Forecasting Groundwater Levels: A Stochastic Procedure

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ABSTRACT

In many existing and potential landslides, groundwater is a major factor contributing to the reduction in soil strength and subsequent movement. One prerequisite for evaluation and effective implementation for remedial measures in landslide management is the prior knowledge of temporal variation of groundwater levels, which may be computed by using deterministic methods based on meteorological data and soil-water parameters, for example, permeability. The reliability of such methods depends on the accuracy of the data used. Alternatively, mathematical models, which use historical groundwater data as the sole input, may be employed to yield results satisfactory for planning needs. By considering the occurrence of groundwater levels as a stochastic process, that is, as random sequences in time, the problems of parameter estimation, hydrometerological factors, and so on, are eliminated. In this study monthly water-level observations from an observation well were used in model building by fitting an exponentially weighted moving average (EWMA). The EWMA forecasts and those from the Box-Jenkins stochastic procedure are used for comparison with observed values. It is shown that both EWMA and Box-Jenkins forecasts are statistically indistinguishable from the actual observations. Several statistical tests applied to the two sets of forecasts indicate that EWMA estimates are significantly closer to the actual observations. It is concluded that groundwater levels can be economically and confidently predicted based solely on past historical data.

Groundwater is defined as that part of the soil-water system that is free to move from point to point under the influence of gravity. The surface of that body of free water, which is at atmospheric pressure, is the groundwater table. Below this level the groundwater will be more or less continuous and pressure increases hydrostatically.

Groundwater plays an important role in the stability of a soil mass. The presence of groundwater can cause excess pressures in the soil or excessive drainage from the soil, depending on its permeability (1,pp.65-82). The problems associated with excessive drainage may be remedied with proper drainage control methods. Excess pressure reduces the normal effective stress in the soil, and the resistance to shear decreases. Draining will reduce the pressures and increase the shear strength. A rational stability analysis or design of a drainage stabilization scheme thus requires a knowledge of groundwater (pressure) distribution. Therefore identification of the sources, movement, amount of water, and water pressure is as important as the identification of the soil or soils.

The factors governing the flow of water through a soil mass and those predicting the water pressure distribution are well understood, but the inherent nonhomogeneous nature and anisotropic behavior of the natural soils make the computation of water pressure distribution difficult. Hence it is often recommended that reliance be placed on water pressures observed directly in the soil mass. Groundwater levels or pressures can be measured by a variety of commercially available piezometers. The most common water-level recording technique, despite more sophisticated methods, is the measurement of the depth to the water table in an uncased bore hole or observation well.

PREDICTION OF GROUNDWATER LEVELS

One prerequisite for the evaluation and effective implementation of remedial measures in landslide management is the advance knowledge of the groundwater levels. Engineers and groundwater hydrologists are currently using a variety of methods that cover a wide spectrum from subjective intuitive methods to rigorous deterministic methods. The latter techniques depend entirely on hydrometerological and soil-related factors that cause groundwater levels to fluctuate and are relatively difficult and expensive to develop. Further, such models do not provide much lead time to develop and implement preventive measures. Statistical models based only on historical groundwater data, however, project future occurrences of groundwater levels, which estimates may be satisfactory for planning purposes. Such models have proven to be useful in predicting lake levels (2,3) and forcasting engineering costs (4).

The purpose of this study is to utilize a forecasting technique called the exponentially weighted moving average (EWMA), which has its roots in the mathematics of the time-series analyses and has been proven to be sufficiently flexible to account for both seasonal and trend variations. The predictive accuracy of EWMA is compared with other available results (5,pp.153-159).

EWMA METHOD

Let d_1, d_2, ..., d_{t-1}, d_t be the depths to the water table measured at equal intervals of time. To estimate the depth to the water table (d_{t+1}) at time (t+1), the estimate ($\hat{d}_{t+1}$) may be obtained as a weighted sum of the past observations; that is,

$$\hat{d}_{t+1} = w_0 d_t + w_1 d_{t-1} + w_2 d_{t-2} + \ldots \qquad (1)$$

in which w_0, w_1, w_2, ... are the weights attached to the known observations of water-table depths. It would seem reasonable and sensible to attach more weight to recent observations and progressively less weight to observations further in the past. An intuitively appealing set of weights are those that decrease in geometric progression (6). Equation 1 may then be expressed as

$$\hat{d}_{t+1} = \lambda d_t + \lambda(1 - \lambda)d_{t-1} + \lambda(1 - \lambda)^2 d_{t-2} + \ldots \quad (2)$$

in which λ is called a smoothing constant and lies in the range of $0 < \lambda < 1$. Equation 2 implies an infinite number of past observations that are required to estimate $\hat{d}_{t+1}$; in practice, however, only a finite number of observations are available. Let Equation 2 be expressed in the following form:

$$\begin{aligned}\hat{d}_{t+1} &= \lambda d_t + (1 - \lambda)[\lambda d_{t-1} + \lambda(1 - \lambda)d_{t-2} + \ldots] \\ &= \lambda d_t + (1 - \lambda)\hat{d}_t \quad (3)\end{aligned}$$

which is an EWMA.

Equation 3 may be written as follows:

$$\hat{d}_{t+1} = \lambda(d_t - \hat{d}_t) + \hat{d}_t = \lambda e_t + \hat{d}_t \quad (4)$$

in which e_t is the error in estimating the depth to the water table at time t. The magnitude of the smoothing constant λ depends on the characteristics of the time series. For a chosen value of λ, the expression

$$\sum_{i=1}^{t} e_i^2$$

is calculated. This computation is repeated for several values of λ in the range of zero to unity. That value of λ corresponding to the minimum such computation is the optimum λ that is used in estimating the depth to the water table at time (t + 1).

Winters (7) has generalized the foregoing method to deal with time series that contain trend and seasonal variations. Let M_t be the estimated current mean, T_t be the estimated trend (i.e., the expected change in current mean), and S_t be the estimated seasonal factor in period t. As each set of new observations becomes available, the terms M_t, T_t, and S_t are updated. The seasonal variation in the time series may possess either a multiplicative or an additive effect. Should the amplitude of the seasonal pattern be proportional to the level of the observations, a multiplicative, or ratio, seasonal effect is said to exist. If the amplitude, however, is independent of the levels, an additive effect should be considered. A graphical plot of the data must be examined to determine whether an additive or multiplicative seasonal effect is present. The updating equations for M_t and S_t in an additive seasonal effect are as follows:

$$M_t = \alpha(d_t - S_{t-s}) + (1 - \alpha)(M_{t-1} + T_{t-1}) \quad (5a)$$

$$S_t = \beta(d_t - M_t) + (1 - \beta)S_{t-s} \quad (5b)$$

in which α and β are the smoothing constants with $0 < \alpha < 1$ and $0 < \beta < 1$ and s is the seasonal span (s = 12 for monthly data). The current mean and seasonal factors are thus updated by linear superposition of known past values. If the seasonal variation is multiplicative, the updating equations will be as follows:

$$M_t = (\alpha d_t/S_{t-s}) + (1 - \alpha)(M_{t-1} + T_{t-1}) \quad (6a)$$

$$S_t = (\beta d_t/M_t) + (1 - \beta)S_{t-s} \quad (6b)$$

The updating equation for the current trend term in both the seasonal effects is

$$T_t = \gamma(M_t - M_{t-1}) + (1 - \gamma)T_{t-1} \qquad 0 < \gamma < 1 \quad (7)$$

The forecast $\hat{d}_{t+h}$ for time (t + h) is given by the following:

$$\hat{d}_{t+h} = (M_t + hT_t)S_{t-s+h} \qquad h = 1, 2, \ldots, s \quad (8)$$

Equations 5, 6, and 7 are of such a nature that if the state of a time series is known at an initial time $t = t_0$, a solution can be obtained for $t > t_0$ and is uniquely determined by Equation 8. The starting values of M_t, S_t, and T_t for this iterative process may be calculated from the initial observations of the time series; that is,

$$M_1 = \sum_{t=1}^{s} (d_t/s)$$

$$M_2 = \sum_{t=s+1}^{2s} (d_t/s)$$

$$T_1 = (M_1 - M_2)/s$$

and

$$S_i = 0.5[(d_i/M_1) + (d_{i+s}/M_2)] \qquad i = 1, 2, \ldots, s \quad (9)$$

For example, for monthly groundwater data the first (2s=) 24 observations are used to calculate M_1, M_2, T_1, S_1, S_2, ..., S_{12}.

The three smoothing constants α, β, and γ are varied in the range of zero and unity, and the quantity Σe^2 is computed. The set of values for (α,β,γ) corresponding to the minimum of the computed Σe^2 is the optimum set for (α,β,γ), which is used in updating the equations for M_t, S_t, and T_t, which in turn are substituted in Equation 8 to estimate d_{t+h} for the horizon of time h.

Few comments may be made about the magnitudes of the smoothing constants. Some time-series components experience little random effect; therefore the value of the corresponding smoothing constant will be small or even zero, because there is no use changing the original and still accurate estimate. In other time series there may exist substantial drift, in which case two possibilities may occur: (a) little random effect will lead to large values for the smoothing constant, weighting current estimates heavily, and (b) a large random effect will yield relatively smaller values.

DATA CHARACTERISTICS

The average monthly water-level depths in an observation well (Figure 1) are taken as the data for this study. The depth to the water table is measured below a fixed reference datum. The observation well consists of a 3.50-in.-diameter hole drilled to a depth of 210 ft below the ground surface; the top 80 ft is enclosed in a 4.25-in.-diameter steel casing. The general sequence of soils consists of bluish-brown medium-plasticity clay to an approximate depth of 65 ft lying over 65-ft-thick greenish-brown high-plasticity shale, which is underlain by 8-ft-thick greyish-blue sandstone; the remainder of the bore hole consists of greyish-brown shale and siltstone.

The average depths to the water table were recorded on the hydrographs for the period January 1961 to December 1976. The data for the initial 14 years (a total of 168 observations) were used in building the mathematical model employing the EWMA method. The next 24 observations were used to test the forecasting model: making a forecast, moving along one set of observations of period s (=12 for monthly data), comparing the forecasts with recorded data, absorbing the actual observations into the forecasting model, making the forecasts for the next period, and repeating the cycle. Such a method of

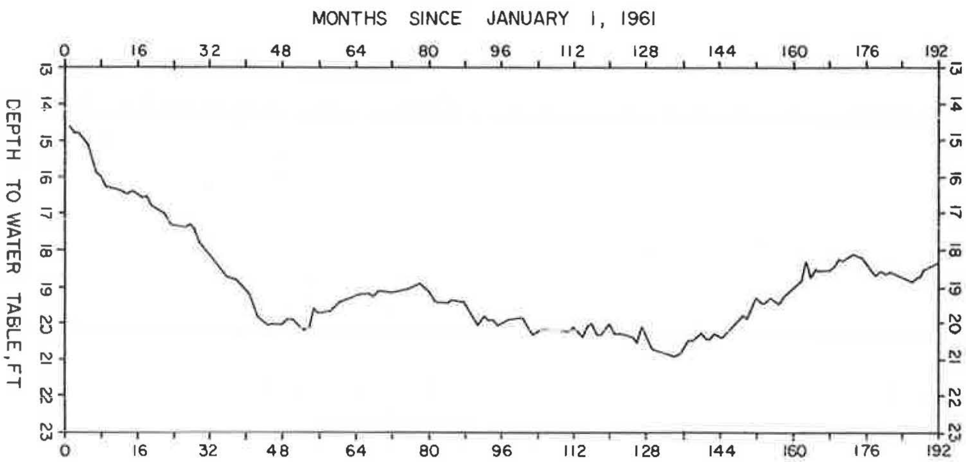

FIGURE 1 Water levels in an observation well.

model building for a certain time period and comparing the (model) forecasts with known observations of a subsequent time period is called ex post forecasting.

The first step in model building is to study a plot of the groundwater data (Figure 1). A visual inspection of the plot suggests that the data have no fixed periodicity and do not exhibit any discernible trend.

STUDY RESULTS

The calculated values of mean squared error, $\Sigma(\text{actual minus forecast})^2/24$, are presented in Tables 1 and 2 for a grid of values of the smoothing constants α, β, and γ. A coarse grid of all possible combinations of the values 0.0, 0.2, 0.4, 0.6, 0.8, and 1.0 for the smoothing constants is given in Table 1, which shows a minimum value of 5.25 for Σe^2, in which e, the error, which is the actual value minus the forecast value, is obtained. A finer grid of α, β, and γ in steps of 0.01 yields the results shown in Table 2; the value of Σe^2 is rather flat near its minimum. The grid of values for α, β, and γ was further refined and the optimum set of the smoothing constants is α = 0.295, β = 0.999, and γ = 0.026. The smoothing constant β associated with the seasonal variation is large, indicating that seasonal adjustments are quite pronounced in the groundwater data. The smoothing constant α corresponding to the current mean is small, suggesting that the mean values of the groundwater data require occasional updating. The value for γ is negligibly small; that is, the trend parameter needs slight or no revision. This shows that no abrupt shifts in groundwater-level trends occur. A comparison of EWMA forecasts with the observed groundwater levels for the years 1975 and 1976 is presented in Figure 2 and Table 3. A visual appraisal of Figure 2 reveals that the forecasts are in excellent agreement with the recorded observations and the largest deviation appears to be of the order of 0.30 ft.

COMPARISON OF FORECASTS

Koppula (5) applied the Box-Jenkins stochastic time-series method (8) to model and estimate the depths to groundwater. The Box-Jenkins approach identifies the stochastic components in a time series, that is, the autoregressive and moving average components, whereas the EWMA incorporates readily any drifts over time into its model and filters out substantial random effects that may be present in the recorded observations.

A summary of the comparison among the EWMA method, the Box-Jenkins forecasts, and the actual observations is presented in Table 3. The predictive accuracy is evaluated by using the mean error ($\Sigma e/24$), mean absolute error ($\Sigma|e|/24$), and the mean squared error ($\Sigma e^2/24$); the lower the values for these quantities, the better are the forecasts. As may be seen, EWMA forecasts are closer to the actual observations. Both the criteria $\Sigma|e|/24$ and $\Sigma e^2/24$ are important because it is difficult to determine the consequences of forecast errors. Whenever the consequence or consequences of one large error are more serious than that of several small errors, the mean squared error will be a more appropriate criterion. The mean absolute error gives the total absolute deviation over the horizon of forecasts; in this case it is over a period of 24 months.

Mincer and Zarnowitz (9,pp.15-25) define the accuracy of a set of forecasts F(t) based on the following:

$$A(t) = \alpha_0 + \alpha_1 F(t)$$

where

A(t) = the observation at time t,
F(t) = the corresponding forecast, and
α_0 and α_1 = constants.

If $\alpha_0 = 0$ and $\alpha_1 \rightarrow 1$, the forecast is said to be accurate. The constants α_0 and α_1 are determined by the application of linear least-squares regression to the actual observations for the period 1975-1976 and to the corresponding forecasts. By regressing the actual observations the following equations were obtained:

Actual = -3.14 + 1.18 EWMA $\quad R^2$ = 50 percent
SE = 0.16

Actual = -0.27 + 1.02 Box-Jenkins $\quad R^2$ = 19 percent
SE = 0.21

The coefficients 1.18 and 1.02 are not significantly different from unity at the 95 percent confidence level. Also the constants of regression -3.24 and

TABLE 1 Sum of Mean Squared Error: Coarse Grid

	λ					
	0.0	0.2	0.4	0.6	0.8	1.0
α = 0.						
β=0.0	*	*	*	*	*	*
0.2	*	*	*	*	*	*
0.4	*	*	*	*	*	*
0.6	87.65	87.54	87.46	87.35	87.15	85.57
0.8	41.84	41.79	41.75	41.70	41.61	40.87
1.0	22.85	22.82	22.80	22.77	22.72	22.34
α = 0.2						
β=0.0	35.36	37.11	71.48	*	*	*
0.2	26.21	6.71	10.10	13.41	*	*
0.4	22.41	5.75	10.69	19.37	*	*
0.6	18.86	5.63	12.36	33.21	*	*
0.8	16.36	5.45	16.59	*	*	*
1.0	14.62	5.28	*	*	*	*
α = 0.4						
β=0.0	20.80	57.93	80.73	*	*	*
0.2	13.80	16.36	57.10	*	*	*
0.4	15.68	5.25[a]	36.43	*	*	*
0.6	15.99	5.40	72.95	*	*	*
0.8	16.75	15.38	*	*	*	*
1.0	17.42	16.50	*	*	*	*

	λ					
	0.0	0.2	0.4	0.6	0.8	1.0
α =0.6						
β=0.0	18.91	52.55	45.19	28.70	29.58	42.17
0.2	11.39	57.94	*	63.12	27.72	46.22
0.4	9.86	39.14	*	*	64.57	*
0.6	11.41	12.52	*	*	*	*
0.8	13.77	15.15	*	*	*	*
1.0	14.91	37.53	*	*	*	*
α =0.8						
β=0.0	18.52	48.32	43.07	38.66	42.91	48.27
0.2	14.49	53.14	47.72	30.09	30.52	39.05
0.4	11.87	60.35	62.79	25.77	20.81	31.50
0.6	10.03	68.04	95.63	27.20	23.95	30.70
0.8	8.82	73.79	*	35.59	76.70	28.17
1.0	8.18	74.83	*	60.18	*	*
α =1.0						
β=0.0	18.43	46.26	42.67	38.27	35.15	29.38
0.2	18.43	46.26	42.67	38.27	35.15	29.38
0.4	18.43	46.26	42.67	38.27	35.15	29.38
0.6	18.43	46.25	42.66	38.26	35.15	29.38
0.8	18.43	46.25	42.66	38.26	35.14	29.37
1.0	18.43	46.25	42.67	38.27	35.15	29.38

* The value is larger than 1×10^2

[a] Minimum Σe^2

TABLE 2 Sum of Mean Squared Error: Finer Grid

	λ				
	0.02	0.03	0.04	0.05	0.06
α =0.28					
β=0.96	2.65	2.18	2.83	3.34	3.72
0.97	2.63	2.17	2.81	3.32	3.70
0.98	2.62	2.17	2.80	3.30	3.68
0.99	2.60	2.16	2.78	3.28	3.66
1.00	2.61	2.17	2.79	3.29	3.67
α =0.29					
β=0.96	2.43	2.18	2.83	3.35	3.74
0.97	2.42	2.17	2.82	3.33	3.72
0.98	2.40	2.16	2.80	3.32	3.70
0.99	2.38	2.15[a]	2.79	3.30	3.68
1.00	2.39	2.16	2.79	3.30	3.69
α =0.30					
β=0.96	2.35	2.18	2.85	3.38	3.77
0.97	2.33	2.17	2.83	3.36	3.75
0.98	2.32	2.16	2.82	3.34	3.73
0.99	2.31	2.16	2.80	3.32	3.71
1.00	2.33	2.17	2.81	3.33	3.73

	λ				
	0.02	0.03	0.04	0.05	0.06
α =0.31					
β=0.96	2.45	2.19	2.88	3.42	3.82
0.97	2.44	2.18	2.86	3.39	3.79
0.98	2.43	2.17	2.84	3.37	3.77
0.99	2.44	2.16	2.83	3.35	3.75
1.00	2.45	2.17	2.84	3.36	3.76
α =0.32					
β=0.96	2.64	2.21	2.91	3.46	3.88
0.97	2.63	2.20	2.90	3.44	3.85
0.98	2.63	2.19	2.88	3.42	3.83
0.99	2.61	2.17	2.86	3.40	3.80
1.00	2.63	2.19	2.87	3.39	3.82

[a] Minimum Σe^2

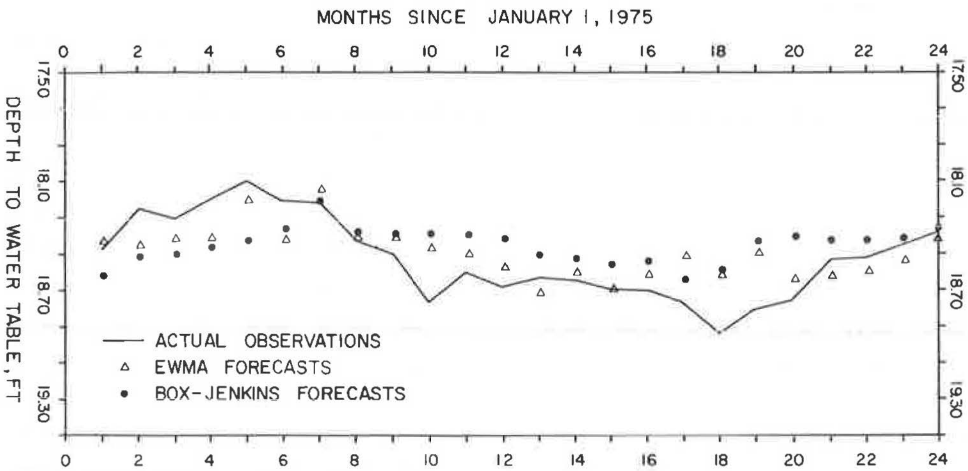

FIGURE 2 Forecast comparison of groundwater levels.

TABLE 3 Depth to Groundwater: Forecast Evaluation

		EWMA Method[a]				Box-Jenkins Method[b]			
Date	Actual Observation	Estimated Value	Error (e)	|e|	Σe^2	Estimated Value	Error (e)	|e|	Σe^2
1975									
January	18.47	18.42	0.05	0.05	0.0025	18.61	-0.15	0.15	0.0225
February	18.25	18.45	-0.20	0.20	0.0400	18.50	-0.25	0.25	0.0625
March	18.30	18.41	-0.11	0.11	0.0121	18.48	-0.18	0.18	0.0324
April	18.20	18.40	-0.20	0.20	0.0400	18.44	-0.24	0.24	0.0576
May	18.10	18.20	-0.10	0.10	0.0100	18.40	-0.30	0.30	0.0900
June	18.20	18.41	-0.21	0.21	0.0441	18.35	-0.15	0.15	0.0225
July	18.22	18.14	0.08	0.08	0.0064	18.20	0.02	0.02	0.0004
August	18.43	18.40	0.03	0.03	0.0009	18.37	0.06	0.06	0.0036
September	18.50	18.39	0.11	0.11	0.0121	18.38	0.12	0.12	0.0144
October	18.77	18.45	0.32	0.32	0.1024	18.37	0.40	0.40	0.1600
November	18.60	18.49	0.11	0.11	0.0121	18.38	0.22	0.22	0.0484
December	18.68	18.55	0.13	0.13	0.0169	18.40	0.28	0.28	0.0784
1976									
January	18.63	18.71	-0.08	0.08	0.0064	18.50	0.13	0.13	0.0169
February	18.64	18.59	0.05	0.05	0.0025	18.51	0.13	0.13	0.0169
March	18.69	18.68	0.01	0.01	0.0001	18.54	0.15	0.15	0.0225
April	18.70	18.60	0.10	0.10	0.0100	18.53	0.17	0.17	0.0289
May	18.77	18.52	0.25	0.25	0.0625	18.62	0.15	0.15	0.0225
June	18.94	18.60	0.34	0.34	0.1156	18.59	0.35	0.35	0.1225
July	18.80	18.47	0.33	0.33	0.1089	18.42	0.38	0.38	0.1444
August	18.75	18.63	0.12	0.12	0.0144	18.40	0.35	0.35	0.1225
September	18.53	18.61	-0.08	0.08	0.0064	18.40	0.13	0.13	0.0169
October	18.52	18.58	-0.06	0.06	0.0036	18.42	0.10	0.10	0.0100
November	18.45	18.52	-0.07	0.07	0.0049	18.40	0.05	0.05	0.0025
December	18.38	18.40	-0.02	0.02	0.0004	18.35	0.03	0.03	0.0009

[a]$\Sigma e/24 = 0.0375$; $\Sigma|e|/24 = 0.1317$; $\Sigma e^2/24 = 0.0265$.
[b]$\Sigma e/24 = 0.0812$; $\Sigma|e|/24 = 0.1871$; $\Sigma e^2/24 = 0.0467$.

-0.27 are not significantly different from zero. Thus the accuracy criterion defined by Mincer and Zarnowitz is satisfied by the two mathematical models. The Box-Jenkins method yields results that can explain only 19 percent, whereas EWMA forecasts explain 50 percent of the variations inherent in the actual observations; further EWMA forecasts possess smaller standard error of regression. Thus a complete statistical evaluation suggests that the forecasts of groundwater levels from the EWMA method are significant and are closer to the actual observations.

CONCLUDING REMARKS

The description of a mathematical procedure, EWMA, to forecast future occurrences of groundwater levels is presented. The EWMA estimates are compared with those made by the Box-Jenkins method. It is shown that both methods yield results that are statistically indistinguishable from the actual observations. The EWMA method, however, provides better forecasts, is relatively simple to use, and is inexpensive.

The object of this study has been to demonstrate the availability of stochastic methods, which use historical data as the sole input, to estimate future groundwater levels for use in the evaluation of the stability of existing or potential landslides. Having obtained reasonably accurate forecasts, advance strategic planning and design may be undertaken for remedial measures in landslide management.

The time-series analysis is a useful and powerful predictive tool. It should be emphasized that model building and forecasting therefrom are a continuous process; as new observational data become available, they should be used to update the mathematical model.

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Predictions of Pore-Water Pressure and Soil Suction Conditions in Road Cut Slopes in St. Lucia, West Indies: A Methodology to Aid Cut Slope Design

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ABSTRACT

There is evidence in the tropics that soil suction may play a most significant role in slope stability. In many developing areas of the tropics, relatively rapid assessments of both road alignment and road maintenance frequently have to be made. A prediction capability is sought for soil suction in selected residual soils of relevance to road cut slopes in St. Lucia, West Indies, and the topographic, material, and precipitation controls on the soil suction are established. It is shown that a dummy variable regression model employing material permeability, precipitation, and qualitative site factors provides good estimates of the recorded soil suction. In addition, the variable importance of three-dimensional slope topography on soil suction is identified. Failures logged during the study period conform to the high-risk sites estimated by the soil suction prediction model. The low site investigation requirement combined with the accuracy of soil suction prediction render such a procedure of potential use to road design and maintenance in tropical areas where only limited geotechnical investigations are possible.

There is mounting evidence within the tropics that soil suction might make a significant contribution to slope stability. Sweeney and Robertson (1), for example, stated that although the influence of soil suction on soil strength has not yet been quantified, there is the likelihood that soil suction contributes to soil strength, especially in the finer-grained soils. More recently, Ho and Fredlund (2, pp. 263-295) were able to demonstrate with a single triaxial test the increase in strength due to soil suction. In addition, they remark that there is no reason to expect a reduction in suction during rain-