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ESTIMATING EROSION RISKS ASSOCIATED WITH LOGGING AND FOREST ROADS IN NORTHWESTERN CALIFORNIA[1]

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ABSTRACT. Erosion resulting from logging and road building has long been a concern to forest managers and the general public. An objective methodology was developed to estimate erosion risk on forest roads and in harvest areas on private land in northwestern California. It was based on 260 plots sampled from the area harvested under 415 Timber Harvest Plans completed between November 1978 and October 1979. Results confirmed previous findings that most erosion related to forest management occurs on a small fraction of the managed area. Erosion features larger than the minimum size inventories in this study (> 13 yd^3) occupied only 0.2 percent of the area investigated. Linear discriminant analysis was used to develop two equations for identifying critical sites (sites with erosion >100 yd^3ac^{-1}). The equations were based on slope, horizontal curvature (an expression of local topography), and soil color (on road sites) or the strength of the underlying rocks (on harvest sites). The equations can be used in planning to estimate the erosion risk of proposed activities. They can also be used to estimate acceptable risk thresholds based on the value of competing resources.
(KEY TERMS: logging; forest roads; soil erosion; risk analysis; northwestern California.)

INTRODUCTION

Excessive erosion resulting from logging and forest road-building has long been a concern to forest managers and the general public. Such concerns recently led to a number of studies in California. The findings (Dodge *et al.*, 1976; Rice and Datzman, 1981; McCashion and Rice, 1983; Peters and Litwin, 1983) differed somewhat, but all the studies concluded that most erosion occurring on timber harvesting areas was due to large mass wasting found on a small fraction of the harvest sites. For example, Rice and Datzman (1981) found that 68 percent of the measured erosion occurred on 4 percent of their plots and Peters and Litwin (1983) found that 82 percent of measured erosion came from 24 percent of their plots and that 77 percent of the total erosion was by mass movements. Peters and Litwin (1983) proposed that, because just a few sites were responsible for most of the erosion, identifying those sites, rather than trying to estimate erosion volume, was the key to reducing erosion from logged areas and forest roads. Their proposal was also appealing because attempts to predict erosion volume had not been very successful. For example, Rice and Datzman's (1981) regression analysis had a coefficient of determination of 0.43.

This paper is based on a study that developed a way of estimating the risk that logging or road construction would lead to a "critical" rate of erosion, (>100 yd^3 ac^{-1}). This threshold was proposed by Peters and Litwin (1983) because plots yielding this amount produced 68 percent of the erosion measured by Rice and Datzman (1981), 85 percent of that measured by Dodge *et al.* (1976), and 82 percent of the volume eroded from their plots. Two analyses were performed: one based on logged areas and one based on forest roads. A more complete description of the study can be found in Volume II of the Critical Sites Erosion Study report (Lewis and Rice, 1989).

This paper presents simple, three-variable equations that estimate the probability that a site will yield more than 100 yd^3 ac^{-1} of erosion if the timber is harvested or if a road is built there. The investigation, a joint effort by the California Department of Forestry and Fire Protection (CDF) and the Pacific Southwest Forest and Range Experiment Station (PSW), attempted to remove from the political arena one controversial issue that is amenable to rational analysis. Although the equations presented here are valid only

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in northwestern California, forest managers else where might ask themselves whether these equations (or similar locally developed equations) might be superior to their current way of estimating erosion risk.

THE STUDY

Sampling

The study was based on data collected from a sample of the 1104 Timber Harvesting Plans completed in California between November 1978 and October 1979. The term "THP" will be used to refer to the plans and as shorthand for the area covered by the plans. Owners of the properties covered by 655 THPs grant ed us permission to include their land in our study (Figure 1). We were able to assure ourselves that denial of access was not related to erosion occurring on the THPs. The state was divided into three Analysis Units (AUs) to reduce the variability in climate and geology (Figure 1).

After reconnoitering nearly 30 percent of AU 3 we concluded that we would be unable to find enough critical sites to analyze AU separately. We thought it unwise to include it in a state-wide analysis because of its low erosion rate and large area. Such an analysis would inevitably contrast AU 3 (which would contain 71 percent of the randomly drawn noncritical plots) with AU 1 where the bulk of the erosion was found (Table 1). That decision limited our sampled population to 415 THPs in AU 1 and AU 2.

Our analyses contrast critical plots with noncritical plots - plots yielding <100 yd^3 ac^{-1}. The square two acre plots were randomly selected from their respective subpopulations, except for harvest area critical sites, all of which were included. Sites included in our samples are referred to as plots. Based on commonly used rules-of-thumb, samples of more than 40 critical plots and 40 noncritical plots were needed for our analyses. We were unable to find the required 40 critical plots in AU 3, but determined that. a. combined analysis of both AUs was as effective as conducting a separate analysis of AU 1 and a combined analysis only for AU 2. The numbers of plots used in the combined analyses were randomly selected in proportion to the areas of the two AUs. The road analysis contrasted 106 critical plots with 54 noncritical plots, and the harvest analysis contrasted 51 critical plots with 49 noncritical plots.

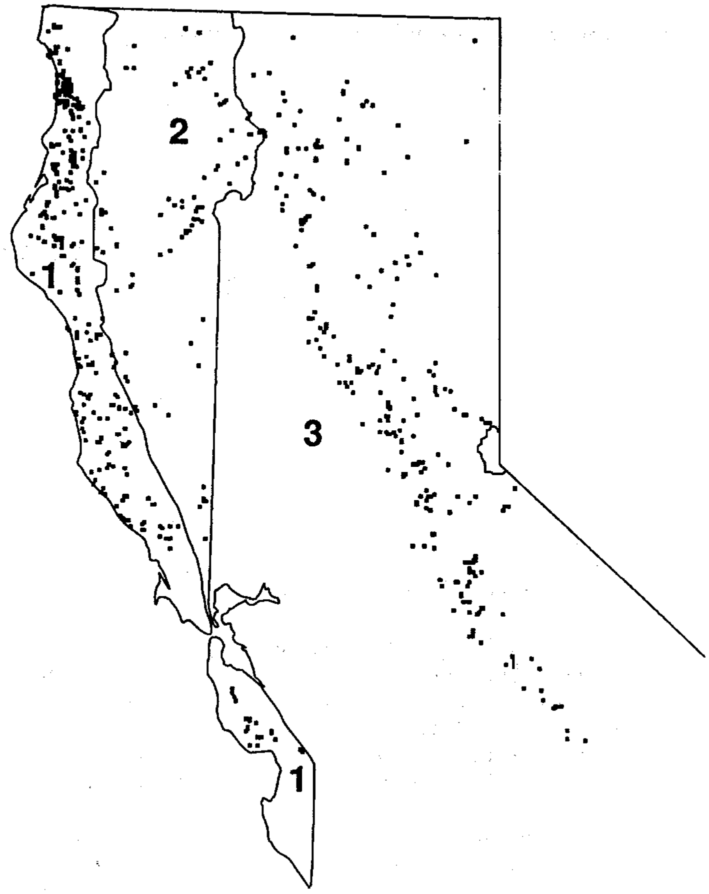

Figure 1. Three Analysis Units Were in the Critical Sites Erosion Study. Dots represent Timber Harvest Plan areas to which access was granted by the landowner (the sampled population).

Measurements

The data we collected relate to conditions at a point. However, study plots were nominally two acres in area, square, and oriented normal to the slope. Average plot area was 1.8 ac after excluding parts of plots that extended into areas unrelated to the sam ple point, such as across a creek or ridge, or into uncut areas. The area beyond the erosion feature or noncritical point being characterized was used to estimate variables having areal extent such as crown cover or ground disturbance. A total of 172 variables was recorded for each plot. Only 31 of these were used in the harvest area analysis and 25 in the road analysis. The remainder were measured to ensure that each plot was sufficiently well characterized to explain any anomalies that might crop up in the analyses. The analytical variables included descriptors of topography, geology and soil, hydrology, vegetative

TABLE 1. Estimated Erosion Tabulated by Site Type and Analysis Unit (AU) in Northern California.*

AU	Site Type	Area in Unit (acres)	Road Length (miles)	Erosion Rate yd^3ac^{-1}	Erosion Rate yd^3mi^{-1}
1	Critical Road Sites	60	12.2	3,580.6	17,621.0
	Noncritical Road Sites	2,605	529.1	26.4	130.1
	All Road Sites	2,665	541.3	106.4	523.7
1	Critical Harvest Sites	~~246~~ *134*		393.0	
	Noncritical Sites	~~36,617~~ *36,729*		~~3.2~~ *1.8*	
	All Harvest Areas	36,863		~~5.8~~ *3.2*	
1	**Total in AU 1**	**39,528**		**~~12.6~~** *10.1*	
2	Critical Road Sites	~~1,027~~ *6*	~~208.6~~ *1.2*	~~23.1~~ *8,253.8*	~~113.5~~ *40,626.0*
	Noncritical Road Sites	1,027	208.6	23.1	113.5
	All Road Sites	1,033	209.8	69.0	339.4
2	Critical Harvest Sites	23		167.9	
	Noncritical Sites	16,055		1.1	
	All Harvest Areas	16,078		1.4	
2	**Total in AU 2**	**17,111**		**5.4**	
3	**Total in AU 3**	**120,116**		**0.31**	
	Whole Study Area	**176,755**		**3.6**	

*Road areas are estimated by the product of the plot width and the average width of roads measured in our study (295 ft. x 40.6 ft). Harvest areas are the difference between total area and road area. *[NOTE: Table entries in red are corrections subsequent to publication]*

cover, weather and climate, and management impacts.

We measured only erosion features that left cavities of 13 yd^3 (10 m^3) or more. We set this lower limit to expedite field work and because studies had found rill erosion to be 8 percent (Rice and Datzman, 1981) and 11 percent (Peters and Litwin, 1983) of total erosion. As the result of our 13 yd^3 limit, gullies traversing our plots had to have an average cross section greater than 1.2 ft^2 to be recorded. Our results confirmed the findings of previous studies. Extrapolating our plot measurements to the total area of THPs completed in 1978-1979, we estimated that only 0.2 percent of the area was scarred by erosional features displacing more than 13 yd^3 of soil. The types of erosion features measured on critical plots were tallied. Practically all of them were mass movements (Table 2). Road rights-of-way had 21.5 times the erosion of harvest areas (Table 1), a ratio similar to the 17X found by McCashion and Rice (1983).

Analyses

Linear discriminant analysis (Fisher, 1936) is a statistical procedure that is well suited to distinguishing critical sites from stable ones. Based on multiple measurements on each member of the two subpopulations being contrasted, discriminant analysis produces an equation that can be used to estimate the probability that a site will become critical if logged or roaded.

Past experience (Furbish and Rice, 1983; Rice *et al.*, 1985; Rice and Lewis, 1986) has shown a tendency to retain too many variables that may be useless, or even detrimental, when making predictions with new data. Consequently, a rather elaborate procedure was used to screen variables for inclusion in our discriminant functions. One important element in the screening of variables was the inclusion of four random variables in each analysis. Our rationale was that any variable having less explanatory power than one of the random variables was useless, regardless of the plausibility of its link to erosion.

As a final step we used bootstrapping (Efron, 1983) to see which of the candidate equations was the most stable. Bootstrapping consists of repeatedly sampling with replacement from the data and performing the analysis on the samples created. We analyzed 500 bootstrap samples. We considered the classification accuracy and frequency of occurrence of candidate equations as well as the frequency of occurrence and explanatory power of individual variables. The discriminant function for forest roads was:

TABLE 2. Distribution of Erosion Features Larger than 13 yd^3 on Critical Plots Using the Nomenclature of Bedrossian (1983).

Failure Type	**Road Plots** Percentage by		**Harvest Plots** Percentage by	
	Number	**Volume**	**Number**	**Volume**
Debris Flow	17.0	18.4	35.3	45.4
Debris Slide	43.4	31.5	47.1	41.7
Earthflow	2.8	21.0	2.0	0.6
Slump	12.3	4.1	2.0	0.8
Gully	9.4	2.8	0.0	0.0
Translational/Rotational	6.6	18.2	3.9	7.2
Deep-Seated Translational	7.5	3.4	3.9	1.9
Rotational	0.9	0.6	2.0	0.8
Streambank Erosion	0.0	0.0	3.9	1.5

$$DS = -0.0281 - 0.1142*SLOPE + 75.16*HCURVE + 1.0075*HUE, \qquad (1)$$

and for logged areas it was:

$$DS = 5.032 - 0.1633*SLOPE + 67.88*HCURVE - 1.215*WEAKROCK, \qquad (2)$$

where:

DS = the discriminant score;

SLOPE = the terrain slope in degrees;

HCURVE = the horizontal curvature of the road centerline in Equation (1) and of the terrain in Equation (2). Horizontal curvature was the reciprocal of the radius of a circle passing through the measurement site and two other points on the same contour about 60 ft. on either side of the site. It was measured in feet and coded negative for swales and positive for ridges, being zero on planar slopes;

HUE = the Munsell hue of moist subsoil, coded: 1=5Y, 2=2.5Y, 3=10YR, 4= 7.5YR; 5=5YR;

WEAKROCK = coded +l if a bedrock specimen crumbles or deforms under hammer blows and -1 if it fractures. This variable is a simplification of a more refined scale of rock strengths proposed by Williamson (1984), and it was equally effective at contrasting stable and unstable sites. We held the specimen by hand and used a 1 lb. geologist's hammer, but any hammer of simi lar weight should be adequate.

Both functions seem stable and efficient. No road function containing more variables had a greater apparent prediction accuracy than Equation (1). Prediction accuracy of Equation (2) was slightly exceeded by that of the four-variable and five-variable models, but we chose the three-variable function as a guard against overfitting our data. The estimated accuracies of the equations, corrected for bias using bootstrapping, are 78 percent (Equation 1) and 69 percent (Equation 2).

DISCUSSION

The accuracies of Equation (1) and (2) may seem acceptable and they provide good separation between critical and noncritical sites (Figure 2). Critical sites, however, are rare. They occupy only about 2 percent of the road plots and 0.5 percent of the harvested plots. The proportion of the total area occupied by erosion scars is even smaller: 0.2 percent. If represented at the same scale, the graph of noncritical road sites (Figure 2a) should be 49 times taller than shown and the graph of noncritical harvest sites (Figure 2b) should be 199 times taller. In most cases, therefore, many more noncritical sites than critical sites have the same discriminant score. Consequently, if every site was arbitrarily classified as stable, these predictions would be correct more than 98 percent of the time. The objective, however, is not to accurately prophesy; it is to prudently manage competing forest resources. The costs due to failing to identify an unstable site are quite different from those due to calling a stable site unstable.

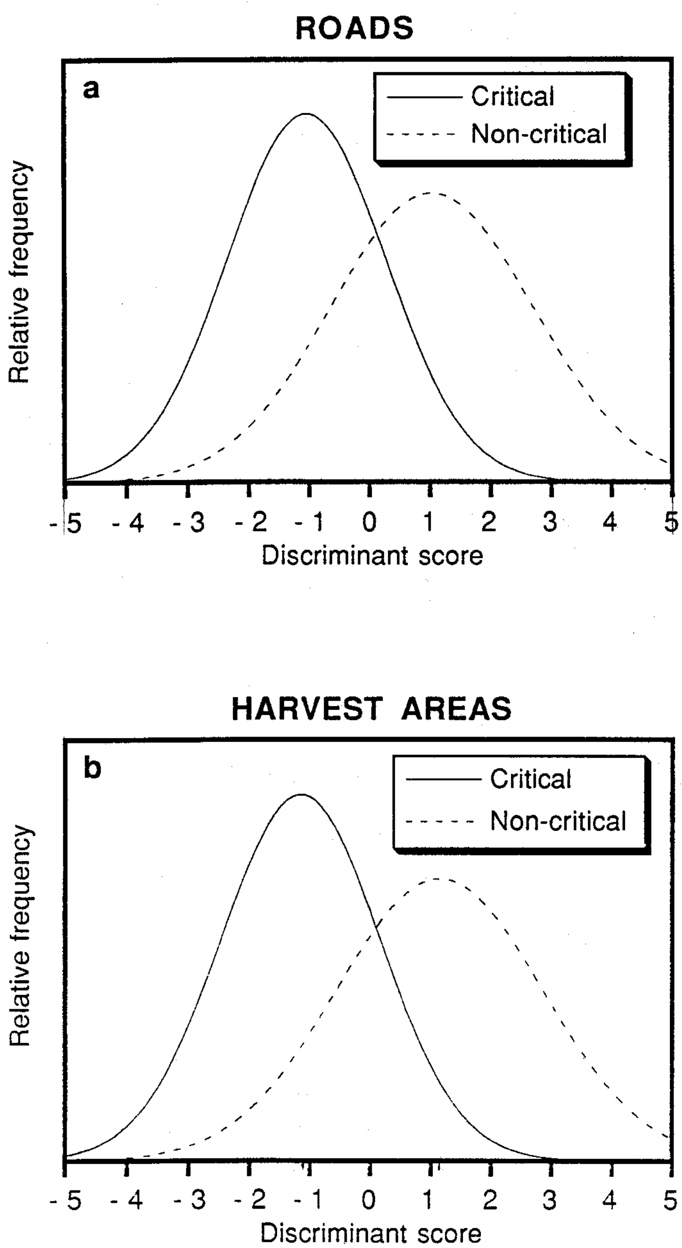

Figure 2. Relative Frequencies of Discriminant Scores of Critical and Noncritical Sites in the Sampled Population. The two distributions have been scaled to approximately the same height to show more clearly the separation between the two subpopulations. Actually, the ordinates of the noncritical road sites (a) should be about 49 times taller than shown and the ordinates of the noncritical harvest sites should be about 199 times taller.

Variables

An axiom in statistical inference states that correlation does not imply causation. Nonetheless, a predictive equation will inevitably be judged, in part, by the reasonableness of its variables. We think that Equations (1) and (2) meet this criterion quite well. SLOPE indexes the partitioning of the force of gravity into two components: a normal component increasing friction and fostering stability, and a tangential component promoting down-slope movement and failure. HCURVE may index the accumulation of unstable amounts of colluvium in swales and the convergence of subsurface water, which can lead to high pore water pressures that cause failure. HUE also proba bly indexes subsurface water because most all of the 5Y soils were gleyed soils of low chroma, which indicated waterlogged conditions. WEAKROCK indexes the strength of materials resisting failure. The variables, therefore, appear to be reasonable surrogates for the quantities used in engineering computations of slope stability.

The simplicity of the equations may be an impediment to their acceptance. Forest managers and earth scientists are accustomed to considering a large number of factors bearing on a problem before arriving at a decision. In spite of their pleas for simple procedures, people may distrust equations that do not include variables that they know are related to erosion. To be sure, a three-variable equation is a very constrained approximation of reality. For us to include a variable in the equation the variable had to be strongly related to the difference between critical and noncritical sites. Some variables were not included because they did not differ sufficiently on critical and noncritical sites.

For example, rainfall intensity is certainly an important variable affecting stability (Sidle, 1986). We had a range of return periods of the maximum post-treatment daily precipitation from 0.5 year to 30 years. However, rainfall intensity was useless as a predictor because both critical and noncritical sites spanned the range of precipitation. Similarly, none of the nine variables describing the way that timber harvests were conducted showed promise as a predictor of instability. The best of these variables, the percentage of crown cover removed, was only about 40 percent as useful as the weakest variable in Equation (2). The lack of importance of management variables agrees with the findings of Durgin *et al.* (1988). They measured 13 site variables and 57 management variables and yet concluded: "Natural site conditions were found to be most important in determining the susceptibility of an area to slope stability problems, . . ." Perhaps the limitations placed on harvests and road construction by California's Forest Practice Rules (State of California, 1990) restrict the variation in management practices to such a degree that differences were undetectable in our analyses. Other variables, such as those describing stratigraphy and fracturing, had to be dropped because they could not always be determined in the field. Even in the subset of plots having such measurements, these geologic variables did not perform well.

Just because a variable is not in our equation does not mean that it should be ignored when estimating the stability of a particular site. The predictions of our equations can be tempered by observed site conditions that the models do not consider. However, such fine tuning should be done with great caution. Studies have shown that experts tend to overestimate risk (McGreer and McNutt, 1981), possibly because of their overexposure to high risk sites, and they tend to overestimate the precision of their estimates (Hynes and Vanmarcke, 1976), perhaps because they rarely have the opportunity to verify their predictions. For planning, which is probably the best application of our equations, it is probably safer to accept the equations' predictions unaltered.

Estimating Risk

The simple classification of a site as critical or noncritical is usually inadequate. Obviously some sites are more risky than others and some sites present greater hazards to water quality, transportation systems, fish habitat, etc. One of the strengths of discriminant analysis is that it can make fine distinctions of risk. It can be used to estimate the probability that new sites being classified by a discriminant function belong to a particular population (in this case, that they are critical sites). In the field, critical site risk could be either calculated using a programmable pocket calculator or estimated from tables (Lewis and Rice, 1989).

We used bootstrapping (Efron, 1983) to estimate standard deviations for estimates of critical site risk for each observation in the data set from which the model was developed. Logistic regression was fitted to these values to estimate the confidence bands for plus and minus one standard deviation around predictions of critical site risk (Figure 3). Clearly, the errors associated with risk estimates increase markedly as the estimated risk increases. This fact may, in part, explain why experts overestimate risk. There are many stable sites that appear identical to unstable sites, within the precision of our measurements.

Risk Management

The management of risks involves more than estimating the risk at a site or for an activity. All risks are not equal. The erosion hazard associated with logging in the watershed of a major metropolitan water supply is quite different from the hazard associated with logging in the watershed of a short coastal stream that does not support fish. Consequently, any attempt to manage risks must also consider the associated hazards.

A manager trying to decide what constitutes an acceptable risk when logging is confronted with four alternative outcomes of the decision (Figure 4). Since knowledge of the outcome of a decision is not perfect, some portion of the land to which a particular risk threshold is applied will likely fall into each of the cells in the pay-off matrix. The terrain in a harvest area may be classified as stable and actually be stable (Condition A), meaning that it is appropriate to log as planned. Some part of the terrain may be classified as unstable when it is actually stable (Condition B), possibly leading to wasting resources on unneeded mitigation measures or foregoing timber revenues unnecessarily. Some part of the terrain may be called stable and produce unacceptable erosion as the result of logging (Condition C). Or, a portion of the area is correctly designated as unstable, and appropriate mitigative steps are taken (Condition D). If a manager can attach a value to each of these four outcomes, it is possible to compute the risk threshold that is optimum for that manager's value system [Lewis and Rice, 1990) based on regional estimates of risk. Alternatively, an algorithm has been developed using site-specific data to determine the risk threshold that maximizes the rewards in terms of the manager's value system (Rice *et al.*, 1985).

A simpler approach to risk management would be to use decision tables displaying the classification accuracy that can be expected using each discriminant score as an acceptable risk threshold (Tables 3 and 4). By inspecting the classification accuracies for critical and noncritical sites, the manager can decide which risk threshold best balances competing values.

CONCLUSIONS

Results of this study and the appraisal of the interdisciplinary team that collected the data (Durgin *et al.*, 1988) suggest that site conditions are more important than management practices in determining the erosional consequences of logging or road construction. Equations developed in this study can be used to

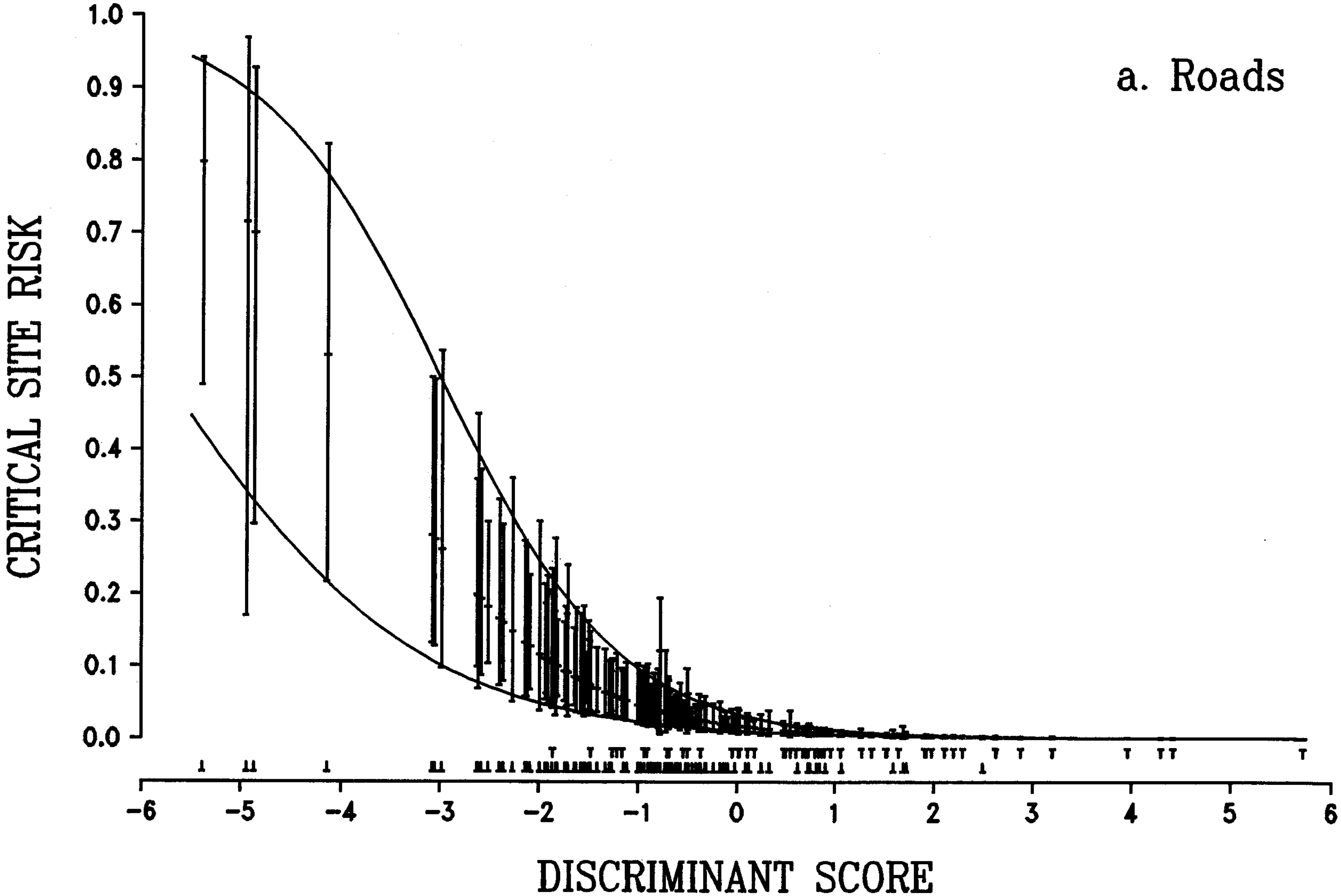

Figure 3. The Risk of Critical Erosion on (a) Road Sites Given a Regional Risk of 0.0177, and (b) on Harvest Sites Given a Regional Risk of 0.005 (risk in Analysis Units 1 and 2 was combined). The confidence bands are the bootstrap estimates of plus and minus one standard deviation, fitted using logistic regression. Beneath the plot, a T represents the discriminant score of a noncritical plot and the inverted T indicates a critical plot.

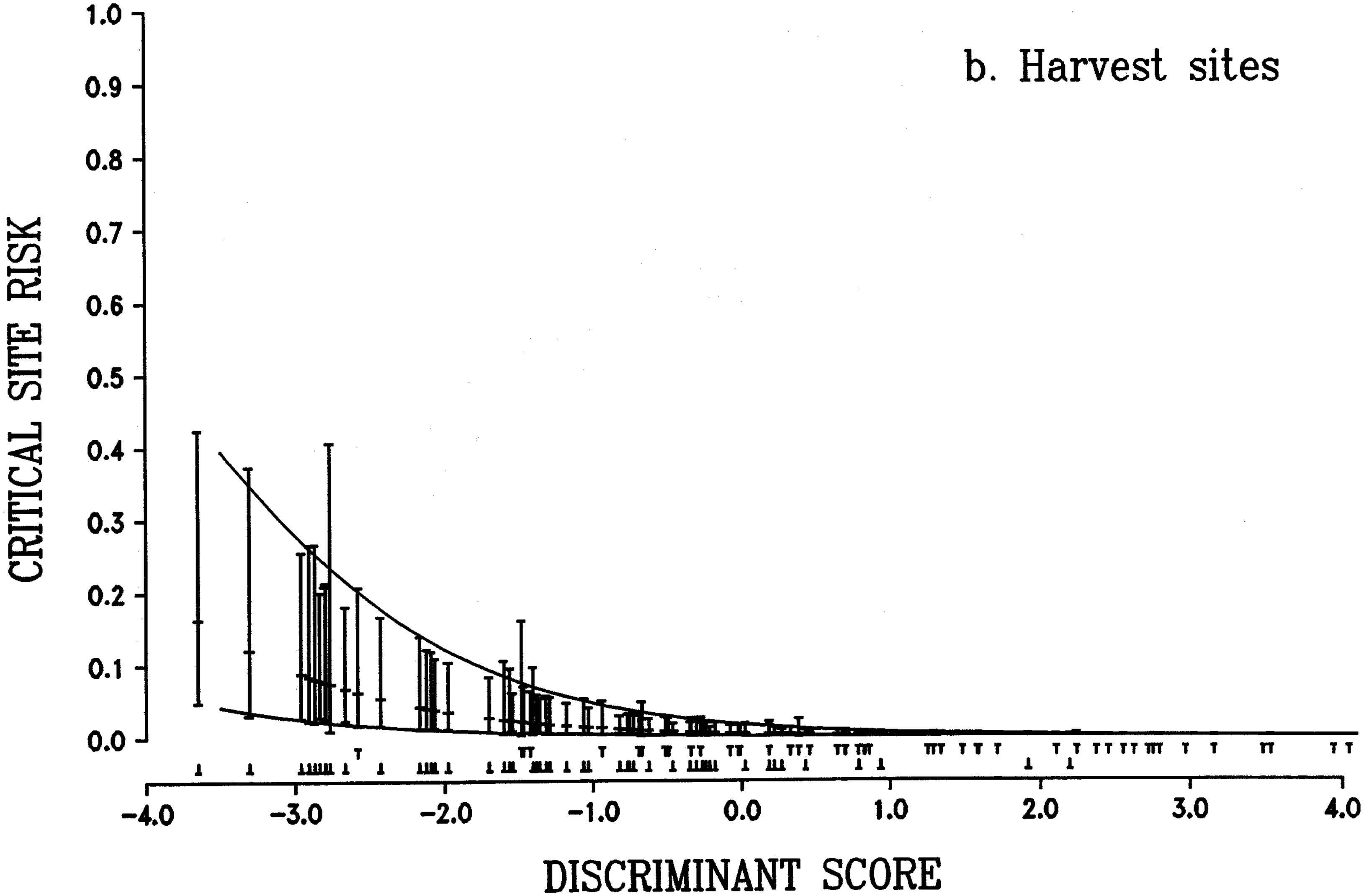

Figure 3. The Risk of Critical Erosion on (a) Road Sites Given a Regional Risk of 0.0177, and (b) on Harvest Sites Given a Regional Risk of 0.005 (risk in Analysis Units 1 and 2 was combined). The confidence bands are the bootstrap estimates of plus and minus one standard deviation, fitted using logistic regression. Beneath the plot, a T represents the discriminant score of a noncritical plot and the inverted T indicates a critical plot (cont'd.).

estimate erosion risk associated with logging or road construction. Using those risk estimates a manager can decide more objectively on environmental trade offs and display the value system that those decisions support.

	Predicted Condition	
Actual Condition	Stable	Unstable
Stable	**A**	**B**
Unstable	**C**	**D**

Figure 4. Pay-Off Matrix Displaying the Possible Outcomes of a Prediction Concerning Erosion Risk.

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TABLE 3. Decision Table for Roads and Landings

Decision Discriminant[a] Score	Threshold Critical Site Risk AU 1[b]	AU 2[c]	Percentage Classified Correctly: Critical Sites	Noncritical Sites
-6.0	0.90	0.69	0	100
-5.0	0.77	0.45	0	100
-4.0	0.56	0.23	1	100
-3.6	0.46	0.17	2	100
-3.2	0.36	0.12	5	99
-2.8	0.27	0.085	9	99
-2.4	0.20	0.058	15	98
-2.0	0.15	0.040	23	97
-1.8	0.12	0.033	28	96
-1.6	0.10	0.027	33	94
-1.4	0.085	0.022	39	93
-1.2	0.071	0.018	45	91
-1.0	0.059	0.015	51	89
-0.8	0.049	0.012	57	86
-0.6	0.040	0.010	63	84
-0.4	0.033	0.0083	69	81
-0.2	0.027	0.0068	74	77
0.0	0.022	0.0056	79	73
0.2	0.018	0.0046	83	69
0.4	0.015	0.0038	86	65
0.6	0.012	0.0031	89	60
0.8	0.010	0.0025	92	56
1.0	0.0084	0.0021	94	51
1.2	0.0069	0.0017	96	46
1.4	0.0056	0.0014	97	41
1.6	0.0046	0.0011	98	37
1.8	0.0038	0.0009	98	32
2.0	0.0031	0.0007	99	28
2.4	0.0021	0.0005	100	21
2.8	0.0014	0.0003	100	15
3.2	0.00093	0.0002	100	10
3.6	0.00063	0.0001	100	6
4.0	0.00042	0.0001	100	4
5.0	0.00015	0.0000	100	1
6.0	0.00006	0.0000	100	0

[a]Based on the equation

DS = -0.02807 - 0.1141*SLOPE + 75.16*HCURVE
+ 1.0075*HUE.

[b]Assumes the regional probability of a critical site is 0.02245.
[c]Assumes the regional probability of a critical site is 0.00559.

TABLE 3. Decision Table for Harvest Areas.

Decision Discriminant[a] Score	Threshold Critical Site Risk AU 1[b]	AU 2[c]	Percentage Classified Correctly: Critical Sites	Noncritical Sites
-6.0	0.73	0.37	0	100
-5.0	0.50	0.18	0	100
-4.0	0.27	0.074	1	100
-3.6	0.20	0.051	3	100
-3.2	0.14	0.035	6	99
-2.8	0.10	0.023	10	99
-2.4	0.069	0.016	17	98
-2.0	0.047	0.011	26	97
-1.8	0.039	0.0088	31	96
-1.6	0.032	0.0072	37	95
-1.4	0.027	0.0059	42	93
-1.2	0.022	0.0048	48	92
-1.0	0.018	0.0040	55	90
-0.8	0.015	0.0032	61	87
-0.6	0.012	0.0027	66	85
-0.4	0.0099	0.0022	72	82
-0.2	0.0081	0.0018	77	79
0.0	0.0067	0.0015	81	75
0.2	0.0055	0.0012	85	71
0.4	0.0045	0.00098	88	67
0.6	0.0037	0.00080	91	63
0.8	0.0030	0.00066	93	58
1.0	0.0025	0.00054	95	54
1.2	0.0020	0.00044	96	49
1.4	0.0017	0.00036	97	44
1.6	0.0014	0.00029	98	40
1.8	0.0011	0.00024	99	35
2.0	0.00091	0.00020	99	31
2.4	0.00061	0.00013	100	23
2.8	0.00041	0.00009	100	17
3.2	0.00027	0.00006	100	11
3.6	0.00018	0.00004	100	8
4.0	0.00012	0.00003	100	5
5.0	0.00004	0.00001	100	1
6.0	0.00001	0.00000	100	0

[a]Based on the equation

DS = 5.0317 - 0.1633*SLOPE + 67.88*HCURVE
- 1.215*WEAKROCK.

[b]Assumes the regional probability of a critical site is 0.00667.
[c]Assumes the regional probability of a critical site is 0.00146.