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Quantifying the parameter uncertainty in the cross-sectional dimensions for a stream restoration design of a gravel-bed stream

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Abstract: Public agencies spend significant funds on stream restoration projects to improve the quality of impaired stream reaches. Many sources of uncertainty can potentially influence project outcomes, such as knowledge gaps in our understanding of fluvial systems as well as the natural stochasticity of parameters involved with the channel design process. A two-phase uncertainty analysis was performed on a two-stage channel stream restoration design for Stroubles Creek in Blacksburg, Virginia. Monte Carlo simulation was used to calculate the distribution of possible design outcomes for cross-sectional dimensions. Outcomes included width and depth of the main channel (stage 1) and width and depth of an inset floodplain (stage 2). The analysis incorporated stochastic uncertain parameters (bankfull discharge and grain-size distribution) and knowledge uncertain parameters (Manning's *n* and critical Shield's number). The results indicate that the design width can vary on average by 300% with respect to the deterministic solution. Design discharge was the most sensitive parameter for defining the stage 1 channel, while Manning's *n* was the most sensitive for stage 2. The range in statistically probable design outcomes emphasizes the large uncertainty in channel design and suggests the potential for the channel planform and cross section of restored streams to evolve over time as established riparian vegetation matures. Additional uncertainties in need of future evaluation include (1) longitudinal variability of stream morphology, (2) design of instream structures, (3) temporal variability, and (4) knowledge errors in design models and measurements.

Key words: bankfull discharge—Monte Carlo simulation—stream restoration design—two-stage channel—uncertainty analysis

In the United States, approximately one billion dollars is spent each year on stream restoration projects (Bernhardt et al. 2005). These projects have goals ranging from bank stabilization to improving water quality to ecological restoration (Kauffman et al. 1997; Shields et al. 2003; Wheaton et al. 2008). Ecological restoration, also known as landscape restoration, is loosely defined as the practice of returning an ecosystem to a sustainable level of ecological and social utility after a natural or man-made disturbance. Ecological restoration is a broad field that also includes projects such as promoting revegetation of inactive mines and quarries (Martín-Moreno et al. 2013; Porqueddu et al. 2013), improving the ecological quality of roadsides (Jimenez et al. 2013), and restoring the soil fertility of degraded rangelands (Li et al. 2013). These projects, similar to stream restoration, are designed to restore long-term ecological sustainability.

Many stream restoration goals are qualitative in nature, which makes it difficult to set quantitative measures of design effectiveness (Kondolf 1995, 1996; Johnson and Brown 2001; Lemons and Victor 2008). Restoration projects are also affected by multiple sources of error and variability that create uncertainty in the final design, most of which is not fully incorporated or quantified (Wilcock 2004). Ineffective stream restoration design can have severe consequences, such as excessive costs and design failure (Niezgoda and Johnson 2007). In a study of stream restoration projects in North Carolina, 60% of the projects underwent a change of at least 20% in channel capacity (Miller and Kochel 2010). The authors note that "it is extremely difficult to design a channel whose dimensions maintain an average condition given the site's hydrologic and sedimentologic regime which may be changing through time" (Miller and Kochel 2010).

The qualitative nature of stream restoration results in many sources of uncertainty. Graf (2008) classified uncertainty into four general categories: (1) restoration theory, (2) the research process, (3) the communication of results, and (4) scientific bias. Johnson and Brown (2001) characterized uncertainties in stream restoration as model uncertainty, parameter uncertainty, randomness, and human error. In general, uncertainty in any modeling project or engineering design can be grouped into two classes: natural stochasticity (both spatial and temporal variability) and knowledge error (MacIntosh et al. 1994; Hession and Storm 2000). Knowledge error can be further divided into model error (resulting from our assumptions and representation of the system) and parameter error (resulting from measurement and interpolation errors). Due to the many types of uncertainty, it is difficult for designers to account for uncertainty in the overall project.

Uncertainty analysis provides a method for quantifying the amount of variability in model results and project outcomes. One method of uncertainty analysis commonly used is Monte Carlo simulation (MCS). Monte Carlo simulation is a technique where many model iterations are performed using different input values (taken from a distribution) to derive a distribution of possible output values instead of a single deterministic result. Monte Carlo simulation has been applied to many hydrological and ecological applications, such as watershed modeling (Hession and Storm 2000; Shirmohammadi et al. 2006) and population dynamics modeling (Skarpaas et al. 2005). Recently, Stewardson and Rutherfurd (2008) applied MCS to a stream restoration project quantifying the volume of water needed to flush fine sediment and recommended using larger sample sizes as a way to reduce hydraulic

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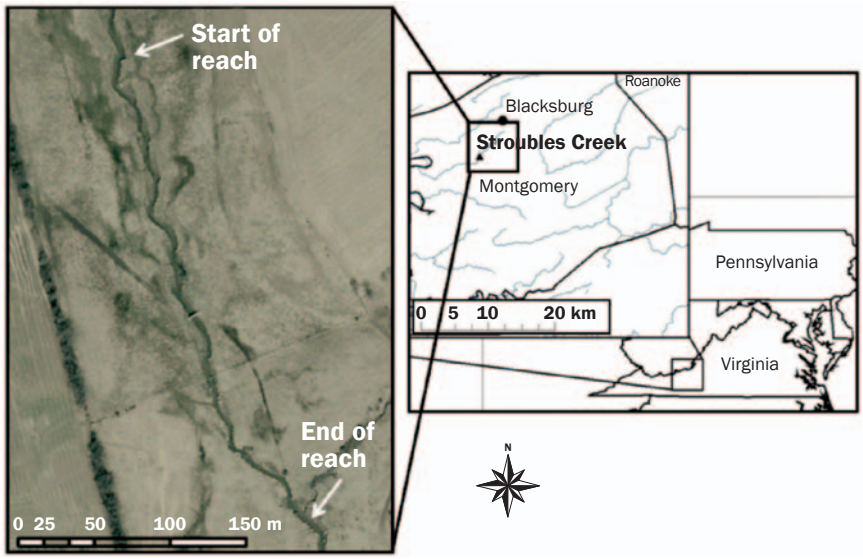
model uncertainty. Other aspects of stream restoration uncertainty that have been studied include bankfull flow (Johnson and Heil 1996), bedload transport (Chen and Stone 2008), and sediment transport (Wilcock 2004). However, further research is needed to expand our knowledge of how model parameter uncertainty affects stream restoration design outcomes.

Objectives and Approach. The objective of this study was to investigate the parameter uncertainty associated with the cross-sectional dimensions of a stream restoration design for a two-stage channel. A two-phase MCS and sensitivity analysis were implemented to evaluate and compare stochastic variability and knowledge error. The uncertainty in the design outcomes, i.e., width and depth of the two channel stages, were quantified for an example restoration project of a gravel-bed stream in Virginia. We then explored the implications of uncertainty in design practices and identified areas for further research.

Figure 1

Site of stream restoration project at Stroubles Creek in Blacksburg, Virginia. Image taken from Virginia state orthophotos in 2006.



Materials and Methods

Study Site. The study site for the stream restoration design uncertainty analysis was a 500 m (1,640 ft) reach of Stroubles Creek, a gravel-bed stream in Blacksburg, Virginia (figure 1). Stroubles Creek is on the Environmental Protection Agency (EPA) 303(d) list of impaired streams due to a weak benthic macroinvertebrate community and bacterial contamination (Benham et al. 2003). Sediment was identified as a major stressor; management actions were identified in a total maximum daily load implementation plan to reduce sediment load due to streambank erosion by 77% (Yagow et al. 2006). In 2009, a stream restoration project was designed and implemented along the 0.5 km (0.31 mi) stream section (Smith 2009; Wynn et al. 2010). The restored reach has a drainage area of 17.1 km^2 (4,226 ac) and exhibits a weakly formed riffle-pool structure with a highly embedded gravel substrate. Emergent herbaceous wetlands are present on the floodplain in close proximity to the stream channel. A small levee separates the wetlands from the main channel and maintains water levels in the wetlands. The restored section of Stroubles Creek is located downstream of the Town of Blacksburg and the Virginia Tech main campus. The stream historically had cattle access and is influenced by both agricultural and urban impacts. Stroubles Creek has also been the site of other hydraulic research, such as measuring streambank retreat with erosion pins (Utley and Wynn 2008) and terrestrial laser scanning (TLS) (Resop and Hession 2010), and determining seasonal changes in streambank erodibility and critical shear stress (Wynn et al. 2008). In addition, a stage-discharge curve was developed over the past five years, and suspended sediment concentration and flow were measured for multiple storm events.

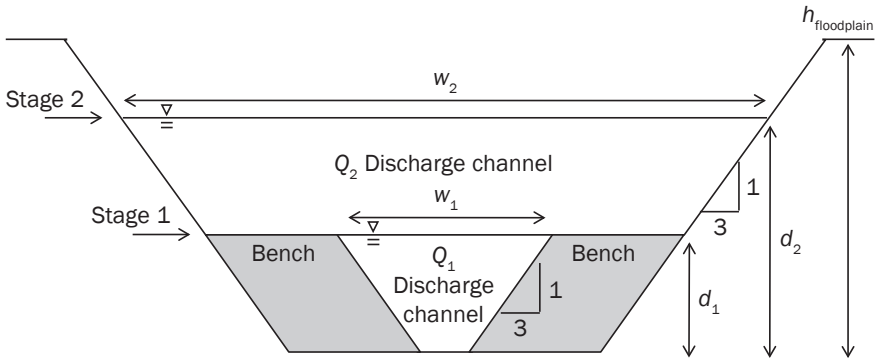
Stream Restoration Design Considerations. The primary goal of this restoration project was to improve ecological integrity by reducing sediment loads from streambank retreat, with the ultimate goal of removing Stroubles Creek from the list of impaired waters. A two-stage channel design was chosen, which incorporates two levels of streamflow: the first level (stage 1) for channel-forming discharge and the second level (stage 2) for floodplain discharge (figure 2) (NRCS 2007b). In our case, stage 1 was designed based on regional curves as the median bankfull flow expected in a natural watershed of this size within the Valley and Ridge Physiographic Province (Keaton et al. 2005). Stage 2 was designed to handle flows observed over the past five years of annual monitoring that fill the existing incised stream channel to capacity (8.5 cms [300 cfs]) (Wynn et al. 2010). The design included 3:1 (horizontal to vertical) bank slopes. Herbaceous and woody vegetation were planted on the bank and bench surfaces to provide stability and habitat (Wynn et al. 2010).

The design outcomes for stream restoration include width, depth, slope, and planform (NRCS 2007a). For this study, channel slope and planform were held constant to minimize impact to existing floodplain wetlands by removing the channel levees, and because the existing stream sinuosity was similar to that of a reference reach. Width and depth are determined using parameters such as water discharge, sediment discharge, bank composition, and bed composition (NRCS 2007a). As with most stream restoration projects, sediment discharge was unknown for this study and so the methodology relied on measures of the other three parameters. In relation to the two-stage channel design, the design variables were defined as channel width and depth (w_1 and d_1) (stage 1) and inset floodplain width and depth (w_2 and d_2) (stage 2) (figure 2). The stage 2 dimensions include the stage 1 dimensions. For this design, the current floodplain height above the bed ($h_{floodplain}$) was maintained at existing elevations to protect floodplain wetlands.

The specific design considerations for this stream restoration project were (1) the stage 1 discharge (Q_1) defines the stage 1 channel dimensions (w_1 and d_1); (2) the stage 2 discharge (Q_2) inundates the benches and defines the stage 2 inset floodplain dimensions (w_2 and d_2); (3) bed

Figure 2

Cross-section diagram illustrating the general layout of the two-stage channel design, adapted from the Natural Resources Conservation Service (NRCS 2007a). The stage 1 discharge (Q_1) defines the channel dimensions (w_1 and d_1), and the stage 2 discharge (Q_2) defines the inset floodplain dimensions (w_2 and d_2).



particles smaller than D_{84} (the 84th quantile of the grain-size distribution) can move based on the average boundary shear stress at either stage while bed particles larger than D_{84} are not transported; and (4) the stage 2 channel depth is less than or equal to the existing floodplain height.

Stream Restoration Design Process. When using analytical methods for stream restoration design, two types of equations are typically utilized; (1) hydraulic resistance equations and (2) sediment transport equations (Skidmore et al. 2001; NRCS 2007a). Manning's equation (equation 1) and the continuity equation (equation 2) were used together for the hydraulic resistance equations, defined as:

$$V = \frac{1}{n} R_h^{2/3} S^{1/2} \tag{1}$$

and

$$Q = VA, \tag{2}$$

where V is the channel velocity (m s^{-1}), n is Manning's coefficient, R_h is the hydraulic radius (m), S is the slope of the energy grade line (0.004 m m^{-1}, assumed equal to the channel slope), Q is the discharge (cms), and A is the cross-sectional area (m^2).

Because the bedload transport rate was unknown, incipient motion was evaluated based on the design goal to scour sand-sized and smaller particles from the bed, while maintaining riffle structure at "bankfull" flows. Incipient motion was analyzed by comparing the critical shear stress (τ_c) from Shield's entrainment function (equation 3) and the average boundary shear stress (τ_a) (equation 4). Theoretically, sediment moves if τ_a is greater than τ_c, so the design solution was iteratively solved until τ_a was approximately equal to τ_c. Shield's entrainment function is defined as follows:

$$\tau_c = (\rho_s - \rho_w) g D_{84} \tau^*, \tag{3}$$

where τ_c is the critical shear stress (Pa), ρ_s is the density of the bed sediment (kg m^{-3}), ρ_w is the density of water (kg m^{-3}), g is the acceleration due to gravity, D_{84} is the 84th quantile of the grain-size distribution (m), and τ^* is the critical Shield's number or dimensionless critical shear stress (Stewardson and Rutherfurd 2008). The average boundary shear stress was calculated as

$$\tau_a = \rho_w g R_h S, \tag{4}$$

where τ_a is the average boundary shear stress (Pa).

Manning's n was defined for the surfaces of both channel stages. For the stage 1 channel, n was calculated using Strickler's equation:

$$n = \frac{1}{21.1} D_{50}^{1/6}, \tag{5}$$

where D_{50} is the 50th quantile of the grain-size distribution (Ghani et al. 2007). For the floodplain bench and bank, n was assumed to be a function of vegetation and was based on values from Chow (1959). Manning's n for the entire stage 2 channel was calculated as a weighted average of n's from both sections using Pavlovskii's equation:

$$n_e = \left(\frac{\sum_i^N (P_i n_i^2)}{P} \right)^{1/2}, \tag{6}$$

where n_e is the equivalent Manning's n for the channel, P_i is the wetted perimeter of section i, n_i is the Manning's roughness value for section i, and P is the total wetted perimeter of the channel (Djajadi 2009).

The two stages were designed sequentially: first stage 1 followed by stage 2. A value for channel-forming discharge was selected and the initial stage 1 channel width was set. Depth was determined using the hydraulic resistance equations (equations 1 and 2). Critical and average boundary shear stresses were calculated using the incipient motion equations (equations 3 and 4) and compared. If the absolute difference between the two shear-stress values was above a minimum threshold (0.1 Pa), then the width was incremented or decremented by a small amount and the process was repeated to solve for depth. When the critical and average shear stresses were approximately equal, then the values for width and depth were used for the final design channel dimensions. Once the dimensions for stage 1 were optimized, the design process solved for the stage 2 dimensions and total channel depth was compared with the floodplain height.

Uncertainty Analysis—Parameter Selection. For any stream restoration design, the parameters used to calculate channel dimensions experience a degree of uncertainty (Wilcock 2004; Chen and Stone 2008; Stewardson and Rutherfurd 2008). For this study, two parameters were selected for each type of uncertainty (stochastic and knowledge) as a way to examine the effect of parameter uncertainty on design outcomes. Stochastic variability, the randomness of parameters over space and time, was represented by grain size and design discharge. Knowledge error, our incomplete understanding of a system when developing models, was represented by Manning's n and critical Shield's number. For each parameter, a probability distribution and a range of values were determined.

Stochastic Variability. While there are numerous parameters in the design process that could be considered stochastic in nature (both spatially and temporally), we included bed grain size and design discharge for this analysis (table 1). These parameters were chosen due to the magnitude of their variability and the fact that they can be difficult to define. Other varying parameters, such as stream cross section and slope, were assumed constant or deterministic.

Table 1
Assumed distributions of the input parameters used for the stream restoration design Monte Carlo simulation.

Input parameter	Stage 1 distributions	Stage 2 distributions
Stochastic variability		
Bed grain size (D) (mm)	Lognormal (2.5, 0.52) *	Same as stage 1
Event discharge (Q) (cms)	Triangular (1.8, 5.6, 15.6) †	Triangular (4.7, 8.5, 18.5)
Knowledge error		
Critical Shield's number (τ^*)	Triangular (0.03, 0.045, 0.06)	Same as stage 1
Manning's n	$f(D_{50})$ + Uniform (−20%,+20%) ‡	Uniform (0.025, 0.160)

* Lognormal distribution (mean and standard deviation).
† Triangular distribution (minimum, mode, and maximum).
‡ Uniform distribution (minimum and maximum).

Grain-size distribution is commonly measured using a method such as the Wolman pebble count (Wolman 1954). The practitioner selects 100 random grains from the stream bed and measures the intermediate axis diameter. This is a parameter that can exhibit both stochastic variability (since the grain distribution varies over the length of the stream) and measurement error (due to biases of the practitioner) (Chen and Stone 2008; Stewardson and Rutherfurd 2008). For this study, a Wolman pebble count was conducted over 10 riffles of Stroubles Creek. A lognormal distribution was fit to the measured values (Stewardson and Rutherfurd 2008). For each MCS run, a random sample of 100 grain sizes was generated from this distribution. The 50th and 84th quantiles of grain size (D_{50} and D_{84}) were then used as input variables.

Design discharge can be difficult to select due to the uncertainty in how it is defined (Johnson and Heil 1996). There are many methods for defining design discharge, including effective discharge, discharge at a recurrence interval, and bankfull discharge (Johnson and Heil 1996; Shields et al. 2003; Doyle et al. 2007). Bankfull discharge can be determined multiple ways, such as using regional curves, combining field-based inspection with stage-discharge rating curves, hydraulic modeling, and comparing with a reference reach. For this study, a triangular distribution of possible values for stage 1 discharge was developed based on the bankfull discharge regional curves for the Valley and Ridge Physiographic Province (Keaton et al. 2005). The distribution mode was set by the expected value and the upper and lower limits were set by the 95% confidence interval (CI). The stage 2 discharge is difficult to measure directly and so it was estimated from field data.

Knowledge Error. There are many examples of knowledge error in stream restoration design, ranging from pure measurement error (slopes, cross-sectional parameters, and bed grain-size distributions) to the parameters used for hydraulic and incipient motion equations, which are difficult to directly measure. For this analysis, we focused on errors associated with estimating Manning's n and critical Shield's number τ^* (table 1). Calibration of these parameters is possible with intensive field measurements, but these methods are not performed for most designs and instead n and τ^* are generally estimated. These parameters can also exhibit a degree of stochastic variability within the stream reach (spatial and temporal), but we did not address this aspect in this study.

The critical Shield's number (τ^*) is a difficult parameter to estimate due to the wide range of values found in literature, particularly for gravel-bed streams (Buffington and Montgomery 1997). Since the true distribution of τ^* is unknown, a simple triangular distribution was used for this study. The mode of the distribution was set to the average value in most literature, 0.045, while the limits were set to the extremes commonly found, 0.03 and 0.06 (Petit 1994; Zimmermann and Church 2001; Wilcock 2004; Thompson et al. 2007).

The distribution of Manning's n depended on the channel stage. For the natural bankfull discharge channel (stage 1), n was calculated from equation 5, and a random error from a uniform distribution of ± 20% was added to account for uncertainty in the different Strickler-type formulas that have been developed (Kim et al. 2010). For the benches, a uniform distribution was used based on the minimum and maximum values selected from Chow (1959), ranging from short grass to dense brush, thus incorporating both spatial and temporal variability, assuming woody vegetation was the target riparian vegetation. A weighted n was then calculated for the entire stage 2 channel using equation 6.

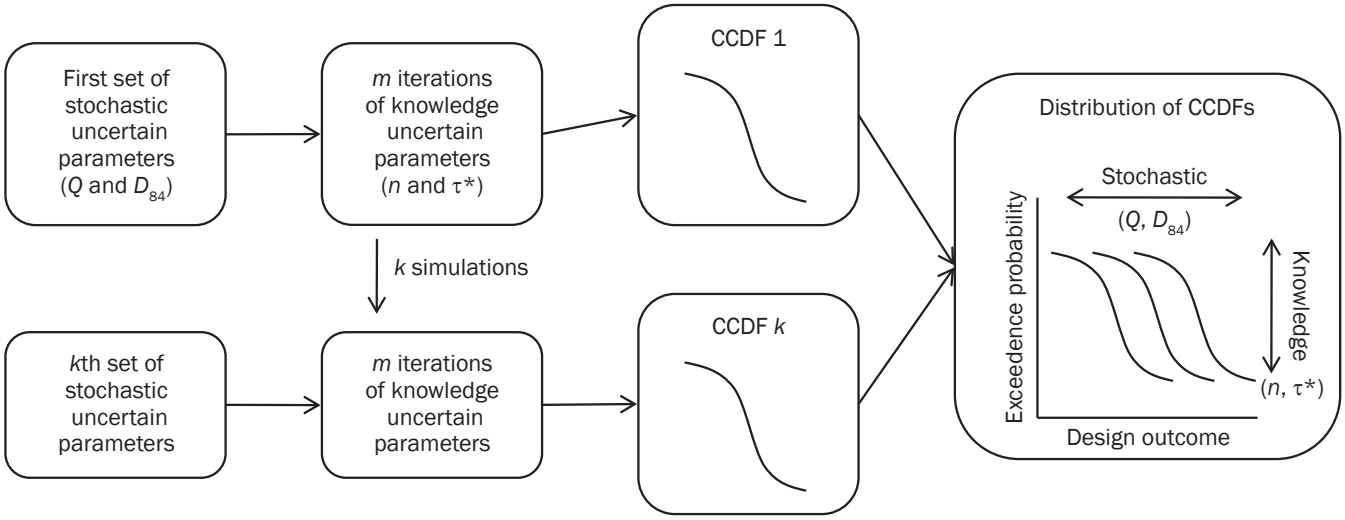
Monte Carlo Simulation. Monte Carlo simulation was used to quantify the uncertainty in width and depth for both channel stages. A two-phase MCS was conducted based on the methods used by Hession et al. (1996) (figure 3). The purpose of the two-phase analysis was to explore the variability associated with both types of uncertainty (stochastic and knowledge) separately, since knowledge error can be reduced, but stochasticity is a property of the natural world (Hession and Storm 2000). A nested, two-step iteration was performed where a set of values was selected at random from the stochastic parameters (Q and D_{84}) followed by m sets of values selected at random from the knowledge parameters (n and τ^*). The design was calculated with each set of values and repeated for k iterations of random stochastic parameters. For stage 2, the stage 1 width and depth were fixed to the median values. The result was a set of complementary cumulative distribution functions (CCDFs) for the design outcomes. Complementary cumulative distribution functions are functions that define the probability that a certain value will be exceeded (Helton and Shiver 2007).

The sizes of m and k were chosen by running simulations of increasing sample size starting with m and k = 5. The knowledge parameters were varied first while the other parameters were held constant. A sample size was selected when the mean and standard deviation of stage 1 design width stabilized. This process was then repeated for the stochastic parameters. This process resulted in m = 1,000 and k = 100.

Latin hypercube sampling (LHS) was used to select values for each parameter during the MCS to ensure representation across the range of possible values. Latin hypercube sampling divides the probability distribution function of each parameter into j equal probability intervals and then selects a value at random from each interval (Shirmohammadi et al. 2006). To satisfy the requirement for LHS, it was assumed that the input variables were independent. While n is dependant on grain size in stage 1, this study focused on the knowledge uncertainty associated with the model error from Strickler's (equation 5), which was assumed to be independent from grain size.

Figure 3

The two-phase Monte Carlo stimulation (MCS) uncertainty process separating stochastic variability (*k*) and knowledge error (*m*) and resulting in a distribution of complementary cumulative distribution functions (CCDFs), adapted from Hession et al. (1996). *Q* is design discharge, D_{84} is the 84th quantile of grain size, *n* is Manning's *n*, and τ* is the critical Shield's number.



Sensitivity Analysis. After the MCS was complete and all 100,000 simulations were executed, a sampling-based sensitivity analysis was performed for each parameter. The input data were normalized by subtracting the average and dividing by the standard deviation. The design outcomes (width and depth) for both stages were then plotted against the normalized parameter values and a simple linear regression equation was fit to the data. The slope and r^2 of each equation were then used to determine the relative sensitivity of each parameter, based on methods used by Hession (1995) and MacIntosh et al. (1994). A greater slope signifies that a similar change in value between two parameters results in a greater change in value in the design variable.

Results and Discussion

Deterministic Design Solutions. The deterministic solution for the stream restoration design was calculated using the expected value for each input parameter (Q, D_{84}, n, and τ*) (table 2). The resulting design had stage 1 dimensions of 9 m (29.5 ft) width and 0.47 m (1.5 ft) depth and stage 2 dimensions of 50.2 m (164.7 ft) width and 0.80 m (2.6 ft) depth. The channel met all of the design objectives so that the dimensions for both stages were defined by the design discharges. The total depth of the stage 2 inset floodplain was less than the floodplain height (estimated as 1.17 m [3.8 ft] from nine measured cross sections), so it is ideal for periodically flooding the channel benches. The average boundary shear stress for stage 2 was 17 Pa (2.5×10^{-3} psi), so bed particles smaller than the D_{84} will be transported by the design discharges.

Uncertainty Analysis Design Solutions. Both the width and depth for the natural bankfull discharge channel (stage 1) exhibited a wide range of values over the 100,000 simulations performed by MCS (figure 4). Based on the combined CCDF for all simulations, the 95% CIs for width and depth were 5.8 to 30.5 m (19 to 100.1 ft) and 0.28 to 0.71 m (0.92 to 2.33 ft), respectively. Thus, 95% of design solutions, assuming theoretically possible input values, had dimensions somewhere in between these values. Compared with the deterministic solution, the size of the 95% CI (upper bound minus lower bound) was approximately 275% the width and 90% the depth, which represents a considerable amount of uncertainty in the design process. Evaluating both types of uncertainty separately was performed by comparing the variability between CCDFs (stochastic variability, estimated as the difference in medians of the 2.5th and 97.5th percentile curves) to the variability within CCDFs (knowledge error, estimated as the 95% CI of the median curve). For width the size of the 95% CI was 19.2 and 16.2 m (63 and 53.1 ft) for stochastic and knowledge, respectively, and for depth it was 0.19 and 0.35 m (0.62 and 1.15 ft). These results demonstrate that both types of uncertainty contribute to the overall variability of the stage 1 design.

The inset floodplain dimensions (stage 2) were determined assuming the median values for the stage 1 dimensions (width = 12.8 m [42 ft] and depth = 0.43 m [1.41 ft]). All of the simulations for the second stage met the design objective of having the total channel depth less than the floodplain height. Once again, the simulated design solutions from MCS show a wide range in possible values for inset floodplain width and depth over both the stochastic and knowledge parameters (figure 5). The 95% CIs over all simulations for width and depth were 17.8 to 180.7 m (58.4 to 592.8 ft) and 0.54 to 0.85 m (1.77 to 2.79 ft), respectively (figure 6). The size of the 95% CI was 324% of the deterministic solution with respect to width and 39% with respect to depth. Comparing both uncertainty types individually, for width the size of the 95% CI was 77.9 and 130.8 m (255.6 and 429.1 ft) for the stochastic and knowledge parameters, respectively, and for depth it was 0.12 and 0.32 m (0.39 and 1.05 ft) for stochastic and knowledge, respectively. In both cases the knowledge uncertainty (due to n and τ*) was greater than the stochastic uncertainty.

Sensitivity Analysis. The individual effect of each parameter on design width was investigated through a sensitivity analysis (table 3). For the stage 1 channel, discharge was the most sensitive parameter, emphasizing the importance of defining discharge. As an example, the change in discharge from the lower to higher value of the 95% CI of

Table 2

The deterministic solutions for channel dimensions calculated from the expected input values and the uncertainty analysis summarized by the median and the upper and lower bounds of the combined 95% confidence interval over all simulations.

	Stage 1 channel			Stage 2 channel		
Deterministic input parameters						
Discharge (Q) (cms)	5.6			8.5		
Grain size (D_{84}) (mm)	21.0			21.0		
Manning's n	0.023			0.086		
Critical Shield's number (τ^*)	0.045			0.045		
Deterministic design solution						
Width (m)	9.0			50.2		
Depth (m)	0.47			0.80		
Uncertainty analysis design solutions	Lower	Median	Upper	Lower	Median	Upper
Width (m)	5.8	12.8	30.5	17.8	61.7	180.7
Depth (m)	0.28	0.43	0.71	0.54	0.72	0.85

the regional curve (2.4 to 14.4 cms [85 to 509 cfs]) results in a 430% increase in design channel width (4.8 to 25.3 m [15.7 to 83 ft]). For stage 2, the most sensitive parameter was Manning's n. The strong correlation between roughness and the stage 2 channel dimensions is likely due to the variability allowed for n on the benches due to the effect of vegetation growth and succession from the initial herbaceous material to dense brush and shrubs. Ranging n from grass to shrubs (0.02 to 0.16) results in a 700% increase in channel width (16 to 129.2 m [52.5 to 423.9 ft]). As bench vegetation develops over time, n will increase, reducing flow conveyance, shear stress, and sediment incipient motion on the floodplain, and increasing these dynamics in the main channel. Changes in riparian vegetation and roughness thus lead to an increase in overall channel width. These findings are supported by research by Anderson et al. (2004), who examined the correlation between stream width and vegetation and found that for smaller streams those with denser vegetation tended to have wider channels.

Implications for Stream Restoration Design. The wide range of possible design solutions for both channel stages produces serious implications for stream restoration designers. For example, one of the criteria for this stream restoration design is that sediment larger than the D_{84} grain size is not transported by either design discharge event. The deterministic design model resulted in a critical shear stress for this threshold of 17 Pa (2.5×10^{-3} psi), which was set to the average boundary shear stress. However, 60% of the MCS design solutions had a critical shear stress, a function of the uncertainty in D_{84} and τ^*, that was smaller than the deterministic average boundary shear stress, assuming a stage 2 discharge event (figure 7). In the uncertainty analysis design solutions, this difference is accounted for in the process by adjusting the channel dimensions until the critical and average boundary shear stresses were equal. However, in the deterministic solution if the true critical shear stress is smaller than the average boundary shear stress, it could result in more bed material being mobilized than desired and ultimately lead to channel incision or erosion. As a result of the uncertainty analysis, this possible danger can be anticipated.

Figure 4

Distribution of the complementary cumulative distribution functions (CCDFs) for the stage 1 channel dimensions of (a) width and (b) depth summarized by the median and 95% confidence interval. Each CCDF represents the distribution of results for a set of stochastic parameters (Q and D_{84}) over the range of knowledge parameters (n and τ^*).

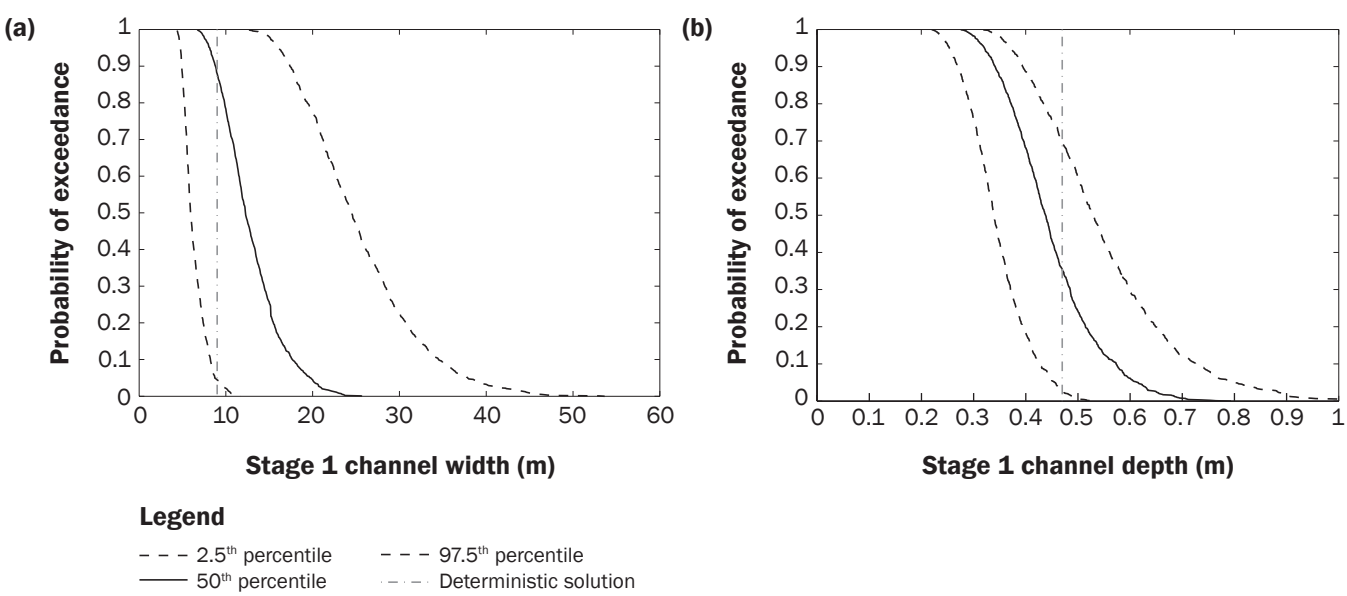


Figure 5

Distribution of the complementary cumulative distribution functions (CCDFs) for the stage 2 channel dimensions of (a) width and (b) depth represented by the median and 95% confidence interval.

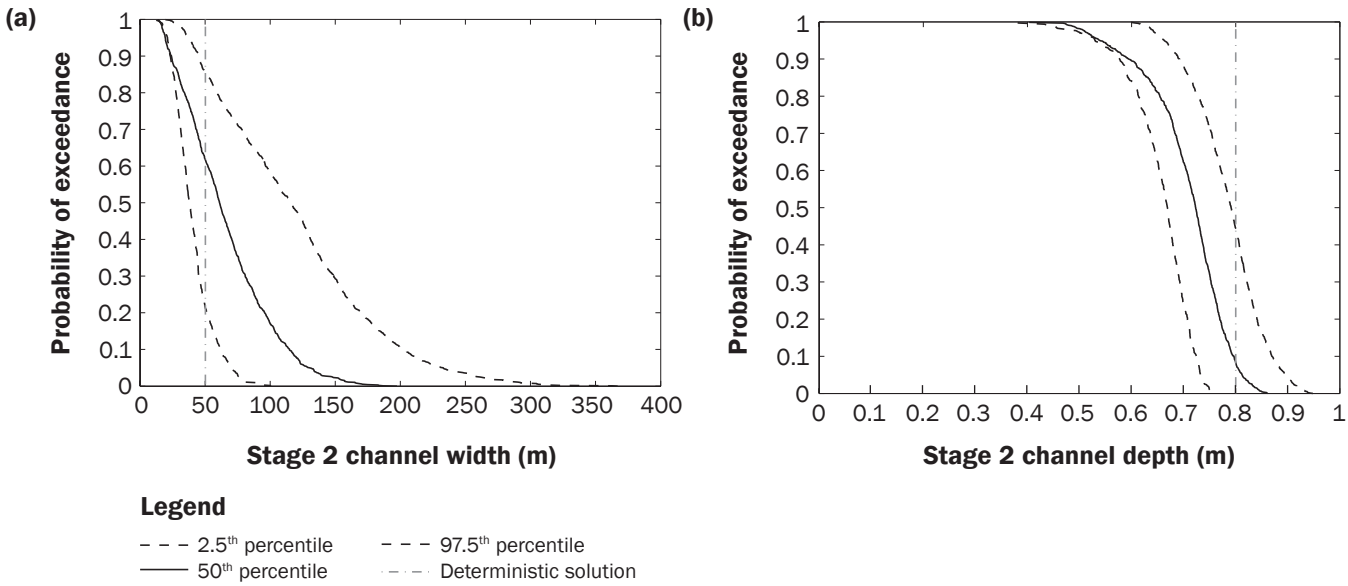


Figure 6

The 95% confidence intervals for the bankfull discharge channel (stage 1) and the inset floodplain (stage 2) design outcomes. The range of possible values for the stage 2 width and depth assume the median stage 1 width (12.8 m) and depth (0.43 m). The channel dimensions w_1 and d_1 are defined by the stage 1 discharge (Q_1) and the channel dimensions w_2 and d_2 are defined by the stage 2 discharge (Q_2).

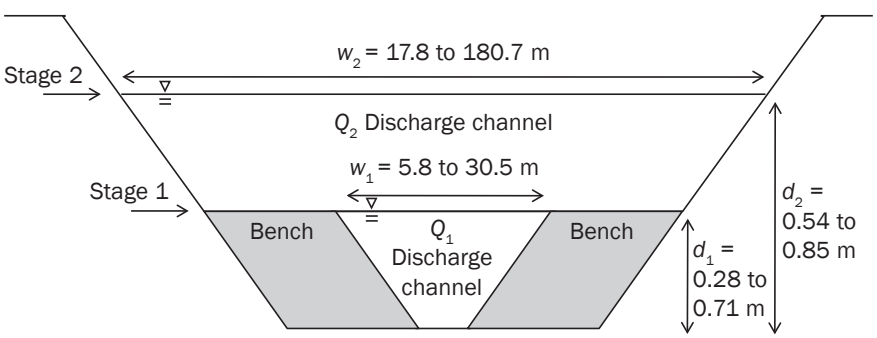


Table 3

The sensitivity analysis compares the uncertain parameters to the design variable (width) based on the slope and r^2 of the best-fit regression line. The results show that discharge (Q) was the most sensitive parameter for stage 1 and n was the most sensitive parameter for stage 2.

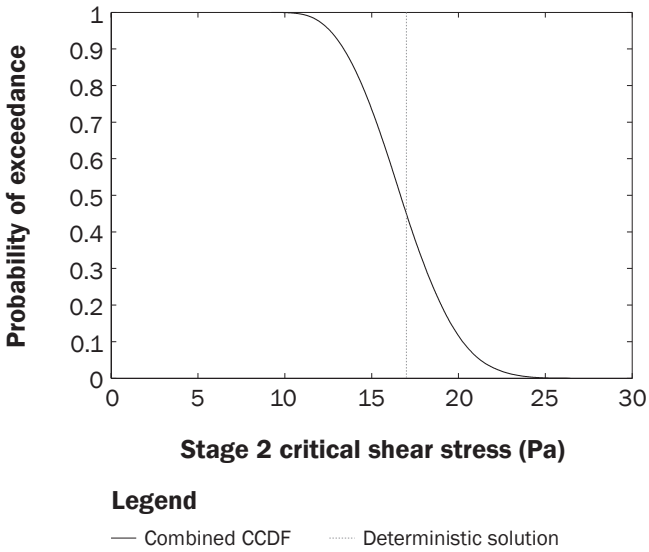
	Stage 1 channel		Stage 2 channel	
Input parameter	**Slope**	**r^2**	**Slope**	**r^2**
Discharge (Q) (cms)	4.8	0.53	17	0.16
Grain size (D_{84}) (mm)	−1.7	0.07	−8.2	0.04
Manning's n	1.3	0.04	31	0.50
Critical Shield's number (τ^*)	−2.7	0.17	−16	0.13

Assume that a stream restoration practitioner in this example study designs a channel based on the deterministic solution with a stage 1 width of 9 m (30 ft). Over the combined 100,000 uncertainty simulations about 75% of the solutions called for a greater width, which is likely due to the variability in stochastic parameters, like design discharge, outside of the practitioner's control. Constructing a channel that is too narrow could lead to bank scour if not properly protected or to more frequent flooding of the inset floodplain than desired. Alternative approaches might instead use the median design width of 13 m (43 ft) from the uncertainty analysis or use a more involved design of channel width and depth that attempts to anticipate some of the variability. From another perspective, other factors might constrain how large the bench width should be constructed, such as existing infrastructure, natural resources, property boundaries, and project budget. In these situations, performing uncertainty analysis along with the stream restoration design can provide a better understanding of the risk involved with the final design.

In addition to quantifying uncertainty we need to develop methodologies that incorporate uncertainty into the design process and create tools for practitioners to utilize this information. There are many sources of uncertainty that contribute to the stream

Figure 7

The combined complementary cumulative distribution function (CCDF) for the critical shear stress on the inset floodplain (stage 2) as well as the deterministic average boundary shear stress (17 Pa). The CCDF represents the risk associated with accepting the deterministic solution, with 40% of the uncertainty solutions having a greater critical shear stress.



restoration design process. Further research should be done to reexamine and evolve the design process from a deterministic model to a more realistic stochastic model. Natural streams are stochastic systems; the variability involved with them should be incorporated into the design process as much as possible. Stream design could also consider the uncertainty in ecological quality and include "ecologically"-based assessments to the design process, such as allowing for the stream to retain a natural dynamic equilibrium and including floodplain wetlands or riparian buffers, as discussed by Palmer et al. (2005) and Jansson et al. (2005). We should use uncertainty to our advantage to produce a more complete design process that is better suited for designing successful restoration projects and predicting improvements in stream quality.

Other Sources of Uncertainty. The focus of this study was on the uncertainty of four parameters: design discharge, grain-size distribution, Manning's n, and critical Shield's number. There are many other sources of uncertainty that should be quantified and incorporated into the stream restoration design process. These uncertainties include (1) longitudinal variability of stream morphology due to riffle-pool spacing or sinuosity; (2) design of instream structures; (3) temporal variability due to seasonal or future changes in herbaceous vegetation, land use, or climate; and (4) knowledge errors such as hydraulic model assumptions, Shield's diagram errors, and measurement errors.

We provided an example for designing a single stream cross section (assuming a constant slope and floodplain height and not considering longitudinal variability). Stream restorations typically involve lengths of stream and include changes in slope (riffles and pools), meanders (Rinaldi and Johnson 1997), and cross-section profiles with longitudinal position. For example, the outside of a meander bend would typically be designed with a different cross-sectional geometry than a straight riffle section. The design may also include instream structures such as vanes, weirs, and boulders, which add further complexity (Johnson and Brown 2001; Byrd and Melching 2005). The uncertainty within our cross section example is sizeable; one can imagine the extent of the uncertainty when developing a complex, reach-scale stream restoration design.

For this study we did not consider temporally stochastic parameters, such as Manning's n varying seasonally or annually with changes in riparian vegetation (size, density, and flexibility). Upstream watershed developments also have the potential to modify sediment or hydrologic regimes over time. Our results show that the variability in n affects design channel dimensions; however, further research should be done to explore how the uncertainty in roughness due to vegetation maturity affects future channel change, as discussed by McBride et al. (2010). Another temporal factor is the effect of extreme discharge events that occur at rare recurrence intervals, such as a 100- or 500-year storm, which has been shown to promote channel change (Serrano-Muela et al. 2013). More work could be done in quantifying the risk to stream restoration projects by these types of extreme events.

There are other knowledge errors we did not include in this study where further research is needed. One example is the uncertainty in using a 1D flow model for assuming uniform flow in a 3D fluvial system. The use of Shield's diagram for modeling sediment transport is another example of uncertainty. Shield's diagram was developed assuming uniform sediment; however, stream beds in reality contain a mixture of sediment sizes and shapes (Johnson and Heil 1996). Another example is the measurement error resulting from using standard field methods for determining stream topography. For instance, there are interpolation errors inherent to creating stream cross sections from a limited number of measured points. These measurement errors have the potential to propagate to the final design. One potential area of research is to use a high-resolution surveying tool, such as TLS, as a reference dataset to compare with traditional methods such as total station surveying and Wolman pebble counts (Entwistle and Fuller 2009; Resop and Hession 2010; Resop et al. 2012).

Summary and Conclusions

In this study we demonstrated how uncertainty principles can be applied to a two-stage channel stream restoration design. The uncertainties associated with four parameters involved with the design process, divided into stochastic variability (Q and D_{84}) and knowledge error (n and τ^*), were used to develop a distribution of statistically possible channel-dimension design outcomes. The uncertainty analysis implemented for a case study involving a restoration of a gravel-bed river (Stroubles Creek) could easily be applied to any restoration project.

The calculation of channel dimensions can be a considerable source of uncertainty among the many involved in the stream restoration design process. For the design

width, the size of the 95% CI was on average 300% the size of the deterministic solution between both stages. The uncertainty in the channel depth was smaller, averaging 65% of the deterministic solution. Miller and Kochel (2010) assessed 26 restoration projects in North Carolina and found highly variable changes in channel form following construction and suggested applying "enhanced" restoration methods when possible, such as riparian buffers and vegetated banks. Our results support this finding in that stream channel design is not a deterministic solution but instead highly dependent on uncertain parameters like design discharge that are outside of our control.

The most sensitive parameter in calculating the stage 1 channel dimensions was design discharge, which stresses the importance of properly defining this highly uncertain parameter. Small changes in the assumed discharge can have large effects on channel dimensions. For stage 2, the most sensitive parameter was Manning's *n*, which is highly dependant on the roughness of the bench vegetation. This result illustrates the potential for channel dimensions to evolve over time as vegetation planted on the bench and bank matures.

It is important for designers to acknowledge the inherent uncertainties in design, perform uncertainty analyses when possible, and utilize stochastic results to apply levels of risk to their design choices. For example, confidence intervals could be used to determine the probability that the stream will stay within the design criteria. As another example, while some parameters are outside of the control of the practitioner (such as discharge), other parameters, such as the roughness coefficient *n*, can be controlled by the amount and type of vegetation planted on banks and benches. Ultimately, as a result of the wide range of probable design outcomes due to parameter uncertainties, designing a "stable," unmoving channel is difficult for many projects and a balanced design that considers as many factors as possible is necessary.

Since stream stability depends on balancing sediment and water transport, traditional engineering design practices for reducing risk, such as including a factor of safety in channel dimensions, cannot be used. In most engineering projects, a factor of safety incorporates a margin of error into the design to allow for loads larger than expected. However, this concept does not translate well into stream restoration. For example, if the designer makes the stream channel deeper, also known in open channel design as adding a freeboard, the frequency at which discharges can flood out on the inset floodplain would be reduced. This would have the added effect of concentrating more flow in the main channel and inducing channel scour. If the designer makes the channel wider than necessary, then sediment deposition would increase. For this reason, a more nuanced approach is needed in stream restoration designs that accounts for changes in the streams' dynamic equilibrium by considering potential parameter uncertainties.

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