Advancements in predicting bank erosion processes with the Bank Stability and Toe Erosion Model (BSTEM)

Michael Ursic, Civil Engineer, USDA ARS National Sedimentation Laboratory, Oxford, MS, mick.ursic@usda.gov
Eddy Langendoen, Research Hydraulic Engineer, USDA ARS National Sedimentation Laboratory, Oxford, MS, eddy.langendoen@usda.gov

Abstract

Modeling bank erosion is problematic not only because of limiting process assumptions but also constraints associated with assigning discrete values for controlling variables. Often, repeated in-situ tests will result in a range of potential values for a given parameter which can make it difficult on the modeler to determine the appropriate input. To account for the variability associated with testing, and potential spatial and temporal variability, the dynamic version of the Bank Stability and Toe Erosion Model (BSTEM) has been updated to include stochastic predictions using Monte Carlo analyses. Values for bank profile parameters used to determine fluvial erosion rates and resistance to bank failure can be generated using a variety of stochastic distributions. The ability to vary parameters within known ranges provides the user with quantified confidence in BSTEM results. The new BSTEM improvements and capabilities were demonstrated by assessing the retreat of a bank with a simple, bi-linear profile.

Introduction

BSTEM is designed to perform quasi-two-dimensional modeling of hydraulic and geotechnical erosional forces to simulate bank retreat at a given location with respect to time. The modeling is accomplished by the core bank failure and fluvial erosion algorithms. The bank erosion routines simulate potential planar and cantilever failures using the analyses of horizontal layers of Simon et al. (2000) and Thorne and Tovey (1981), respectively. Fluvial erosion routines are based on steady, uniform, clear-water flow assumptions where the shear stress is distributed along the bank profile as a function of the partitioned, local hydraulic radius. BSTEM iterates between the fluvial and bank failure routines through the simulation period, where forces change with time, to determine a resultant bank profile. The resultant profile can be used by river managers to determine bank stabilization or protection scenarios.

In addition to the core capabilities of BSTEM, there are numerous options that increase the usability of the model. For instance, the eroding bank can be modeled with up to five distinct bank layers with the option to supply user defined grain size distributions and general soil characteristics such as unit weight, friction angle, and effective cohesion for each layer (Simon et al. 2000). The vertical distribution of pore-water pressure, an important control on bank stability, is updated dynamically based on the relative elevations of the free water and phreatic surfaces. Moreover, cohesion due to root systems can be estimated and automatically applied utilizing the RipRoot routine developed by Pollen and Simon (2005). RipRoot has incorporated data from over twenty vegetation species, including willows, grasses, and large trees, or the user may enter their own data. Additionally, increased resistance to erosion from geotextiles or riprap can be simulated in BSTEM.

More recently, advancements of BSTEM include the option to conduct Monte Carlo analyses by varying model input parameters providing the user with a probabilistic estimate of bank profile predictions. Bank material parameters used to determine fluvial erosion rates and resistance to bank failure can be generated using a variety of stochastic distributions. Having the ability to vary parameters within a known range provides the user with quantified confidence in BSTEM results.

Stochastic Model Description

Probabilistic BSTEM results are generated by use of Monte Carlo analyses which runs model sets with a prescribed range of input parameters associated with bank stability and resistance to erosion properties. The parameters that can be varied are saturated unit weight, cohesion, friction angle, suction angle, critical shear stress, erodibility coefficient, hydraulic conductivity, and Manning n. To prescribe the input parameters, probability distribution functions that describe the variability in measured data are implemented. Realizations, or sets of bank material input parameters, are generated based on the density functions defined for each variable. The user can choose from one of the following distributions for each parameter and soil layer: uniform, normal, lognormal, triangular, and gamma. Depending on the chosen distribution, two parameters (a, b) may need to be defined in addition to the minimum and maximum values of the bank material input parameter at which the distribution is constrained. Figure 1 illustrates each of the available distributions and identifies what variables for each function are input parameters in the model. The triangular distribution requires parameter a and the normal, lognormal, and gamma distributions require both parameter a and parameter b. The number of realizations to be created, which inherently determines the number of model runs and the length of time to complete simulations, is user defined. Upon completion of BSTEM simulations, results are surmised by providing the user with probabilistic bank retreat profiles by calculation of percentiles of erosion distance for each bank node.

Example Model

The example described herein is hypothetical and demonstrates the differences between the stochastic and deterministic BSTEM models which are both available in that latest dynamic version. Generic sediment parameters available to the user and generic bank profiles were used in example model development. The generic bank profile is 5 meters tall with a 85 degree bank angle and a 1 meter toe that has a 25 degree bank angle (Figure 2A). The bank profile consists of two sediments: a moderate silt 3-meter base overlain by 2 meters of resistant silt. The input stage hydrograph for both the stochastic and deterministic models is provided in Figure 2b. The initial groundwater elevation, which is an input parameter for the deterministic model, is set to the initial stage which is consistent with the stochastic model.

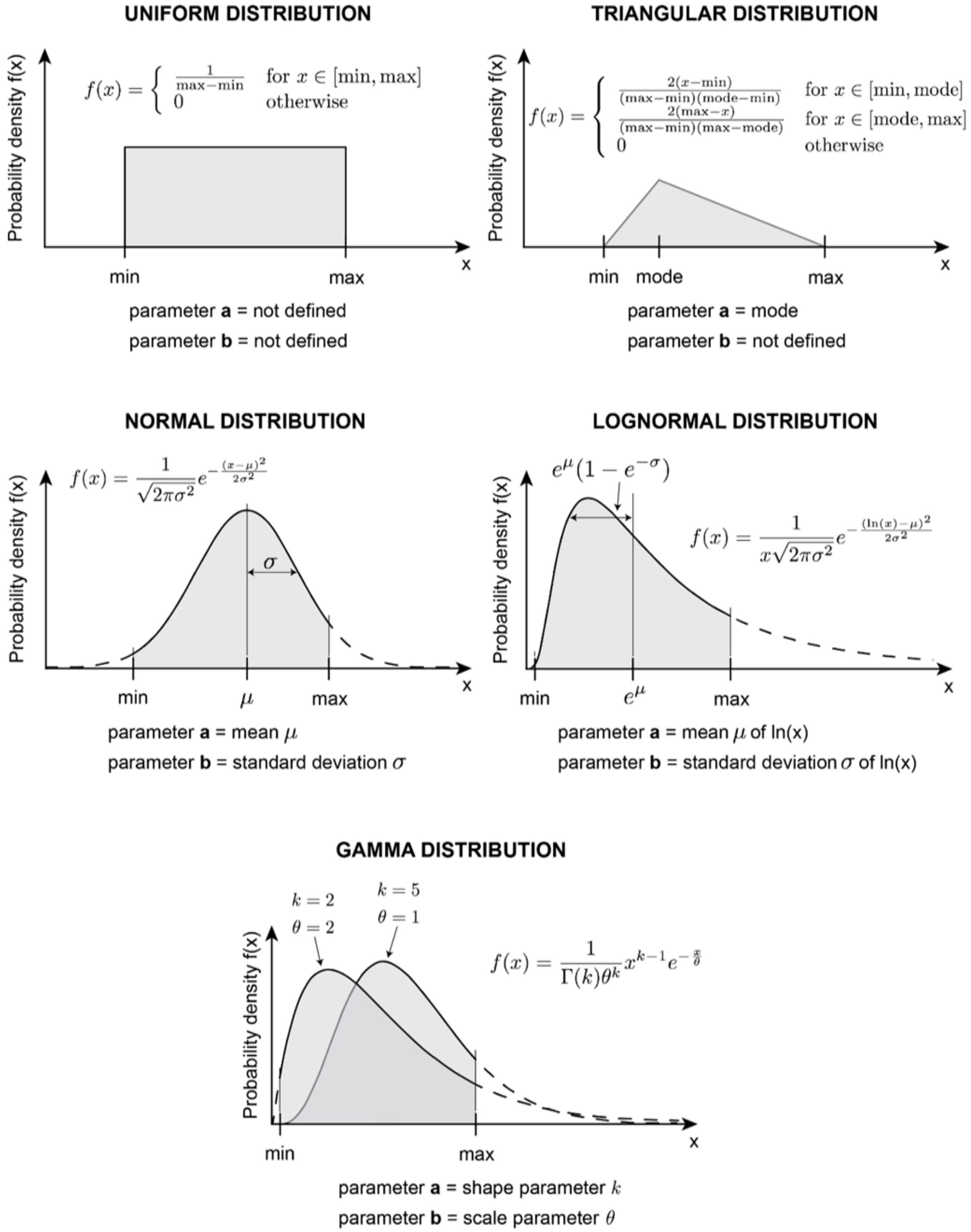

Figure 1. Probability distribution functions available to the user for each bank material input parameter by layer.

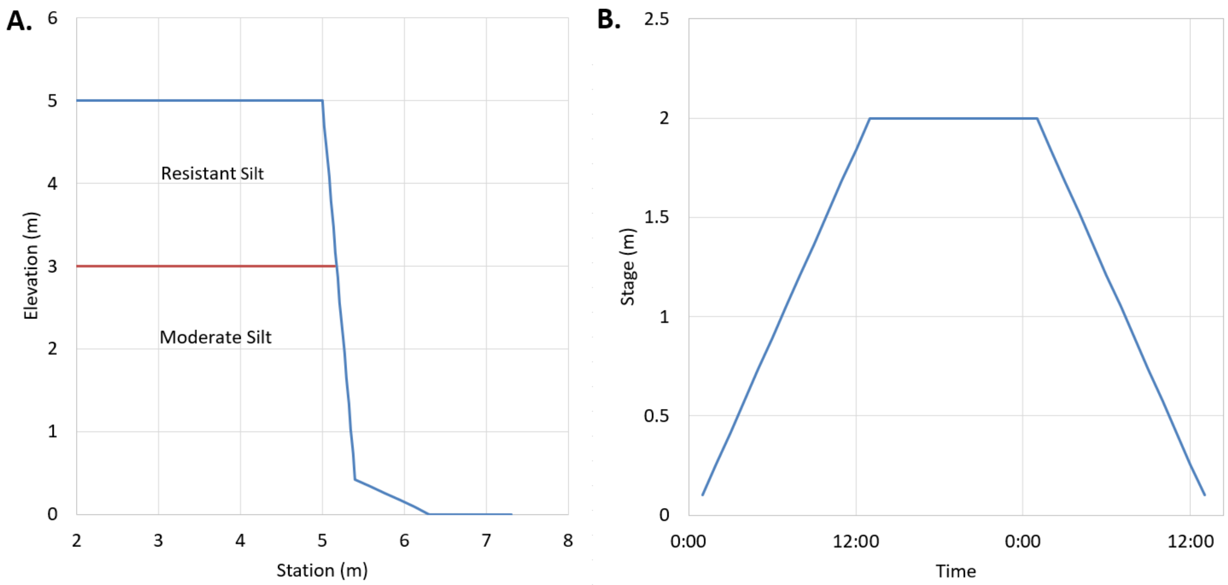

Figure 2. A) Bank profile and B) hypothetical hydrograph used for the example model.

Deterministic

The deterministic model provides a prediction of bank retreat for a single set of input parameters. The default values defined within BSTEM for resistant and moderate silt are provided in Table 1. No other options such as bank protection or added cohesion due to roots were added to the model. The only required inputs to run the model are the bank geometry, stage hydrograph, bank material properties, and initial groundwater elevation.

Table 1. Bank material properties for the deterministic model.

Material	Friction angle (degrees)	Suction angle (degrees)	Cohesion (kPa)	Saturated unit weight (kN/m^3)	Hydraulic conductivity (m/s)	Critical shear stress (Pa)	Erodibility coefficient (cm^3/Ns)
Moderate silt	26.6	10	4.3	18	5.06E-06	5	0.089
Resistant silt	26.6	10	4.3	18	5.06E-06	50	0.028

Deterministic results provide not only a prediction of bank retreat but also valuable time series information such as groundwater levels, shear stress, and bank retreat estimates that can be used for calibration purposes. Example results are provided in Figure 3.

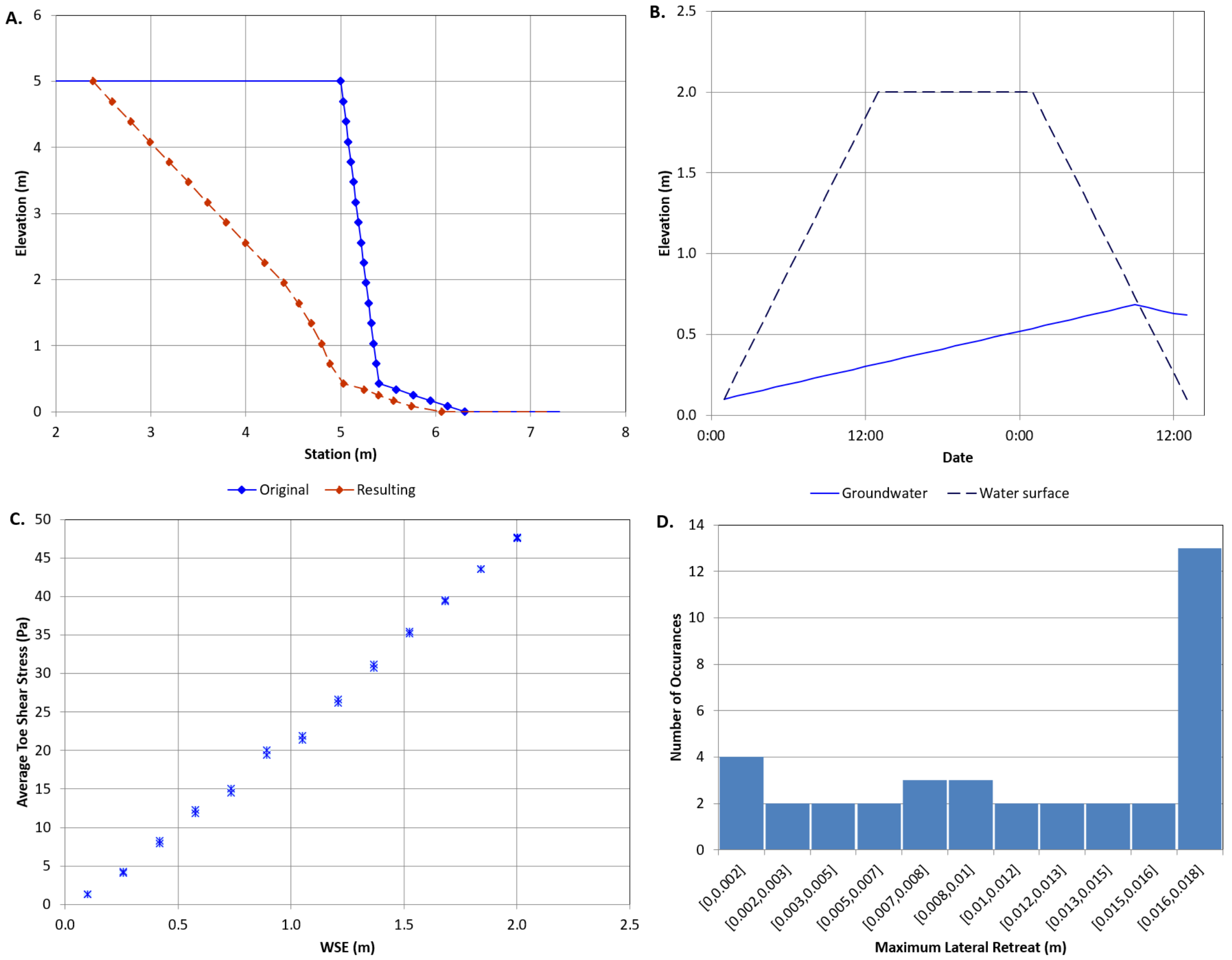

Figure 3. Deterministic results: A) bank retreat profile, B) time series of water surface and groundwater elevation, C) shear stress as a function of water surface elevation (WSE) and D) histogram of bank retreat estimates.

Stochastic

Default parameters (p) used for each bank layer from the deterministic model are varied by a uniform distribution with minimum and maximum values calculated by Equation 1 for the stochastic model. Table 2 provides the values implemented in the hypothetical stochastic model example.

$$p_{\text{stochastic min/max}} = p_{\text{deterministic}} \pm 0.5p_{\text{deterministic}} \tag{1}$$

Figure 4 provides resulting profiles after running a series of 50 realizations with uniformly distributed bank material properties. Each bank node is determined by calculating percentiles of the resulting bank retreat estimates from all realizations. It should be noted that time series data for individual realizations are not maintained when running stochastic simulations.

Table 2. Bank material properties for the stochastic model.

Material	Friction angle (degrees)	Suction angle (degrees)	Cohesion (kPa)	Saturated unit weight (kN/m^3)	Hydraulic conductivity (m/s)	Critical shear stress (Pa)	Erodibility coefficient (cm^3/Ns)
Moderate silt (min)	13.3	5	2.15	9	2.53E-06	2.5	0.0445
Moderate silt (max)	39.9	15	6.45	27	7.59E-06	7.5	0.1335
Resistant silt (min)	13.3	5	2.15	9	2.53E-06	25	0.01415
Resistant silt (max)	39.9	15	6.45	27	7.59E-06	75	0.04245

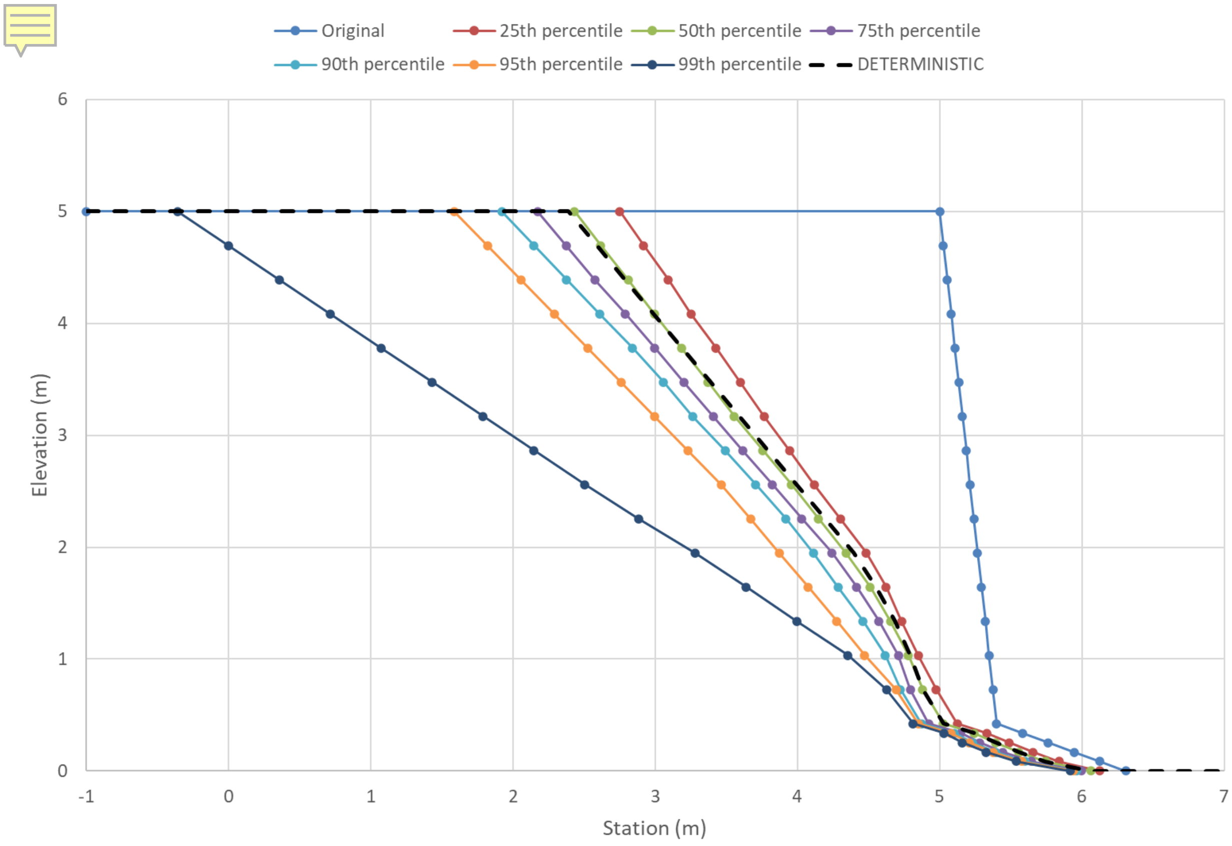

Figure 4. Stochastic model results for hypothetical model.

Discussion

The simple hypothetical example model presented illustrates the differences between stochastic and deterministic BSTEM models. It can be seen, as would be expected from employing uniform distributions on the stochastic parameters, that the 50th percentile bank retreat profile from the stochastic results agree with the bank retreat results of the deterministic model (Figure 4). Having the ability to test ranges of input parameters is a great benefit to modeling bank erosion processes as often there is considerable variability that results from testing bank material properties. Additionally, the deterministic version of BSTEM provides the best platform for model calibration.

References

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