Impact of Uncertainty on the Design of Vegetative Filter Strips[1]

Abstract

Design of vegetative filter strips for trapping sediment and sediment-borne chemicals can be done on a storm-event basis using VFSMOD. This approach requires confidence in a number of input parameters such as soil infiltration characteristics, surface topography, vegetative composition and roughness, and incoming sediment load and particle size distribution. We have developed a simple program, UH, to estimate runoff hydrographs and sediment transport from a source area based on the NRCS Unit Hydrograph Method and the Modified Universal Soil Loss Equation (MUSLE). VFSMOD uses this information from the source area to predict the amount of sediment trapped in the filter strip. UH and VFSMOD have been integrated into one system using a graphical user interface program, VFSMOD-W. For a given design case, we demonstrate the use of an integrated design tool to 1) identify and rank the input parameters of UH and VFSMOD relative to their sensitivity on sediment trapping, 2) develop probability density functions for the most sensitive input parameters, 3) use Monte Carlo Simulation to sample the input parameters and develop a probability density function for sediment trapping. We demonstrate the use of VFSMOD-W to assess the uncertainty of a design based on uncertainty in the inputs parameters for the source area and the vegetative filter strip.

Keywords: model, uncertainty, vegetative filter strips

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Introduction

Model development and testing are important activities in hydrology and water quality. These represent major undertakings that help users to develop confidence in model use and applicability. However, many models are released to the user community with little or no attention to how uncertainty affects the model results. Most model development activities do include an assessment of model sensitivity to changes in input parameters. The sensitivity analyses help potential users determine where to invest their effort in input dataset development. In most cases, the range selected for the input parameters represents all possible values. For an application of a model, we generally can narrow down the ranges for some or all of the input parameters based on the properties of the application site. For example, if the soil is sandy clay, the range of possible vertical saturated hydraulic conductivities can be narrowed down to those expected for this soil type. This can be very important in cases where the model output's response to changes in the input parameter is nonlinear.

Uncertainty analyses are not often done as part of the model development and testing phase. One primary reason is that uncertainty analysis usually involves considerable effort. Uncertainty can be associated with the estimation of input parameters that vary spacially and temporally, or based on user interpretation. A model is always an approximation leading to errors associated with the simplifying assumptions adopted in its description. Assigning uncertainty to the most sensitive model inputs requires extensive field measurements, which are costly and often not available for a given site. These are often estimated from available research from other sites that are thought to be as similar as possible. However, even with these limitations, most model users are eventually asked to assign a level of certainty or confidence to their results. Haan et al. (1995) emphasized the importance of conducting uncertainty analyses as part of any model evaluation effort.

In this work, we propose integrating sensitivity and uncertainty analyses in the modeling and design process of a common BMP, vegetative filter strips, to control runoff and sediment outflow from upslope disturbed areas. Modifications to enable built-in sensitivity and uncertainty analyses were made to the vegetative filter strip modeling system, VFSMOD, that was developed and tested at North Carolina State University (Muñoz-Carpena 1993; Muñoz-Carpena and Parsons, 1999). This paper discusses the modifications introduced and demonstrates how sensitivity and uncertainty analyses strengthen the use of the system in a design context.

Models and User Interface Program

The vegetative filter strip, VFS, modeling system consists of a front-end graphical user interface program, VFSMOD-W, the source area program, UH, and the vegetative filter strip model, VFSMOD. The front-end graphical interface program was developed in 2000 to provide an integrated environment for users to evaluate potential designs of vegetative filter strips for trapping sediment from upslope source areas. The program enables users to develop input datasets for the source area program, UH, and for the vegetative filter strip model, VFSMOD, for evaluating potential vegetative filter strip designs for trapping sediment from upslope source areas.

The source area program, UH, allows the user to estimate runoff hydrographs and sediment losses from upslope source areas for a storm event. For each storm event, a rainfall hyetograph is generated as described by Haan et al. (1994). Based on land use and topography of the source area, runoff is determined using the NRCS curve number methods and a runoff hydrograph is generated using the NRCS unit hydrograph method (USDA NRCS, 1986). Sediment losses are estimated using the Modified Soil Loss Equation (Wischmeier and Smith, 1978; Williams, 1975). These are output formatted for use in VFSMOD. Suwandono et al. (1999) presented detailed descriptions of the procedures.

The vegetative filter strip model, VFSMOD, was developed and tested in North Carolina in 1995 (Muñoz Carpena and Parsons, 1999). VFSMOD is a field scale, mechanistic, storm-based model developed to route incoming hydrographs and sedimentographs from an adjacent field through VFS. Outputs from VFSMOD include surface runoff from the VFS, infiltration in the VFS, and sediment trapping efficiency of the VFS. The model handles time dependent hyetographs and runoff hydrographs, space distributed filter parameters (vegetation roughness or density, slope, infiltration characteristics) and varying particle sizes of incoming sediment. In addition, the model has been successfully tested under experimental conditions in Canada (Abu-Zreig, 2001). The combination of VFSMOD and UH is intended as a powerful design tool to evaluate offsite sediment losses from a source area – VFS combination as demonstrated by Suwandono et al. (1999) using an example from the North Carolina Piedmont region.

Modifications for Uncertainty

Haan et al. (1995) outlined the statistical procedure for evaluating hydrology and water quality models. Their procedure included: conducting sensitivity analysis, generating probability distributions for model inputs, generating probability distributions for the model outputs, and using the probability distributions of the model outputs to assess uncertainty. Using an example model, they conducted a sensitivity analysis to identify the input parameters that have the most impact on the outputs. The absolute and relative sensitivities of a parameter are defined as

$$S_i = \frac{\partial O}{\partial P_i} \quad \text{and} \quad S_{ri} = \frac{\partial O}{\partial P_i}\frac{P_i}{O} \qquad (1)$$

where S_i and S_{ri} are the absolute and relative sensitivities of the output parameter, O, with respect to changes in the input parameter, P_i. Once these inputs were identified, probability distributions were assigned based on based on previous literature and field research.

Two possible methods were presented for generating the general probability distributions of the output variables of interest (Haan et al. 1995). The first method was First Order Approximation (FOA) (Morgan and Henrion, 1990). In this method, the mean or expected value of the output is estimated as

$$E(O) = Model(P_b) \text{ and } Var(O) = \sum_{i=1}^{n}\left[\frac{\partial O}{\partial P_i}\right]^2 Var(P_i) + 2\sum_{i=1}^{n}\sum_{j=i+1}^{n}\frac{\partial O}{\partial P_i}\frac{\partial O}{\partial P_j}Cov(P_i, P_j) \qquad (2)$$

where O is the output parameter of interest, P_b is the base parameter values for the selected input variables, P_i is the input parameter i, n is the number of parameters, Var is the variance and Cov is the covariance. If the input parameters are independent and uncorrelated, then the second term in the variance equation is 0 ($Cov(P_i, P_j) = 0$). The slope of the sensitivity relationship between O and P_i is S_i. With these assumptions, the variance equation becomes

$$Var(O) = \sum_{i=1}^{n} S_i^2 Var(P_i) \quad (3)$$

This type of analysis produces good estimates of the mean and variance of the output parameter, O, when the coefficient of variation (Mean/Standard Deviation) of the input parameter is small and the relationship between O and P_i, over the range of potential inputs, is linear.

An alternative more general approach is the technique of Monte Carlo Simulations (MCS). An outline of this procedure is: 1) select the most sensitive input parameters, 2) develop probability distribution functions for each input parameter, 3) randomly generate input parameter datasets based on the probability distributions, 4) perform the model simulation with the randomly generated input dataset, 5) repeat steps 3 and 4 for a large number of trials, 6) generate probability distribution functions for the model outputs of interest, and 7) use the output probability distribution functions to evaluate uncertainty in the model by placing confidence levels on the outputs.

The graphical user interface, VFSMOD-W, was modified to incorporate both sensitivity and uncertainty analysis in the VFS design system. A number of input parameters were identified as candidates for inclusion in the graphical user interface program. These were identified based on previous detailed sensitivity analysis with VFSMOD (Muñoz-Carpena, 1993; Muñoz-Carpena et al., 1999) and literature suggestions for the procedures used in the UH program.

The UH program uses the NRCS Curve Number Method to generate the volume of runoff from the upslope source area. In this method, the curve number is assumed to be the most sensitive parameter and therefore very important in the uncertainty analysis. Haan et al. (1995, 1998) assigned lognormal probability distributions for the S, the storage value or maximum soil water retention, based on observed data from a watershed in Oklahoma. S is found from

$$S = \frac{25400}{CN} - 254 \quad (4)$$

where CN is the curve number for the source area based on soil type, land use and antecedent moisture conditions. Since this implementation of VFSMOD is primarily targeted at design scenarios, CN was selected in this study instead of S. We also assumed that the uncertainty associated with CN was mainly due to interpretation of the source area. In addition, a selection represents an average source area land use and also depends on the timing of the storm event. The selection may or may not be representative of the actual curve number at the time of the storm.

The other procedure in the UH program chosen for analysis was the Modified Universal Soil Loss Equation (MUSLE). The equation for MUSLE is:

$$A = R_m \quad K \quad LS \quad C \quad P \qquad (5)$$

where A = computed soil loss per unit area for the storm; R_m = storm modified rainfall factor; K = soil erodibility factor; LS = slope - length factor; C = crop practice factor; and P = conservation practice factor. Since UH is used to generate idealized design storms for the area, the rainfall factor and slope length factors were not included for the uncertainty analysis even though both of these parameters would be important if considering testing on actual field conditions. The K, C and P factors were selected for inclusion in the uncertainty analysis.

VFSMOD parameters for inclusion in the sensitivity and uncertainty analyses were selected based on the initial model testing and sensitivity analysis (Muñoz-Carpena, 1993; Muñoz-Carpena et al., 1999). This was used to guide selection of the candidates for inclusion. From this analysis, the input parameters selected include the saturated hydraulic conductivity, initial soil water content in the buffer strip, the average soil particle diameter of the sediment from the source area, and the average vegetation stem spacing.

The user first selects a base set of inputs for UH and VFSMOD. These inputs provide base values for performing the sensitivity or uncertainty analyses. In the sensitivity analysis section, the user selects the minimum and maximum value and an increment for varying the input parameter. Next, the simulations are done and the user can view the results. Simple statistics are computed along with graphs of the relationships. The data is stored in a dataset compatible with other programs for further analyses.

The uncertainty analysis section enables the user to do MCS and investigate the interaction between input parameters to assess the uncertainty of design outputs. For each parameter, VFSMOD-W includes a selection of possible input distributions. The input distributions include the normal, lognormal, triangular and uniform along with parameters to define the distribution. Figure 1 shows selecting the distribution and parameters in VFSMOD-W.

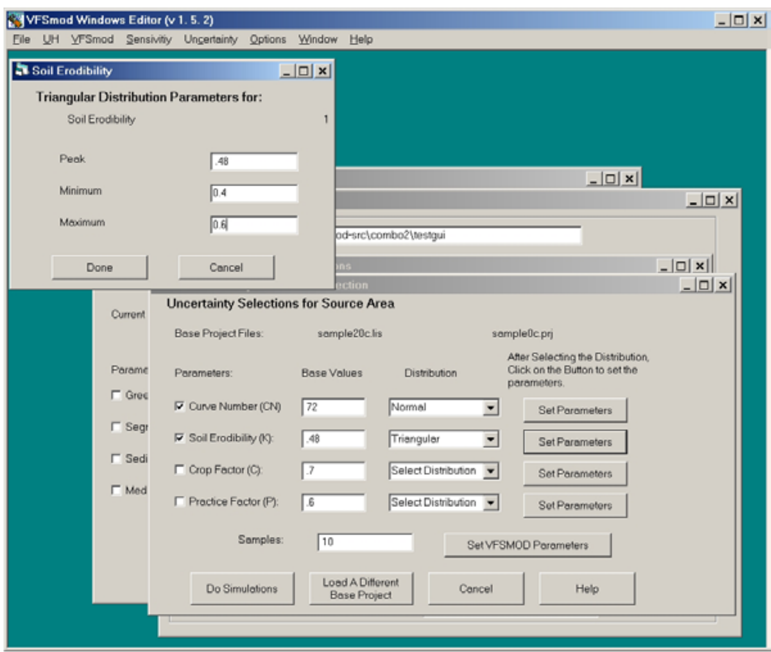


Figure 1. Selection of Input Parameters for Uncertainty Analysis

Illustrative Case Study

The utility of incorporating sensitivity and uncertainty analyses in our modeling applications enables the user to concentrate on specific site parameters. In this way, the user can use *a priori* knowledge of local variability and simulate better (or more certain) predictions for their design case. A typical application of VFSMOD is to evaluate the effectiveness of VFS given a source area and storm event. For this we consider an application in the Piedmont region of North Carolina. An agricultural field is upslope from the planned VFS. We assume that the agricultural production is a row crop (with a curve number of 85) and the soil type is sandy clay. The slope of the source area is

2%. A 54 mm six-hour storm event (1 year return period) was selected for evaluation. The VFS parameters are selected to represent a good stand of grass such as fescue with a VFS length of 5 m.

Table 1 shows the parameters used in the sensitivity analysis along with their ranges. The ranges were selected to be representative of those expected for the simulation area. For example, the vertical saturated conductivity input for the Green Ampt procedures can vary between 6 and 20 cm/h for the sandy clay soil type.

Table 1. Parameter values for sensitivity analysis.

Parameter	Base Value	Minimum	Maximum	Increment
Curve Number, CN	85	78	90	0.05
Soil Erodibility, K	0.33	0.25	0.40	0.01
Crop Factor, C	1.0	0.2	1.0	0.05
Ksat, Green Ampt (cm/h)	11.99	6.0	20.0	1.0
Theta Initial, Green Ampt (cm^3/cm^3)	0.125	0.05	0.25	0.025
Particle Class Diameter, dp (um)	66	10	100	2.0

The graphical user interface system allows the analysis of all outputs listed in Table 2. SDR and RDR were selected since these are non-dimensional and allow easy comparisons between various source area – filter strip combinations. Both SDR and RDR range from 0 to 1. The absolute sensitivity of SDR and RDR can be found from equation 1. If the relationship between the output and the input parameter is linear, then the absolute sensitivity is the slope of the line. Table 3 summarizes the linearity of SDR and RDR in relation to each of the input parameters.

Table 2. Output parameters saved from Simulations.

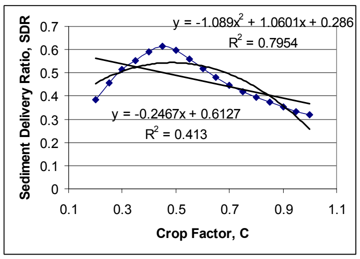
Parameter	Description
Source Runoff	Runoff from the source area as a depth (mm) and volume (m^3)
Filter Runoff	Runoff from the VFS as a depth (mm) and volume (m^3)
Filter Infiltration	Infiltration in the VFS as a volume (m^3)
Source Sediment	Mass (kg) and concentration (g/L) of sediment from the source area
Filter Sediment	Mass (kg) and concentration (g/L) of sediment from the VFS
Sediment Delivery Ratio (SDR)	Ratio of Mass of Sediment lost from the Filter to Mass of Sediment entering the Filter from the source area
Runoff Delivery Ratio (RDR)	Ratio of Filter Runoff to Runoff from the source area

Table 3. Summary of the Sensitivity Analyses.

Input Parameter	Output Parameter	Linear Slope	Linear Intercept	Linear Fit (r^2)
Curve Number, CN	SDR	0.0094	0.4918	0.88
	RDR	0.0071	0.313	0.98
Soil Erodibility, K	SDR	0.9341	0.6501	0.94
	RDR	-	-	-
Crop Factor, C	SDR	-0.2467	0.6127	0.41
	RDR	-	-	-
Ksat, Green Ampt (cm/h)	SDR	-0.001	0.3306	0.99
	RDR	-0.006	0.9891	0.99
Theta Initial, Green Ampt (cm3/cm3)	SDR	0.0013	0.3188	0.14
	RDR	0.0234	0.9133	0.96
Stem Spacing, SS (cm)	SDR	0.2191	0.1481	0.87
	RDR	-	-	-

In the case of soil erodibility there was no effect on RDR, which is expected since the soil erodibility is used to determine the sediment lost from the source area. The linear relationship between RDR and curve number yields an increase of 0.0071 RDR for each unit increase in the curve number. The soil erodibility ranged from 0.25 to 0.4 and the slope of the fitted line indicates that there was 0.9341 SDR increase for each unit increase in soil erodibility. From this type of information, the FOA statistics could be computed using Equations 2 and 3 if the user can estimate the expected variance of the input parameter. This was not done for this analysis but is being considered as a possible addition to analysis options in VFSMOD-W.

Figure 2 shows the sensitivity of SDR with relation to the crop factor, C. The fit is not linear. Examination of the sediment lost from the source area and from the filter strip indicates that the filter strip sediment trapping increased to approximately 750 kg. However, the sediment delivered from the source area continued to increase. For C>0.5, the SDR declined from 0.6 to 0.3. This is interesting to note since the crop factor is usually determined as an average value for a given land use. In this case, a row crop, the crop factor can vary from near 1 at planting to 0.2 as the crop matures. The performance of a selected VFS length will vary not only based on the size of the storm event but also with factors such as the crop development.



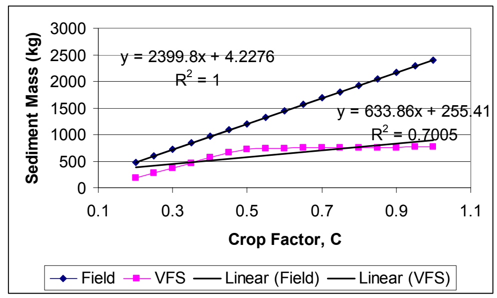


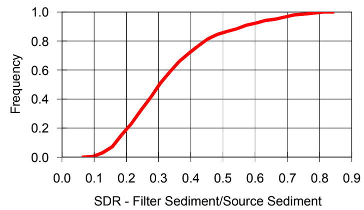
Figure 2. Sensitivity Relations for the Crop Factor, C.

For the MCS analysis, VFSMOD and UH were run 1800 times sampling inputs from the parameters in Table 4. The distributions and statistics were chosen to illustrate the VFSMOD-W capabilities. The base input parameters were the same as those used for the sensitivity analysis. The objective for selecting the distributions and statistics was to represent possible selections based on the design problem. For example, a triangular distribution with a peak of 85 and minimum and maximum of 79 and 90 was selected for the curve number to represent the range of possible curve numbers for the source area. Soil erodibility, K, and average particle class diameter, dp, were assumed to be normal distributions with means of 0.33 and 66 and standard deviations of 0.05 and 10, respectively. A lognormal distribution was used for Ksat with a mean of 11.99 cm/h and standard deviation of 3. The initial soil water content, ThetaI (Green Ampt parameters), was assigned a uniform distribution and allowed to vary randomly between 0.05 and 0.25 cm^3/cm^3.

Table 4. Input distributions for MCS.

Parameter	Base Value	Distribution	Statistics		
Curve Number, CN	85	Triangular	Peak=85	Min=79	Max=90
Soil Erodibility, K	0.33	Normal	Mean=0.33	Stdev=0.05	
Ksat, Green Ampt (cm/h)	11.99	Lognormal	Mean=12.0	Stdev=3.0	
ThetaI, Green Ampt (cm^3/cm^3)	0.239	Uniform	Min=0.05	Max=0.25	
Particle Class Diameter, dp (um)	66	Normal	Mean=66	Stdev=10	

SDR and RDR were selected to investigate the uncertainty. The base SDR and RDR from the base input datasets were 0.318 and 0.916, respectively. The mean values for SDR and RDR resulting from the 1800 simulations were 0.348 and 0.926, respectively, and the resulting cumulative probability density functions are given in Figure 3. The certainty of our predictions of SDR and RDR can be derived from these probability density functions. For SDR, we see that 0.8 or less is close to 100% certain for this case. It is also interesting to note that our base SDR of 0.318 has a probability of occurrence of approximately 0.55. For RDR, the base of 0.916 has a probability of occurrence of approximately 0.45 and RDR is less than 0.99 with a certainty of 100%.



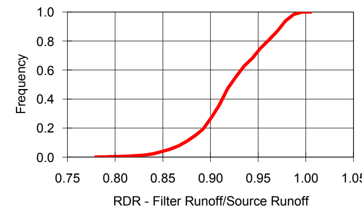


Figure 3. Cumulative probability density functions for simulated SDR and RDR.

Summary and Conclusions

The vegetative modeling system consists of a graphical user interface program, VFSMOD-W, along with the programs UH and VFSMOD for evaluating the effectiveness of vegetative filter strips for trapping sediment from upslope source areas. The UH program generates storm hyetographs, runoff hydrographs, and erosion estimates from the source area in a format compatible as inputs for VFSMOD. VFSMOD simulates transport and fate of sediment through a VFS. VFSMOD-W was modified to integrate sensitivity and uncertainty analysis for a given design scenario. A number of input parameters for UH and VFSMOD can be included in sensitivity and uncertainty analyses. The user can base sensitivity and uncertainty analyses a particular design scenario and site.

An example using a design scenario from the Piedmont region of NC illustrates the approach. Input parameters for a source area with a row crop and a VFS of 5 m in length were developed. The sensitivity analyses and uncertainty analyses were based on input parameter ranges and probability distributions appropriate for the design scenario. MCS were conducted and probability distribution functions were derived for selected outputs. The certainty of the outputs can be assigned based on the variability in the inputs for a given design scenario. A 1-year return period storm was used to evaluate the use of VFSMOD-W's sensitivity and uncertainty procedures with the 5 m buffer width. The probabilities for the base RDR and SDR's of 0.92 and 0.318 or less were found 0.56 and 0.55, respectively. VFSMOD-W offers a new tool to evaluate uncertainties associated with specific design parameters.

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