# GEOMORPHIC RESPONSE MODEL FOR PREDICTION OF JUNE MONTHLY SEDIMENT PRODUCTION RATE FROM SMALL WATERSHEDS

*Sandip P. Nikam*[1] *and Subhas K. Upadhye*[2]

[1]*Asstt. Professor (Ph.D. Scholar), Dept. of Agril. Engg., College of Agriculture, Dhule (M.S.)*

[2]*Asstt. Prof. of Soil & Water Cons. Engg., Operational Research Project, AICRPDA, Solapur Mahatma Phule Krishi Vidyapeeth, Rahuri*

| Received: 21/07/2017 | Edited: 29/07/2017 | Accepted: 07/08/2017 |
|---|---|---|

**Abstract:** *Quantitative assessment of runoff, soil erosion and sediment yield are needed for proper management of land and water resources especially for optimum agriculture production. Globally, nearly 2 billion ha or about 13 per cent of the land surface has suffered some type of human induced land degradation. The origin of all sediment coming into a reservoir lies in its catchment. Most of the watersheds in India are unguaged which faces the problems to the development planners to get the realistic sediment data for planning various projects. In this study, GIS based geomorphic response models was developed for prediction of June monthly sediment production rate (SPR) from small watersheds of Tapi basin of Maharashtra state. It is observed that the per cent deviation between observed and predicted values For SPR model with runoff, SPR model with rainfall and SPR model without considering rainfall and runoff, the percentage deviation ranges from 1.8 to 15.7, 0.3 to 9.7 and 3.1 to 46.7 respectively. These models can be used for other watersheds having similar physiographic conditions.*

**Key words**: *Geomorphological parameters, Sediment production rate, Principal component analysis, watershed.*

## Introduction

Water erosion alone, being a global phenomenon, contributes about 55 per cent and, has been found to be the main cause of land degradation (Yu, 1998). It has been estimated that total of 16.4 t $ha^{-1}$ of soil per year is being eroded annually. Also, the country's rivers carry about 29 per cent of the total eroded soil and lost permanently to the sea, 10 per cent is deposited in reservoirs resulting in loss of storage capacity of 1-2 per cent and 61 per cent eroded soil is being transported from one place to another (Dhruvanarayana and Rambabu, 1983).

About 6000 MT of soil is eroded every year in India from about 80 Mha of culturable land losing 8.4 metric tones of nutrients. The nutrient losses in this way are much greater than the quantity that is presently used in the country (Singh, 2000). A great amount of sediment is carried annually by the Indian rivers down to the reservoirs, lakes, estuaries, bays and oceans. Analysis of silt load data in India as well as in other parts of the world revealed that all watersheds are not equally susceptible to erosion. Therefore, it is required to identify the critical watersheds so that these can be treated on priority basis. A watershed development programme planned without priority setting can result in questionable investments and considerable waste (Gupta *et al.,* 2005).

Sahoo *et al*., (2008) developed mathematical model using geomorphological parameters for the Muchkund catchment. Delmas *et al*., (2009) and Vijith *et al*., (2011) tried to find out the sediment loss using different watershed parameters. The rainfall and watershed characteristics in the form of geomorphic parameters can be utilized in the development of reliable response model for predicting runoff and sediment yields from small watersheds. The geomorphologic parameters directly or indirectly reflect almost the entire watershed based causative factors affecting runoff and sediment loss. In recent past, Geographical Information System (GIS) has emerged as comprehensive tool for description of hydrological processes at basin scale and facilitates easy determination of the hydrologic and geomorphic characteristics of a watershed (Jain and Kothyari, 2000 and Pandey *et al.*, 2004). In this study geomorphic response model was developed for prediction of June monthly sediment production rate (SRR) from selected watersheds of Tapi basin of Maharashtra state, India.

**Material and Methods**

**Study area**

The study area is situated between 68°30' to 70°45' E longitudes and 22°18' to 23°25' N latitude. The Tapi estuary is a tidal estuary originating in the Multai Ghats in Betoul district of Madhya Pradesh (India) at an elevation of 750 m. The Tapi River basin covers an area of 65,145 km² that makes up almost two percent of the total area of India. The study was confined to 10 watersheds of Tapi catchment for which annual time series data on rainfall, runoff and mean monthly sediment yield was used for development of models.

**Digitization and Georeferencing of Toposheets in GIS**

Toposheets of the study area are obtained from the Survey of India (SOI), Dehradoon and Geological Survey of India, Pune regional office in the 1: 250000 and 1: 50000 scale. These toposheets were then used for digitization and georeferencing with the help of ArcGIS 9.3 software. After rectification a new dataset will form in GRID, TIFF or ERDAS IMAGINE format. These rectified maps are then further used for creating new digitized layers of watershed boundary, drainage lines and contour lines of selected watersheds.

**Evaluation of Geomorphic Parameters**

The geomorphic parameters used in the present study to predict geomorphic responses were evaluated from the quantified watershed characteristics and ArcGIS 9.3 software interface. The selected geomorphological parameters are average slope of the watershed ($S_a$), elongation ratio ($R_e$), circulatory ratio ($R_c$), basin shape factor ($S_b$), relief ratio( $R_f$), relative relief ($R_r$ ), ruggedness number ($R_N$), main stream channel slope ($S_c$), drainage factor ($D_f$), stream length ratio ($R_l$), bifurcation ratio ($R_b$), and length width ratio ($L_{bw}$). These twelve parameters are already dimensionless. The other three terms $R/\sqrt{A}$ , $P/\sqrt{A}$ and $SPR/\sqrt{A}$ are termed as runoff factor, rainfall factor and SPR factor respectively.

**Correlation matrix and PCA**

The intercorrelation matrix was developed to study the intercorrelation among the selected geomorphic parameters. This matrix was then subjected to Principle Component Analysis (PCA) to screen out non significant parameters and to find out the physically significant groups of remaining geomorphic parameters. These parameters from each physically significant group are being used for development of geomorphic annual SPR models.

**Development of Deterministic Prediction Models**

After regrouping the geomorphic parameters into physically significant components, SPSS 16.0 software was used to develop dimensionally homogeneous and statistically optimal models of the following linear and log linear form:

$$Y = a_0 + a_1X_1 + a_2X_2 + a_3X_3 + a_4X_4 + a_5X_5 \quad \text{.... (1)}$$

$$Y = a_0(X_1)^{a_1}(X_2)^{a_2}(X_3)^{a_3}(X_4)^{a_4}(X_5)^{a_5} \quad \text{.... (2)}$$

Where, Y is the dependent variable and $X_1, X_2, X_3, X_4, X_5$ are the independent variables $a_0, a_1, a_2, a_3, a_4, a_5$ are the regression coefficients.

The subroutine applies multiple regression techniques and calculates regression coefficients, multiple correlation coefficients, F-test value, standard error and the percentage variation explained by the model. In order to obtain the best fit June monthly SPR prediction models, the data sets were used to regress the SPR factor, $SPR/\sqrt{A}$, on three independent variables, 3 variables being the same, i.e. one from each component and fourth as the runoff factor, $R/\sqrt{A}$ rainfall factor, $P/\sqrt{A}$ and without rainfall and runoff. Here also the regression analysis was performed using logarithms of the data sets. In order to select out the best fit model, out of eighteen combinations, the criteria adopted here is the lowest standard error of estimate, highest correlation coefficient and F-test value.

The best fit models thus identified were used to compute the predicted values of June monthly SPR and compared with the observed values to find the percentage deviations. The validation of model has been carried out. The data of first eight watersheds was used for development of models and remaining two was used for validation of the models.

**Results and Discussion**

Geomorphic characteristics of the selected watersheds were evaluated using ArcGIS 9.3 software interface and are presented in Table 1. Using these parameters a correlation matrix was obtained to find out the correlation among the parameters. It is observed that out of twelve parameters, two parameters such as $S_a$ and $R_b$ were not correlated significantly to other parameters. After subjecting correlation matrix of twelve parameters to PCA, it is observed that all the parameters were grouped into three physically significant groups having Eigen value greater than one. The parameters $S_a$ and $R_b$ were screened out in the PCA because they are poorly correlated with all the three components and having less significance in explaining the component variance (Table 2).

In order to formulate dimensionally homogenous and statistically optimal models for predicting the June monthly SPR from small watershed of Tapi catchment SPSS 16.0 software was used. Two different models *viz* June monthly SPR with runoff and June monthly SPR with rainfall as dependant parameters were developed.

Total of 18 (6x3x1) combinations were tried for the ten geomorphic parameters from three principal components. Out of 18 combinations, Eq. 3, 4 and 5 were found to be the best fit models selected on the basis of lowest standard error and highest correlation coefficient.

**Monthly SPR Model with Runoff – June**

$$S_f = \frac{SPR}{\sqrt{A}} = 0.019(R_f)^{0.941}(L_{bw})^{-0.866}(R_F)^{-0.435}(S_c)^{-0.353} \qquad \ldots\ldots (3)$$

The value of multiple correlation coefficient (r=0.992) and F-test value (F=46.561) are higher in case of log linear form of the model than in the linear one.

**Monthly SPR Model with Rainfall – June**

$$S_f = \frac{SPR}{\sqrt{A}} = 0.292 + 0.009P_f - 0.028R_l - 7.722R_r - 0.204S_c \qquad \ldots\ldots (4)$$

The value of multiple correlation coefficient (r = 0.988) and F-test value (F = 29.927) are higher in case of linear form of the model than in the log linear one.

**Monthly SPR Model without Rainfall and Runoff – June**

$$S_f = \frac{SPR}{\sqrt{A}} = 0.030(D_f)^{-0.651}(R_n)^{-0.362}(S_c)^{-0.817} \qquad \ldots\ldots (5)$$

The log linear model is chosen as statistically best fit optimal model. The multiple correlation coefficient (r=0.899) and F-test value (F=5.606) are higher than those in linear case.

It is observed that the percent deviation between observed and predicted values For SPR model with runoff (Eq.3), SPR model with rainfall (Eq. 4) and SPR model without considering rainfall and runoff (Eq.5), the percentage deviation ranges from 1.8 to 15.7, 0.3 to 9.7 and 3.1 to 46.7 respectively. The largest range of deviation in SPR was found for SPR model without considering rainfall and runoff for which the correlation coefficient (r=0.89) and F-test value (F=5.606) was also less as compared to other models. Therefore this model cannot be considered for prediction of monthly SPR. The SPR model with rainfall (Eq.4) for June shows minimum deviations well within 10 percent for all the watersheds therefore this model can be used for predicting the SPR which is due to the fact that the correlation coefficient (r=0.988) and F-test value (F=49.927) for this model is highest amongst all other models .

## Conclusion

It is concluded that intercorrelation matrix and principle component analysis can be used to find out the physically significant geomorphological parameters for developing hydrological response models. The developed geomorphic models for prediction of June monthly sediment production rate with combination of rainfall was found to be useful for prediction of SPR from small watersheds having similar physiographic conditions. It is also concluded that according to the predicted values of SPR from small watersheds within the basin, watershed prioritization can be done to carry different soil and water conservation works.

## References


Delmas, M., O. Cerdan, J.Manchel and N. Garcin. (2009). A method for developing a large scale sediment yield index for European river basins. J. Soils Sediments. 9: 613-626.

Dhruvanarayana, V.V. and Rambabu. (1983) Estimation of soil erosion in India. J. Irrigation and Drainage Engg. 109(4): 419-433.

Gupta, A.K., R.C. Purohit, J. Singh, R.S. Singh and V. Mohan. 2005. Geomorphometric and Hypsometric analysis for watershed prioritization: A GIS Based Approach. Edi. book; Hydrology and Watershed Management, Himanshu Publications, Udaipur pp: 273-283.

Jain, M.K. and U. C. Kothyari. (2000). Estimation of soil erosion and sediment yield using GIS. J. Hydrol. Sci. 45(5): 771-786.

Pandey, A., V.M. Chaudhary and B.C. Mal. (2004). Morphological analysis of watershed management using GIS. Hydrol. J. IAH. 27(2 & 3): 71-84.

Sahoo, N., T.B.S. Rajput and A.R. Rao. (2008). Geomorphological parameter based watershed sediment yield estimation. J. of Agril. Engg. 45(1): 47-56.

Singh, P.K. 2000. Watershed Management (Design and Practices). e-media publications, Udaipur.

Vijith, H., Sum, M., Rekha, U.B., C. Shiju and P.G. Rejith. (2011). An assessment of soil erosion probability and erosion rate in a tropical mountainous watershed using remote sensing and GIS. Arab J. Geosci. *DOI 10.1007/s12517-010-0265-4*.


**Table 1: Selected Dimensionless Geomorphic Parameters**

| | $S_a$ | $R_e$ | $R_c$ | $S_b$ | $R_F$ | $R_r$ | $R_N$ | $S_c$ | $D_f$ | $R_l$ | $R_b$ | $L_{bw}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **W1** | 3.652 | 0.785 | 0.806 | 2.064 | 0.020 | 0.0065 | 0.305 | 1.223 | 0.433 | 0.811 | 3.303 | 1.685 |
| **W2** | 1.180 | 0.853 | 0.922 | 1.751 | 0.012 | 0.0040 | 0.167 | 0.217 | 0.397 | 0.849 | 2.280 | 1.791 |
| **W3** | 2.332 | 0.697 | 0.828 | 2.624 | 0.009 | 0.0035 | 0.332 | 0.499 | 0.487 | 1.127 | 3.863 | 2.082 |
| **W4** | 3.472 | 0.622 | 0.763 | 3.286 | 0.021 | 0.0082 | 0.637 | 0.476 | 0.442 | 0.879 | 4.570 | 2.826 |
| **W5** | 2.875 | 0.685 | 0.846 | 2.712 | 0.010 | 0.0041 | 0.232 | 0.518 | 0.527 | 1.117 | 2.890 | 2.613 |
| **W6** | 4.566 | 0.738 | 0.816 | 2.335 | 0.016 | 0.0055 | 0.368 | 0.374 | 0.291 | 0.800 | 2.917 | 1.975 |
| **W7** | 0.909 | 0.482 | 0.639 | 5.475 | 0.007 | 0.0028 | 0.145 | 0.464 | 0.536 | 1.042 | 3.319 | 4.101 |
| **W8** | 2.297 | 0.502 | 0.613 | 5.053 | 0.008 | 0.0031 | 0.477 | 0.448 | 0.387 | 1.148 | 3.707 | 4.399 |
| **W9** | 1.269 | 0.798 | 0.760 | 2.001 | 0.021 | 0.0063 | 0.531 | 0.527 | 0.476 | 0.968 | 3.213 | 2.084 |
| **W10** | 2.317 | 0.782 | 0.769 | 2.080 | 0.022 | 0.0069 | 0.415 | 0.103 | 0.595 | 0.955 | 4.467 | 1.788 |

**Table 2 Principal Component Loading Matrix of Final Geomorphic Parameters**

| **Parameters** | **Principal Components** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **1** | **2** | **3** | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| $R_e$ | 0.974 | -0.106 | -0.165 | 0.103 | 0.003 | -0.040 | 0.007 | -0.001 | 0.000 | 0.000 |
| $R_c$ | 0.906 | -0.314 | -0.241 | 0.137 | 0.039 | 0.057 | 0.003 | 0.000 | 0.000 | 0.000 |
| $S_b$ | -0.975 | 0.049 | 0.162 | -0.140 | -0.013 | 0.015 | 0.000 | -0.001 | 0.000 | 0.000 |
| $R_f$ | 0.881 | 0.463 | 0.071 | -0.013 | -0.06 | -0.018 | 0.002 | 0.001 | 0.000 | 0.000 |
| $R_r$ | 0.840 | 0.527 | 0.103 | -0.046 | -0.051 | 0.035 | 0.000 | 0.001 | 0.000 | 0.000 |
| $R_N$ | 0.155 | 0.978 | 0.103 | 0.007 | 0.095 | -0.004 | 0.000 | 0.000 | 0.000 | 0.000 |
| $S_c$ | 0.286 | -0.250 | 0.907 | 0.184 | 0.005 | 0.002 | 0.000 | 0.000 | 0.000 | 0.000 |
| $D_f$ | 0.818 | -0.48 | 0.146 | -0.276 | 0.051 | -0.014 | 0.000 | 0.002 | 0.000 | 0.000 |
| $R_l$ | -0.955 | 0.024 | -0.126 | 0.268 | 0.009 | -0.012 | 0.000 | 0.002 | 0.000 | 0.000 |
| $L_{bw}$ | -0.981 | 0.081 | 0.128 | -0.119 | 0.005 | 0.011 | 0.012 | 0.001 | 0.000 | 0.000 |
| Eigen Value | **6.852** | **1.86** | **1.013** | 0.247 | 0.02 | 0.007 | 0.000 | 0.000 | 0.000 | 0.000 |