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Sensitivity analysis and calibration of the Modified Universal Soil Loss Equation (MUSLE) for the upper Malewa Catchment, Kenya

V. O. ODONGO[1], J. O. ONYANDO[2], B. M. MUTUA[3], P. R. van OEL[4], and R. BECHT[5]

Abstract

Simulation models are widely used for studying physical processes such as surface runoff, sediment transport and sediment yield in catchments. Most models need case-specific empirical data for parameterization before being applied especially in regions other than the ones they have been developed. Sensitivity analysis is usually performed to determine the most influential factors of a model so that they can be prioritized for optimization. In this way uncertainties in model outputs can be reduced considerably. This study evaluates the commonly used modified universal soil loss equation (MUSLE) model used for sediment yield simulation for the case of the upper Malewa catchment in Kenya. The conceptual factors of the model are assessed relative to the hydrological factors in the model. Also, the sensitivity of the model to the choice of the objective function in calibration is tested. The Sobol' sensitivity analysis method was used for evaluating the degree of sensitivity of the conceptual and hydrological factors for sediment yield simulations using the MUSLE model. Nash-Sutcliffe Efficiency (NSE) and the modified Nash-Sutcliffe Efficiency (NSEm) are used to test the sensitivity of the model to the choice of the objective function and robustness of model performance with sediment data measured from upper Malewa catchment, Kenya. The results indicate that the conceptual factors are the most sensitive factors of the MUSLE model contributing about 66% of the variability in the output sediment yield. Increased variability of sediment yield output was also observed. This was attributed to interactions of input factors. For the upper Malewa catchment calibration of the MUSLE model indicates that the use of NSEm as an objective function provides stable results, which indicates that the model can satisfactorily be applied for sediment yield simulations.

Key words: MUSLE, Sobol'sensitivity analysis, Sediment yield, Objective function, Upper Malewa catchment

1 Introduction

Knowledge on suspended sediment yields and their dynamics poses a major environmental challenge to catchment management (Owens et al., 2005; Zhou and Wu, 2008; Navratil et al., 2011; Qiu et al., 2012). Sediment yield from a catchment provides an important measure indicative of the trend and severity of land degradation (Mutua et al., 2006; Sadeghi and Saeidi, 2010). Information on soil erosion and sediment yield from catchments is important in achieving sustainable land use and maintaining water quality in streams, lakes and other water bodies. In addition, the estimation of the suspended sediment yield provides managers, engineers, hydrologists and geomorphologists with information that can be used for designing hydraulic structures such as dams, river morphological computations, and evaluation studies of the effects of various land use management practices (Kothyari et al., 1997; Lana-Renault et al., 2007; Sadeghi et al., 2008a; Sadeghi et al., 2008b). However, estimates of erosion and sediment yield are rarely available through measurements. This challenge is further compounded by the fact that catchments, as natural systems, are heterogeneous units with geomorphological characteristics and hydrological regimes that vary in both space and time (Onyando et al., 2005; Zhang et al., 2010; Zarris et al., 2011).

Accurate estimations of soil erosion and sediment yield from catchments are therefore difficult to obtain. In order to

[1] PhD student, University of Twente, Faculty of Geoinformation Science & Earth Observation (ITC), P. O. Box 217, 7500 AE Enschede, the Netherlands. E-mail: odongo18835@itc.nl
[2] Assoc. Prof., Egerton University, Department of Agricultural Engineering, P. O. Box 536-20115, Egerton, Kenya. E-mail: jonyando@gmail.com
[3] Assoc. Prof., Egerton University, Department of Agricultural Engineering, P. O. Box 536-20115, Egerton, Kenya. E-mail: bmmutua@yahoo.com
[4] Postdoc, University of Twente, Faculty of Geoinformation Science & Earth Observation (ITC), P. O. Box 217, 7500 AE Enschede, the Netherlands.E-mail: oel@itc.nl. Assis. Prof., Wageningen University, Water Resources Management Group, P.O. Box 47, 6700 AA Wageningen, the Netherlands. E-mail: pieter.vanoel@wur.nl
[5] Assis. Prof., University of Twente, Faculty of Geoinformation Science & Earth Observation (ITC), P. O. Box 217, 7500 AE Enschede, the Netherlands. E-mail: becht@itc.nl

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overcome this, models that provide proxy estimates of erosion and sediment yields are generally used (Onyando et al., 2005; Mutua et al., 2006; Pandey et al., 2009; Wang et al., 2009; Hrissanthou et al., 2010; Haregeweyn et al., 2012; Wang et al., 2012). However, evaluation of the applicability of these models requires information on sensitivity, calibration and validation especially for regions other than the ones for which they were developed. This information is important in reducing output uncertainty and increasing user confidence in model ability making the simulations more effective (Qiu et al., 2012).

Nevertheless, a number of studies (Onyando et al., 2005; Mutua et al., 2006; Sadeghi and Mizuyama, 2007; Pandey et al., 2009) have tested applicability of models for regions for which they had not been developed without calibration and found that sediment yields were satisfactorily simulated. A widely used model is the Universal Soil Loss Equation (USLE) model and its subsequent revised versions (Revised Universal Soil Loss Equation (RUSLE) and the Modified Universal Soil Equation (MUSLE) (Mishra et al., 2006; Sadeghi and Mizuyama, 2007). The USLE was developed to estimate long-term annual soil loss at plot scales of 22 m in length. Attempts to apply it for individual storm events and at larger scales than the 22 m length plots have been stated to lead to increased errors because it does not directly consider runoff which is a key component in sediment concentration (Kinnell, 2005). Nevertheless, its accuracy has been shown to increase when coupled to a hydrological rainfall excess model (Novotny and Olem, 1994). Modifications and improvements to USLE have also been proposed in literature. These include the RUSLE (Renard and Ferreira, 1993), MUSLE (Williams, 1976) and USLE-M (Kinnell, 1998) models. Besides these, other approaches such as the use of sediment delivery ratios (SDR) in combination with gross erosion estimates from erosion models have also been explored for estimating sediment yields from catchments. Development of SDR models may require determining factors similar to those employed in USLE and other models. However, this becomes an unnecessary and time consuming procedure if the main goal is estimation of sediment yield, unless an SDR model already exists (Sadeghi et al., 2007a). In most applications where SDR have been used, they have been assumed constant yet they have been shown to vary for storm events (Walling, 1983; Kinnell, 2004; Chang, 2006). Due to these limitations, Williams and Berndt (1977) proposed to use the MUSLE model which replaced the rainfall factor with a runoff factor. Williams and Berndt (1977) argued that this eliminated the need of SDR and improved the prediction of sediment yield at the outlet of a catchment. Specifically, the MUSLE model estimates sediment yield on a single storm basis and the output is interpreted as sediment yield coming at the outlet of the catchment. This is computed based on a combination of runoff and catchment characteristics. The MUSLE model (Shown in Eq. (1)) has been used to estimate sediment yield in a number studies (Williams and Berndt, 1977; Walling, 1983; Sadeghi et al., 2004; Casagrande and De Paiva, 2005; Sadeghi and Mizuyama, 2007; Sadeghi et al., 2007a; Sadeghi et al., 2007b; Pandey et al., 2009; Zhang et al., 2009; Arekhi and Rostamizad, 2011).

$$Y = \alpha\left(Q \times q_p\right)^{\beta} KLSCP \tag{1}$$

where Y is the sediment yield from an individual storm in metric tons, Q is the storm runoff volume in m^3, q_p is the peak runoff rate in m^3 sec^{-1}, K is soil erodibility factor in Mg MJ^{-1} mm^{-1}, LS is the slope length (dimensionless) and gradient factor (topographical factor) (dimensionless), C is the crop management factor (dimensionless), P is the erosion control practice factor (dimensionless), α and β are location specific conceptual factors.

In some studies, the MUSLE model has been calibrated to improve sediment yield simulation for new catchment conditions (Casagrande and De Paiva, 2005; Sadeghi et al., 2007a; Pongsai et al., 2010). However, most of these studies have not evaluated the sensitivity of the model factors. Sensitivity analysis provides a first step in modeling for determining the most influential parameters of a model, allowing for a reduction in the number of parameters incorporated during calibration (Saltelli et al., 2000; Nossent et al., 2011).This is normally realized by factor fixing (FF), where less influential parameters are set to a fixed value, or by factor prioritization (FP), where the focus is on more influential parameters that have the potential to greatly reduce the output uncertainty in a model (Sobol', 1993; Saltelli et al., 2004; Hamm et al., 2006; Cibin et al., 2010; Nossent et al., 2011).This way sensitivity analysis provides information on the influence of specific parameter values on the associated model outcome and on the model processes thus facilitating the understanding and interpretation of models (Saltelli et al., 2000). Furthermore, little attention has been given to the impact of objective function on calibration, outlier effect of input data or consequence of extreme events in estimation of the model factors. Such testing is required to improve understanding of the model to assist in prioritizing model development activities and to gauge confidence in the model outputs. This paper describes evaluation of the MUSLE model by performing a variance based Sobol' sensitivity analysis (Sobol', 1993), testing the stability of model factors against choice of objective function and exploring the effect of an extreme event on the estimation of conceptual factors using results of the upper Malewa catchment. This catchment is part of the headwaters of Lake Naivasha Basin in Kenya. This Lake is a Ramsar[6] wetland under decline, and sediments from upper Malewa catchment

[6] RAMSAR wetlands are a part of an International convention on Wetlands of International Importance. The convention is an intergovernmental treaty for the conservation and sustainable utilization of wetlands. The treaty functions to protect the progressive encroachment and loss of wetlands in the present and future, Recognizing the fundamental ecological functions of wetlands and their economic, cultural, scientific, and recreational value. It is named after the Iranian town called RAMSAR where the convention was first institutionalized in 1971. Source: http://www.ramsar.org/

have been attributed as one of the possible causes of the lake decline (Verschuren, 1999; Becht et al., 2005). However, availability of observed sediment data draining into this lake is non-existent.

2 The study catchment

The Malewa catchment is situated in the Kenyan Rift Valley approximately 70 km from Nairobi at a latitude of 0° 09′ to 0° 55′S and longitude of 36° 09′ to 36° 24′E. The maximum altitude is about 3,990 m above mean sea level (a.m.s.l) on the eastern side of the Aberdare Ranges to a minimum altitude of about 1,980 m (a.m.s.l). The catchment area is approximately 1,428 km^2 and is part of the Lake Naivasha basin (Fig. 1). The present study focuses on the upper Malewa River catchment, which is approximately 382 km^2, and Wanjohi River catchment, approximately 151 km^2, which is a sub-catchment within the upper Malewa River catchment. Erosion and sediment yield from this part of the catchment has been postulated to cause degradation of the Lake ecosystem (Tarras-Wahlberg et al., 2002). The map of the location of the Malewa catchment, upper Malewa catchment and the Wanjohi River catchment are shown in Fig. 1. The sampling stations, at the outlet of the Wanjohi River Catchment, 2GB04 and the main upper Malewa catchment, 2GB08 are also shown in Fig. 1. The sampling stations used are designated by the Water Resources Management Authority (WRMA) of the Kenya Government.

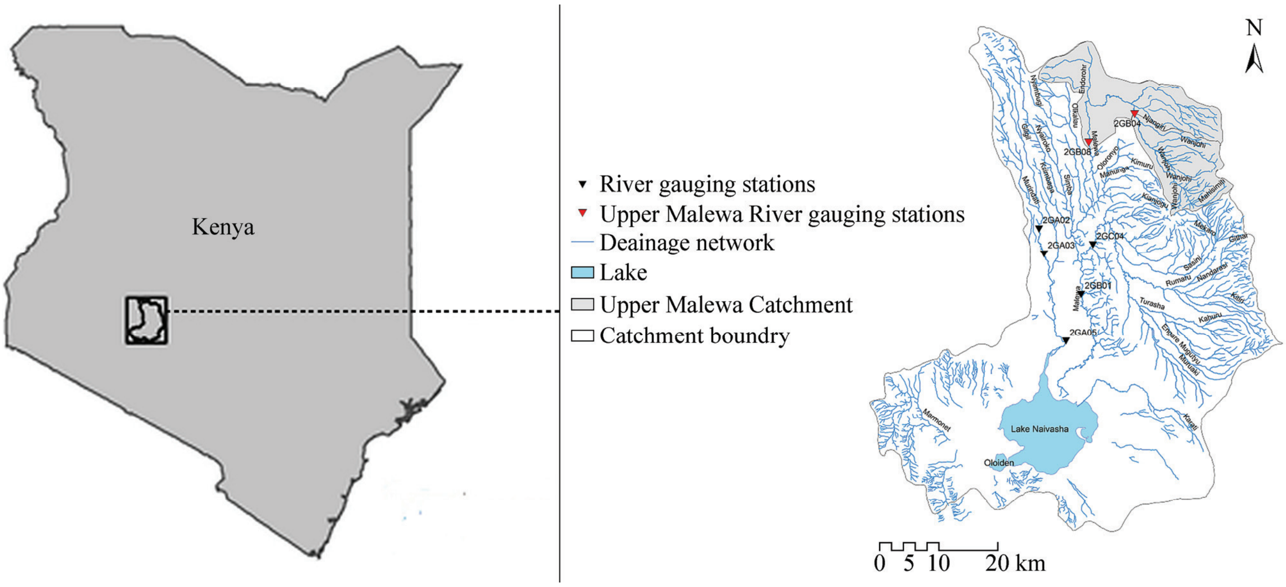

Fig. 1 Location of upper Malewa catchment within the Naivasha basin showing the drainage network and gauging stations

The major soils in the study area are of volcanic origin. The soils found on the mountain and major escarpments of the catchment are developed from olivine basalts and ashes of major older volcanoes. They are generally well drained, very deep (1.2-1.8 m) and vary from dark reddish brown to dark brown, clay loam to loamy soils with thick acid humic topsoil in shallow to moderately deep and rocky places (Rachilo, 1978; Nyandat, 1984). Climatic conditions in the study area are quite diverse due to considerable differences in altitude and relief. The annual mean temperature ranges from 8 °C to 30 °C. The rainfall regime within the catchment is influenced by local relief with the catchment being in the rain shadow of the Aberdare ranges to the East and the Mau Escarpment to the West. There are two rainy seasons experienced in this catchment. Long rains occurring in the months of March to May and the short rains experienced between October and November. The Malewa basin experiences an average annual rainfall of 610 mm, and the wettest slopes of the Aberdare ranges receive as much as 1525 mm. Figure 2 summaries the monthly average precipitation and temperature variation sin the Lake Naivasha catchment.

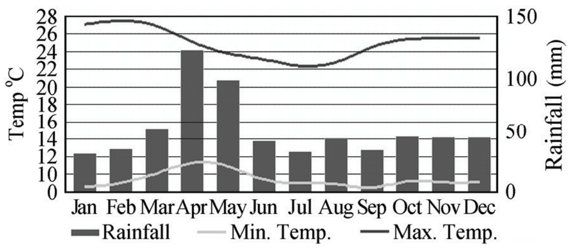

Fig. 2 Monthly climate average distribution of temperature and rainfall for Lake Naivasha

The predominant land cover of the area of study consists of forest and scrubs which cover most of the Aberdare Ranges sloping downwards to the foothills. This comprises about 43% of the catchment. The rest is a mixture of agricultural land and grassland.

3 Methodology

3.1 Hydrological factors of the MUSLE model

Ten storm events, flow discharges and suspended sediment yield at the outlet of the catchment were minutely recorded during the short raining period between the 21st Sept. 2007 and 13th Dec. 2007. Stream flow measurements were recorded every two hours using a diver and correlated with staff gauge readings installed at the outlet of upper Malewa River catchment shown in Fig. 1. The recording was pre-set for every two hour because time of concentration of the catchment was longer (≥16 hours) following a precipitation. This is due to the predominant flat terrain preceding the Aberdare ranges. Flow rating equation for the station was later used to compute the flow discharges. Figure 3 shows the flow discharge measurements with daily precipitation recorded during the study period. Sediment samples were collected by lowering aDH-48 depth integrating sampler which was gently lowered into the stream and raised to the surface at the same rate. Three traverses were made across the stream section for a representative suspended sediment concentration at intervals of approximately one hour covering the rising and receding limbs of the hydrograph. Standard Whatman™ 934-AH™ glass microfiber filters were used to filter samples. The filter papers were first dried in the oven for 1 h at 105 °C and then cooled overnight in a desiccator jar following the analytical procedure of Knott et al., (1992). Forthwith, the filtration analytical procedure (Knott et al., 1992) for determining sediment concentration in water samples was applied and necessary calculations were subsequently conducted. The weight of the sediment was converted into sediment yield in tons for a particular storm using the direct runoff volume obtained from the each storm hydrograph. Figure 4 illustrates the relation of observed sediment against observed runoff volume during the study period.

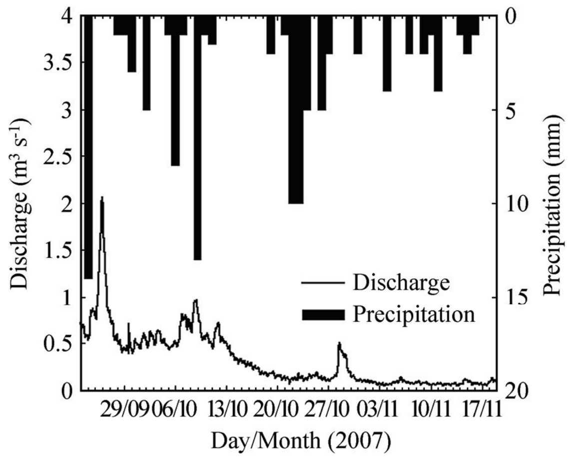

Fig. 3 Daily total precipitation (top) and Hydrograph (bottom) during the study period 2007 in upper Malewa catchment, Lake Naivasha Basin in Kenya

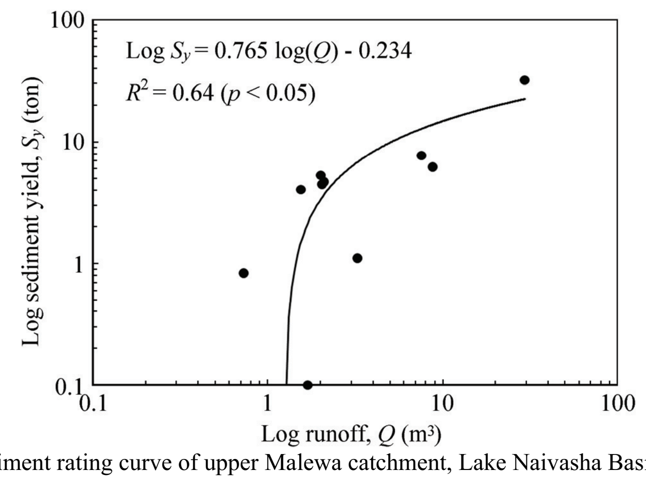

Fig. 4 Sediment rating curve of upper Malewa catchment, Lake Naivasha Basin in Kenya

3.2 Physical factors

Erosivity factors of volume and peak runoff rate were calculated from the storm hydrographs. These are shown in Table 3. The other physical variables of the model shown in Eq. (1) i.e. soil erodibility (K), topographical factor (LS), crop management (C) and soil erosion control practice (P)factors were determined based on the original methodology (Wischmeier and Smith, 1965; Wischmeier and Smith, 1978), and procedure suggested by Renard et al. (1997). The soil erodibility, crop management and soil erosion control practice factors, which are known to be sensitive to temporal variations than other catchment factors, were assumed constant since the study period was short, and no tillage activities were taking place during the study (Kinnell, 2005).

The soil erodibility factor (*K*) for the study area ranged from 0.020 to 0.363Mg MJ^{-1} mm^{-1} for the entire catchment with an average of 0.230 Mg MJ^{-1} mm^{-1} (Hamududu, 1998). The topographical factor (*LS*) was calculated from ASTER DEM (30m resolution) based on overland flow theory proposed by Moore and Wilson (1992) and Mitasova et al. (1996) shown in Eq. (2). The authors developed a simple soil-erosion index, which accounts for major hydrological and terrain factors affecting erosion. This index is considered equivalent to the *LS* factor in *RUSLE*, which is a more improved version of determining the *LS* factor contrary to the traditional determination using the length which tends to overestimate erosion (Mitasova et al., 1996). The index considered the generation of overland flow based on upslope contributing area and integrating it into the Mitasova et al. (1996) *LS* model (Eq. (2)). The importance of replacing the slope length by upslope contributing area improves estimation of erosion in areas of concentrated flow and allows identification of areas with potential for gully erosion (Mitasova et al., 1996).

$$LS(r) = (m+1)[A(r)/a_o]^m [Sin\beta(r)/b_o]^n \quad (2)$$

where *r* is a point on a hill slope (x, y), *A*(*r*) is the upslope contributing area per unit contour width, β is the slope angle in degrees, a_o is 22.1m, b_o = 9%, *m* and *n* are conceptual factors. Values of *m* = 0.6, *n* = 1.3 were adopted for this study as they have been shown to give results consistent with the *RUSLELS* factor for slope lengths < 100m and slope angles < 14 degrees (Moore and Wilson, 1992)for slopes with negligible tangential curvature. Land use/cover map was generated by classifying an ASTER satellite imagery of August 2007 covering the area of study. For each land use/cover class, the cover management factor (C) from adopted from Hamududu (1998) were assigned to each land use/cover. The supporting conservation practice factor (P), study (Novotny and Olem, 1994; Renard, 1997; Hamududu, 1998; Sadeghi et al., 2007a).

4 Model testing and evaluation

4.1 Sensitivity analysis

The MUSLE model was first tested using its original conceptual factors for each individual storm event. The output of this was then compared to the measured suspended sediment yield at the outlet of the catchment. Secondly, sensitivity analysis of the conceptual factors was undertaken to determine which factors or a combination of factors were more sensitive to the model output. This was done using the variance-based sensitivity analysis, to highlight the most sensitive parameter. This approach was preferred over other approaches such as one at a time (OAT), also known as local sensitivity which entail varying each parameter (by a given percentage) at a time while holding other factors constant (Hamby, 1994; Saltelli et al., 1999). The added value of the variance based sensitivity analysis approach, are highlighted compared to results of OAT approach. To achieve this analysis, MUSLE model input factors were categorized into three groupings based on the MUSLE model structure; conceptual, physical and hydrological input factors. Conceptual factors were α and β that needed optimization through calibration. Physical factors were KLSCP which were estimated by remote sensing and GIS. These were assumed constant during the duration of study. Hydrological factors were runoff volume and peak runoff discharge which varied according to storm events and time of concentration. Thus sensitivity analysis was performed on both the conceptual and the hydrological factors using the Sobol'approach (Sobol', 1993). Sobol' (1993) provided an efficient method of estimating variance based sensitivity indices using Monte Carlo simulation. The method is a global and model independent sensitivity analysis that is based on variance decomposition. It aims to quantify the amount of variance that each parameter and their interactions contribute to the unconditional variance of the model output. Let the model be represented by a function

$$Y = f(x_1, x_2, ..., x_k) \quad (3)$$

where x_1, x_2, ……, x_k are independent input factors and *Y* is the model output.Sobol' suggested the decomposition of the function *f* into terms of increasing dimensionality, i.e.

$$f(x_1, x_2, ..., x_k) = f_0 + \sum_i f_i + \sum_i \sum_{j>i} f_{ij} + ... + f_{12...k} \quad (4)$$

where each term is function only of the factors in its index, i.e. $f_i = f_i(x_i)$, $f_{ij} = f_{ij}(x_i, x_j)$ and so on. The decompositionis unique provided that the input factors are independent and that the individual terms $f_{i_1 i_2 ... i_s}$ in (4) are square integrable and have zero mean over the domain of existence.

The total unconditional variance is defined as:

$$V(y)=\sum_i V_i+\sum_i\sum_{j>i}V_{ij}+...+V_{12...k} \tag{5}$$

where

$$V_i=V\left(E\left(Y\middle|x_i\right)\right) \tag{6}$$

$$V_{ij}=V\left(E\left(Y\middle|x_i,x_j\right)\right)-V_i-V_j \tag{7}$$

and so on. Equation (5) contains k terms of the first order V_i, $\frac{k(k-1)}{2}$ terms of the second order V_{ij} and so on, till the last term of order k, for a total of 2^k-1 terms. The V_{ij} terms are the second order terms that explain that part of the effect of x_i and x_j that is not described by the first order terms. This way the variance contributions of individual factors and their interactions, to the total output variance, can be determined. The variance contributions can then be computed as sensitivity indices:

$$S_i=\frac{V_i}{V} \tag{8}$$

$$S_{ij}=\frac{V_{ij}}{V} \tag{9}$$

$$S_{Ti}=S_i+\sum_{j\neq i}S_{ij}+......S_{12......k} \tag{10}$$

The first order index, S_i, is a measure of the variance contribution of individual parameter x_i to the total variance of the model output. The partial variance V_i shown in Eq. (8) is computed by the variance of the conditional expectation shown in Eq. (6). The S_i is also called the main effect of x_i on Y. It can be described as the fraction of the model output variance that would disappear on average when x_i would be fixed to a value in its range. The impact on the model output variance of the interaction between factors x_i and x_j is given by S_{ij}. S_{Ti} is the result of the main effect of x_i and all its interactions with the other factors up to the k^{th} order.

4.2 Input ranges distribution and data range

It has been argued that assigning of data input range and specifying their associated probability distribution functions to be the most difficult and subjective stage when applying Monte Carlo analysis to hydrologic studies (Muleta and Nicklow, 2005). The reason being that it would be cost prohibitive to collect numerous, random samples of inputs to determine their true or approximate probability distribution functions and ranges. Moreover, it has also been argued that proper assignment of input ranges is more important on sensitivity analysis results than the knowledge of the actual probability distribution functions (Helton, 2008). In this study, the input factors and the irranges used in the sensitivity analysis and calibration were assumed to follow a triangular distribution. This was based on information of the factors reported in literature, previous studies and knowledge of the catchment. Also, a number of studies have suggested that simple distributions such as triangular may represent some factors better than uniform distribution (Haan et al., 1998; Muleta and Nicklow, 2005). Table 1 shows the assigned ranges for each input parameter. The ranges of α and β were obtained from literature and approximated to vary from 1 to 65 and 0.1 to 1 for α and β respectively. The ranges of runoff volume and peak runoff discharge were obtained from the measured values obtained during the study.

Table 1 Model factors considered for sensitivity analysis and calibration

Factors	Minimum	Maximum
α	1	65
β	0	1
Q	0	30
q	0	3

4.3 Calibration and validation

Calibration and validation of the model was then performed by splitting the data into two sets with each set composing near equal proportions in magnitude (i.e. a mix of high and low flows) of the observed sediments. The shuffled complex evolutionary-University of Arizona (SCE-UA) algorithm (Duan et al., 1992) was adopted for the optimization procedure of the factors of the model. The SCE-UA algorithm is a global optimization algorithm that combines the strength of the simplex method, random search, competitive evolution and complex shuffling (Duan et al., 1992). The Nash-Sutcliffe Efficiency (NSE) (Nash and Sutcliffe, 1970), shown in Eq. (11), and the modified version of it by Legates and McCabe (1999), shown in Eq. (12), were chosen as the objective functions during the optimization process to approximate the conceptual factors.

$$NSE = 1 - \frac{\sum_{i=1}^{N} (O_i - P_i)^2}{\sum_{i=1}^{N} (O_i - \overline{O})^2} \tag{11}$$

$$NSE_m = 1 - \frac{\sum_{i=1}^{N} |O_i - P_i|}{\sum_{i=1}^{N} |O_i - \overline{O}|} \tag{12}$$

Where O_i is measured sediment, P_i is simulated sediment, $\overline{O}$ is the mean of measured sediment, N is the number of observations. NSE values can range from- ∞ to 1. An efficiency of 1 is indicative of a perfect model prediction compared to the observed data. An efficiency near to 0 indicates that the model predictions are as accurate as the mean of the observed data, whereas an efficiency of < 0 occurs when the observed mean is a better predictor than the model estimate. Essentially, the closer the NSE is to 1, the more accurate the model is. The concept of using the two chosen objective functions was based on the fact that NSE in its original form has been known to be sensitive to extreme values whereas the modified version has been shown to diminish this shortcoming by using the absolute values of the deviations to the first power (Legates and McCabe, 1999; Harmel and Smith, 2007).

The model was evaluated against measured data using statistical criteria. Since the available measured data were few and sparse, model results were evaluated using the percent error (PE) as an additional statistical criteria. It has been previously recommended that multiple statistical evaluation of model performance is necessary to assess the amount of intrinsic (i.e. model structure) and extrinsic (i.e. data quality) uncertainty (Moriasi et al., 2007; Karpouzos et al., 2011).

5 Results

5.1 Sensitivity analysis

The results of the OAT approach shown in Fig. (5) show that α had the steepest gradient suggesting that the smallest change in the parameter resulted in much larger change in sediment yield. Hence α was the most sensitive parameter followed by runoff volume, peak discharge and β in that order. On the other hand, the results of the variance based sensitivity analysis show that α and β are the most sensitive factors with each contributing about 27 and 12%, respectively in the variance of sediment yield output simulated by MUSLE model. This was followed by runoff volume and peak discharge contributing a variability of 11 and 5%, respectively. The results are presented in Table 2 and Fig. 2. In total, these four factors constitute 55% of the output variance of the model. The remaining 45% is due to non-linearity in the model and could be the result of interactions among factors. The total order index is an indication of the interaction of factors. Total interaction of α was reported as 35%, an increase of 8% of its individual contribution. Total interaction of β , Q and q was reported as 31, 22 and 13%, respectively. Though β , Q and q suggested less individual contribution of the variability of sediment yield output, they showed substantial influence on interaction with other input factors. These results were obtained by running a Monte Carlo simulation with a minimum sample size (n) of 10,240, resulting in 1,024 model executions, which was found to yield satisfactory convergence (Fig. 6) of sensitivity indices.

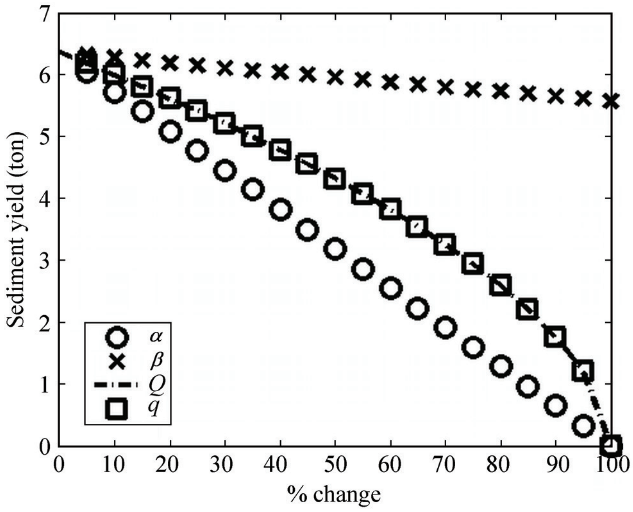

Fig. 5 One at a time (OAT) sensitivity analysis of input factors *α,β,* Q, and q

Table 2 First order and total sensitivity indices

Parameter	First order indices	Total order indices (normalized)
α	0.270167	0.349661
Runoff volume (Q)	0.112538	0.216536
Peak discharge (q)	0.047670	0.125356
β	0.119715	0.308448

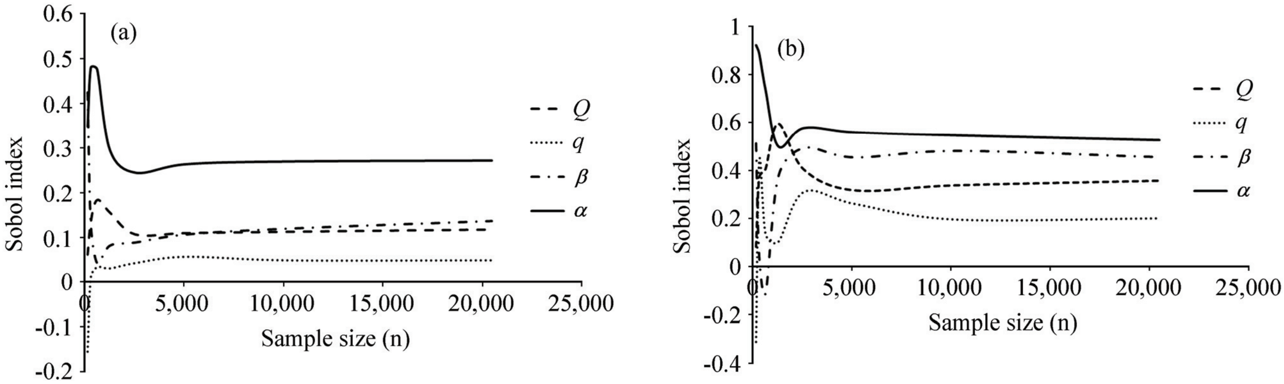

Fig. 6 Evolution of sensitivity to convergence (a) Main effect of individual parameter (b) Interaction with other factors

5.2 Parameter stability under choice of objective function during calibration and validation

Adopting the original conceptual factors of the MUSLE model with respective coefficient and exponent of 11.8 and 0.56, resulted in over-estimation of sediment yields from the ten storms available during the study (Table 3, Fig. 7). The NSE of the model reported at -0.005 was also low suggesting the mean was a better predictor of sediment yield than the model. To improve this, calibration was initialed to fine tune the model factors to investigate whether there could be any model improvements.

Table 3 Model performance using original conceptual factors (before calibration)

Event #	Date	Q (m^3)	q ($m^3 s^{-1}$)	Measured sediment, (ton)	Simulated sediment, (ton)	Percent error
1	25-Sep-07	29.63	2.06	32.12	55.85	-73.89
2	30-Sep-07	1.55	0.54	4.03	5.06	-25.51
3	2-Oct-07	2.02	0.63	5.29	6.36	-20.26
4	3-Oct-07	2.05	0.64	4.4	6.48	-47.12
5	5-Oct-07	0.73	0.52	0.83	3.25	-289.55
6	8-Oct-07	7.6	0.97	7.71	17.09	-121.53
7	10-Oct-07	2.09	0.61	4.63	6.4	-38.13
8	11-Oct-07	3.27	0.72	1.1	9	-719.48
9	28-Oct-07	8.79	0.51	6.15	12.9	-109.81
10	17-Nov-07	1.7	0.13	0	2.4	–

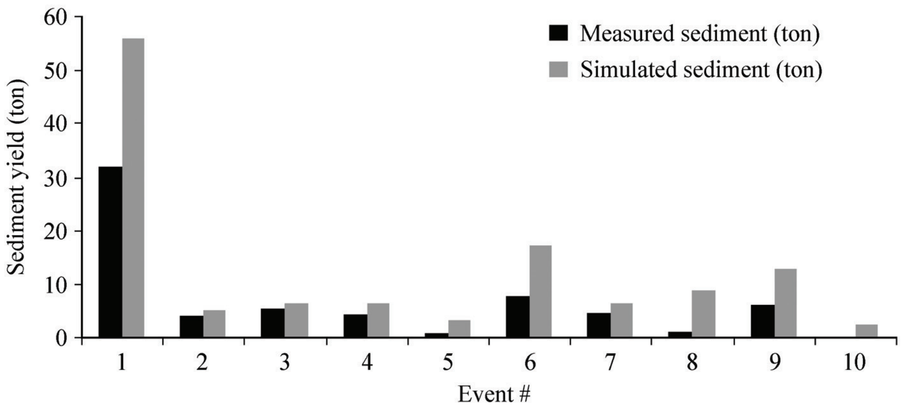

Fig. 7 Measured and simulated sediment yield using original conceptual factors (before calibration)

A choice of two objective functions allowed for testing the stability of parameter estimation under low and high magnitude events. Calibration using NSE as the objective function over the entire dataset resulted in improved model performance (NSE=0.97) with α estimated at 5.43 and β at 0.613 (Table 4, Fig. 8). Notable though was the high magnitude event of the 25th September 2007. This event was treated as an outlier event due to its high value compared to the other events. This was postulated to influence the calibration results and subsequently was excluded and the calibration repeated without it. The model performance reduced substantially (NSE=0.58) with α estimated at 6.44 and β at 0.45. Interestingly, it was found that even though the NSE value was low, the percent error of individual event estimates reduced significantly in six out of nine events (Table 5, Fig. 9). This was indicative that these factors were better than the ones estimated when the extreme event was included in the calibration.

Table 4 Calibration using NSE with extreme value

Event #	Date	Q (m^3)	q (m^3 s^{-1})	Measured sediment, (ton)	Simulated sediment, (ton)	Percent error
1	25-Sep-07	29.63	2.06	32.12	31.91	0.63
2	30-Sep-07	1.55	0.54	4.03	2.31	42.83
3	2-Oct-07	2.02	0.63	5.29	2.96	44.02
4	3-Oct-07	2.05	0.64	4.4	3.02	31.41
5	5-Oct-07	0.73	0.52	0.83	1.42	-70.16
6	8-Oct-07	7.6	0.97	7.71	8.73	-13.2
7	10-Oct-07	2.09	0.61	4.63	2.98	35.67
8	11-Oct-07	3.27	0.72	1.1	4.33	-294.13
9	28-Oct-07	8.79	0.51	6.15	6.42	-4.39
10	17-Nov-07	1.7	0.13	0	1.02	–

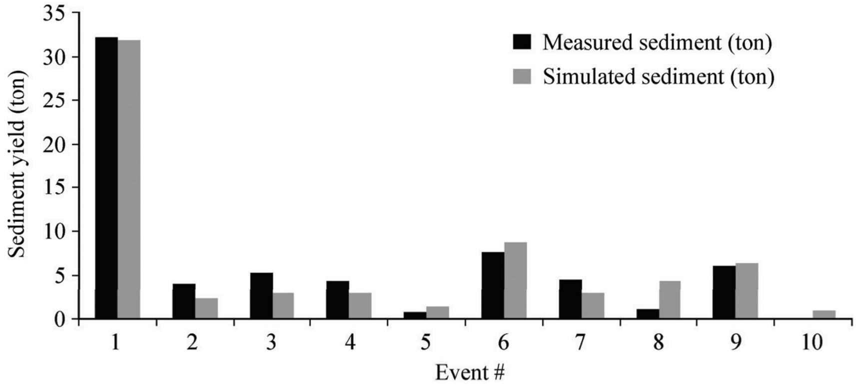

Fig. 8 Measured and simulated sediment yield following calibration using NSE with the extreme value included

The use of NSEm as objective function on the whole dataset resulted in increased accurate estimation of higher magnitude events than the use of NSE even though the NSEm index was lower (NSEm=0.76) than using NSE as an objective function. Events dated 25th Sept. 2007, 8th Oct. 2007 and 28th Oct. 2007 which were high in sediment yield measured at the catchment were estimated with percent error deviation of 3.95×10^{-7}%, 9.5% and 6.89×10^{-5}% respectively. This was better than NSE estimates for the same events reported as 0.63%, -13.2% and -4.4% respectively. The percent error estimates are shown in Table 4 and Table 6. Nevertheless, the rest of the events were slightly underestimated with the exception of the events of 11th Oct. 2007 and 17th Nov. 2007 which were poorly simulated in all cases. The factors α and β estimated using the NSEm were estimated at 5.05 and 0.63 respectively when the outlier event of 25th Sept. 2007was included.

However, model calibration using NSEm and excluding the extreme event resulted in an NSEm value of 0.44 (Table 7, Fig. 11). Interestingly though, the percent error of estimation of the individual events was much improved than the use of NSE with and without the inclusion of the extreme event. The percent error was also better than NSEm with the extreme event included in the calibration. Five out of nine of the events showed improved estimation of sediment yield. The conceptual factors, α and β were estimated at 8.54 and 0.32, respectively. These were substantially different from the factors estimated using NSEm as the objective function and including the outlier event.

An attempt was also done to calibrate the model by splitting the data samples into two; one for calibration and the other for validation. The results are highlighted in Tables 8-9 and Figs. 12–13.

Calibration on this data yielded a NSE value of 0.88 (Fig. 12). On validation the NSE value was reported as 0.74. Much of this was contributed by the outlier event of 25th Sept. 2007. Excluding this event from the validation analysis the NSE value drops to -0.12. This was suggestive that observed mean of sediments was a better predictor than the model in the catchment based on the available data. However, re-calibrating the model using NSEm and subsequent validation (Fig. 13), the NSEm was reported as 0.48 on validation. On excluding the outlier event from the validation set, the NSEm subsequently improved to 0.67 indicative that the model was a better predictor than the mean. It was also noted that the conceptual factors estimated were different in both cases. Using NSE, α and β were estimated at 7.13 and

0.42, respectively. Use of NSEm estimated α and β at 8.54 and 0.32 respectively, which was similar to the results of NSEm calibration using the whole dataset but excluding the extreme event. This was suggestive that the factors obtained using NSEm as the objective function were much stable.

Table 5 Calibration using NSE excluding the extreme value

Event #	Date	Q (m^3)	q ($m^3 s^{-1}$)	Measured sediment, (ton)	Simulated sediment, (ton)	Percent error
1	25-Sep-07	29.63	2.06	32.12	19.52	39.21
2	30-Sep-07	1.55	0.54	4.03	2.82	30.11
3	2-Oct-07	2.02	0.63	5.29	3.39	35.94
4	3-Oct-07	2.05	0.64	4.4	3.44	21.91
5	5-Oct-07	0.73	0.52	0.83	1.97	-136.41
6	8-Oct-07	7.6	0.97	7.71	7.52	2.57
7	10-Oct-07	2.09	0.61	4.63	3.41	26.51
8	11-Oct-07	3.27	0.72	1.1	4.48	-308.11
9	28-Oct-07	8.79	0.51	6.15	5.99	2.547
10	17-Nov-07	1.7	0.13	0	1.54	–

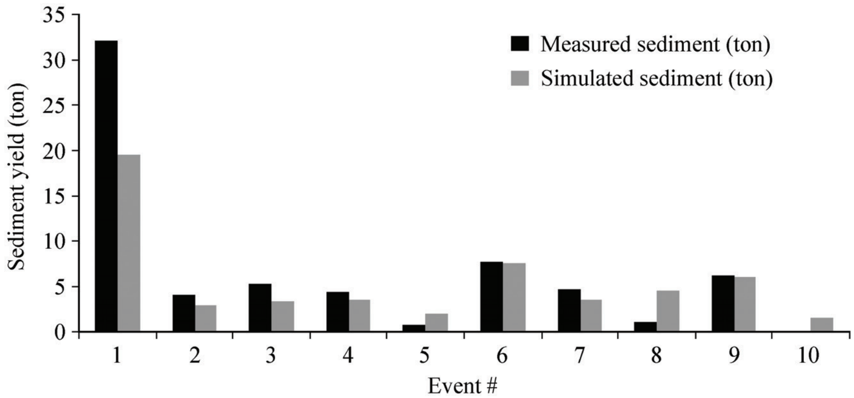

Fig. 9 Measured and simulated sediment yield following calibration using NSE and excluding the extreme value

Table 6 Calibration using NSEm with extreme value

Event #	Date	Q (m^3)	q ($m^3 s^{-1}$)	Measured sediment, (ton)	Simulated sediment, (ton)	Percent error
1	25-Sep-07	29.63	2.06	32.12	32.11	3.95E-07
2	30-Sep-07	1.55	0.54	4.03	2.14	46.94
3	2-Oct-07	2.02	0.63	5.29	2.77	47.64
4	3-Oct-07	2.05	0.64	4.4	2.83	35.8
5	5-Oct-07	0.73	0.52	0.83	1.3	55.59
6	8-Oct-07	7.6	0.97	7.71	8.44	9.46
7	10-Oct-07	2.09	0.61	4.63	2.79	39.89
8	11-Oct-07	3.27	0.72	1.1	4.1	272.98
9	28-Oct-07	8.79	0.51	6.15	6.15	6.89E-05
10	17-Nov-07	1.7	0.13	0	0.92	–

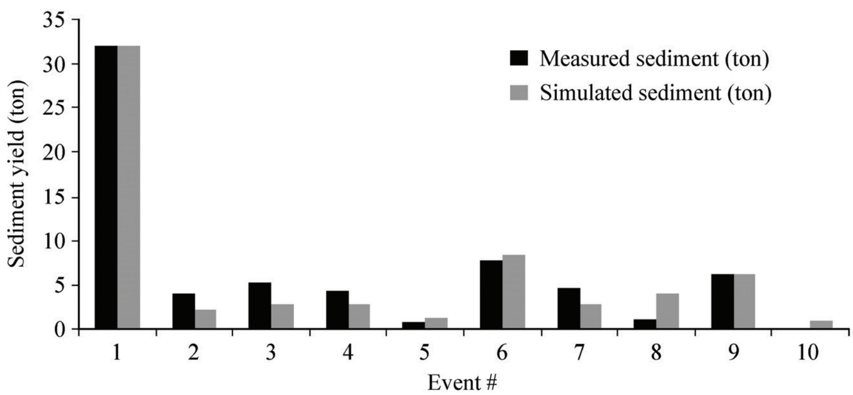

Fig. 10 Measured and simulated sediment yield following calibration using NSEm and including the extreme value

Table 7 Calibration using NSEm excluding the extreme value

Event #	Date	Q (m^3)	q (m^3 s^{-1})	Measured sediment, (ton)	Simulated sediment, (ton)	Percent error
1	25-Sep-07	29.63	2.06	32.12	15.29	52.38
2	30-Sep-07	1.55	0.54	4.03	3.82	5.33
3	2-Oct-07	2.02	0.63	5.29	4.36	17.62
4	3-Oct-07	2.05	0.64	4.4	4.4	3.95E-05
5	5-Oct-07	0.73	0.52	0.83	2.95	254.4
6	8-Oct-07	7.6	0.97	7.71	7.71	4.68E-07
7	10-Oct-07	2.09	0.61	4.63	4.37	5.63
8	11-Oct-07	3.27	0.72	1.1	5.33	384.82
9	28-Oct-07	8.79	0.51	6.15	6.56	6.65
10	17-Nov-07	1.7	0.13	0	2.48	–

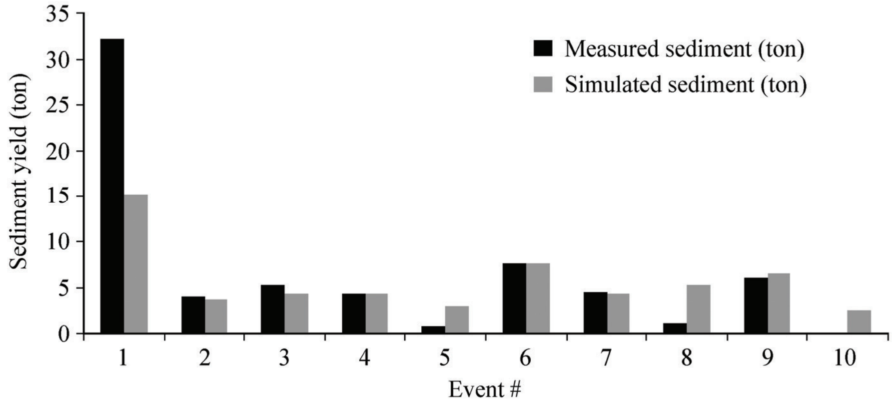

Fig. 11 Measured and simulated sediment yield following calibration using NSEm and excluding the extreme value

Table 8 Calibration based on split sample using NSE (NSE = 0.88, α = 7.13, β = 0.42). Validation (NSE = 0.74)

Event #	Date	Q	q	Measured sediment, (ton)	Simulated sediment, (ton)	Percent error
4	3-Oct-07	2.05	0.64	4.4	3.77	14.3
7	10-Oct-07	2.09	0.61	4.63	3.74	19.3
6	8-Oct-07	7.6	0.97	7.71	7.87	-2.03
5	5-Oct-07	0.73	0.52	0.83	2.24	-168.25
9	28-Oct-07	8.79	0.51	6.15	6.36	-3.45
3	2-Oct-07	2.02	0.63	5.29	3.73	29.63
2	30-Sep-07	1.55	0.54	4.03	3.13	22.37
1	25-Sep-07	29.63	2.06	32.12	19.31	39.88
10	17-Nov-07	1.7	0.13	0	1.78	–
8	11-Oct-07	3.27	0.72	1.1	4.84	-340.82

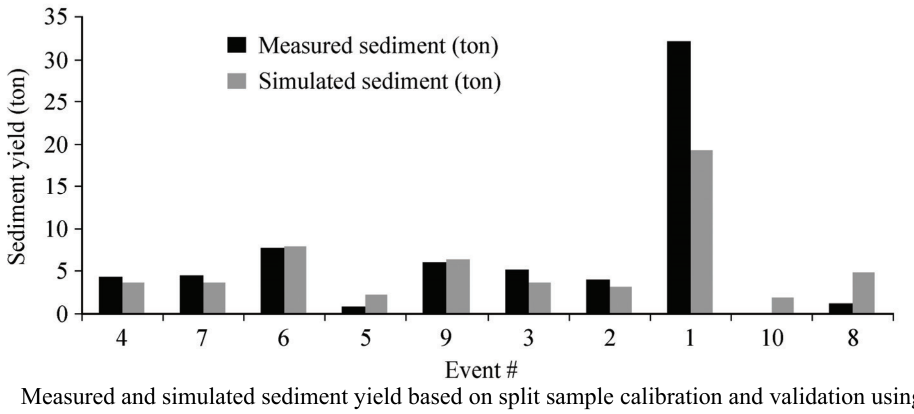

Fig. 12 Measured and simulated sediment yield based on split sample calibration and validation using NSE

Table 9 Calibration based on split sample using NSEm (NSEm= 0.68, α = 8.54, β = 0.32). Validation (NSEm= 0.48)

Event #	Date	Q	q	Measured sediment, (ton)	Simulated sediment, (ton)	Percent error
4	3-Oct-07	2.05	0.64	4.4	4.4	1.88E-06
7	10-Oct-07	2.09	0.61	4.63	4.37	5.63
6	8-Oct-07	7.6	0.97	7.71	7.71	1.08E-05
5	5-Oct-07	0.734	0.52	0.83	2.95	254.41
9	28-Oct-07	8.8	0.51	6.15	6.56	6.65
3	2-Oct-07	2.02	0.63	5.29	4.36	17.62
2	30-Sep-07	1.55	0.54	4.03	3.82	5.33
1	25-Sep-07	29.63	2.06	32.12	15.29	52.38
10	17-Nov-07	1.7	0.13	0	2.48	–
8	11-Oct-07	3.27	0.72	1.1	5.33	384.82

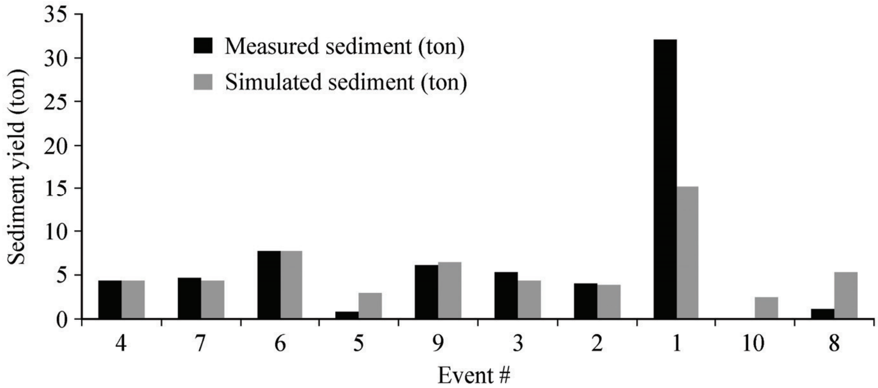

Fig. 13 Measured and simulated sediment yield based on split sample calibration and validation using NSEm

6 Discussion

6.1 Sensitivity analysis

OAT sensitivity analysis showed that α was the most sensitive parameter followed by *Q*, *q* and *β*. Incidentally, variance based sensitive analysis also suggest that α is the most sensitive parameter of the MUSLE model. However, this was followed by *β*, *Q* and q in that particular order. Though OAT is most widely used sensitivity analysis approach, it does not address sensitivity of the entire parameter distribution but rather sensitivity relative to point estimates chosen (Hamby, 1994). In cases where models are nonlinear and high-dimensional, OAT is known to be misleading because at some space of the input factors different patterns of sensitivity may exist or several factors may interact with each other (Saltelli, 1999; Muleta and Nicklow, 2005). On the contrary, global based techniques such as the variance based sensitivity analysis explore the full range of input factors, allows the exploration of sensitivity by simultaneously varying the input factors and any possible interactions among factors (Tarantola et al., 2002; Muleta and Nicklow, 2005). To show the added value of this argument, variance based sensitivity analysis results showed that the most sensitive factors of the MUSLE model were the conceptual factors with both contributing about 66% of the variability in the output sediment yield. The most revealing finding was the degree of interaction among input factors. The results showed that α had the highest total effect, though *β*, *Q* and *q* showed significant increase in variability of sediment yield due to interaction among them. In previous sensitivity and calibration studies where the model has been applied for sediment yield simulation, mostly integrated in SWAT (e.g. Muleta and Nicklow, 2005; Zheng et al., 2009; Song et al., 2011), attention has been on the cover factor, soil erodibility factor, the practice support factor and runoff volume. In this study the physical factors were assumed constant as the duration of the study was short. Hence to test the applicability of the model, it was important to investigate the degree of influence of conceptual factors and their interaction with the runoff volume and peak. The runoff volume and peak discharge were accurately monitored over the duration of the study. Consequently, the conceptual factors were prioritized for calibration to determine the most optimal parameter values for the upper Malewa catchment in Naivasha, Kenya.

6.2 Parameter stability under choice of objective function during calibration and validation

Relatively few studies (Sadeghi and Mizuyama, 2007; Sadeghi et al., 2007a; Pongsai et al., 2010) have attempted to robustly test the MUSLE model outside the USA where it was originally developed. Furthermore, most commonly adopted objective function for model optimization in hydrological studies is the Nash-Sutcliffe Efficiency (NSE). Also rarely tested (McCuen et al., 2006) in model calibration is the effect of outlier or extreme values of the measured constituent on the stability of the estimated conceptual factors. This study stands alone from other studies that are based on multi-objective functions and those that present a set of factors as is the case with pareto front approach. Instead, the study presents a simple approach of analyzing the impact of outlier and extreme event on parameter estimation during optimization which ideally affects calibration of models and remains a challenge to all calibration efforts in hydrology. This was tested using two different choices of objective functions with differing properties, NSE which is known to be biased towards extreme values and NSEm that minimizes the effect of the high magnitude values. Calibrating the model using the whole data with NSE as the objective function yielded an NSE value of 0.97 suggesting that the MUSLE model was well tuned. However, a close examination of the data determined that the NSE value was highly exaggerated due to a presence of a high magnitude event in the data. Exclusion of this event and re-calibrating the model yielded a reduced NSE value of 0.58 suggesting that the model performed less better than when the high magnitude event was included. Interestingly though, the percent error of individual event simulations reduced significantly in six out of nine events (Table 5, Fig. 9) ($R^2 = 0.59$) compared to the use of NSE as objective function with the extreme event included ($R^2 = 0.56$). This finding was in agreement with similar findings in other studies (Legates and McCabe, 1999; McCuen et al., 2006; Jain and Sudheer, 2008; Muleta, 2012) which have highlighted the limitation of NSE when used for model evaluation where the data set included extreme or outlier values. For example, McCuen et al. (2006) tested the efficacy of NSE using seven turbidity data which were regressed against discharged data. The authors found out that by censoring an outlier event in the analysis, the model performance improved significantly.

Adopting the original conceptual factors of the MUSLE model resulted in overestimation of sediment yield. This was similar to findings reported by Sadeghi (2004) and Sadeghi et al. (2007a). However, this simulation yielded poor model efficiency criteria and hence calibration was initiated using NSE and compared with the output of NSEm.

Results of NSEm showed that high magnitude events in the data set were more accurately simulated on calibration than the use of NSE as the objective function. Events of 25th Sept. 2007, 8th Oct. 2007 and 28th Oct. 2007 which had considerably high sediment yield measured at the catchment outlet were estimated with percent error deviations of 3.95×10^{-07}, 9.5 and 6. $\times10^{-5}$%, respectively. This was better than NSE estimates for the same events reported as 0.63, -13.2 and -4.4%, respectively, though the rest of the events were slightly underestimated with the exception of the events of 11th Oct. 2007 and 17th Nov. 2007 that were poorly simulated in all cases. The coefficient of determination under this scenario was reported at $R^2 = 0.56$ which was similar to model simulation when NSE was used with all events. The poor simulation of sediment by MUSLE for events of 5th Oct. 2007 and17th Nov. 2007 confirms further finding by Williams & Berndt (1977) and Sadeghi (2004)that MUSLE is unsuitable for prediction of sediment yield of small storms due to low discharge realized during such events. Poor simulation of sediment for the 11th Oct. 2007 was likely due to limited supply of sediment following exhaustion of sediment from previous day runoff. This agrees with studies of Walling and Webb (1982) that showed sediment exhaustion during subsequent runoff events in a number of catchments in Devon, UK. However, this is not the case for the 2nd and 3rd Oct. 2007 events. A possible explanation could be that during the two events, precipitation distribution varied spatially coupled with the fact that sediment sources are different throughout the catchment. This result compares favorably with that reported by Sadeghi and Mizuna (2007) for the case of Khanmirza catchment, Iran.

Removal of the extreme event and re-calibrating the MUSLE model using NSEm as the objective function yielded improved simulation results with $R^2 = 0.60$. The percent error of estimation of the individual events was improved than when NSE was used with and without inclusion of the extreme event. Interestingly, however, the NSEm value was reported at 0.44 which was much lower than the previous cases. NSEm has not been widely adopted and there is a lack of comparative literature on the same (Moriasi et al., 2007). Nevertheless, the findings in this study enhance the recommendation of Legates and McCabe (1999) suggesting the adoption of the NSEm over correlation-based measures and stating that NSE was sensitive to extreme values due to the squared differences in residuals. This findings also agree with recently published works by Muleta (2012) which also suggest that objective functions based on minimizing absolute value residuals were most effective when used to simulate both low and high flows.

Further, testing of the model by attempting to split the data into two sets for calibration and validation also suggested the robustness of NSEm over NSE as an objective function. Calibration of the data yielded a NSE value of 0.88. Validation of the conceptual factors yielded an NSE value of 0.74. Much of this was contributed by the extreme event of 25th September 2007. Excluding this event from the validation analysis the NSE value dropped to -0.12. This was suggestive that observed mean of sediments was a better predictor than the model in the catchment based on the available data. However, re-calibrating the model using the modified version of NSE and subsequent validation, the NSEm was reported at 0.48. On excluding the extreme event from the validation data set, the NSEm subsequently improved to 0.67 indicative that the model was a better predictor than the mean. It was also noted that the conceptual factors estimated were different in both cases. With NSE, α and β were estimated at 7.13 and 0.42 respectively. NSEm estimated α at 8.54 and β at 0.32 which was similar to the results of NSEm calibration using the whole dataset but excluding the extreme event. This was suggestive that the factors obtained using NSEm as the objective function were much stable than those obtained when NSE was used. These findings agree with those reported in literature emphasizing the need to use multiple efficiency criteria to assess model performance (Legates and McCabe, 1999; Krause et al., 2005; McCuen et al., 2006; Moriasi et al., 2007; Muleta, 2011; Muleta, 2012). Specifically, relying on NSE alone may lead to rejection or acceptance of a good or poor model and other indices are a necessary inclusion to evaluate model performance. Consequently, these findings have wider implications in hydrological studies involving prioritizing model factor inputs, calibration and validation and highlight the need for careful assessment of the MUSLE model for sediment yield estimation.

7 Conclusion and recommendations

OAT and variance based (Sobol') sensitivity analysis suggest that α was the most sensitive parameter in the model. Considering that OAT is limited to robustly explore factor prioritization due to input factor interaction in the whole factor distribution range, the Sobol' method provided a quantification of the variance contribution of each parameter and the variance contribution of their interactions to the sediment yield output from the catchment. The results showed that the most sensitive factors of the MUSLE model were the conceptual factors with both α and β, contributing about 66% of the variability in the output sediment yield. The most revealing finding was the degree of interaction among input factors. Of note was the significant increase in variability of sediment yield due to interactions among β, Q and q. Subsequently, the conceptual factors in the model were calibrated to determine their optimal values for the catchment.

The calibration of the MUSLE model indicated that the use of NSEm as an objective function provided more stable results indicating that the model can be applied for sediment yield simulation in the upper Malewa catchment. NSE was found sensitive to extreme value events and the use of it alone can lead to judging a good model bad or a bad model being judged good. This raised the concern over continued use of NSE as an index of model evaluation and usage as objective function in model calibration. Ideally, the present study questioned the integrity of NSE as model efficiency criterion. NSEm has not been widely used; however, it provided insight into model evaluation by not over-emphasizing on model performance compared to NSE. This study recommends the adoption of the NSEm index, at least for sediment yield modeling and evaluation. This study further proposes regionalization of the calibrated versions of the model to test its efficacy in catchments with similar hydro-geomorphological conditions in the region of study.

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