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MODELING DELIVERY OF LANDSLIDE MATERIALS TO STREAMS

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ABSTRACT

Landslides can be a significant source of sediment in watersheds. Landslide materials which enter stream channels can create unwanted responses such as blockage or diversion of the stream and significant degradation of the aquatic and riparian habitats. Estimates of amount of material delivered to a stream channel by a landslide would be of great value to watershed managers. In this study, current methodology was reviewed and new models were developed for estimating the delivery of landslide materials to a stream channel.

A mutually beneficial collaboration was developed with researchers at the University of Newcastle-upon-Tyne, Great Britain, regarding a review of the state-of-the-art and conceptualization of new approaches. A very important literature review was produced by the British group.

New models were developed from landslide measurements collected in Idaho between 1974 and 1976. Over 1300 observations were screened and utilized to produce a two-step approach for estimating delivery. In the first step, site characteristics of landslide length, distance of the landslide from the stream, and the slope gradient are entered in a logistic model. The logistic model defines whether the landslide will reach the stream. If landslide material does reach or "makes it" to the stream, a multivariate model is used to estimate the percent of delivery. The multivariate model is conditioned on the observation that a slide reaches the stream. Although the confidence intervals on the delivery estimates can be quite large, the models combine physically meaningful site characteristics accounting for spatially variable landslide delivery. The models developed in this study will be useful in suggesting directions for further research and watershed modeling approaches.

INTRODUCTION

General

Landslides in upland watersheds can produce damage to on-site resources and to downslope areas. If a landslide enters a stream, the landslide materials may be transported far beyond the original depositional location and cause other damages. This is particularly true if the receiving waters are prime fish habitat. Sediment loadings from landslides can far exceed the normal carrying capacity of the streams thus creating a sediment-choked channel unsuitable as fish habitat.

Determining when and where landslides will occur, whether they are human caused or naturally occurring, is a difficult task. Determination efforts have been aided by applying soil mechanics principles, remotely sensed data, extensive field studies, and Geographic Information Systems (GIS). These techniques have come together to yield landslide hazard or potential maps which delineate areas wherein conditions, such as slope gradient, soil materials, ground water and vegetation exists, which can ultimately lead to slope failure.

A slope failure or landslide is a necessary but not sufficient condition to yield materials to a stream channel. This study attempts to determine the link between the occurrence of a landslide and the amount of landslide material delivered to a downslope channel.

Goal and Objectives

This study's goal was to develop a baseline understanding of the factors and processes influencing downslope delivery of landslide materials. To achieve this goal, four objectives were set. These were to:

1. summarize univariate statistics of landslide delivery data, as supplied by the USDA Forest Service, in total and by important influencing factors such as landslide type, site properties, and management factors;

2. develop empirical equations for predicting the percentage of landslide delivery to channels using site factors and landslide properties;

3. locate and describe available models for predicting the downslope delivery of landslide material, and where possible, test the applicability of such models using the supplied landslide data; and

4. present the results and findings in a report.

Collaboration

A mutually beneficial collaborative effort was arranged with Dr. James Bathurst and Dr. Sue White associated with the Water Resources Systems Research Unit (WRSRU), Department of Civil Engineering, University of Newcastle-upon-Tyne, Newcastle-upon-Tyne, U.K. The WRSRU is developing the SHE (Système Hydrologique Européen) model (Abbot et.al. 1986a, b) and has added a landslide erosion and sediment yield routine to the SHETRAN component. SHETRAN is a physically based hydrological sediment transport and contaminant migration modelling system applicable at the basin scale. SHETRAN is an offshoot of the SHE. Bathurst has chosen to use the approach developed by Ward (1976) with an enhancement (routing). As part of the modelling effort, Bathurst (1991) produced an exhaustive literature review. As part of the review, he visited New Zealand and was in turn visited by this writer at the University of Newcastle. Bathurst's review formed a critical part of this study.

METHODOLOGY

General

The two primary products of this research were a review of current modeling approaches and an analysis of existing data to define appropriate models suitable to the data. The first product required a search and synthesis of information from a variety of sources. The second product required extensive use of statistical analyses programs. The statistics package chosen was SAS (SAS Institute 1989), which was available at New Mexico State University and the University of Newcastle. Of particular interest were those algorithms for assessing univariate and bivariate statistics, multivariate regression, and logistic regression.

Data Base

Data for analyses were provided by Dr. Walter Megahan, formerly of the USDA Forest Service Intermountain Research Station in Boise, Idaho. The overall data base is summarized in Table 1.

Table 1. Summary of Data Sets Supplied by USDA Forest Service

Data Set	National Forest	Year Sampled	Number of Samples
BNF75	Boise	1975	792
CNF74	Clearwater	1974	156
CNF75	Clearwater	1975	230
CNF76	Clearwater	1976	188
TOTAL NUMBER OF LANDSLIDES SAMPLED			1366

Each observation (sample) or measured landslide could have as many as 102 characteristics determined for it. Some important characteristics for this study included percent of landslide material delivered to the channel, dimensions of the landslide, source of the landslide, distance of the landslide from the channel, and slope gradient. All variables were not available or measured for each observation. Therefore, each data set was screened to exclude those observations not having variables useful in modeling.

The first filter or screening decision was whether or not there was a recorded percent delivered value for the observation, that is, values greater than or equal to zero (0). The percent delivered variable (%DEL) was determined from the following:

$$\%DEL = \frac{(VOLSLD+VOLEROS)-VOLDEPx100\%}{(VOLSLD+VOLEROS)} \qquad (1)$$

where %DEL = percent of total landslide material delivered to a channel (by volume),

VOLSLD = volume of the landslide either from measurements of length, width and depth or estimated,

VOLEROS = volume of material eroded downslope of the landslide, either calculated from measurements or estimated, and

VOLDEP = volume of deposition, either calculated from measurements or estimated.

In almost all observations, VOLEROS was not recorded. Because of the error and uncertainty in the measured variables of Equation 1, the exact value of %DEL is not known. Therefore, attempts to estimate precisely recorded values of %DEL can be fraught with problems. Observations were also eliminated if they did not contain variables for original slide length (SLDLEN), slide width (SLDWTH), slide depth (SLDDEP), slope gradient (SG), and distance of the slide from a stream channel (STDIST). Observations were classified as to whether or not any slide material entered the channel (MADEIT=0 for No, and=1 for Yes), and by source of slide material (SLDGRP, see Table 2). The slide source "Other" refers to slides resulting from human activities not related to roadways. This would include landings and other slope modifications.

Table 2. Grouping of Landslides by Source

Slide Source	Group #
Other	0
Natural	1
Road Cuts	2
Road Fills without Culverts	3
Road Fills with Culverts	4

The filtering process yielded working data sets from the data base (Table 3). These data sets can be further described by a slide group (SLDGRP) as categorized in Table 4. The data in Table 4 clearly indicate that the predominant number of recorded landslides is associated with road cuts. Table 4 describes the working data sets fairly well and helps define further modeling steps. Plots of %DEL with the other variables were generated for each data set along with descriptive statistics (see Appendix A for descriptive statistics). A general linear model procedure (GLM), of SAS was applied to the data sets to determine if there were differences between data sets and among the slide groups. The GLM is preferred to analysis-of-variance (ANOVA) when the number of observations is unbalanced. Differences were noted between the data sets, but those differences are not believed to be a result of differences in underlying physical processes, but by differences in what was sampled.

Table 3. Results of Preliminary Filtering (screening) of Data Sets

	Number of Observations		
Data Set	As Supplied	After Screening	Percent Retained
BNF75	792	563	71
CNF74	156	135	87
CNF75	230	230	100
CNF76	188	188	100
TOTAL	1366	1116	82

Table 4. Number of Landslides by Data Set and Source

	Slide Group (Source)					
Data Set	Total Number	Other	Natural	Road Cuts	Road Fills w/o Culverts	Road Fills with Culverts
BNF75	563	84	32	270	156	21
CNF74	135	7	4	64	42	18
CNF75	230	4	19	148	31	28
CNF76	188	7	8	121	39	13
TOTAL(%)	1116	102(9)	63(6)	603(54)	268(24)	80(7)

Fuzzy Number Analysis

The application of fuzzy data set concepts was investigated with respect to determining delivery of material to a channel. Fuzzy data set theory was initially proposed by Zadeh (1965). Kaufmann and Gupta (1991) expanded upon Zadeh's ideas with a more thorough treatment of fuzzy arithmetic. In general, fuzzy sets are limits (minimum and maximum values) placed upon a variable of interest. For example, if the variable has a value of 4, and it is known that the variable does not fall below 2 or become greater than 6, then the limits and most likely value of the variable have been established. The next, and most difficult, step is to define the value distribution within the interval [2, 6]. Apriori the chance of 4 occurring is high and is assigned a weight of 1.0, whereas 2 and 6 have weights of 0. Numbers between 2 and 6, except 4, receive weights greater than 0 but less than 1.0. The shape of the curve that joins all points must be known or approximated by the person applying the technique.

Two general shapes are often applied, triangular or rectangular. A triangular shape peaks on the most likely value, in this case 4, and falls to a zero weight at the limits 2 and 6 for this case. A rectangular shape infers that any value over the range has the same weight as any other. Infinitely many other shapes are possible. The primary concept is that over a range of values, some values have a higher **possibility** of occurrence rather than a conventional probability of occurrence. The rules of arithmetic generally apply to the fuzzy data sets, but produce results much different than if random variables were selected from probability distributions using Monte Carlo simulation techniques. For example, if a fuzzy variable described by rectangular distribution is added N times, the resulting distribution is rectangular. In contrast, if a uniformly distributed variate is sampled and added N times, the result is a normally distributed random variable, as predicted from the central limit theorem. Thus, a one-to-one correspondence of **possibility** and **probability** theory does not exist.

Applications of fuzzy data set concepts to civil engineering problems have been growing. Bardossy and Disse (1993) used fuzzy rule-based concepts to model infiltration into soils. Applications were made with two commonly used infiltration models. Lee, Dahab, and Bogardi (1994) used fuzzy sets along with a multicriteria decision-making technique to assess groundwater nitrate risks. The paper by Lee and Juang (1992) presents a qualitative evaluation scheme for assessing slope-failure potential in mudstone terrain. The authors used fuzzy sets and a multibranched decision tree to create their failure potential classification. Juang, Lee, and Sheu

(1992) present a fuzzy set based approach for mapping slope failure potential. The authors used fuzzy set theory, five levels (A through E, A being the most hazardous) of ratings for site variables (such as slope gradient and rainfall), and repetitive Monte Carlo sampling to produce a Slope Failure Potential map for a site in southern Taiwan. A potential approach that may be applied to the landslide data described in this report was summarized by Diamond (1992). In that paper, Diamond described the development of linear models based on imprecisely known or fuzzy data sets. Fuzzy data set theory appears to have potential for application to the data used in this study. One drawback in the application is that the resultant values produced by the fuzzy set approach are fuzzy themselves, such as classification of very high, high, medium, low and very low. In sediment routing and yield studies, these classes will need to be assigned ranges so that crisp numbers can be utilized in computations. Whether or not a slide reaches a stream is a crisp number, yes or no. The volume material reaching the stream can be considered a fuzzy number because of measurement difficulties. For this study, it has decided to apply tradition probabilistic approaches to the data. However, the application of fuzzy number theory to landslide estimation is a topic with high potential benefits and should be pursued.

MODEL TYPES

General

Two types of models were considered for estimating delivery of landslide material to channels. The first type was a logistic model. A logistic model is appropriate if a variable is within a certain classification or grouping. Descriptions of logistic and other nonlinear models can be found in Draper and Smith (1981), Netter, Wasserman, and Kutner (1989), Seber and Wild (1989), and Wadsworth, Jr. (1989). In this study the key grouping variable was MADEIT, that is, whether or not a landslide was recorded as having reached or "made it" to a stream channel. Each observation was assigned 0 or 1 (did not reach or did reach a channel) for the variable MADEIT, then MADEIT was modeled with logistic regression. A general form of the logistic regression model can be expressed as:

$$P\{Y=y\}=\frac{\exp(-X'\beta)}{1+\exp(-X'\beta)} \qquad (2)$$

where P{Y=y}= the probability that a dependent variable Y is equal to an integer value y,

exp ( ) = is the exponential function of the parenthetical values,

X' = a vector containing the independent variables or X_i's, and

β = a vector containing the coefficients fitted to the data.

The logistic model cannot be fit by standard least squares regression techniques because the residuals will be either 0 or 1 (No or Yes). Therefore, likelihood estimators and numerical optimization techniques are applied to the data to determine an appropriate model. For the landslide data sets, the interest is whether or not the observation is in the MADEIT=1 (Yes) group. If so, then the observation should contain variables which would physically enhance the delivery of landslide material to the channel, such as a short distance to a stream or a steep slope gradient. The logistic model is continuous on the interval 0 to 1 but the observations are discrete. Therefore, a cut-off level must be selected so that a balance is struck between the number of underpredictions, that is, predict no delivery when material did reach the channel, and overpredictions, that is, predict delivery when it did not occur.

The logistic model also can be used to estimate the interval groupings assigned to the %DEL variable. In this type of application, the logistic model is fit to the stratified data and each strata receives an intercept value (β_o) but shares the other (β_i) values. One problem with this approach is that the within strata variance of the predictor variables may not be sufficient to permit that variable to be used in the model (not a significant β_i coefficient). Another modeling strategy would be to predict first whether or not a slide will make it to a stream, then estimate the %DEL using multivariate regression.

Multivariate linear regression is a commonly used technique for relating dependent or response variables to independent or control variables. Often the assumptions surrounding multiple regression as a statistical tool are violated by model builders. Regardless of whether or not the statistical assumptions are entirely satisfied, multiple regression is a useful approach for determining optimal coefficients in the model. A number of general statistics and specific linear models texts contain detailed and extensive sections on multivariate linear regression (for example, see Draper and Smith 1981, and Neter, Wasserman, and Kutner 1989).

Variable Selection

The variables used to build the models should be those which make physical sense, are easily calculated in a model of landslide failure, and also can be related to %DEL and MADEIT. The obvious choices for variables include those previously mentioned and various combinations of the variables including the inverse of the distance to the stream (except for those observations where STDIST=0), the ratio of slide length (a measure of size) to distance to the stream (SLLSTD=SLDLEN/STDIST), a potential energy term which is the product of distance to a stream and slope gradient, and various transformations of the different variables. Numerous other variables and variable combinations were examined. Those selected for the models had the highest correlations with the %DEL and MADEIT variables and did not exhibit collinear behavior with the other selected variables. Notes supplied with the original data base were extremely helpful in selecting variables for consideration.

RESULTS AND DISCUSSION

Review of Landslide Delivery Models

Contemporaneously with this study, Bathurst (1991) produced an important report reviewing physically based modeling of landslide erosion and sediment yield (see Appendix B). His extensive literature search did not reveal any models for estimating landslide delivery to a channel. He did find several references to debris-flow modeling including runout characteristics. Bathurst believed that the approach of James (1985) was the only previous attempt to represent landslide erosion and sediment yield in an integrated, process-based, catchment-scale model. Bathurst's work added significantly to this study by saving time, focussing efforts, and providing a basis for development of new ideas.

A number of articles have appeared since Bathurst's (1991) report. Brunsden (1993) discusses numerous research frontiers regarding mass movement. He speaks of many topics related to mapping and modeling of landslides, but does not specifically address landslide delivery. Other recent papers can be divided into two groups, those associated with mapping and prediction, and those associated with process modeling.

The mapping and prediction group includes the paper by Carrara et al. (1991), which combines discriminant analysis factor mapping with GIS technology to map landslide hazards. Carrara et al. explored other analysis techniques for estimating hazards, including linear regression, linear neural network modeling, and logistic regression, before selecting discriminant analysis. They note that logistic regression yielded results almost as sound as provided by discriminant modeling. Carrara et al. used their model to categorize GIS map pixels from a watershed in Italy as landslide or not. They compared their modelling results with what actually occurred. The percentages of correct grouping ranged from 75 to 85 percent.

Ziemer et al. (1991) use empirical and stochastic models to estimate the cumulative effects of forest management activities, specifically changes in sediment production and yield. Their "primitive simulation" (page 360 op.cit.) generates landslides in logged and roaded areas. Failed areas were converted to depth by multiplying by 1.5m. Twenty percent of the eroded volume was then delivered to a stream channel, and transport in the channel was modelled as a function of water discharge and sediment supply.

Auer and Shakoor (1993) studied numerous debris avalanches in the state of Virginia (USA) caused by hurricane Camille in 1969. They used basin physiography to classify basins as stable or unstable based on horizontal curvature and average slope gradient. Of 21 basins classified as unstable with their method, only 14 (67%) were observed to have failed. The primary controlling factor for instability was coarse grained soils that saturated rapidly.

Maharaj (1993) reported on a study in Jamaica, West Indies, wherein 886 failures were mapped. Debris slides accounted for 82 percent of the failures. Most failures occurred within a conglomerate and breccia dominated lithologic unit. Maharaj used factor analysis to create a landslide susceptibility map for the area.

Jade and Sarkar (1993) used information theory (probability) and regression analysis to estimate landslide hazards in the Gharval Himalaya. The information theory approach uses a factor-based model wherein each factor is weighted by its occurrence in landslide-prone areas. Both methods produced similar results when used to map landslide prone areas. In general, the regression approach appeared to be marginally better than the information theory approach.

Garland and Oliver (1993) used rainfall variables to estimate landslide frequencies in the Durlan region of South Africa. They found that a model could be developed for estimating the timing and number of events. They used a data base of 120 landslides.

Cruden and Hu (1993) used steady-state and exhaustion models to predict landslide hazards in the Canadian Rocky Mountains of Alberta. Steady-state assumes that the landslides (rock slides) which have occurred in the area have done so at a steady average rate of one every 150 years, on average, for the last 10,000 years. Exhaustion assumes that once an area fails (slides) it is no longer susceptible and the total susceptible area is thus reduced. The reduction in area, in effect, lengthens the return period assumed by the steady-state model, a fact process models should consider. Conversely, areas which fail can refill and fail again if given enough time.

Several papers have appeared related to landslide flow modelling. Sousa and Voight (1992) used a continuum dynamic flow model to assess the travel distance, velocity, and debris deposit dimensions of a potential landslide. Their model is based on a Bingham rheology approach and considers viscous and plug flow. This method may be applicable when modeling deposition in the streams on an individual landslide basis. However, it does require several parameters not easily obtainable, such as material viscosity.

Davis (1992) used a dual zone approach to model debris flows wherin a steep feeder slope empties onto a flatter accumulation segment. The model, although simple, was not effective in predicting onset of surges, but does provide insight into the processes involved.

Zhang et al. (1993) examined earth flows on forested and grassed slopes in New Zealand. Surface movement on forested slopes was significantly less than on grassed slopes. A primary factor is the modification of soil rheology by interspersed tree roots.

Davis et al. (1993) examined the effects of velocity-dependent strength characteristics of the stability of a sliding mass. They concluded that although complex discrete models, for example, continuum models, will simulate a wider variety of motions, the overall stability of the mass being the same as that for a simpler rigid-body model. This finding is important because it indicates that simpler models can be as effective as more complex types to estimate stability.

O'Brien et al. (1993) present their two-dimensional model of flood and debris flow hazards. Although directed toward suburban/urban hazard prediction, the model can be used to determine deposition extent.

Montgomery and Dietrich (1994) used a topographic model to predict landslide initiation, transport and deposition zones in three small (0.3-1.2 square kilometer) watersheds on the West coast of the USA. Their model included soil moisture, conductivity, slope angle, contributing area above a potential failure zone, soil density, and angle of internal friction. Depositional zones were defined as the first topographic elements (downslope of the a failure zone) wherein slope falls below a threshold (usually 5 percent to 10 percent).

None of the recent papers speaks directly to the question of how to estimate delivery of landslide materials to stream channels. At a complex level of modeling, the papers by Sousa and Voight (1992), O'Brien et al. (1993), and Montgomery and Dietrich (1993) come closest in this regard. However, the complexity of those models is such that they are not appropriate for a large watershed-size analysis.

Descriptive Statistics

This study's data can be described in several different ways according to how it is grouped. Megahan, Day and Bliss (1978) have previously summarized the overall data set. Only information related to the working data set (Table 4) will be described in this study.

Table 4 indicates that most of the landslides were associated with road cuts, a fact discussed by Megahan, Day and Bliss (1978). Of particular interest is the slide volume and percent delivered for each source of landslide. These values can be seen in Table 5. Note that the value of comparison for did-not-reach and did-reach groups is the slide volume, but the value of interest in this study is the percent delivered. It is interesting that although landslides were often observed in road cuts (SLDGRP=2), the percent delivered for this group was less than the other groups. An analysis of variance test was applied to the data sets to determine which groups could be combined. Based on slide volume, (including the log transformed values of slide volume and percent delivered), it was determined permissible to group the data by source before further modeling.

Table 5. Average Slide Volume and Percent of Material Delivered for Each Data Set and Slide Type.

Data Set: BNF75 N=135

	Source				
Slide	*Other*	*Natural*	*Road Cut*	*Road Fill w/o Culvert*	*Road Fill w/Culvert*
Did not reach channel					
N_1	8	4	87[88]	35[39]	0
Slide Volume	53(39)	142(93)	95(179)	112(156)	--
Reached channel					
N_2	75/76	27/28	181/182	117/117	21/21
Slide Volume	240(651)	278(414)	165(363)	189(326)	331(450)
Percent delivered	39(29)	50(39)	4.7(9.1)	27(24)	34(30)

Slide Volumes in cubic yards
Values are listed as means (standard deviations)
N = number of observations based on slide volume for Did not reach channel and on Percent delivered for Reached channel.
N_1= observations for calculating mean of slide volume [total observations in brackets if different]
N_2= observations for mean of slide volume/mean of percent delivered

Table 5 continued. Average Slide Volume and Percent of Material Delivered for Each Data Set and Slide Type.

Data Set: CNF75 N=230

	Source				
Slide	*Other*	*Natural*	*Road Cut*	*Road Fill w/o Culvert*	*Road Fill w/Culvert*
Did not reach channel					
N_1	1	3	50	8[13]	5[6]
Slide Volume	2928	377(378)	216(665)	5150(12182)	7450(9971)
Reached channel					
N_2	3/3	16/16	97/98	17/18	22/22
Slide Volume	360(194)	4224 (15668)	754(3424)	826(958)	1619(2020)
Percent delivered	65(22)	57(33)	7.7(11.8)	43(36)	38(36)

Slide volumes in cubic yards
Values are listed as means (standard deviations)
N = total observations retained
N_1= observations for calculating mean of slide volume [total observations in brackets if different]
N_2= observations for mean of slide volume/mean percent delivered

Table 5 continued. Average Slide Volume and Percent of Material Delivered for Each Data Set and Slide Type.

Data Set: CNF76 N=188

	Source				
Slide	*Other*	*Natural*	*Road Cut*	*Road Fill w/o Culvert*	*Road Fill w/Culvert*
Did not reach channel					
N_1	4	0	6[7]	11[12]	1[2]
Slide Volume	120(44)	--	71(29)	2339(6672)	21
Reached channel					
N_2	3/3	8/8	111/114	26/27	10/11
Slide Volume	3648(6050)	126(109)	308(1187)	398(907)	221(298)
Percent delivered	11(16)	73(35)	5.5(8.71)	49(41)	30(26)

Slide volumes in cubic yards
Values are listed as means (standard deviations)
N = total observations retained
N_1= observations for calculating mean of slide volume [total observations in brackets if different]
N_2= observations for mean of slide volume/mean percent delivered

Table 5 continued. Average Slide Volume and Percent of Material Delivered for Each Data Set and Slide Type.

Data Set: All Observations N=1116

	Source				
Slide	*Other*	*Natural*	*Road Cut*	*Road Fill w/o Culvert*	*Road Fill w/Culvert*
Did not reach channel					
N_1	13	8	171[173]	61[71]	10[12]
Slide Volume	295(793)	216(252)	215(785)	1484(5314)	5605(7840)
Reached channel					
N_2	87/89	53/55	425/430	193/197	65/68
Slide Volume	374(1271)	1443(8620)	457(2057)	345(397)	1051(2352)
Percent delivered	42(30)	57(36)	6.6(11.2)	38(32)	39(33)

Slide volumes in cubic yards
Values are listed as means (standard deviations)
N = total observations retained
N_1= observations for calculating mean of slide volume [total observations in brackets if different]
N_2= observations for mean of slide volume/mean percent delivered

Derived Delivery Models

Logistics and linear models were fit to the grouped data to produce relationships between the site variables and: a) the probability that a landslide would "make it" to a channel, that is, enter the channel, and b) the volume of material the landslide would deliver if it did in fact reach the channel. Because the volume delivered was a very imprecise value based upon field estimates, any estimates of yield will have a large degree of uncertainty. Nevertheless, the models do provide a systematic approach to estimating delivery.

Separate models were fit for the probability and the percent delivery. These two types of models were fit to each landslide type (natural, road cut, etc.) and to all types grouped together. Identification of key variables which were related to probability and percent delivery included scatter plots of untransformed and transformed (logarithmic) values, correlations, and conceptual and practical considerations. Although not all the same variables were important to each data set, the important variables identified for the logistic (probability) model were length of landslide (SLDLEN), distance to nearest stream (STDIST), the ratio of SLDLEN to STDIST (SLLSTD, specifically log base e of SLLSTD or LSLL), and slope gradient (SG). The important site variables for percent delivered (PD, specifically log base e of PD or LPD) were as above SLDLN, STDIS, SLLSTD, and SG or their log base e transformations. Because of the large size of the data sets, these and other variables were "significantly" correlated to one another even though the largest observed linear correlation coefficient was 0.401 for 836 values of LPD and LSLDLN (log base e of SLDLEN). The landslide volume and percent delivered variables were examined to determine if they were normally distributed in the original and transformed values. Tests of normality, stem and leaf plots, and box-plots were applied to the variables with the result that log base e of landslide volume was normally distributed but only for road fills with culverts data (SLDGRP=4). In the other cases, it appeared that the data were skewed or uniformly distributed. The implications for this non-normality is that some assumptions in linear model building may be violated. Still, the models produced do provide insight to the controlling site characteristics.

Logistic (Probability) Models

The basic logistic model for estimating the probability that a landslide reaches a stream can be derived from equation (2) as:

$$p = \frac{1}{1+e^{Y}} \qquad \textbf{(3)}$$

where p = probability the landslide makes it to the stream (0-1),

$Y = \sum_{i=0}^{k} b_i X_i$,

X_i = important site characteristics,

b_i = fitted coefficients, and

k = number of coefficients in the model (i=0 means the intercept term).

The b_i coefficients were fit using the stepwise option in the LOGISTIC procedure of SAS. The results of fitting seven different models are shown in Table 6. Because the road cut data were statistically dissimilar to the other data (caused by type of landslide), models were fit with and without including that data set.

All the fitted models in Table 6 have the same or similar variables. The most frequently selected variable was LSLL. This makes physical sense because large slides (longer slide lengths) close to streams should have a better chance of entering the stream. Steep slope gradients as indicated by the SG variable should increase the chance for the slide entering the stream.

Two exceptions stand out. For natural slides, the probability for reaching a channel was 0.81 (=30/37) without being influenced by any variables. In this case, the data set is too small by itself to build a satisfactory model. The road fills with culverts data set shows a coefficient of positive 0.0210 for the SLDLEN variable. To be consistent with physical constraints, a negative value would be expected. The difference may be caused by the fitting procedure which may have altered the coefficient to coincide with the STDIST variable, that is, some relation between SLDLEN and STDIST.

Table 6. Important Variables, X_i, and Coefficients, b_i, in the Logistic Equation Term $Y=\sum_{i=1}^{k} X_i b_i$.

Data Set	N "made it"	N "did not"	X_i[1]	b_i	Chi-square probability[2]
All data	733	256	Int.	-1.9341	0.0001
			LSLL	-0.4243	0.0001
All data except SLDGRP=2	323	92	Int.	-2.4292	0.0001
			LSLL	-0.6203	0.0001
Other Causes (SLDGRP=0)	68	10	Int.	-2.9305	0.0001
			LSLL	-0.5871	0.0484
Natural (SLDGRP=1)	30	7	Int.	-1.4553	0.005
Road Cuts (SLDGRP=2)	410	164	Int.	-1.5983	0.0001
			LSLL	-0.3067	0.0001
Road Fills w/o Culverts (SLDGRP=3)	177	63	Int.	-0.6521	0.4162
			LSLL	-0.5945	0.0001
			SG	-2.3069	0.0338
Road Fills with Culverts (SLDGRP=4)	48	12	Int.	-4.5659	0.0001
			STDIST	0.00289	0.0134
			SLDLEN	0.0210	0.0191

1 - Int. = intercept term
LSLL = log base e of SLDLEN/STDIST(=SLLSTD)
SG = slope gradient as a decimal
STDIST = distance from slide to the nearest stream, feet
SLDLEN = length of the landslide, feet
Variables listed in order of inclusion into the model

2 - This is a measure of the significance of the b_i coefficient, i.e., the X_i term. Small Chi-square probabilities infer significant variables. Except for the Int. term, variables with Chi-square probabilities ≥ 0.05 were excluded from the model. Note values of 0.0001 should be read as less than or equal to 0.0001.

The models can be demonstrated as shown in the following table using average values for SLDLEN, STDIST, and SG. As Table 7 shows, given representative values the models do a reasonably good job of estimating the overall probability a landslide makes it to a channel as compared with observed values. This is reasonable because the model should be able to estimate the group probability given representative conditions. Individual probability will vary. A major exception is the estimate for road fills with culverts wherein the estimate is much higher. The reasons for this discrepancy were not clear when the data were examined. There may be a problem with the small size of the data set.

Table 7. Estimates of the Probability a Slide Will Enter a Stream Using Equation (3), Coefficients in Table 6, and Representative Variable Values from Appendix A.

Model	Y-Value*	Probability of Slide Entering Stream	
		Model Estimated	Observed = measured/total
All Data	-1.041	0.74	0.74
All Data w/o Road Cuts	-1.303	0.79	0.78
Other	-1.934	0.87	0.87
Natural (no model)	-1.455	0.81	0.81
Road Cut	-0.865	0.70	0.71
Road Fill without Culvert	-0.989	0.73	0.74
Road Fill with Culvert	-2.159	0.90	0.80

*$Y=\sum^{k}_{i=1} b_i X_i$

For example, values of SLDLEN=45 feet and STDIST=369 feet were used in the calculation of the All Data estimate.

Note: LSLL = $\log_e(45/369) = -2.104$

Logistic Model Adequacy

The logistic model of equation (3) provides a continuous estimate probability between zero(0) and one(1). The landslides were denoted as not making it to the channel (0) or making it (1). Therefore, a cutoff probability should be selected so that values above that level would indicate the slide had made it to the channel and values below that level would indicate that the slide had not. This value can be calibrated using the LOGISTIC procedure in SAS. If the value is set too low, then too many <u>success</u> (made it) cases would be predicted. If it is set too high, then too many failures (did not make it) would be predicted. The LOGISTIC procedure produces statistics on number of correctly and incorrectly identified observations based on the preassigned cutoff probability. In this application, the number of correctly identified success (made it) observations were used to select a cutoff level. For example, at a cutoff level of 0.5, the percent correctly identified as success was 98.9 percent, but the percent of correctly identified failures (did not make it) was only 5.5 percent. These results were based on the all-data models of Table 6. A level of correctly identified successes was arbitrarily set at 80 percent based on Carrara et al. (1993) results. The cutoff probability that produced a result near this was 0.674. This value yielded a 80.9 percent correct estimate of success, but only 37.1 percent of failures were estimated correctly. By raising the cutoff level, the number of landslides making it to the channel is underestimated. In contrast, if the cutoff level is dropped to 0.25, then all the successes are correctly predicted, but none of the failures is correctly predicted. If the cutoff level of 0.674 is used in all the models, the percentages of correct estimates will vary. This effect is shown in Table 8.

Table 8. Effects of Setting a Logistic Model Cutoff Level. Cutoff Level = 0.674

Data Set	Percent Correct		Overall
	(MADEIT=1, yes)	(MADEIT=0, no)	
All Data	80.9	37.1	69.6
All Data w/o Road Cuts	84.8	43.5	75.7
Other Causes	98.5	0	85.9
Natural (no model)	100.0	0	81.1
Road Cuts	75.9	34.1	63.9
Road Fills w/o Culverts	77.4	50.8	70.4
Road Fills with Culverts	95.8	58.3	88.3

The selection of an appropriate cutoff level will be based upon what one is trying to balance. If one wants to have more correct estimates of successes (MADEIT=1) then the level should be lowered. However, if MADEIT=0 is of importance, then the level should be raised. As the level is raised and lowered, the overall percentage will vary. The results in Table 8 indicate that a cutoff level of 0.674 may be appropriate for model application. Predictions of whether or not a landslide makes it to a stream is only a first step. The next step is to estimate the percent of the slide mass entering the stream.

Delivery Models

The basic linear model for estimating the percent of landslide mass (volume) which entering a stream can be formulated as:

$$\mathbf{\%DEL=\sum_{i=0}^{k} b_i X_i} \qquad \mathbf{(4)}$$

where %DEL = percent of landslide volume delivered to the stream,

X_i = site characteristics controlling delivery, and

b_i = coefficients fit with the data.

Models were fit to the five slide groups plus all the data combined. Although the models provided estimates that were better than using the mean value only, the predictive capability as judged by the coefficient of multiple determination, R^2, was quite low (but significantly different from zero). In general, the better models were of the form:

$$\mathbf{LPD=\sum_{i=0} b_i Y_i} \qquad \mathbf{(5)}$$

where LPD = $\log_e(\%DEL/100)$,

Y_i = $\log_e(X_i)$, and

b_i = coefficient fit with the data.

Stepwise multiple regression was applied to the data sets. The models selected from the analysis are presented in Table 9. The coefficients in Table 9 have the correct sign (+ or -) as would be expected from physical reasoning. The importance of SLDLEN, STDIST, and SG are again emphasized by these models.

Table 9. Important Variables, X_i's, and Coefficients, b_i's, in the %DEL Models of Equation (5)

Data Set	N	X_i [1]	b_i	Probability[2]	(R^2)[3]
All Data	733	Int.	-5.074	0.0001	0.216
		SLDLEN	0.793	0.0001	(0.001)[4]
		STDIST	-0.206	0.0001	
		exp(SG)	1.157	0.0001	
All Data w/o Road Cuts	323	Int	-2.222	0.0001	0.081
		SLLSTD	0.206	0.0002	(0.0004)
		exp(SG)	1.424	0.0004	
Other Causes (SLDGRP=0)	68	Int.	-2.116	0.0013	0.126
		SLLSTD	0.212	0.0482	(0.0124)
		exp(SG)	1.482	0.0850	
Natural (SLDGRP=1)	30	No variables met the Probability level criteria of 0.15, i.e. probability < 0.15			
Road Cuts (SLDGRP=2)	410	Int.	-4.212	0.0001	0.124
		STDIST	0.256	0.0024	(0.0001)
		SLLSTD	0.429	0.0001	
		exp(SG)	0.435	0.0959	
Road Fills w/o culverts (SLDGRP=3)	177	Int.	-3.431	0.0001	0.103
		exp(SG)	2.289	0.0004	(0.0001)
		exp(SLLSTD)	0.636	0.0017	
Road Fills with culverts (SLDGRP=4)	48	Int.	-1.215	0.0004	0.072
		exp(STDIST)	-0.00163	0.0647	(0.0647)

1 - Int. = intercept term
SG = slope gradient as a decimal
STDIST = distance from slide to the nearest stream, feet
SLDLEN = slide length, feet
SLLSTD = SLDLEN/STDIST
exp ( ) = exponentiation of enclosed term
Variables listed in order of inclusion into the model.

2 - Determined from an F-test of the coefficient value. Values < 0.10 indicate that the coefficients are significantly different than zero.

3 - Coefficient of multiple determination, "r-squared."

4 - Probability determined from F-test of regression. Small values indicate that the R^2 is not actually zero.
Values listed as 0.0001 should be read as less than or equal to 0.0001.

Estimates of %DEL can be made using equation (5) and the model coefficients in Table 9. Assuming the representative characteristic values (Appendix B) allowed development of Table 10.

Two effects can be seen in Table 10. First the large data set of Road Cuts dominates the All Data model and suppresses the model predicted and measured percent delivered. Second, the model estimates the log base e values of %DEL which were then converted to %DEL values. The skew in the original data manifests itself when comparing the log-based predictions

Table 10. Estimates of the Percent of Landslide Volume Delivered to a Stream Using Equation (5) Coefficients in Table 8, and Representative Variable Values from Appendix A

Model	Percent Delivery			
	Model	N*	A.M.	G.M.
All Data	8.6	839	23.7	8.75
All Data w/o Road Cuts	20.4	409	41.6	24.2
Other (Causes)	23.3	89	41.7	25.8
Natural	No model	55	57.4	38.9
Road Cuts	3.2	430	6.6	3.3
Road Fills Without Culverts	17.8	197	37.9	21.0
Road Fills With Culverts	29.4	68	39.4	22.9

* Number of observations from largest data set available for A.M. and G.M. values.
A.M. = arithmetic mean of measured data
G.M. = geometric mean of measured data

with the untransformed data. If the average log-transformed value of %DEL is converted back to %DEL, the differences are not as stark. For instance, the log base e average value for the All Data set was -2.436 which, when converted back, equals 8.75 percent, very close to the estimated 8.0 percent.

Model Application and Limitations

The models presented above for probability of delivery (materials entering stream) and percent of delivery should be used in conjunction with one another. The first step in a basin-wide modeling approach is to estimate the size of failure, such as number of grid cells in a GIS type approach, in order to determine the length of the slide. Second, the distance to the nearest stream and the slope gradient (if needed) can be estimated by different algorithms in a GIS, or manually. Then the probability of the slide reaching the stream can be calculated. If the slide is predicted to reach a stream, then the percent delivered can be estimated. The confidence intervals of these estimates will be quite large because the R^2 values are low. However, the models do provide better estimates with the site specific variables than would be obtained by assuming a fixed delivery rate.

There are certain limitations which should be observed. First, the models are developed from data sets specific to Idaho. The data are dominated by road related landslides. Very few natural or non-road related failures were recorded. The estimates of percent delivered are based on imprecise estimates of slide volume, scour (if noted) and deposition. Second, the cutoff level in the logistic model of 0.674 is arbitrary and was only adjusted for the All Data model. Other cufoff levels may be more suitable for the other models. Third, many of the models are undefined when STDIST=0, that is, the landslide is right next to the stream. In those cases, the data indicate that the %DEL ranged from 1 to 100 percent with a mean of 54 and a standard deviation of 36 percent. Thus if a user is modelling a near stream failure, then 54 percent delivery may be an appropriate choice in lieu of a model value. Finally, the models presented here are not process models. The models help define key variables but do not explain the complex processes involved in delivery of landslide material to streams.

SUMMARY AND CONCLUSIONS

The goal of this study was to develop a baseline understanding of the factors and processes influencing downslope delivery of landslide materials. To achieve this goal, four objectives were set. These were to:

1. summarize univariate statistics of landslide delivery data, as supplied by the USDA Forest Service, in total and by important influencing factors such as landslide type, site properties, and management factors;

2. develop empirical equations for predicting the percentage of landslide delivery to channels using site factors and landslide properties;

3. locate and describe available models for predicting the downslope delivery of landslide material, and where possible, test the applicability of such models using the supplied landslide data; and

4. present the results and findings in a report

A critical contribution to this study was provided by Bathurst (1991). His major review of literature found that there were no models for explicitly predicting landslide delivery to streams. Subsequently reviews, presented in this report, did not find any other models for predicting delivery.

Data supplied by the USDA Forest Service were analyzed to determine the percent of material (volume) delivered to a stream. Delivery percentages did not follow a normal distribution. The arithmetic average percent delivered for 839 slides which were selected after screening 1366 original observations was 23.7 percent. However, the geometric average was 8.75 percent. Both values are influenced by the large number of road cut landslides in the overall sample. This type of slide delivers an arithmetic average of 6.6 percent of the slide volume. Average percent deliveries for other slide types are between 35 and 60 percent.

The data were used to build two types of models. Logistic models were developed to estimate if a slide would enter a stream. For landslides that did in fact reach a stream, linear regression models, based on log-transformed values of percent delivered, were developed. Both types of models contained physically meaningful variables of length of landslide, distance to nearest stream, and slope gradient. Although there is a high degree of uncertainty associated with the two types of models, they jointly produce a method for estimating delivery of landslide materials to stream channels. In that regard, they form a basis or starting point for other modeling approaches.

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APPENDIX A

Descriptive Statistics for Landslide Delivery Data
By Slide Group and Delivery

LEGEND:

PERDEL	=	percent of landslide prism delivered to channel
SLDVOL	=	volume of slide, cubic yards
STDIST	=	distance to the stream, feet
SG	=	slide gradient, percent
SLDAR01	=	slide area, square feet = slide length x slide width
SLDLEN	=	slide length, feet
EROSVOL	=	total volume of erosion, slide plus outrun, cubic yards
SLLSTD	=	ratio of SLDLEN to STDIST
SLTSTD	=	ratio of SLDLEN + outflow length to STDIST
SOILDP	=	soil depth, inches
SLLABV	=	slope length above the slide, feet
DAABV	=	drainage area above the slide, acres
VOLDEL	=	volume of material delivered to the stream, cubic yards

SLDGRP = 0 **Slide Group: Other** **No Delivery**

Variable	N	Mean	Std Dev	Minimum	Maximum
SLDVOL	13	294.769	792.666	13.000	2928.000
STDIST	11	602.636	570.741	60.000	1500.000
SG	13	69.462	24.006	45.000	110.000
SLDAR01	12	1453.170	1248.030	352.000	4650.000
SLDLEN	12	43.583	21.428	16.000	93.000
EROSVOL	12	75.333	50.545	13.000	169.000
SLLSTD	10	0.207	0.220	0.027	0.620
SLTSTD	10	0.207	0.220	0.027	0.620
SOILDP	4	10.000	5.354	7.000	18.000
SLLABV	13	404.077	292.103	35.000	866.000
DAABV	5	0.800	0.671	0.500	2.00

Slide Group: Other **Delivery**

Variable	N	Mean	Std Dev	Minimum	Maximum
PERDEL	89	41.685	30.496	1.000	100.000
SLDVOL	87	373.586	1270.710	16.000	10633.000
STDIST	83	327.843	423.211	0.000	2000.000
SG	89	65.517	16.031	20.000	173.000
SLDAR01	87	2423.380	2671.220	168.000	19220.000
SLDLEN	87	72.632	44.241	12.000	252.000
EROSVOL	84	413.048	1304.620	16.000	10633.000
SLLSTD	68	0.752	1.372	0.024	9.375
SLTSTD	68	0.808	1.365	0.024	9.375
SOILDP	17	20.118	24.225	2.000	110.000
SLLABV	87	534.874	590.210	39.000	5000.000
DAABV	19	29.337	114.010	0.100	500.000
VOLDEL	84	14717.080	38639.780	18.000	318990.000

SLDGRP = 1 **Slide Group: Natural** **No Delivery**

Variable	N	Mean	Std Dev	Minimum	Maximum
SLDVOL	8	216.375	251.863	28.000	778.000
STDIST	7	661.571	596.359	150.000	1500.000
SG	8	71.875	35.643	45.000	150.000
SLDAR01	8	1473.130	829.255	450.000	3000.000
SLDLEN	8	56.125	32.546	25.000	113.000
EROSVOL	5	120.200	93.948	33.000	230.000
SLLSTD	7	0.168	0.169	0.033	0.502
SLTSTD	7	0.168	0.169	0.033	0.502
SOILDP	2	12.000	11.314	4.000	20.000
SLLABV	7	981.143	873.815	135.000	2500.000
DAABV	3	7.000	11.269	0.000	20.000

Slide Group: Natural **Delivery**

Variable	N	Mean	Std Dev	Minimum	Maximum
PERDEL	55	57.382	36.466	2.000	100.000
SLDVOL	53	1443.060	8620.170	9.000	62963.000
STDIST	54	297.593	601.121	0.000	3000.000
SG	52	75.519	19.771	10.000	120.000
SLDAR01	52	4567.770	13804.340	180.000	100000.000
SLDLEN	52	74.538	82.014	7.000	400.000
EROSVOL	36	263.722	400.757	9.000	2000.000
SLLSTD	33	0.720	0.934	0.025	3.600
SLTSTD	33	0.743	0.932	0.025	3.600
SOILDP	6	13.500	8.385	2.000	28.000
SLLABV	54	865.352	768.945	100.000	3000.000
DAABV	25	4.204	8.443	0.000	40.000
VOLDEL	36	17943.500	35777.060	90.000	180000.000

SLDGRP = 2 **Slide Group: Road cuts** **No Delivery**

Variable	N	Mean	Std Dev	Minimum	Maximum
SLDVOL	171	215.222	785.353	4.000	8889.000
STDIST	168	458.696	600.148	30.000	5000.000
SG	171	64.094	17.263	15.000	160.000
SLDAR01	171	2058.510	9473.86	56.000	120000.000
SLDLEN	171	31.947	51.353	6.000	600.000
EROSVOL	116	220.750	850.636	10.000	8889.000
SLLSTD	166	0.205	0.530	0.002	6.000
SLTSTD	166	0.211	0.533	0.002	6.000
SOILDP	60	20.883	17.340	0.000	100.000
SLLABV	169	885.533	1046.89	0.000	5000.000
DAABV	70	7.023	22.128	0.000	150.000

Slide Group: Road cuts **Delivery**

Variable	N	Mean	Std Dev	Minimum	Maximum
PERDEL	430	6.626	11.247	1.000	95.000
SLDVOL	425	457.092	2057.460	2.000	33333.000
STDIST	427	321.405	460.468	0.000	3000.000
SG	428	62.540	19.089	16.000	214.000
SLDAR01	426	1648.010	3058.250	70.000	30000.000
SLDLEN	427	33.302	30.323	4.000	266.000
EROSVOL	314	285.223	945.566	2.000	10800.000
SLLSTD	410	0.284	0.464	0.004	5.000
SLTSTD	410	0.297	0.473	0.004	5.000
SOILDP	279	19.222	24.852	0.000	360.000
SLLABV	425	808.809	847.858	0.000	6000.000
DAABV	303	3.962	8.730	0.000	100.000
VOLDEL	314	2734.910	10975.940	2.000	138000.000

SLDGRP = 3 **Slide Group: Road Fills w/o Culverts** **No Delivery**

Variable	N	Mean	Std Dev	Minimum	Maximum
SLDVOL	61	1484.480	5314.290	17.000	35259.000
STDIST	66	579.667	530.534	25.000	3000.000
SG	67	64.955	13.752	20.000	90.000
SLDAR01	64	2758.910	3254.730	240.000	16800.000
SLDLEN	66	42.424	31.698	9.000	145.000
EROSVOL	46	644.304	3291.660	17.000	22400.000
SLLSTD	64	0.181	0.225	0.005	1.160
SLTSTD	64	0.181	0.225	0.005	1.160
SOILDP	0	-	-	-	-
SLLABV	68	555.029	773.101	0.000	5000.000
DAABV	29	3.793	6.562	0.000	30.000

Slide Group: Road Fills w/o Culverts **Delivery**

Variable	N	Mean	Std Dev	Minimum	Maximum
PERDEL	197	37.949	32.107	1.000	100.000
SLDVOL	193	345.145	597.426	10.000	4080.000
STDIST	194	334.660	394.736	0.000	2500.000
SG	194	69.500	15.020	10.000	120.000
SLDAR01	194	2768.520	3985.250	126.000	40000.000
SLDLEN	194	53.134	75.543	6.000	1000.000
EROSVOL	173	471.075	874.896	10.000	5111.000
SLLSTD	178	0.363	0.469	0.001	3.636
SLTSTD	178	0.502	0.563	0.001	3.636
SOILDP	191	23968.200	29495.360	0.000	175000.000
SLLABV	2	21.500	2.121	20.000	23.000
DAABV	192	701.573	858.386	0.000	5000.000
VOLDEL	173	25547.800	65023.310	10.000	511100.000

SLDGRP = 4 **Slide Group: Road Fills With Culverts** **No Delivery**

Variable	N	Mean	Std Dev	Minimum	Maximum
SLDVOL	10	5605.100	7840.410	21.000	22222.000
STDIST	12	1118.330	979.024	50.000	3000.000
SG	12	52.000	18.350	17.000	70.000
SLDAR01	12	10505.670	13538.610	375.000	40000.000
SLDLEN	12	103.833	73.033	15.000	250.000
EROSVOL	4	1366.500	1523.880	21.000	3556.000
SLLSTD	12	0.263	0.311	0.016	0.882
SLTSTD	12	0.263	0.311	0.016	0.882
SOILDP	0	-	-	-	-
SLLABV	12	833.333	796.964	200.000	2500.000
DAABV	6	6.667	7.373	0.500	20.000

Slide Group: Road Fills With Culverts **Delivery**

Variable	N	Mean	Std Dev	Minimum	Maximum
PERDEL	68	39.382	33.410	1.000	100.000
SLDVOL	65	1051.370	2351.660	13.000	16296.000
STDIST	68	244.294	309.086	0.000	2000.000
SG	66	61.561	18.451	12.000	103.000
SLDAR01	66	3569.980	3799.070	115.000	2200.000
SLDLEN	66	55.955	34.450	10.000	200.000
EROSVOL	41	880.293	1896.480	13.000	10556.000
SLLSTD	50	1.203	3.840	0.010	25.000
SLTSTD	50	1.435	3.902	0.010	25.000
SOILDP	0	-	-	-	-
SLLABV	64	1171.380	1109.730	0.000	5000.000
DAABV	43	18.644	33.960	0.000	200.000
VOLDEL	41	46372.370	125964.410	300.000	633360.000

Representative Values for Table 7 Computations

SLDGRP	SLDLEN (feet)	STDIST (feet)	SG (%)
All Data	45	369	65
All Data w/o SLDGRP=2	62	381	68
0	69	360	66
1	72	339	75
2	33	360	63
3	50	397	68
4	63	375	60

Representative Values for Table 10 Computations

SLDGRP	SLDLEN (feet)	STDIST (feet)	SG (%)
All Data	47	317	65
All Data w/o SLDGRP=2	61	313	68
0	73	327	66
1	75	298	76
2	33	321	63
3	53	335	70
4	56	244	62

APPENDIX B

Available by request only

RESEARCH REPORT 12

APPROACH TO PHYSICALLY-BASED

MODELLING OF LANDSLIDE EROSION

AND SEDIMENT YIELD AT

THE BASIN SCALE

by

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