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Predictings Sediment Loading into Masinga Reservoir and its Storage Capacity Reduction

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Abstract: It is estimated that the annual loss in storage capacity of the world's reservoirs due to sedimentation is around 0.5 - 1.0%. For many reservoirs, however, annual depletion rates are much higher and can go up to 4% or 5%, such that they lose the majority of their capacity after only 25 - 30 years. The Masinga reservoir, one of the main reservoirs in Kenya, designed for hydropower generation, public water supply and irrigation is faced with severe sedimentation. The designed sediment load into this reservoir in 1981 was estimated to be 3.0 x 10⁶ m³ per year (about 1% per annum reservoir reduction). By 2000, annual sediment loading had increased to over 11.0 x 10⁶ m³, nearly four times, thus reducing the designed capacity by more than 15%. As land degradation has become more evident with increasing land use change within Masinga catchment over the years, the operation and life span of Masinga reservoir is thus under imminent danger from erosion and sedimentation. There is need therefore to quantify spatially soil erosion and sediment yield reaching the reservoir with a view to reducing the sediment delivery. In this paper, a comprehensive procedure to predict spatial sediment yield and overall mean annual sediment volume delivered to Masinga reservoir is presented. Geographical Information System (GIS) technology as a tool to support soil erosion and sediment models is employed. Simulations of different land use and management scenarios are performed and their corresponding sediment yields estimated. Predictions show annual sediment loading into the reservoir of about 14.0 x 10⁶ m³ for land use practices in 2003. By simulating the best feasible management practices (BMPs). the achieved results show that the sediment volume reaching the reservoir could be reduced to about 6.0 x 10^6 m³ per year.

Keywords: Reservoir, sediment yield, GIS, soil erosion modelling, catchment management

1. Introduction

Without careful planning, design and operation, the economic life of reservoirs can be shortened and thus the goods and services for which the project was constructed may not be sustained over the desired design period. The results of such a failure can impact local and regional economies and lead to considerable disruption. It is estimated that the annual loss in storage capacity of the world's reservoirs due to sedimentation deposition is around 0.5 - 1.0% according to World Commission on Dams (WCD) (2000). For many reservoirs, however, annual depletion rates are much higher and can go up to 4% or 5%, such that they lose the majority of their capacity after only 25 - 30 years.

Kenya's power generation is dominated by hydropower, which accounts for approximately 70% of the generation capacity. The *Seven Forks* hydropower system on the Tana River Basin provides most of this capacity and Masinga reservoir, which provides upstream regulation storage, is therefore critical for the smooth operation of the cascade system. Masinga reservoir acts as a regulating scheme for the lower dams in the cascade and any loss of storage capacity increases the risk of failure to meet the design objectives in dry periods. Although the emphasis was that the development of these multipurpose reservoirs would be the best measure of meeting Kenya's water demand by the year 2020 (Ongweny et al., 1993), it is evident that environmental problems such as soil erosion and silting of dams could curtail these efforts.

While the issue of Masinga reservoir sedimentation has been of interest in recent years, very little work has been done to estimate the spatial variability of sediment transport from the catchment. The key issue with reservoir sedimentation reduction lies within a proper catchment management.

1.1 Objective

The objective of this study is to apply a spatially distributed sediment delivery model in a Geographical Information System (GIS) environment to Masinga catchment with a view to predicting spatial sediment yield and mean annual sediment volume reaching the main Masinga reservoir.

2. Materials and methods

2.1 Study area

The Masinga catchment area (figure 1) is some $6,255 \text{ km}^2$ in extent, lying to the east of the Aberdare Mountains and south of Mount Kenya. It lies between latitudes 0° 7'S and 1° 15'S and longitudes 36° 33'E and 37° 46'E. The elevations range from 900 to 4000 m (a.m.s.l). The catchment falls within five agro-climatic zones ranging from semiarid in the east to humid in the western side. The mean annual rainfall vary from about 600 to 2000 mm with mean annual temperatures ranging from 21 to 31 °C. The catchment has an estimated population of 2 million people (Opiyo, 1999). The agricultural and grazing activities take about 86% of the total catchment area (Mutua, 2005).



Figure 1 Location of study area on the map of Kenya

2.2 Predicting soil erosion rates

In this study, the Revised Universal Soil Loss Equation (RUSLE) was used to estimate the mean annual soil erosion. The RUSLE model was chosen in this study because its data requirements are not too complex or unattainable, it is relatively easy to parameterise, and it is compatible with GIS. When used in conjunction with raster-based GIS, the RUSLE model can isolate locations of erosion on a cell-by-cell basis, determine the role of individual variables on the rate of erosion, and identify the spatial patterns of soil loss within a catchment (Millward and Mersey, 1999).

In a raster GIS, the mean annual gross soil erosion was calculated at a cell level using six factors, which are composite factors of many others. The RUSLE model is given as:

$$A_i = LS_i R_i K_i C_i P_i \tag{1.1}$$

Where subscript *i* is the *i*th cell; *A* (ton ha⁻¹ yr⁻¹) is the estimated average annual soil loss; *LS* is the combination of the slope steepness and slope length factors; *R* (KJ mm m⁻² h⁻¹ yr⁻¹) is the erosivity factor; *K* (ton ha⁻¹ KJ⁻¹ mm⁻¹ m² h) is the soil erodibility factor; *C* is the cover and management factor and *P* is the support practice factor.

Five primary data themes were required to generate the RUSLE factors. These were the digital elevation model (DEM), the climatic data (precipitation), soil data, land use coverage and conservation support practices. The DEM was required to derive the slope length (L) and the slope steepness (S) factors. The climatic data was required to develop the rainfall erosivity (R) factor. The soil type coverage was required to develop the soil erodibility (K) factor and the land use coverage was used to develop the crop management (C) and conservation practice (P) factors.

One major improvement made by using the RUSLE in this study was the application of upslope area contributing method in determining the slope length and steepness factor, which made the model to act on a semi-distributed form. The use of time series of remote sensing imagery and daily rainfall to incorporate the effects of seasonally varying rainfall intensity, and use of new digital maps of soil and terrain properties allowed the estimation of spatial seasonal erosivities for Masinga catchment.

2.2.1 Simulation scenarios

Four simulation scenarios were performed in this study to estimate the spatial soil erosion within the catchment. Scenario 1 was based on land use/cover and management practices for 2003 and formed the benchmark scenario. Scenario 2 was run by changing the conservation practices while maintaining other factors as in benchmark scenario. Scenario 3 was run by changing the land use and cover types but keeping the other factors constant as in benchmark scenario. The formulation of the new database for scenarios 2 and 3 was done in reference to different slopes, climatic zones, soil properties and the viable management practices for each sub-catchment. Scenario 4 was run by combining the new data sets formulated for scenarios 2 and 3. Predicted soil erosion rates for all scenarios were compared with the tolerable erosion rates for Masinga area. The scenario that gave the least erosion rates was taken to have the best management practices (BMPs) for Masinga.

2.3 Predicting spatial sediment yield

Sediment yield is usually not available as a direct measurement and it is estimated using a sediment delivery ratio (SDR). Erosion rates estimated by RUSLE are often higher than those measured at catchment outlets. Sediment delivery ratio (SDR) is thus used to correct for this reduction effect.

There is no precise procedure to estimate SDR, although the USDA-SCS (1972) published a handbook in which the SDR is related to drainage area. In this study, an attempt was made to develop and apply a spatially distributed sediment delivery model in a GIS environment to Masinga catchment. The developed model is known as the Hillslope Sediment Delivery Distributed (HSDD) model. To apply the model, the catchment was delineated and discretized into morphological units (i.e., areas of defined aspect, length, steepness). The morphological units were then aggregated into seven major sub-catchments (figure 2) based on the pour points (outlets) of the delineated stream network.



Figure 2 Major sub-catchments of the study area

The main spatial physical properties for each sub-catchment were averaged. Table 1 presents the summary of the average physical properties for the discretized sub-catchments.

Basin	Soil	Soil	Area	Hlength	Hslope	UpArea	Elevation	SCS	Max	Manning
ID	*WHC	Depth	(Km ²)	(m)	(m)	(km ²)	(m)	Number	Cover	Coeff.
	(mm)	(cm)						CN		
2	117.178	94.3787	2758	21776.3	1.6912	2757	2143.9	76.4	0	0.065
4	126.942	101.006	821	23002.3	1.9787	820	1897.4	73.3	0	0.045
5	63.8816	102.938	76	5312.6	0.6324	3654	1198	79.8	0	0.025
8	108.168	97.9412	506	34384	1.865	505	1802.5	73.1	0	0.035
10	77.8595	121.901	918	16939.1	0.901	5078	1309.9	76.9	0.00106	0.035
11	112.868	195.415	597	13419.6	0.874	6261	1121	73.9	0.00147	0.075
12	88.6997	150.232	586	18397.8	0.9661	585	1213.9	75.4	0.00106	0.055

 Table 1
 Main average attributes of the discretized sub-catchments

WHC: water holding capacity; Hlength: hillslope length; Hslope: hillslope (m/100m); UpArea: upslope contributing area; SCS: soil conservation service curve number; Max cover: maximum % cover of land that is impervious.

A physically distributed hydrological model, the Stream Flow Model (SFM) was used to generate the sub-catchment response and flow velocity layers in a spatial domain. The SFM was developed using the "C" programming language. The user interface for the SFM was developed using the avenue script and loaded as an extension to the normal ArcView GIS graphical user interface.

Using the land use/cover in conjunction with soil information, rainfall incident on each sub-catchment was partitioned to separate surface runoff from water infiltrating into the soil. The land use/cover and soil data were also used by the SFM to calculate response function of each sub-catchment. The response function described how excess precipitation was routed to the outlet of each sub-catchment.

A relationship between the sediment delivery ratio (SDR) and the sediment travel time expressed as a function of the overland and channel flow, and sub-catchments' responses based on rainfall, evaporation, land cover and soil properties was established in this study. The relationship between SDR and the sediment travel time by the HSDD model is given as:

$$SDR = \exp(-\beta T_{ic}) \tag{1.2}$$

Where β is sub-catchment response coefficient, T_{ic} (hr) is the sum of the overland flow travel time t_o and the shallow concentrated flow travel time t_c of the sediment. It was assumed that the sediment that reaches the stream network takes the same travel time as the runoff.

The time for runoff water to travel from one point to another over the catchment was determined using the flow distance and velocity along the flow paths. This is expressed as:

$$t_{i} = \sum_{i=1}^{N_{p}} \frac{l_{i}}{v_{i}}$$
(1.3)

Where t_i (hr) is the travel time for cell *i*, l_i (m) is the length of segment *i* in the flow path based on the flow direction, v_i (m s⁻¹) is the flow velocity for the cell *i* and N_p is the number of cells traversed by runoff from cell *i* to the nearest channel. For a cell *i*, the cumulative travel time was estimated by summing the travel time along its flow path.

The surface runoff (excess rainfall) was estimated using the SCS curve number method. This was based on the relation:

$$Q_i = \frac{(P_i - 0.2S_i)^2}{P_i + 0.8S_i}$$
(1.4)

Where subscript *i* is the *i*th cell, Q_i (mm) is the daily runoff, P_i (mm) is the daily rainfall and S_i (mm) is the retention parameter estimated using the relation:

$$S_i = 254 \left(\frac{100}{CN_i} - 1 \right)$$
(1.5)

The curve number CN_i for each grid cell was determined using land use/cover and hydrological soil group data. The flow velocity of the runoff was estimated using the Manning's equation based on the coefficient of velocity (equation 1.6). Velocity coefficients for each type of land use/cover were estimated using values given in Table 2 (after McCuen, 1998). The velocity was estimated using the relation:

$$v_i = (\alpha_i s_i^{1/2}) q_i$$
(1.6)

Where v_i is runoff velocity (m s⁻¹), s_i (m/m) is slope of cell *i* and q_i (m s⁻¹) is specific runoff rate (i.e. runoff rate per unit cell area).

Land Cover Description	Velocity Coefficient
Urban and Built-Up Land	6.3398
Dryland Cropland and Pasture	0.4572
Irrigated Cropland and Pasture	2.7737
Cropland/Grassland Mosaic	0.3962
Cropland/Woodland Mosaic	0.3962
Grassland	0.6401
Shrubland	0.4572
Savanna	0.4267

Table 2 Relationship between land use/cover description and velocity coefficient

3. Results and discussion

After running the model, a spatial SDR map (figure 3) was generated. The SDR varies from 0.11 to 1.0 within the sub-catchments and the overall sediment delivery ratio averaged for all the grid cells for the catchment is 0.29. The results show that the further away an area is from the stream, the longer the travel time and hence the lower the SDR. It should be emphasized that any two locations that are equidistant from the outlet may not have the same travel time. This means that travel time does not follow concentric zones. Flow velocity in reality is controlled by conditions such as the surface vegetation type and roughness, and elevation changes over the drainage area. In this study, it was established that longer travel time tended to occur in areas with rougher surfaces (vegetated areas) compared with bare and open land surfaces.

Sediment delivery ratio values obtained in this study did not exhibit a clear relation with the type of land use and land cover. This may be explained by the argument that sediment delivery ratio tends to be affected more significantly by the character of the drainage system than by the land use as shown in figure 3. However, the estimation of spatial sediment delivery ratio allows the identification of critical sediment source and delivery areas as well as site-specific implementation of proper management practices within the catchment. The sediment delivery ratio values imply the integrated capability of a basin for storing and transporting the eroded soil.



Figure 3 Spatial SDR for Masinga catchment



Figure 4 Spatial mean annual sediment yield for Masinga based on 2003 land use and management practices

The SDR map was overlaid with the mean annual soil erosion maps generated in section 2.2. For each scenario described in section 2.2.1, a spatial sediment yield map was generated. Figure 4 shows results of predicted spatial sediment yield based on land use and management practices for 2003. Results of figure 4 show critical source of sediment yield. The results show a great variation in sediment yield within each sub-catchment (Table 3). Such high variations are a result of the diverse land uses and the wide range of land slopes and distance to channels within the individual sub-catchments. The predicted average sediment yields at each sub-catchment outlet show that the sediment yield does not entirely depend on the catchment area but more so on the sub-catchment properties.

In this study, the overall mean annual sediment volume reaching the reservoir is predicted as $14.0 \times 10^6 \text{ m}^3$ and by simulating the best management practices (BMPs), the predictions show that sediment loading into the reservoir could be reduced to about $6.0 \times 10^6 \text{ m}^3$ per year.

Sub-catchment	Area (km ²)	Mean annual sediment yield (ton ha ⁻¹ yr ⁻¹)			
No.		Sediment variation within sub- catchment	Mean sediment yield at sub- catchment outlet		
2	2758	8.9 - 242.9	77.9		
4	821	10.3 – 501.7	84.7		
5	76	2.9 – 51.8	9.7		
8	506	16.1 – 158.7	50.3		
10	918	2.3 – 331.6	30.6		
11	597	1.0 – 106.1	17.9		
12	586	1.8 – 84.8	14.8		

Table 3 Variation of sediment yield within the sub-catchments

Summary

In this study, a new approach of predicting spatial sediment yield for Masinga catchment is presented. The proposed approach based on the concept of the runoff travel time from individual cells allows for the identification of primary sediment source areas and helps to identify and clarify those critical areas with high potential for sediment transport. It also predicts the spatially varying sediment transport capacity, and ultimately, the sediment yield from each area reaching the reservoir. Simulation results show that the RUSLE and the developed HSDD model integrated in a GIS environment can be used to facilitate fast and efficient assessment of different management alternatives, with a view to reducing sediment loading into reservoirs. Predictions show that annual sediment loading into Masinga reservoir based on land use and management practices for 2003 is 14.0×10^6 m³. By simulating the best

feasible management practices (BMPs) for this catchment the achieved results show that the loading rate could be reduced to $6.0 \times 10^6 \text{ m}^3$ per annum. However, there is need for further fieldwork research to improve the parameters of the HSDD model especially through calibration and validation.

References

McCuen R.H. (1998). Hydrologic Analysis and Design. Prentice-Hall Inc, Upper Saddle River, New Jersey.

- Millward A.A. and Mersey J.E. (1999). Adapting the RUSLE to model soil erosion potential in a mountainous tropical watershed. CATENA 38, 109-129.
- Mutua B.M. (2005). Modelling Soil Erosion and Sediment Delivery to Reservoirs at a Large Scale domain, a Strategy for Catchment Management: The case of Masinga Catchment, Kenya. Ph.D Thesis, University of Natural Resources and Applied Life Sciences (BOKU), Vienna, Austria.
- Ongweny G.S., Kithiia S.M. and Denga F.O. (1993). An overview of the soil erosion and sedimentation problems in Kenya. In Hadley, R.F., and Mizuyama, T., editors, IAHS publication No. 217, pp.217-224, Yokohama, Japan.
- Opiyo C.O. (1999). Challenges of Demographic Data Collection and Utilisation: The Case of the 1999 Kenya Population and Housing Census. Population Association of Kenya Occasional Paper Series, Volume 1.
- USDA (1972). Sediment sources, yields, and delivery ratios. National Engineering Handbook, Section 3 Sedimentation.
- WCD (2000). Dams and development. A new framework for decision making. Report on the World Commission on Dams. Earthscan Publications, London, UK.

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