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Modeling the support factor (P) as a function of socio-economic factors for improved erosion prediction on the hillslopes of Lake Victoria Basin of Uganda

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Abstract

A major challenge to erosion prediction using the Universal Soil Loss Equation (USLE) is the uncertainty in parametrizing the support factor (P). This P factor is usually regarded as 1 in areas with no structural management practices. However, in agrarian landscapes which are dominated with agronomic management practices, the P factor is difficult to parameterize. Moreover, the agronomic practices are usually the most simplest and affordable soil and water conservation technologies for mitigating runoff and soil losses in many developing countries. Our objective was to model the support factor (P) as a function of socio-economic factors for adoption of management practices in order to improve erosion prediction. Our methodology involved four (4) steps; namely, (a) estimating potential erosion using RUSLE; (b) establishing the socio-economic for adoption of management practices using Probit regression analysis; (c) integrating socio-economic factors with biophysical parameters to form a Systems Dynamic (SD) model for soil erosion; and (d) validating the Systems Dynamic (SD) model at watershed level using empirical data and RUSLE as the baseline model. Validation results showed that on *Acric Ferralsols* at slope gradient 10-15% the potential erosion as predicted by RUSLE model ranged between 120-140 t $ha^{-1}yr^{-1}$. On the other hand, soil loss as predicted from the Systems Dynamic (SD) model, based on the same slope gradient and soil condition as the case in RUSLE, ranged between 11-50 t $ha^{-1}yr^{-1}$. This accounted for about 67-90% decrease in soil loss. Model outputs were calibrated and validated by field data measured using Un-bound runoff plots (*Gerlach Troughs*). The results showed that in sole banana soil loss increased step-wise with increasing gradient in the measured and predicted data ($P < 0.05$); while in sole coffee contradicting results were achieved. We concluded that modelling the support factor (P) as a function of socio-economic factors provides a pragmatic solution to the uncertainty in its parameterization. Generalizing the support factor (P) as one (1) even in areas with agronomic management technology tends to over-estimate the risk of soil erosion. Thus, it can potentially stand out as a dis-incentive that undermines farmers' efforts to mitigate runoff and soil loss in degraded watersheds.

Key words: 1. Erosion, 2. Geo information science, 3. System Dynamics, 4. Support factor, 5. Uganda

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1. Introduction

Soil erosion is major problem affecting many agrarian landscapes world-wide. Whereas more sophisticated erosion models with high technological precision and accuracy been developed, obtaining quality data for these models for the support factor (P) has remained uncertain. According to Renard *et al*. (1997) erosion is a function of erodibility (K), erosivity (R), slope length and steepness (LS), vegetation cover (C) and support management practices (P). Of all these parameters, the support factor (P) is the most challenging to determine in agrarian landscapes. Moreover, this factor (P) reflects the effects of management practices in reducing runoff and soil loss; and it is represented as a ratio of soil loss by a support practice to that of straight row farming up and down the slope. There are two forms of management practices, namely; structural and agronomic practices. The support factor (P) can easily be estimated under structural management practices. But under agronomic practices, un-systematic procedures and techniques for the support factor (P) have arisen. In light of this, un-realistic information about soil erosion can be obtained and this can jeopardize efficient and effective soil and water conservation planning for the affected landscapes. In some areas models have over- estimated the risk of soil erosion contradicting the farmers' perceptions of the same risk especially where they have adopted agronomic practices. This further has negative implications with respect to effective soil and water conservation planning.

Whereas many procedures and techniques for the support factor (P) estimation are available, namely; using expert knowledge, field observation and aerial photographs, using Very High Resolution (VHR) satellite imagery (Karydas *et al*., 2008; Mutekanga *et al*., 2010), and using empirical equations (Panagos *et al*., 2015); there is no standard method which is universally acceptable for estimating this factor. In most erosion studies the support factor (P) is regarded as unity (1) especially for all areas with no structural management practices (Lufafa *et al*., 2003). Such misrepresentations of the support factor (P) is an illusion; and can lead to erroneous results about the potential risk, spatial extent and magnitude of runoff and soil losses in areas dominated by agronomic management practices.

Besides structural management practices, the value of the support factor (P) is also dependent on the magnitude of the slope upon which the said practices are established. Studies have shown that the support factor (P) is about 0.11 for an area with a slope ranging between (0 - 5 %); 0.12 with slope (5 - 10 %); 0.14 with a slope (10 - 20%); and 0.19 with slope (20 - 30%) (Kefi and Yoshino, 2010). Other than slope magnitude, there are important attributes that one needs to analyze about the management practices in order to derive the support factor (P). These include; the quality, grade and location where management practices are anchored in order to successfully estimate the (P) factor (Angima *et al*., 2003). Therefore, under good conservation, the value of the support factor (P) can be as low as 0.1; while under poor conservation or zero management practices, the (P) factor can be as high as 1.0.

As farmers are not limited on the form of management practices to adopt, more complex challenges arise with respect to the value of support factor (P) in areas dominated by either agronomic practices; or a combination of agronomic and structural management practices (Angima *et al*., 2003). Several studies have shown that agronomic management practices are the commonest technology interventions due to their simplicity and affordability especially in Sub Saharan Africa (SSA) (Pender *et al*., 2004; Vigiak *et al*., 2005). Therefore, generalizing the support factor (P) as 1 in these areas of SSA casts a gloomy picture about runoff and soil loss.

In line with literature, this study upholds the view that the uncertainty in support factor (P) parameterization could be circumvented by an integrated modelling approach which was earlier on postulated by Kessler (2006). Since its values range between 0 and 1 (Panagos *et al*., 2015), we developed an integrated functional relationship for the (P) factor using a STELLA modelling tool with attributes varying between 0 and 1. STELLA modelling is one of the most robust approaches for integrating environmental models with Geo-information technology for easy spatial analysis and visualization (Karimi and Houston, 1996). We integrated the socio-economic factors for adoption of management practices on the hillslopes of Lake Victoria Basin (LVB) into a GIS-based Revised Universal Soil Loss Equation (RUSLE) to establish the (P) factor. Our objective was to model the support factor (P) as a function of socio-economic factors for adoption of management practices in order to improve erosion prediction in the Lake Victoria Basin (LVB) of Uganda.

2. Materials and Methods

2.1 Study site description

The study was conducted in Nabajuzi watershed of the Lake Victoria Basin (LVB) of Uganda (Figure 1); which is located at latitude 0° 00′ 01″ North and 0° 20′ 01″ South of the Equator; and longitude 31° 39′ 00″ and 31° 50′ 00″ East of the Greenwich. This watershed covers a total land area of 837 $Km^{2.}$ The name Nabajuzi derives from River Nabajuzi, which spans a distance of about 40 Km, and is fed by various streams which dissect the area into the watershed. The watershed has dissected hills ranging from 1200 to 1290 m above sea level; and experiences 30 - 120 t $ha^{-1}yr^{-1}$ rates of soil loss, estimated using RUSLE Model (Nadhomi *et al*., 2013 a). Annual rainfall is 1500 mm p.a, occurring at high intensities and this can easily dislodge soil particles particularly under weak structures. This rainfall is also distributed in a bimodal manner during March to May as the first long rains of the rainy season, and September to November as the short rains of the second rainy season. The soil is having a relatively weak structure and sometimes it is friable due to continuous tillage; and this has made them to become highly erodible when subjected to heavy downpours (Lufafa *et al*., 2003). The dominant natural vegetation of Nabajuzi watershed is Cyperus papyrus with patches of Miscanthus Violaceus in most parts. Further inside the wetland exists communities of Kostchya, a common shrub which is associated with Cyperus papyrus. This vegetation helps in hydrological recycling, storing water for ground, water recharge, stabilizing the banks of this catchment and flood control. Unfortunately, overtime this natural vegetation has been transforming into arable landuse, with limited consideration of soil erosion mitigation measures. The region typically grows more annual crops than perennial crops, the latter being famous promoters of soil erosion especially in sloppy landscapes due to lack of undercover and/or appropriate management practices (Tenywa *et al*., 1999; Nadhomi *et al*., 2013 b).

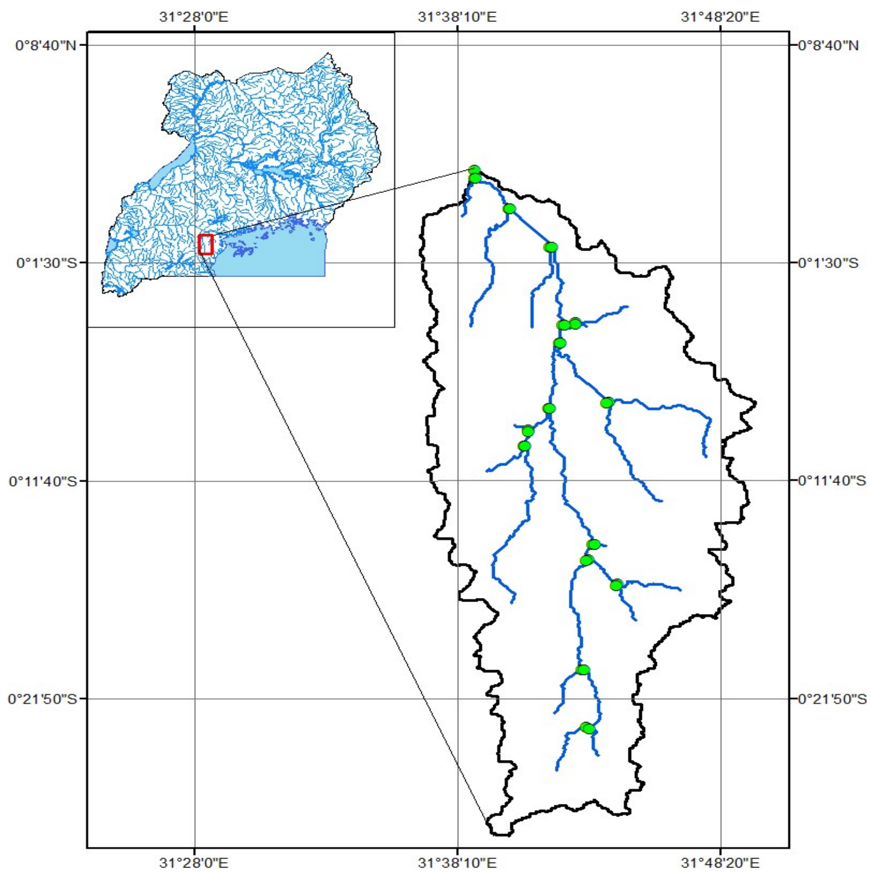

Figure 1: The location of Nabajuzi watershed within Uganda

2.2 Procedure for deriving the support factor (P) as a function of socio-economic variables

The System Dynamics (SD) procedure as embedded in STELLA software was employed. It was loosely coupled with Geo-information science in order to model the uncertainties associated with parameterizing the support factor (P). The other steps involved here were establishing the remaining parameters as in RUSLE (Renard *et al*., 1997) in order to generate two maps; namely, (a) maximum potential erosion risk map; and (b) erosion risk map as modelled based on SD procedure. The difference in these two maps is on the value of their support factor (P). In map (a) the P factor is 1, while in map (b) the P factor is based on other socio-economic variables for adoption of management interventions; hence it ranges between 0 and 1. The Nabajuzi watershed, with a banana-coffee cropping system, as in Figure 1 was used for this investigation. In this watershed farmers have adopted a variety of technological management interventions and was a suitable candidate for this analysis.

2.2.1 System dynamic model architectural design and functionality

The conceptual architecture of this modelling approach is presented in Figure 2. This structure is based on *Building Blocks* or *Stocks*, *Flows*, *Action Connectors* and *Convertors*. Socio-economic drivers, support, cover, erosivity, soil and topographic factors; as well as runoff and soil loss were the main Building Blocks of this model.

The functionality of the SD model is described as follows: Upon statistical analysis, the factors that influence the adoption of management practices/support factor, P are identified as input variables constituting the ingredients of a *Block* of socio-economic factors. These factors are then joined to the biophysical factors for soil erosion as in RUSLE for successful building of this system. Conceptually, a combination of support and cover factors provide a stabilizing effect to the soil. But aggressive rain events coming in as exogenous inputs to the system, dis-stabilize the soil conditions leading to significant processes of soil particle splash, detachment and wash which occur due to runoff effect. By and large, topographic conditions would now cause some runoff water to infiltrate into the soil; and the excess of it to cause significant soil losses. Sediment yield is regarded as the final output from this system, is one of the major pollutants to water resources in the site.

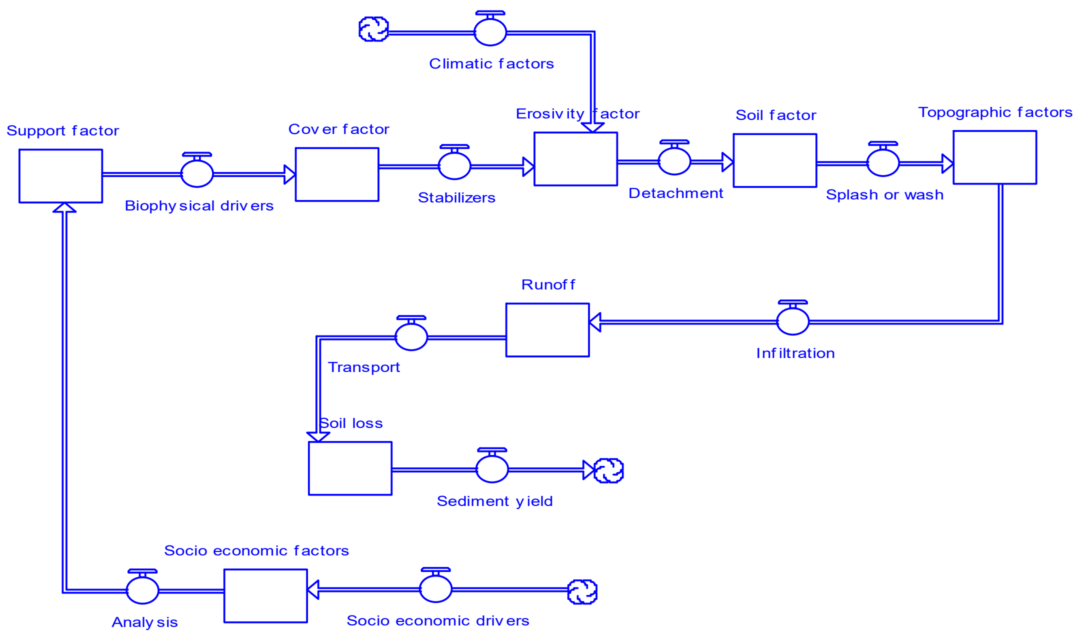

Figure 2: The architecture of the conceptual System Dynamic (SD) model for soil erosion

The support factor (P) was modelled following two complementary and interactive approaches, namely; retrieval of the intrinsic socio-economic variables underlying the risk of soil erosion and System Dynamic Exchange of data into a geo-spatial platform to generate a support factor (P) map.

2.2.2 Collecting and analyzing socio-economic data for the support factor (P)

In the site there were 24,000 households (UBOS, 2012), hence these constituted the population size. A household was regarded as the unit of analysis and sample size selection was determined following Equation 1 (Bartlett *et al*., 2001):

$$n = \frac{pqN}{(SE)^2N+pq} \quad \text{………………………………………………………………........(Equation 1)}$$

Where n = sample size, N = population, p = proportion of population possessing the major attribute (expressed as a decimal), q = 1- p, and SE = standard error of the proportion.

Taking the confidence interval at +5 % and confidence level at 95 %, the standard error of proportion as in Equation 2 was derived:

$$SE = \frac{5\%}{1.96} = 0.025 \quad \text{………………………………………………………….............(Equation 2)}$$

Therefore, our sample size (n) was determined as follows:

$n = \frac{0.5\ X\ 0.5\ X\ 24000}{(0.025)^2\ X\ 24000 + 0.5\ X\ 0.5}$ = 390 households; and these were selected for interviews.

The dependent variable underlying farmer's decision to adopt the management practices was awareness of erosion risk (Hammad and Borresen, 2006). Since the degree of awareness presupposes the farmer's adoption behavior for management practices; awareness has only two possible outcomes. It is on this basis that the Probit Regression Model (Equation 3) was the most effective for data analysis in this study. The independent variables, on the other hand, were broadly identified in accordance with the major categories which were summarized as preferences, resource endowments, market incentives, biophysical factors, and risk and uncertainty (Pattanayak *et al*., 2003); and for this study they included farmer's characteristics, education, type of crop, land ownership, distance to farm from home, access to agricultural extension services, profitability, acceptability and feasibility of the management technologies.

$Y = \beta + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots\ldots\ldots\ldots\ldots\ldots + \beta_{12} X_{12} + e$ ……………………………........(Equation 3)

Where: $\beta_1 \ldots\ldots \beta_{12}$ = coefficients to be estimated by the regression model;

e = random error term;

Y= farmer's awareness of the risk of erosion;

X_1= age of house head (*in years*);

X_2= family size (*excluding* extended family members);

X_3=education level of house head (*in years of schooling*);

X_4= marital status of house head;

X_5 =distance to the garden from home (*in metres*);

X_6= land size (*in acres*);

X_7=total spending in *SWC* as a proxy for income of house head;

X_8=land quality of the parcel;

X_9=length of time for accessing the land parcel (*in years*);

X_{10}=farmers' access to agricultural training and extension services;

X_{11}=land tenure and ownership system operating in the watershed;

X_{12}=crop type grown.

The data were entered in Statistical Package for Social Sciences (SPSS) version 21, and then transferred to STATA for easy performance of the necessary statistical analyses. The outliers in the data, normality (distribution) and symmetry (skewness and kurtosis) were all checked using explanatory data analytical procedure. All the identified outliers were discarded because they would affect the final results of the Probit Model. The data were also found to be normally distributed with no skewness or kurtosis. This was a good indicator to guarantee the performance of the model for further statistical analyses which included Multi-collinearity that was tested using Variance Inflation Factors (VIFs) and a Covariance Matrix (CM). The CM showed no Multi-collinearity in the data and all variables showed VIF values which were less than 10, as proof that the degree of linear relationship among them was good.

The results from this step as in (Table 1) indicated that farmer's awareness of erosion risk (Y) is better explained by the absolute values of the linear expression of the Probit Model as in Equation (4):

$Y = 0.68\ X_1 + 0.27\ X_2 + 0.6\ X_3 + 0.18\ X_4 + 0.2\ X_5 - 0.65\ X_6 - C$ ……………….........(Equation 4)

Where: Y = Farmers' awareness of the risk of soil erosion on land;

X_1 = Farmer's income;

X_2 = Family size;

X_3 = Distance from home to the farm;

X_4 = Education level of farmer;

X_5 = Farmers' access to agricultural training and extension services;

X_6 = Age of the farmer; and

C = Constant (-0.29).

As identified in Equation 4, these socio-economic factors were then used to finally establish the System dynamic model for soil erosion as presented in Figure 3.

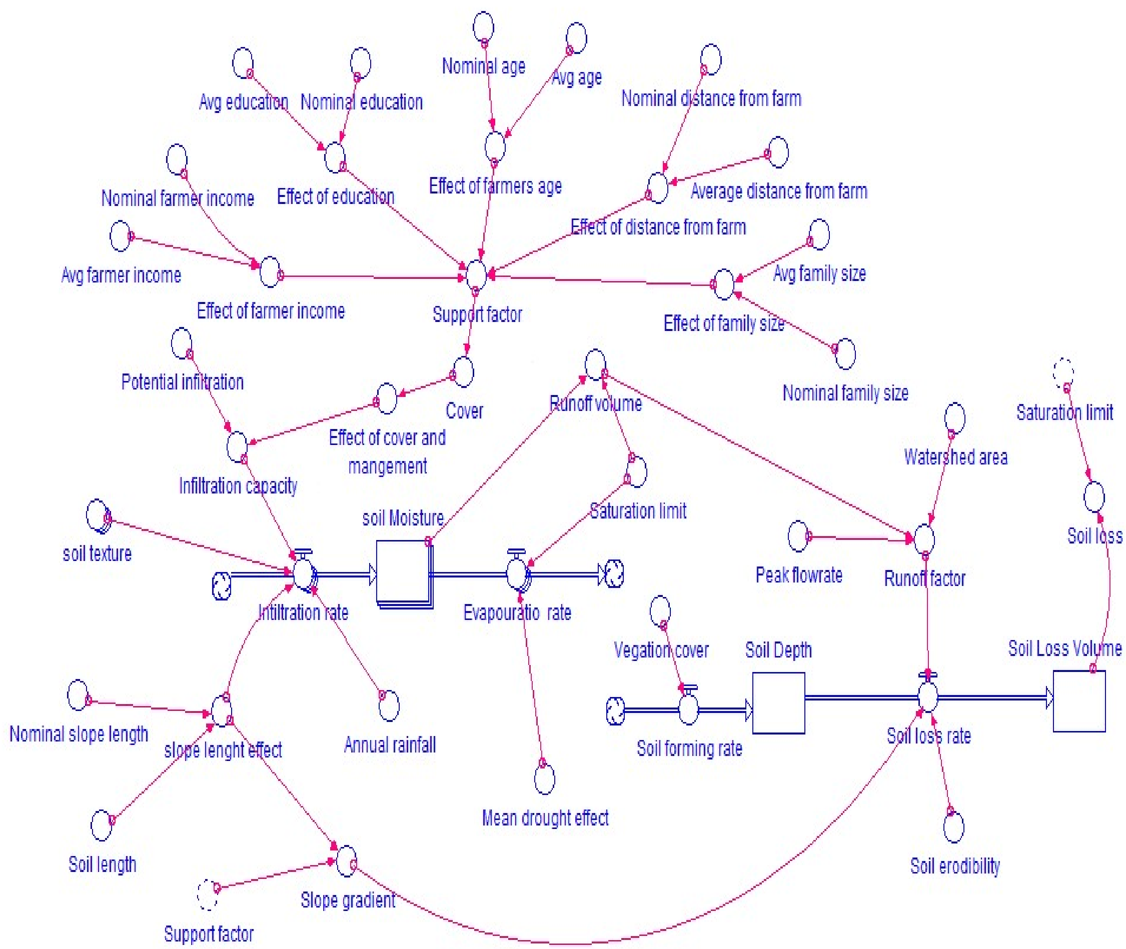

Figure 3: System dynamic model for soil erosion in Nabajuzi watershed

2.2.3 Deriving a system dynamic functional relation for the support factor (P)

For this step we based on the standard and widely used erosion equation (RUSLE) as shown in Equation 5 (Renard *et al*., 1997). This function represents the equation(s) that are used to model the support factor (P). Therefore, the support factor (P) was modified to encompass the socio-economic factors for the adoption of erosion management practices which were identified earlier in Equation (4).

$A = R*K*LS*C*P$ ……………………………………………………………........... (Equation 5)

Where: R = Rainfall erosivity factor;

K = Soil erodibility factor;

L = Slope length factor;

S = Slope steepness factor;

C = Cover management factor; and

P = Support factor

The modified expression of the RUSLE coupled with socio-economic factors is presented in Equation (6).

$A = R*K*LS*C*F_{aw}$ ……………………………………………………………........... (Equation 6)

Where:

R = Rainfall erosivity factor;

K = Soil erodibility factor;

L = Slope length factor;

S = Slope steepness factor;

C = Cover management factor;

F_{aw} = A function representing the support practice factor. This factor depends on farmers' awareness of erosion risk and their decision to adopt management practices.

The functional relation (F_{aw}) for the support factor (P), for use in the modified RUSLE model (Equation 6) was established on the basis of farmers' awareness of the erosion risk. The F_{aw} was mathematically obtained on condition of the Set Function of the Boolean as described in Equation (7). According to this function, maximum erosion potential of an agro-ecological area is obtainable as of when the farmers are not aware of the erosion risk; and consequently have not adopted or applied any management practices. Thus, under this case the support factor P is 1. But in agro-ecological areas where farmers are aware of the erosion risk; and have adopted or applied some management interventions, soil erosion potential is not at its maximum. Therefore, support factor (P), under such a scenario would vary between 0 and 1.

$$F(aw) = \begin{cases} 1, \; if \; farmers \; are \; not \; aware \; of \; erosion \; risk \\ 0 < P < 1, \; if \; farmers \; are \; aware \; of \; erosion \; risk \end{cases} \quad \text{.................. (Equation 7)}$$

Where:

$F(aw)$ = a function of awareness of erosion risk;

P = RUSLE's support factor whose values vary between 0 and 1.

2.2.4 Spatial modelling of the support factor (P)

The support factor (P) was modelled by System dynamic data integration with GIS. The functional relation (Equation 7) was integrated into ArcGIS version 10 using STELLA modelling tools. The in-built STELLA Function, Array, was executed to cater for the range of values applicable to the P factor in the site. The data were loosely coupled, with MICROSOFT EXCEL being the medium for data exchange into a Geo-spatial database. The generated tabular data were then related to the Table of Attributes (TOA) for the shapefile of the study area using the Join Function. Since some farmers had adopted soil erosion management practices such as contour bunds, mulches, grass barriers, trash lines and deep tillage (Nadhomi *et al*., 2013 a), the associated P factor values to these practices were assigned. The P factor layer was produced based on the 90 x 90 M resolution DEM of this watershed using the Spatial Analyst Tool. In this DEM, percentage slope was established; it was classified with defined intervals; and later the same DEM was converted from Raster to Polygon format using Conversion Tools. The TOA of this polygon was opened, and the attributes corresponding to each management practice were sorted in ascending order and merged together from the Editor function. Using the Add Field function from the TOA, all the P values accruing to each management practice were added to this polygon; and this polygon was then re-converted back to Raster format using Conversion Tools. Figure 4 shows the spatial distribution of the P factor in Nabajuzi watershed after its integration with socio-economic data.

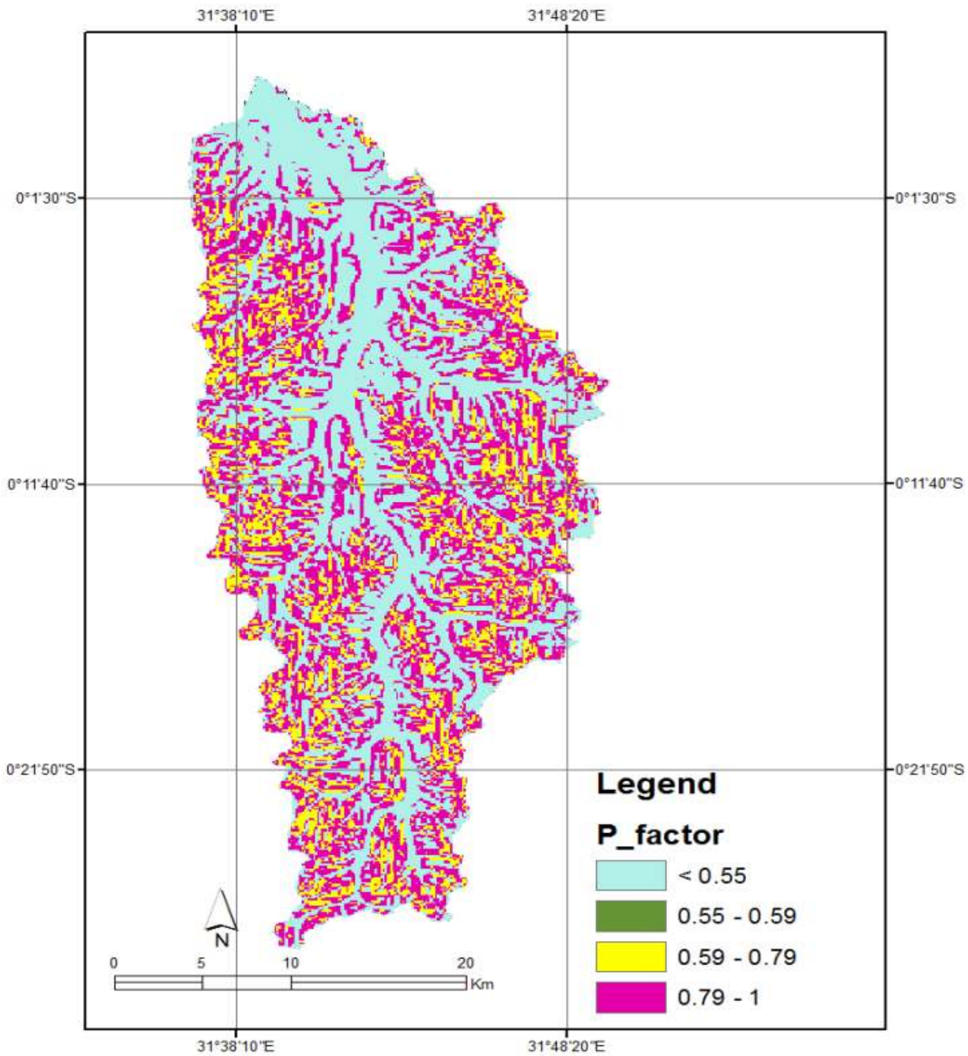

Figure 4: P factor modelled as a function of socio-economic factors in Nabajuzi watershed

2.3 Determining other erosion parameters based on RUSLE in Nabajuzi watershed

2.3.1 Soil erodibility, K factor

Since soil erodibility factor K refers to the susceptibility of the soil to erosive agents as determined under standard unit plot conditions, its measurement is based on parameters that include; soil texture, soil organic carbon content, soil structure, profile permeability and surface stone cover (Rosewell, 1993; Wischmeier and Smith, 1978). We obtained soil texture, pH, Cation Exchange Capacity and soil organic matter from thirteen (13) locations across all soil units identified in the site at slope gradients of 18, 16, 14, 12, 10 and 8% as shown in Table 1.

Table 1: Variability of soil nutrients in different cropping systems and slopes in Nabajuzi watershed

Location		Cropping system	Slope (%)	pH (H_2O)	SOM	CEC ($cmol.kg^{-1}$)	Textural class
Latitude	Longitude						
0º05'58.62"S	31º39'05.84"E	Sole banana	16	6.8	3.71	3.42	SCL
0º05'54.43"S	31º39'23.59"E	Sole banana	16	6.7	3.52	3.05	SC
0º05'43.96"S	31º40'08.60"E	Sole banana	18	6.9	3.42	2.73	SC
0º12'05.20"S	31º47'27.15"E	Sole banana	14	6.5	3.64	2.33	SCL
0º14'45.02"S	31º46'17.46"E	Sole banana	8	6.6	3.81	2.71	SC
0º14'43.25"S	31º46'18.12"E	Sole banana	12	6.7	3.53	2.24	SC
0º14'46.63"S	31º46'21.50"E	Sole banana	10	6.5	2.62	2.21	SC
0º14'49.49"S	31º46'24.03"E	Sole coffee	16	6.4	2.23	2.72	SCL
0º17'55.16"S	31º45'17.01"E	Sole coffee	10	6.7	3.14	2.83	SCL
0º17'54.38"S	31º45'18.25"E	Sole coffee	18	6.6	2.92	2.94	SCL
0º14'10.20"S	31º43'51.13"E	Sole coffee	14	6.5	2.44	2.64	SC
0º14'09.13"S	31º43'47.46"E	Sole coffee	12	6.8	2.63	2.82	SCL
0º14'09.78"S	31º43'48.43"E	Sole coffee	8	6.6	3.24	2.91	SC

SOM = Soil organic matter; *CEC* = Cation exchange capacity; *SCL* = Sandy clay loam; *SC* = Sandy clay

The K factor was then calculated from the Equation (8) by Wischmeier and Smith, 1978) as follows:
$K = 2.8 \times 10^{-7} \times (12- OM) \times M^{1.14} + 4.3 \times 10^{-3} \times (s-2) + 3.3 \times 10^{-3} \times (p-3)$ .... Equation (8)
Where: K = soil erodibility factor;
OM = percent organic matter content in the soil;
s = soil structural code, which ranges between 1 and 4; whereby 1 represents Friable, 2 for Fine polyhedral, 3 for Medium to coarse polyhedral, and 4 for Solid;
p = permeability code, which ranges between 1 and 6; whereby 1 represents Fast, 2 for moderate to fast, 3 for moderate, 4 for slow to moderate, 5 for slow and 6 for very slow; and
M = (% Silt + % Very fine sand) x (100 - % Clay).
The parameters, s and p, were directly obtained from the field; while M was determined from soil texture following Routine Analytical procedure. Lastly, by using the plotted co-ordinates from the GPS, a point map of K factor was generated in ArcGIS10. These points were interpolated through the Krigging method in order to produce the K factor map of Nabajuzi watershed as in Figure 5.

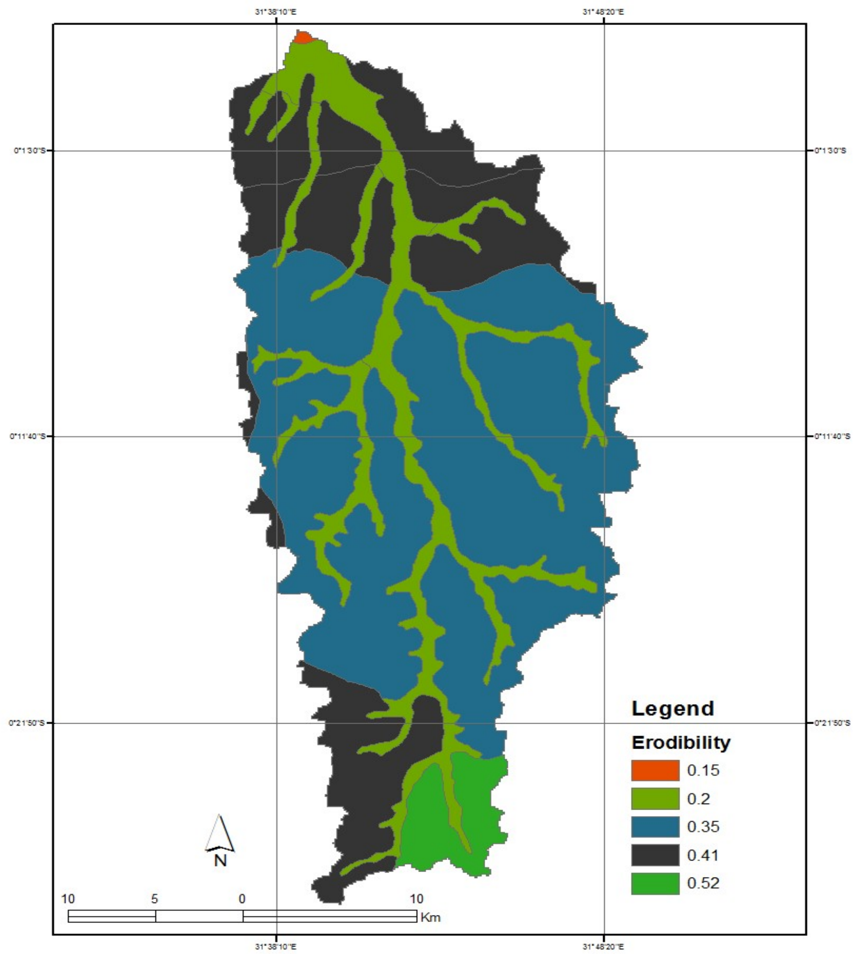

Figure 5: The variation of soil erodibility factor (K) in Nabajuzi watershed of Uganda

2.3.2 Rainfall erosivity, R factor

Rainfall erosivity (R factor) represents a measure of the erosive force and intensity of the rain in a normal year. It is dependent on the total energy (E) and maximum 30-minute intensity (I_{30}) of the storm. The R factor is usually the sum of the product of these two components (Renard *et al*., 1997). The EI_{30} imply the individual storm index values which are equals to E, the total kinetic energy of a storm, multiplied by I_{30} which is the maximum rainfall intensity in 30-minutes. The multiplication of EI reflects the total energy and peak intensity combined in each particular storm. Continuous rainfall records are necessary to calculate the maximum 30-minute rainfall intensity (EI_{30}). To obtain an accurate R factor, EI_{30} needs to be calculated with continuous records over multiple years, for multiple stations located at the area of the study site. In most cases, this is rather difficult to achieve and the computation of the R factor becomes a nightmare. The basic Equation (9), however, for determining the R factor was earlier developed by Wischmeier and Smith (1965).

$$R = \frac{1}{n} * \sum_{j=1}^{n}\left[\sum_{k=1}^{m}(E) * (I_{30})\right] \quad \text{(Equation 9)}$$

Where R = Rainfall erosivity factor (J M^{-2});
E = Total storm kinetic energy (MJ ha^{-1});
I_{30} = Maximum 30-minute rainfall intensity;
j = Index representing the number of years used to compute the average;
k = Index representing the number of storms in each year;
n = Number of years to obtain the average; and
m = Number of storms in each year.

But this equation is premised on total energy (E) and maximum 30-minute intensity (I_{30}); for which the EI_{30} values are usually calculated from each rainfall event that exceed 13 mm in depth. Studies however, have shown that even light rains (less than 13 mm in depth) can cause significant erosion. It is only an interplay of other factors such as soil properties, slope length, steepness, antecedent moisture and vegetation cover (Bagoora, 1998), that are paramount in setting forth the occurrence of erosion processes. In light of this, indices that base on mean annual rainfall values such as the Modified Fournier Index (Hussein, 1986) have become useful in estimating the R factor. With respect to this argument, the average annual EI_{30} which is expressed in MJ ha^{-1} mm^{-1} hr^{-1} can be calculated from Equation 10.

$EI_{30} = 0.3 * \sum (p_i/P)^{1.93}$..(Equation 10)

Where: p_i = Mean monthly rainfall (mm); and

P = Mean annual rainfall (mm).

The application of the mean annual rainfall values is fundamental in the R factor estimation most especially in areas where data are scanty. For instance, in Vietnam, Ha (1996) pointed out that rainfall erosivity indices could simply be determined from mean annual totals as presented in (Equation 11).

$R = 0.548257P - 59.9$ ………………………………………………………… …. (Equation 11)

Where: R = rainfall erosivity (J M^{-2}); and

P = mean annual rainfall of the area (mm).

While, in Indonesia, Bols (1978) recommended the use of Equation (12) to determine the rainfall erosivity factor for erosion studies.

$R = 2.5*P^2/[100(0.078P + 0.78)]$………………………………………………… (Equation 12)

Where: R = rainfall erosivity (J M^{-2}); and

P = annual rainfall (mm).

In Ethiopia, most especially under dry rainfall conditions, Hurni (1985) recommended the use of the formula as in Equation 13 to generate rainfall erosivity factor:

$R = - 8.12 + (0.562*P)$ .... (Equation 13)

Where: R = Rainfall erosivity factor (J M^{-2})

P = Mean Annual Precipitation of a place (mm)

While, in East Africa, Moore (1979) had earlier recommended that the erosivity factor can be determined from Equation (14):

$R = 0.029 (3.96P + 3122) - 26$…………………………………………………… (Equation 14)

Where: R = Rainfall erosivity (J M^{-2}); and

P = Mean annual rainfall of the area (mm).

Therefore, we obtained rainfall data from a nearby automatic weather station which was located at Kawanda Agricultural Research Institute (KARI). These data were supplemented by field data obtained from agro-meteorological stations located within the watershed; and also in a buffer zone of less than 5 Km around the same watershed. These agro-meteorological stations included: Masaka Forest, Kyamulibwa, Kiteredde Mission, Katigondo WFM, Kako Tea Estate, Kalungu, Kyanamukaaka, Lwengo GHQs, Matete GHQs, Kyamanda Catholic Mission, Lwamaga GHQs and Lyantonde Dispensary. Mean annual rainfall records from 1943 to 2010 pertaining to each Meteorological Station were obtained and used to compute the R factor. The R factor was estimated from Equation (14), which was developed by Moore (1979) for use in erosion studies in East Africa. We then generated a point map for each weather station with these rainfall erosivities in ArcGIS 10. By means of a Minimum

Curvature Spline interpolation method we spatially distributed rainfall erosivity factor (R) as a raster file of Nabajuzi watershed as shown in Figure 6.

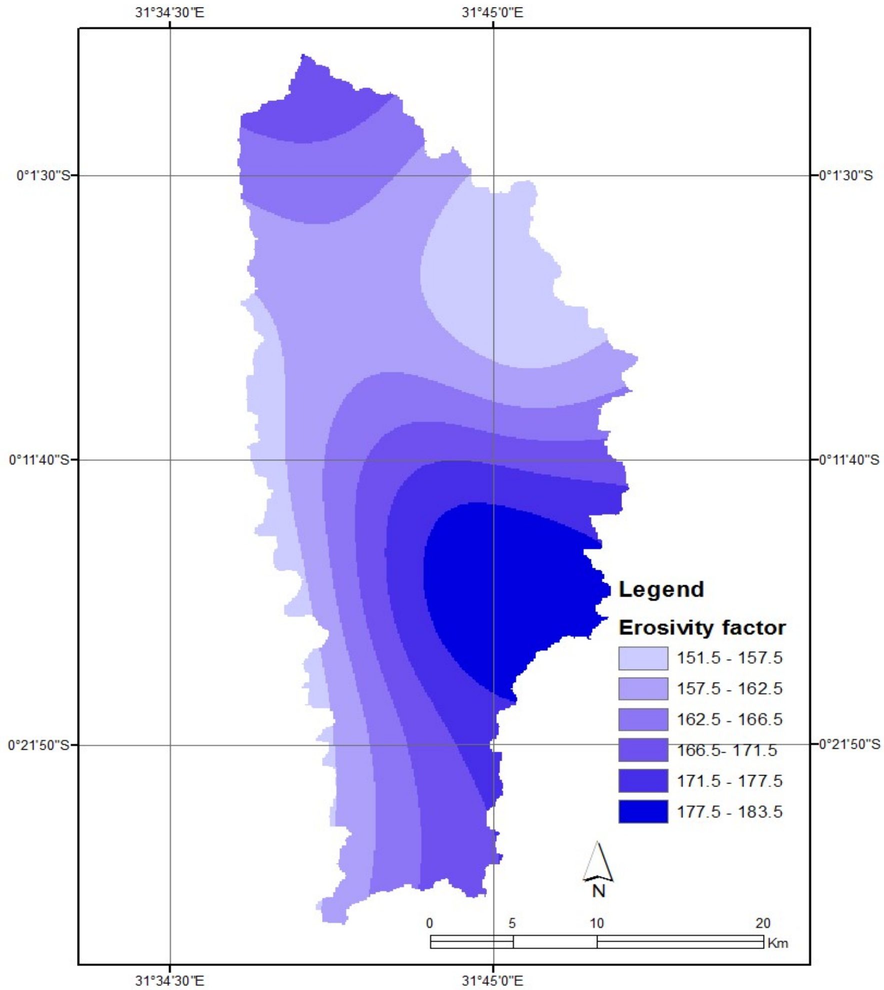

Figure 6: Distribution of rainfall erosivity factor (R), values in Nabajuzi watershed of Uganda

2.3.3 Slope length and steepness LS, factor

Slope length describes the distance from the point of origin of overland flow to the point where the slope gradient decreases to generate deposition (Wischmeier and Smith, 1978). The slope length and steepness, LS factor is a fundamental factor in water erosion studies; unfortunately it is again one of the most difficult to parameterize (Renard *et al*., 1997). Field measurements for the LS factor could be done, but they are usually curtailed by time and costs involved most especially at watershed scale. Let alone, LS factor measurements usually lack accountability for the terrain variations particularly for hilly areas (Khosrowpanah *et al*., 2007). To circumvent all these challenges in Nabajuzi watershed, an Arc Hydro approach which is an extension of ArcGIS 10 was employed.

This was based on the Shuttle Radar Topography Mission (SRTM DEM) which was delineated to form a watershed. The watershed DEM was reconditioned using the Terrain Processing tool; and later its sinks were filled using the Fill Sinks tool. This was followed by establishing the flow direction on the watershed DEM, which consequently guided the computation of Flow Accumulation with flow direction being the input raster in this process. Slope was calculated in degrees by selecting the tool Slope in Arc Hydro. Finally, the LS factor was calculated by employing Raster Calculation basing on Equation (15) (McCool *et al*., 1987); and the LS factor map generated is presented in Figure 7.

*LS = Power (Flow acc.*Cell size/22.13, 0.4)* Power (Sin slope_deg/0.0896, 1.3)* ………..(Equation 15)
Where: LS = denotes the combined slope length and slope steepness factor; Flow acc. = Flow accumulation; Cell size = the size of the grid (in this study it is 90 by 90 m); and Sin slope_deg = Sine of the slope in degrees.

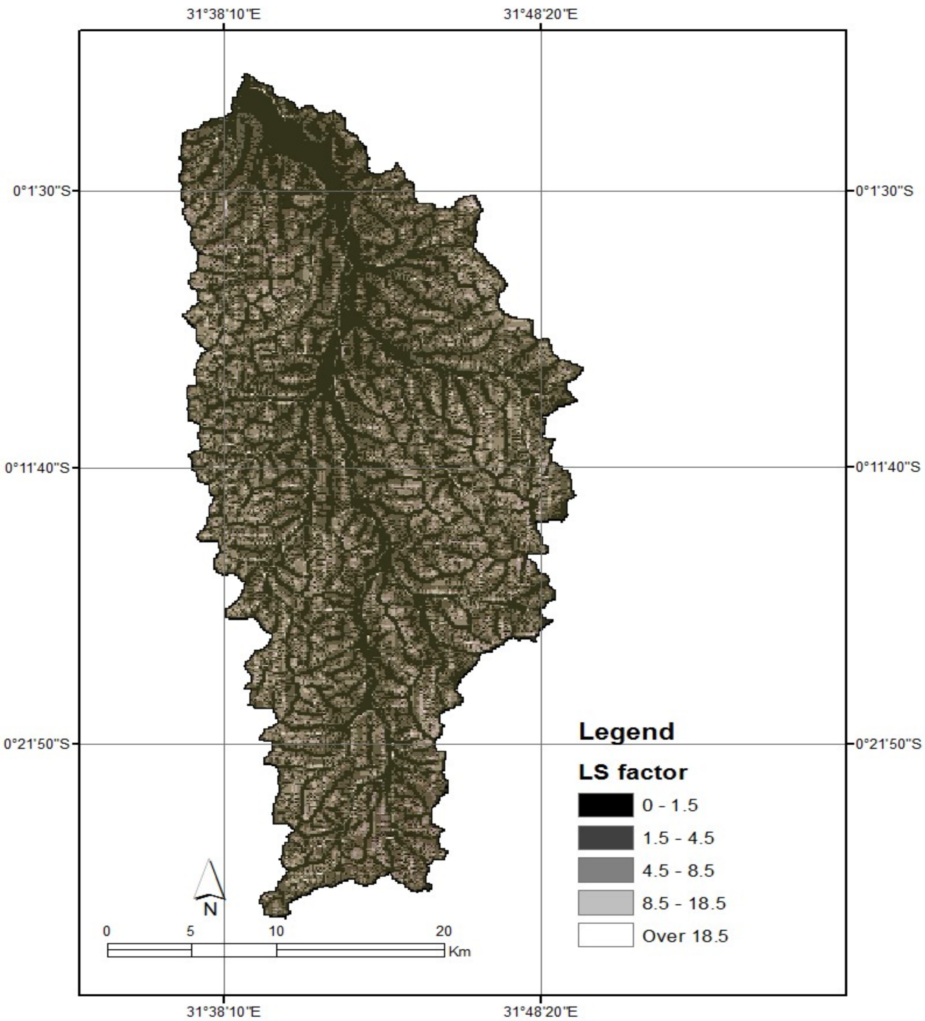

Figure 7: Slope length and slope steepness (LS) factor in Nabajuzi watershed of Uganda

2.3.4 Vegetation cover, C factor

The values for the cover factor (Figure 8) were extracted from a satellite image. A Landsat Enhanced Thematic Mapper (30 by 30 M) image of 2010 was acquired and processed for this purpose using procedures described by Lillesand *et al*. (1994). The image was stretched using a linear image enhancement technique, minimum-maximum linear contrast, to increase visibility of the features in this image. Then, a Pseudo Colour Composite with Band combination 4, 3 and 2, was created. Various land cover and land use types were identified in the watershed. This image was then classified using supervised classification procedure in Erdas imagine 9.2 software. A preliminary land use and cover map was then obtained using the maximum likelihood classifier algorithm. A field ground truthing exercise was conducted in Nabajuzi watershed to identify the particular land use and cover categories in the site. These categories were synchronized with the standard classified FAO system for Uganda whose data (in shape file), were obtained from National Forestry Authority (NFA), Nakawa, Uganda. The cover layer was derived by adding the *C* values to the Table of Attributes (ToA) of this layer. Prior to this, the added C values to ToA were obtained based on percentage bio-mass values for each cover class based on the Equation (16), which was developed by Shi *et al*. (2004).

$C = 0.6508 - 0.343\log c$; for $0 < c < 78.3\%$ ....(Equation 16)
Where: C equals 1 and 0, if c is equal to 0% and $\geq 78.3\%$, respectively; and c is percentage canopy/surface cover.

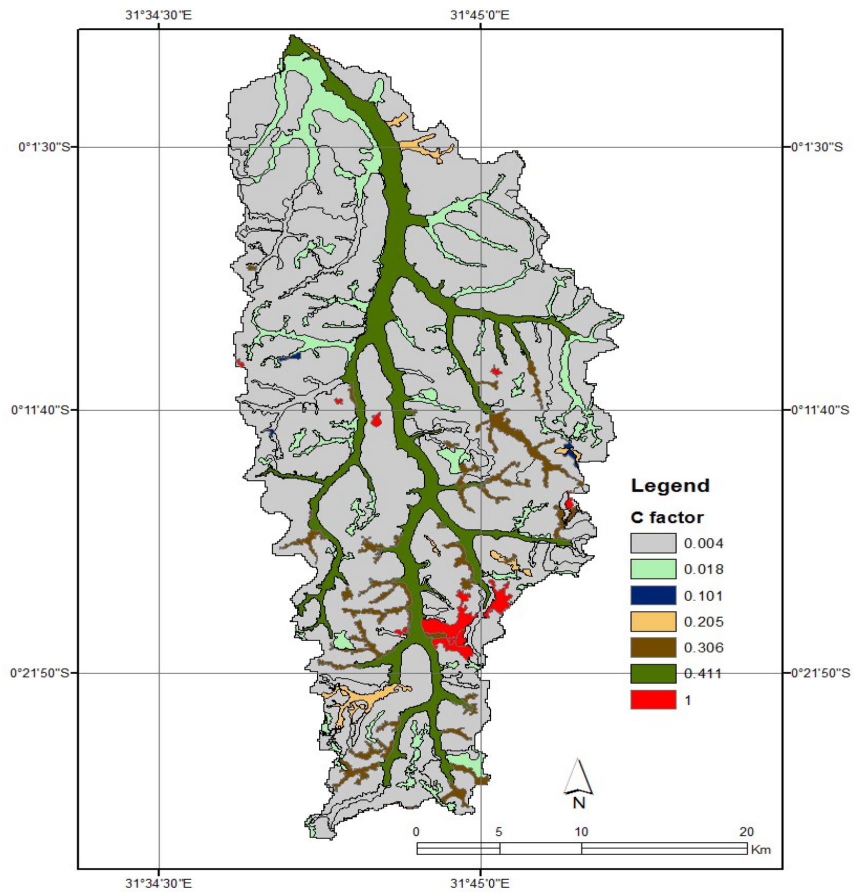

Figure 8: Distribution of the cover factor (C), values in Nabajuzi watershed of Uganda

2.4 Erosion modelling approaches

2.4.1 Prediction using System Dynamics (SD) model in Nabajuzi watershed

In this step, erosion prediction was made where the support factor (P) was modelled as a function socio-economic factors as modified in Equation (6). Thus, soil erosion risk in Nabajuzi watershed was modelled as a product of those parameters. All the generated maps for each of the parameters were converted into Raster Format; then Multiplication Operation was executed using a Map Algebra Tool. The Raster Calculator Tool was selected, and all the Raster images for soil erodibility, rainfall erosivity, slope length and slope steepness, cover and management, and support factors were multiplied to obtain an erosion risk map of Nabajuzi watershed. This map was further classified as according to FAO (1990) erosion risk severity categories for easy assessment of this problem.

2.4.2 Prediction of maximum erosion risk using RUSLE model

This was modelled on the basis of RUSLE. In order to obtain the maximum potential soil loss risk in Nabajuzi watershed, the P factor was regarded as one (1); implying a situation with no management practices. The remaining erosion risk parameters, as derived earlier on (Section 2.3), were used to predict the maximum erosion risk under the RUSLE modelling framework (Renard *et al*., 1997). The output derived here was then used to compare with the SD model output as a way of validating the latter's prediction capacity. By and large, policy implementation on SWC is essentially premised on such maximum potential soil loss risk rates. This, however, does not provide the realistic picture about erosion and its management most especially where farmers are practicing agronomic management practices.

2.4.3 Validation of the SD model

This model was validated on three principles; namely, the in-built STELLA software tools, field measurements by Gerlach Troughs, and comparing model outputs with other predictions erosion models such as RUSLE. Gerlach experiments were earlier on laid by Nadhomi *et al*. (2006) in the site on 8, 12 and 16 % slope gradients in sole banana and sole coffee; and the results were used to validate the SD model. Additionally, the SD model was also validated based on the outputs by RUSLE prediction model which was run for the watershed. In light of this, all results from these approaches were compared. At PIXEL (picture element) level, the SD and RUSLE model outputs from sole banana and sole coffee Acric Ferralsols existing on 8, 12 and 16% slope gradients were also compared.

3. Results and Discussion

3.1 Performance of erosion models against experimental data in sole banana

Results showing the performance of the SD and RUSLE models were validated based on observed experimental data measured using Gerlach troughs on Acric Ferralsols (FAO, 1990) on slope gradient 8, 12 and 16 % in sole banana are presented in Figure 9. Soil loss increased step-wise with increasing slope gradient in both the measured and predicted data ($P < 0.05$). The observed data were almost similar to the SD outputs; less variations existed among the two at all slope gradients. This is opposed to RUSLE model results which were extremely high at all measured slope gradients. Soil loss was highest at slope 16% and lowest at slope 8% most probably due to Soil Organic Matter (SOM) accumulation at lower gradients than at upper gradients (Table 1). Where SOM is accumulated, it improves aggregate stability; a condition which is essential in reducing soil loss in such areas. Besides in sole banana, sufficient mulch cover was available at lower slope gradients; and this could have contributed in reducing soil loss in these slope positions.

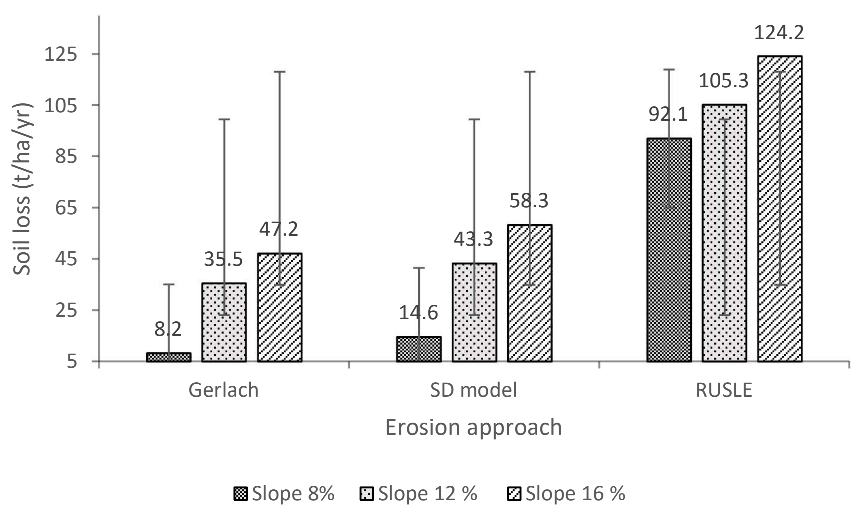

Figure 9: Validation of the SD and RUSLE models against observed data in sole banana

3.2 Performance of erosion models against experimental data in sole coffee

The performance of the SD and RUSLE models were validated based on observed experimental data measured using Gerlach troughs. Experiments were conducted on Acric Ferralsols (FAO, 1990) on slope gradients of 8, 12 and 16 % in sole coffee as presented in Figure 10. Like in sole banana, soil loss in sole coffee increased step-wise with increasing slope gradient in both the measured and predicted data ($P < 0.05$). Although variations in soil loss were recognized in both models against the observed data, RUSLE prediction results were extremely high in this crop. This was attributed to the poor management practices adopted by farmers in this crop. However poor such practices were, they attracted a certain factor which was used to compute the SD model. This was opposed to RUSLE model where a factor one (1) was used in all cases, hence; making its estimates much higher than the rest of models here tested.

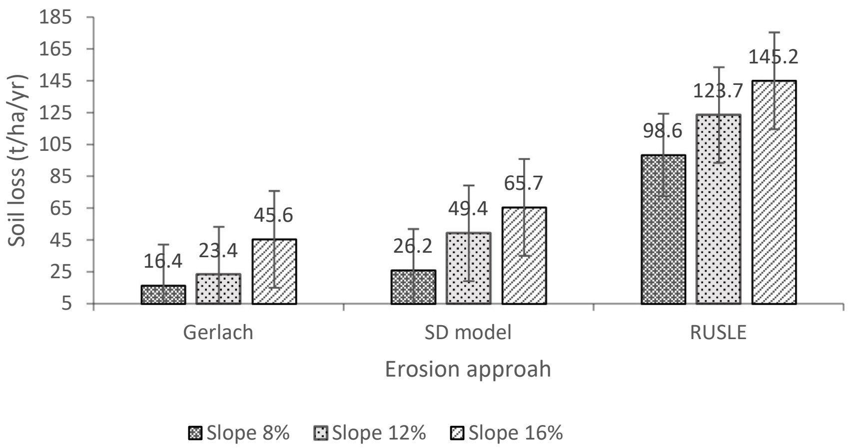

Figure 10: Validation of the SD and RUSLE models against observed data in sole coffee

3.3 Assessment of the erosion risk by the two models in Nabajuzi watershed

3.3.1 Erosion risk by SD model

Results showing the spatial distribution of soil erosion risk when the P factor is modelled as a function of socio-economic factors are presented in Figure (11). Depicting from its Legend and Table 2, this map indicates that erosion risk ranges between 0 to more than 90 t $ha^{-1}yr^{-1}$. A greater portion (93.63% of area coverage) is under very mild to moderate; while a very small portion (6.37% of area coverage) is under severe to very severe risk of soil erosion. Furthermore, no areas were predicted to have an extremely severe risk of soil erosion.

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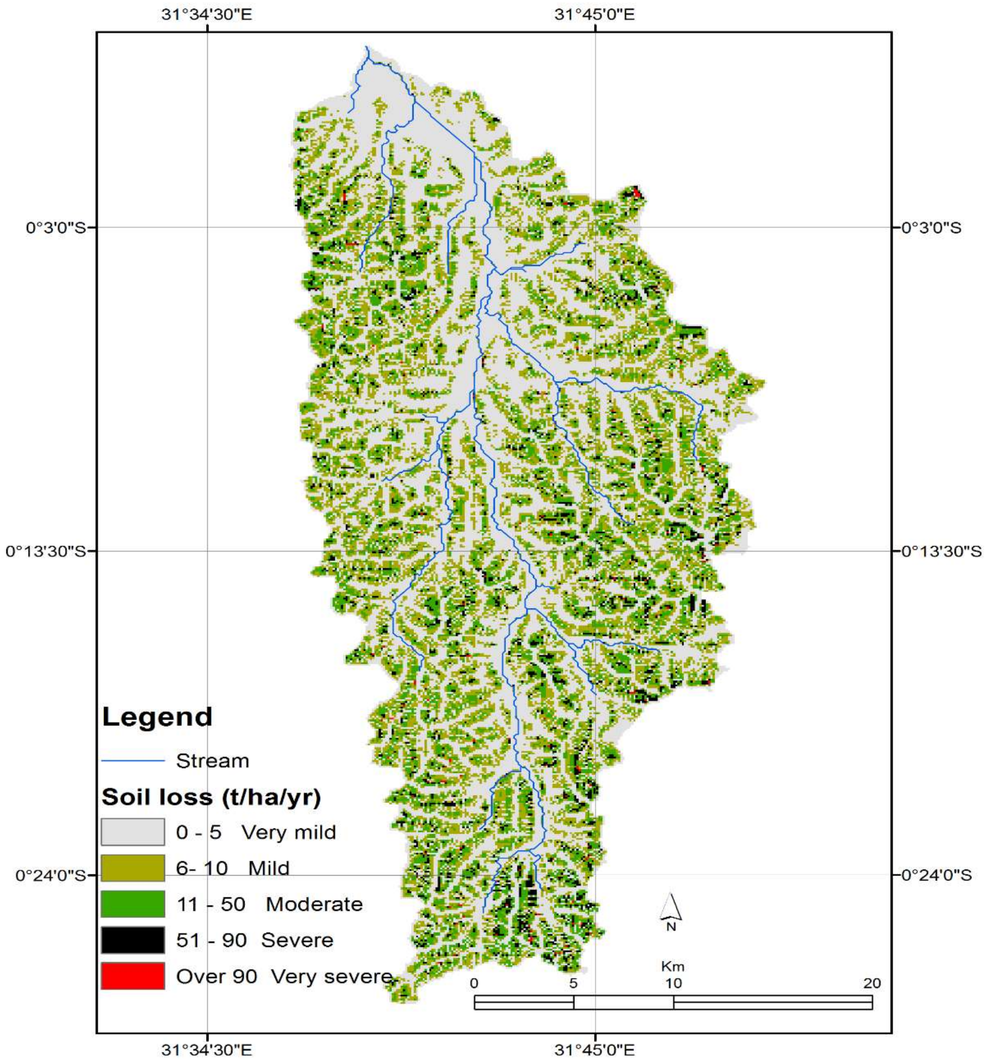

Figure 11: Erosion risk where P is modelled as a function of socio-economic factors in Nabajuzi watershed of Uganda

Table 2: Distribution of erosion risk as predicted by the SD model in Nabajuzi watershed

Erosion class	Soil loss rate (t $ha^{-1}yr^{-1}$)	Degradation risk rating	Spatial coverage in the watershed (%)
1	0 - 5	Very mild/negligible	16.24
2	6 - 10	Mild	24.22
3	11 - 50	Moderate	53.17
4	51 - 90	Severe	4.19
5	> 90	Very severe	2.18
Total			100.00%

3.3.2 Erosion risk by RUSLE model

The results of the maximum erosion risk expected when P factor is modelled as one (1) are presented in Figure 12. Deducing from Table 3, this map indicates that a greater portion (79.39% of the area coverage) is under mild to moderate; while 9.57% area faces severe to very severe risk of soil erosion. In addition to this, 11.14 % of this watershed is facing extremely severe risk of soil erosion. The variations in the rates and in risk of soil erosion is a manifestation of the differences in management practices adopted by farmers. Very severe risk of erosion is expected to occur in areas with scanty vegetation, steep slopes, soil with high erodibility, and soil with no management practices. The identification of such areas in a watershed is pivotal in planning for soil and water conservation.

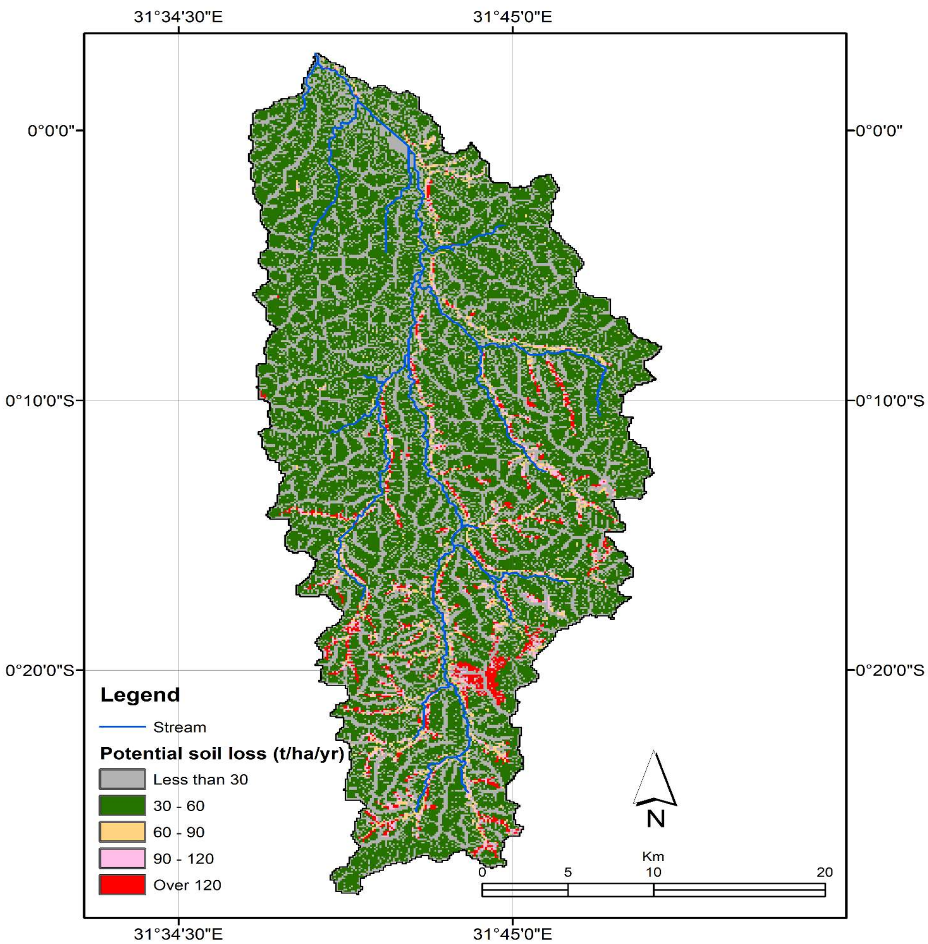

Figure 12: Maximum potential erosion risk where P is modelled as one (1) in Nabajuzi watershed of Uganda

Table 3: Distribution of erosion as predicted by RUSLE in Nabajuzi watershed

Erosion class	Soil loss rate (t $ha^{-1}yr^{-1}$)	Degradation risk rating	Spatial coverage in the watershed (%)
1	< 30	Mild	12.08
2	30 - 60	Moderate	67.21
3	60 - 90	Severe	03.34
4	90 - 120	Very severe	06.23
5	> 120	Extremely severe	11.14
Total			100.00%

4. Conclusions

Modeling the management factor (P) as a function of socio-economic drivers provides a solution to the uncertainty in its parameterization. Efficient erosion prediction is guided by accuracy of its parameters; and this is one of the key issues in soil and water conservation. Generalizing the P factor as one (1) over-estimates the risk of erosion; and it is a disincentive which undermines farmers' efforts to mitigate soil loss in degraded watersheds.

5. Conflicts of Interest: The authors declare no conflict of interest.

6. Appendices

Appendix A

Table 1: Results of the factors for adoption of erosion management practices

```
                                                    Number of observations =  390
                          LR chi2(10)    =     78.76
                          Prob > chi2    =    0.0000
Log likelihood = -100.11821              Pseudo R2     =    0.2823
Awareness_     | Coef.     Std. Err.   z     P>|z|     [95% Conf. interval]
------------------------------------------------------------------------------
Age            |-.645777   .3072047  -2.10  0.036**   -1.247887  -.0436669
Farmer income  |.6800275   .280724    2.42  0.015**    .1298185   1.230236
Family size    |.2707459   .0793255   3.41  0.001***   .1152707    .426221
Farm distance  |.5960017   .2119934   2.81  0.005**    .1805024   1.011501
Education      |.1772243   .0388721   4.56  0.001***   .1010363   .2534123
Farmer training|.0238471   .0140307   1.70  0.089*    -.0036526   .0513468
     _cons     |-2.854128  .7734741  -3.69  0.000     -4.37011   -1.338147
------------------------------------------------------------------------------
```

* Significant at P ≤ 0.1; ** Significant at P ≤ 0.05; *** Significant at P ≤ 0.01

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