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Impact of Uncertainty on the Design of Vegetative Filter Strips

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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. 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 will demonstrate the use of confidence intervals for sediment trapping based on uncertainty in the inputs parameters for the source area and the vegetative filter strip.*

Keywords. model, uncertainty, vegetative filter strips

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 of a real world system 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 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. Suwandono et al. (1999) demonstrated this 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. As with most uncertainty analyses, they presented an example based on a specific set of inputs for the Small Watershed Monthly Hydrologic Modeling System (SWMHMS). First, 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

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.

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

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 term is the slope of the sensitivity relationship between O and P_i or S_i. With these assumptions, the variance equation becomes

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
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. This approach enables the user to start with a base set of inputs and evaluate the uncertainty in the resulting performance of the VFS. As a starting point, 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, it was assumed that the curve number was the most sensitive parameter and therefore very important in the uncertainty analysis. Haan et al. (1995) and Haan et al. (1998) assigned probability distributions for the S, the storage value or maximum soil water retention, used in this method. They assumed that the uncertainty in S could be described as lognormal distribution based on observed watershed data from a watershed in Oklahoma. S is found from

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 curve selection represents an average source area land use and depending on the timing of the storm event, this 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:

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 some 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. An example of selecting parameters is shown in Figure 1. Next, the simulations are done and the user can view the results as shown in Figure 2. Simple statistics are computed and the data is stored in a dataset that can be used in other programs for further analyses.

Figure 1. Example of selecting a VFSMOD input parameter for sensitivity analysis

Figure 2. Example of the sensitivity results.

The uncertainty analysis section enables the user to do MCS and investigate the interaction between input parameters to assess the uncertainty on 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 the respective parameters to define the distribution. Examples of the sampled distributions for saturated hydraulic conductivity, Ksat, and the curve number, CN, are given in Figure 3. The mean and standard deviation for the lognormal distribution for Ksat was 4.79 cm/hr and 0.5 cm/hr. The sampling for the curve number was from a normal distribution with a mean of 72 and a standard deviation of 3. Figure 4 shows selecting the distribution and parameters in VFSMOD-W.

Figure 3. Examples of sampled inputs for Ksat (lognormal) and Curve Number (normal) for 1559 samples.

Figure 4. Selection of Input Parameters for Uncertainty Analysis

Once the inputs are selected, VFSMOD-W, generates input datasets and executes UH and VFSMOD saving a number of output parameters for uncertainty analysis. The output parameters are given in Table 1. The data format of the output file is easily read by other programs for further analysis.

Table 1. Output parameters saved from Simulations.

Parameter	**Description**
Source Runoff (mm)	Runoff from the source area as a depth
Source Runoff (m3)	Runoff from the source area as a volume
Filter Runoff (mm)	Runoff from the VFS as a depth
Filter Runoff (m3)	Runoff from the VFS as a volume
Filter Infiltration (m3)	Infiltration in the VFS as a volume
Source Sediment (kg)	Mass of sediment from the source area
Source Sediment Concentration (g/L)	Concentration of sediment from the source area

Filter Sediment (kg)	Mass of sediment from the VFS
Filter Sediment Concentration (g/L)	Concentration of sediment from the VFS
Sediment Delivery Ratio	Ratio of Mass of Sediment lost from the Filter to Mass of Sediment entering the Filter from the source area
Runoff Delivery Ratio	Ratio of Filter Runoff to Runoff from the source area

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. This is illustrated with an example. A typical application of VFSMOD is to evaluate the effectiveness of VFS given a source area and storm event. For this we consider and 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. The VFS length was fixed at 5 m.

Table 2 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 2. 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 3. For these analyses, we selected Sediment Delivery Ratio (SDR) and Runoff Delivery Ratio (RDR). SDR and RDR were computed as

These outputs were selected since these are non-dimensional and allow easy comparisons between various source area – filter strip combinations. Both SDR and RDR can range from 0 to 1. The absolute sensitivity of SDR and RDR can be found from equation 1. In the case that the relationship between these outputs 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 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	-	-	-

Figure 5 shows the relationships between SDR and RDR and the inputs parameters curve number and soil erodibility. 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. In the case of the curve number, 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 information, the FOA statistics could be computed using Equations 2 and 3. This was not done for this analysis but is being considered as a possible addition to analysis options in the graphical user interface.

Figure 6 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. From a crop factor of 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 5. Sensitivity Relationships for Curve Number and Soil Erodibility.

Figure 6. 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 VFS modeling systems capabilities. The base input parameters were the same as those used for the sensitivity analysis. The objective for selecting the distributions and statistics were 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.

For the 1800 simulations, Figure 7 shows the sampled distributions for curve number and soil erodibility. SDR and RDR were selected to investigate the uncertainty generated by the input probability distributions given in Table 4. The base SDR and RDR from the base input datasets were 0.148 and 0.789, respectively. The mean values for SDR and RDR resulting from the 1800 simulations were 0.318 and 0.916, respectively. The resulting distributions for SDR and RDR are given in Figure 8. The cumulative probability density functions are given in Figure 9. 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 is has a probability of occurrence of approximately 0.55. The base RDR has a probability of occurrence of approximately 0.45 and RDR is less than 0.99 with a certainty of 100%.

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	
Theta Initial, Green Ampt (cm3/cm3)	0.239	Uniform	Min=0.05	Max=0.25	
Particle Class Diameter, dp (um)	66	Normal	Mean=66	Stdev=10	

Figure 7. Sampled distributions for Curve Number and Soil Erodibility.

The effect of storm size and buffer length was examined using the same base input datasets and running 1502 simulation for a six-hour 5-year return period storm of 85 mm with a 10 m buffer length. The resulting cumulative probability density functions for SDR and RDR compared with those for the 1-year return period storm with a 5 m buffer length are shown in Figure 10. The SDR probability density function is shifted to left for 5-year return period storm as compared to the 1-year return period storm. The base SDR's for the 1-year return period storm is 0.32 and 0.17 for the 5-year return period storm. Even though the cumulative probability density function for the 5-year return period storm is skewed to the left, the probabilities that the results are less than the base values are the same, 0.55. The results for RDR were very similar in both cases with the 5-year return period storm skewed to the right of the 1-year return period storm. The base RDR's were nearly the same, 0.92 for the 1-year return period storm and 0.94 for the 5-year return period storm. There were only slight differences in the probabilities that the simulated RDR's were less than those simulated for the base values. From this it is clear that one fit for the probability density functions will probably not work across all possible design combinations. Future modifications to the uncertainty portion of the VFS modeling system will incorporate some of these analyses directly in the graphical user interface.

Figure 8. Simulated distributions for SDR and RDR.

Figure 9. Cumulative probability density functions for simulated SDR and RDR.

Figure 10. Comparison of simulated probability density functions for SDR and RDR with a 5 m buffer width and 1-year return period storm and a 10 m buffer width with a 5-year return period storm.

Summary and Conclusions

The vegetative modeling system consists of a graphical user interface program, VFSMOD-W, along with the programs UH and VFSMOD to assist in developing input datasets for evaluating the effectiveness of vegetative filter strips for trapping sediment from upslope source areas. The UH program generates storm hyetographs and 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.

The graphical user interface program was modified to enable easy execution sensitivity and uncertainty analysis for a given design scenario. Input parameters for UH and VFSMOD were selected as possible candidates for inclusion in sensitivity and uncertainty analyses based on initial model testing of VFSMOD. The user can base sensitivity and uncertainty analyses on input parameters associated with a particular design scenario.

An example application using a design scenario from the Piedmont region of North Carolina is used to illustrate the approach. Input parameters for a source area consisting of a row crop along with grass buffers of 5 m and 10 m lengths were developed. The sensitivity analyses yield absolute sensitivity parameters based on input parameter ranges appropriate for the design scenario. Uncertainty analyses were illustrated by assigning distributions and ranges based on the design scenario. Monte Carlo Simulations were conducted and probability distribution functions were derived for selected outputs. The degree of confidence in 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 the system with the 5 m buffer width. Base RDR and SDR's of 0.92 and 0.318 were found to be greater MCS values with a probability of 0.56 and 0.55, respectively. Distributions generated with a 5-year return period storm and a 10 m buffer were compared to the 1-year return period storm with a 5 m buffer. The larger rainfall event and buffer combination gave a cumulative probability density function skewed to the left of the 1-year return period – 5 m buffer function for SDR. The cumulative probability density function for the larger storm buffer combination was skewed to the right for RDR. Although the probabilities associated with the base values were similar, the differences suggest that uncertainty analysis based on the specific design parameters can be a useful approach.

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