2006; Schölkopf and Smola, 2002; Tipping, 2001). Let X_t be the daily reconstructed time series of a water quality parameter with standard numerical target X^*. We then define compliance (S) and noncompliance states (F) as:

$S : \{X_t \le X^*\}$ is compliance state ($X_t > X^*$, e.g., for Dissolved Oxygen)
$F : \{X_t > X^*\}$ is noncompliance state ($X_t \le X^*$, e.g., for Dissolved Oxygen)

A compliance event is one where the reconstructed water quality data is below (or above in case of Dissolved Oxygen or DO) the standard numerical target for one or more successive days, and is noncompliant otherwise. Then using the definitions of risk measures given by Hashimoto et al. (1982) and Hoque et al. (2012), reliability (p) is defined as the probability of the system to be in compliant state. Mathematically it can be written as

$$p = 1 - P\{X_t \in F\} = 1 - \frac{1}{n}\sum_{t=1}^{n} z_t \tag{1}$$

where $z_t = 1$ when $X_t \in F$ and 0 when $X_t \in S$, and n is the total number of data points.

Similarly, resilience (r) is defined as the probability of the system to recover from a non-compliance state and can be mathematically written as below: