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Research papers

Incorporating a trend analysis of large flow perturbations into stochastic modeling of particle transport in open channel flow

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ABSTRACT

In extreme flow conditions, both the flow carrying capacity and movement of particles may abruptly change from those associated with regular flows. This study investigates movement of sediment particles in response to extreme flow events using a Lagrangian stochastic jump diffusion particle tracking model (SJD-PTM). The study attempts to investigate the frequency change of extreme flow event occurrences and its impact on suspended sediment particle movement. Using the concept of logistic regression, the trend magnitude of extreme flow events can be used as an input of the proposed stochastic jump diffusion particle tracking model with Logistic regression (SJ-PTM_LR) to account for the potential effects of environmental change. The predicted frequency change of extreme flows from available data in the Chijiawan region in central Taiwan is illustrated in this study. Both ensemble mean and variance of particle trajectory can be quantified under such predicted frequency trend change of extreme flow occurrences via simulations of SJ-PTM_LR. Results show that particle movement uncertainty may undergo a significant increase by taking the effect of the predicted flow frequency trend into consideration. Such probabilistic outcome provides a valuable means for assessing the probability of failure (i.e., risk) resulting from sedimentation processes.

1. Introduction

Suspended sediment concentrations are typically estimated using either the advection-diffusion equation or sediment rating curves in a deterministic manner. Models based on mass balance have been commonly adopted (e.g., Tsujimoto et al., 1994; Nicholas and Walling, 1997; Middelkoop and Van der Perk, 1998; Fang and Wang, 2000). Use of empirical relationships with other variables (e.g., stream discharge) derived from measurements such as sediment rating curves (e.g., Olive et al., 1980; Walling and Webb, 1981; VanSickle and Beschta, 1983; Lemke, 1990; Kurashige, 1993, 1998) is frequently used. More recently, particle-based approaches for estimating mass concentrations or concentrations of soil particles in a tidal estuary or air flow (e.g., Heemink, 1990; Hunter et al., 1993; Harris and Davidson, 2009; Ancey, 2010). Man and Tsai (2007) proposed a stochastic differential equation for the movement of sediment particles with an advection-diffusion equation to quantify the statistical characteristics of sediment concentrations. And more recently, Oh et al. (2015) proposed a stochastic approach for quantifying the probabilistic characteristics of sediment concentrations that can account for the uncertainty associated with flow randomness.

Modeling of suspended sediment particle movement in surface water can be achieved by stochastic particle tracking model (PTM) approaches. In PTM approaches, particle movement is mainly subject to the mean drift flow as well as flow turbulence. In addition to the mean drift flow and randomness found in turbulence, particle movement is augmented by the presence of extreme flow events or large flow perturbations. Consequently, in recent years, increased attention has been paid to the change in occurrence frequencies of these events. In extreme flow conditions, both the flow carrying capacity and movement of the particles change from those found in normal flow conditions. In this study, we define large flow perturbations as extreme flow events that have a probability of occurrence less than 10%.

Interest in identifying trends in extreme flow events and the associated potential for severe and adverse impacts on human life, civil infrastructure, and ecosystems as well as other far-reaching socioeconomic consequences has recently increased (Frei and Schär, 2001). When observing long term records of extreme events such as temperature, precipitation or flow discharge, one might identify trends in the frequency that are indicative of changes in environment such as land cover change and climate change.

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Moreover, extreme flow induced sediment transport can accelerate geomorphologic change and severely intensify local erosion and deposition. Therefore, the relationship between the stochastic features of hydrologic events and sediment transport modeling has also gained higher awareness (Man and Tsai, 2007; Oh and Tsai, 2010).

Many researchers have shown that the increase of extreme events may be attributed to environmental change, such as climate change and land cover change. Zwiers and Kharin (1998) pointed out that climate change may have a significant impact on the frequency and magnitude of extreme events. Birsan et al. (2005) identified significant trends in occurrences in both space and time, and addressed the relationship between the observed change in streamflow, temperature and precipitation. As stated by the Intergovernmental Panel on Climate Change (IPCC), confidence has increased that "some weather events and extremes will become more frequent, widespread or intense during the 21st century" (Solomon, 2007). On the other hand, changes of occurrence frequency of extreme flow events may also be attributed to the changes in land use or land cover. Schilling et al. (2014) proposed quantitative data to analyze the relationship between downstream flood risks and different land uses for the large, intensely agricultural. Dornblaser and Striegl (2009) stated that the above factors have the potential to alter future suspended sediment loads.

It is found that many environmental factors may lead to changes in the frequency of extreme events, which may also play an important role in sediment transport. Consequently, if the trend in extreme events is not taken into account in future infrastructure, then such changes or variability can lead to underestimation/over estimation of design parameters for water infrastructure, and increase the likelihood of water shortages, water stresses, and agricultural failures (Şen, 2011). Using trend analysis as a means to examine long-term changes in heavy precipitation events, Frei and Schär (2001) concluded that this change of frequency is not reflected in mean values. Based on historical long-term records, trend analyses provided an insight into the tendency in magnitude and frequency of hydrologic extreme events during the last several decades. Francipane et al. (2015) stressed that the hydrologic and geomorphic responses of watersheds to changes in climate are increasingly needed. Therefore, more efforts are needed to develop a PTM that accounts for the trends in extreme events that drive sediment transport processes.

As an application of this trend assessment methodology, this study aims to investigate sediment transport and long-term changes in extreme flow event frequency, both in large and small timescales, augmented by environmental change. The event frequencies, also called counting events, are determined from historical records, and then linked to a logistic regression model. In the logistic regression model, the count records are used to estimate the trends of the frequency of extreme flow events. The proposed statistical model is based on an estimation of past occurrences of extreme flow events as opposed to most other methods which tend to focus on the intensity of the extreme flow events or the time series of the extreme quantities such as Hilbert-Huang Transform (HHT) (Huang et al., 1998). This study analyzes frequency trends of large flow perturbations from historical records from the Chijiawan region in central Taiwan. Thus, by incorporating a trend analysis, the jump term in PTM can explicitly account for sediment transport due to extreme flow events and their associated changes in frequency.

In this paper, the introduction is followed by the methodologies which consist of logistic regression and particle tracking models. The stochastic jump diffusion particle tracking model is used to simulate the sediment particle trajectory. Regarded as the input of the SJD-PTM, the logistic regression model is applied to determine the trend magnitude. The third section describes the setting of the simulations of flow events of different time scales. In addition, the selection of the time step and the computational procedure is provided. Results and discussions are presented following the simulations. Finally, summaries and conclusions are drawn.

2. Methodologies

In this paper, we present a conceptual framework for linking the stochastic jump diffusion particle tracking model and the logistic regression model to describe sediment transport affected by changes in the frequency of extreme flow events or large flow perturbations.

2.1. Particle tracking model

In recent years, researchers have become increasingly interested in individual particle transport using the particle tracking models (PTMs). Over last few decades, Lagrangian approaches in simulating the movement of fluid particles have been used in the field of fluid mechanics. For instance, physics of turbulent flows can be described by using the mathematical properties of the Langevin equation, which is a sample stochastic model and a prototype of the stochastic differential equation (SDE). Sawford and Borgas (1994) and Pope (1994) attempted to model fluid particle properties, including particle position and velocity, in turbulent flows. The Langevin equation has also been adopted in particle tracking models to delineate particle properties, including particle velocity and position (Pope, 1994; Sawford and Borgas, 1994; Spivakovskaya et al., 2005; Man and Tsai, 2007; Oh and Tsai, 2010).

2.1.1. Governing equation of SJD-PTM

The stochastic jump diffusion particle tracking model (SJD-PTM), introduced by Oh and Tsai (2010) and Tsai et al. (2014), addressed the movement of particles in surface flows subject to a sequence of random occurrences of extreme flow events. The stochastic jump diffusion particle tracking model (SJD-PTM) is governed by the stochastic differential equation (SDE), Eq. (1). There are three main terms in Eq. (1) including a mean drift motion term, a Wiener process representing random turbulent motion, and a Poisson process describing the abrupt movement of particles caused by probabilistic occurrences of the extreme flow perturbations

$$d\mathbf{X}_t = \underbrace{\bar{\mathbf{u}}(t,\mathbf{X}_t)}_{\text{drift term}} + \underbrace{\boldsymbol{\sigma}(t,\mathbf{X}_t)d\mathbf{B_t}}_{\text{random term}} + \underbrace{\mathbf{h}(t,\mathbf{X}_t)d\mathbf{P_t}}_{\text{jump term}} \tag{1}$$

where $\boldsymbol{X}_t = \{x(t), y(t), z(t)\}^T$ represents the trajectory of a particle, and $\mathbf{h}$ is a jump amplification factor. Parameters $\bar{\mathbf{u}}$, $\boldsymbol{\sigma}$, which are all continuous functions corresponding to sediment transport, are comparable to the stochastic diffusion process. Based on the relationship between the Fokker-Planck equation and the advection-diffusion equation, Man and Tsai (2007) expressed the drift term $\bar{\mathbf{u}}$ as follows:

$$\bar{\mathbf{u}}(t,\boldsymbol{X}_t) = \overline{\boldsymbol{U}} + \nabla\mathbf{D} = \begin{cases} \overline{U}(t,x,y,z) + \partial D_x/\partial x \\ \overline{V}(t,x,y,z) + \partial D_y/\partial y \\ \overline{W}(t,x,y,z) - w_s + \partial D_z/\partial z \end{cases}$$

where $\overline{U}$, $\overline{V}$ and $\overline{W}$ are the mean drift fluid velocities at $\boldsymbol{X}_t$ in time t in the streamwise, transverse and vertical directions, respectively. D_x, D_y and D_z are defined as the turbulent diffusivity in the x, y and z direction, respectively. Herein, the diffusion coefficient tensor $\boldsymbol{\sigma}$ is

$$\boldsymbol{\sigma}(t,\boldsymbol{X}_t) = \begin{bmatrix} \sigma_{xx} & 0 & 0 \\ 0 & \sigma_{yy} & 0 \\ 0 & 0 & \sigma_{zz} \end{bmatrix}$$