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Resilience changes in watershed systems: A new perspective to quantify long-term hydrological shifts under perturbations

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SUMMARY

Natural hydrological regimes are essential to the stability of river basins. While numerous efforts have been put forth to characterize flow regime alterations driven by climate change and human activities, few approaches have been proposed to explore changes in watershed resilience. The present study attempted to introduce a systematic approach that can be used to identify the resilience change of river basins based on annual river discharge through the application of a convex model and the principle of critical slowing down. Specifically, a resilience indicator (p_i) that reflects streamflow autocorrelation at a given time was proposed to represent the temporal variation of the system resilience, and annual water discharge at representative hydrological stations located in upstream, midstream, and downstream regions of a river basin was used to reflect alterations in long-term hydrological processes and the stability of river basins. The application of this method to the Yellow River basin and Yangtze River basin indicated that the system resilience was lower in downstream regions compared to upstream regions. The Yellow River basin has suffered a decrease in resilience in its lower reaches since 1971, which extended to the middle reaches in 1987 and upper reaches in 1990. Similarly, recent observation of the resilience change in the Yangtze River basin indicated that resilience in its lower reaches has likely decreased since 2002, and this low resilience extended to the middle reaches in 2005. Overall, our study presents a new method to predict potential decreases of resilience in complex large scale watershed systems where mechanistic insight is insufficient to build reliable basin-scale hydrological, climate, ecosystem integrated models.

1. Introduction

At the global scale, watersheds are now suffering from severe perturbations due to both climate change and anthropogenic disturbances, and notable examples include the Amazon basin and the Mississippi River basin (Davidson et al., 2012; Kidder, 2006; Levine et al., 2016; Liu and Zheng, 2002). In the Amazon basin, which is the location of the world's largest rainforest, unprecedented deforestation has caused a series of changes at the local and regional scales that have involved alterations in energy and water cycles (Davidson et al., 2012). As a representative of the capacity of a watershed to absorb and recover from perturbations or disturbances (Folke et al., 2010; Hoque et al., 2012; Randhir, 2014; Wilson and Browning, 2012), watershed resilience and associated transitions in watershed systems has becomes a critical topic in river basin conservation and management (Davidson et al., 2012). In order to understand the vulnerability and resilience of river basins in the face of change, numerous studies have strived to improve knowledge of the linkages between natural variability, drivers of change, ecosystem responses, and feedbacks within a watershed system or its subsystems; these studies have employed both tendency analysis of perturbations and watershed structure (Costa et al., 2003; Zhang et al., 2014a; Zhao et al., 2015a) and process-based model simulations (Coe et al., 2002, 2011; Hu et al., 2015; Levine et al., 2016). For example, Nemec et al. (2014) calculated watershed resilience with nine watershed structure properties, i.e. ecological variability, diversity, modularity, acknowledgement of slow variables, tight feedbacks, social capital, innovation, overlap in governance, and ecosystem services. Hirota et al. (2011) recognized forest, savanna, and treeless state as three distinct attractors and empirically reconstructed the basin of attraction through analyzing the response of the global tree abundance pattern to precipitation. Levine et al. (2016) predicted the stability of the Amazon rainforest to climate change with coupled vegetation–climate models. Furthermore, Cosens and Williams (2012) analyzed resilience mechanisms in the Amudarya River basin through an agent-based model.

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The problems are that (1) while existing statistical analyses based on temporal variation tendency of hydrological sequences, climate sequences, and other anthropogenic events are able to quantify the hydrological alteration and its main contributors, and are also direct, efficient, and scale flexible. Yet they have much limitation in deducing necessary information on the vulnerability and resilience change of river basins over time; (2) process-based modeling approaches including hydrological models, climate change models, and ecological models, which typically have more clear structural relationships between each segment within the model, are promising for detecting resilience change, however, use of these model is associated with tradeoffs between structural complexity and outcome uncertainties due to the coarse or even incomplete representations of inner processes (Lewis et al., 2011; Malhi et al., 2009; Marengo, 2004; Marengo et al., 2008; Rammig et al., 2010). This shortcoming may enlarge the uncertainty of a simulated outcome and estimated tipping points when combining climate change, hydrological responses, and ecological feedbacks into one integrated model even if this is technically feasible. We believe that with progress in modeling, the uncertainties can be narrowed by elucidating a process-level understanding of key relationships (Clark et al., 2015, 2016; Fatichi et al., 2016), but we wonder if before that, there might be another way that can shed some light on how basin resilience responds and if the river basin is under transition.

As a phenomenon that connects diverse ecosystems, human activities, and atmospheric processes within a watershed, the water cycle is not only crucial in maintaining watershed health, but it is also vulnerable to climate change and excessive human activity (Milly et al., 2008; Ouyang et al., 2009; Sun and Feng, 2013; Xu et al., 2007; Zhao et al., 2012). Consequently, long-term river flow regimes (streamflow) are acknowledged to be the accumulated representation of the upstream hydrological cycle and thus are widely used to reflect the disturbance suffered by the upstream subcatchments (Belmar et al., 2013; Yang et al., 2008; Zhang et al., 2014b, 2015). In addition, with the acknowledgement of the complexity of watershed systems, preliminary attempts have been made to study hydrological systems with the application of complex network theory, and this had shed light on how best to employ systematic angles to study the connections and complexities of hydrological networks through spatiotemporal correlations of flow regimes (Jha et al., 2015; Sivakumar and Woldemeskel, 2015).

The present study explores the usefulness of systematic theory for studying the stability and resilience of watershed systems that are naturally and anthropogenic disturbed. To this end, critical slowing down theory was introduced and we then proposed a resilience indicator (p_i) to quantify the temporal variation in the resilience of a watershed system based on a convex model and critical slowing down features. Consequently, we applied the p_i indicator to the Yellow River and Yangtze River basins to identify differences in the resilience trends between the river basins with different functions. The spatial and temporal variations in the resilience of each river basin was analyzed with the supplementation of background information on the perturbations that they experienced. This study provides an attempt to study watershed resilience. The reliable identification of watershed resilience alterations is important because such data can indicate the development orientation of a watershed, and if need be, the results can be sent as alarm signals to local water resource management organizations.

2. Methodology

2.1. Background

To describe the stability and resilience of complex systems, researchers have used conceptual models with the resilience intuitively expressed as the stability fate of a ball in a landscape of hills and valleys, which are also known as attraction basins (Fig. 1a and b) (Dakos et al., 2010; Peterson et al., 1998).

Recent theoretical work has suggested that a critical slowing down, as measured by the increased autocorrelation of a state variable (Fig. 1e and f), can be a generic leading indicator of low resilience and an early warning signal for critical transitions, even when mechanistic insight is insufficient for reliable predictive models (Dakos et al., 2010, 2012b; Scheffer et al., 2009). This critical slowing down means that a system state variable will recover slowly from small perturbations in the vicinity of bifurcation points between two adjacent attraction basins (Fig. 1c and d). Such critical slowing down has been observed across an array of complex dynamic systems, such as those pertaining to ecosystems (Dakos and Bascompte, 2014; Dakos et al., 2010, 2012a; Wouters et al., 2015) climate (Dakos et al., 2008; Lenton, 2011; Lenton et al., 2012), medicine (Meisel et al., 2015; Trefois et al., 2015), and social-financial markets (Tan and Cheong, 2014).

2.2. Indicator of system resilience based on a convex model

Since a system state variable recovers slowly from small perturbations near the transition between two adjacent attraction basins, for the same observation frequency, more intermediate data, which are neglected in a high resilience state, can be recorded in a low resilience system (black points in Fig. 1c and d). Based on the convex model for a time-variant variable from Jiang et al. (2014), we built a convex set to show this calculation (Fig. 1e and f). For each $X(t) \sim X(t+\tau)$, $\tau \in 2, \ldots, n$, most points were located around a centerline with a slope of 1 (dashed line in Fig. 1e and f), which constituted a set of $\Omega(X \mid i, \tau)$. The deviation of a point from the centerline was positively correlated with the difference between $x_{i+\tau}$ and x_i. To quantify the neighboring points that deviated too much from x_i (red points in Fig. 1e and f), a convex set boundary was set (red lines in Fig. 1e and f).[1] Finally, the i and $i+\tau$ value for each outlier (x_i, $x_{i+\tau}$) in each $X(t) \sim X(t+\tau)$ were counted and stored in a variable named *Count*.

The resilience of the system at time i was reflected by the differences in x_i and its neighboring points $\{x_{i-n}, \cdots, x_{i-2}, x_{i-1}, x_{i+1}, x_{i+2}, \cdots, x_{i+n}\}, n \in N^*$, and $2n$ was the number of neighboring points considered. Larger differences corresponded to a higher resilience. Thus, we proposed an indicator p_i to count the number of adjacent points with a strong deviation from x_i, and this value reflects the resilience of a system at time i. The calculation proceeded as follows:

$$D_i = \{x_{i-n}, \cdots, x_{i-2}, x_{i-1}, x_{i+1}, x_{i+2}, \cdots, x_{i+n}\}, n \in N^* \tag{1}$$

and for $x_j \in D_i$,

$$f_{i,j} = \begin{cases} 1 & |x_i - x_j| \geqslant \varepsilon \\ 0 & |x_i - x_j| < \varepsilon \end{cases}, \varepsilon = 0.5\lambda(X_{\max} - X_{\min}) \tag{2}$$

$$p_i = \sum_{j=i-n}^{j=i+n} f_{i,j} \tag{3}$$

where ε is the threshold that determines if x_j deviates too much from x_i. $X_{\max}$ and $X_{\min}$ are the maximum and minimum of the state variable X, respectively. $\lambda \in (0,1)$ and the value of λ directly define the boundary of the convex set: $\lambda = 0$ corresponds to an empty set and $\lambda = 1$ corresponds to the largest convex set that includes all observation points inside. Here, we set $\lambda = 0.75$, which means the area of the convex set was equal to 75% of the area of the largest

[1] For interpretation of color in Fig. 1, the reader is referred to the web version of this article.