1 Sediment management modelling in the Blue Nile Basin

2 using SWAT model

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11 Abstract

Soil erosion/sedimentation is an immense problem that has threatened water resources 12 13 development in the Nile, particularly in Eastern Nile (Ethiopia, Sudan and Egypt). An insight 14 into soil erosion/sedimentation mechanism and mitigation methods plays an imperative role for 15 the sustainable water resources development in the region. This paper presents daily sediment vield simulation in the Upper Blue Nile under different Best Management Practices (BMPs) 16 scenarios. Scenarios were existing condition, filter strips, stone bunds (parallel terrace), and 17 18 reforestation. The Soil and Water Assessment Tool (SWAT) was used to model soil erosion, 19 identify soil erosion prone areas and assess the impact of BMPs on sediment reduction. The study found satisfactory agreement between daily observed and simulated sediment 20 21 concentrations with Nash-Sutcliffe efficiency (NSE) = 0.88, percent bias (PBIAS) = -0.05%, 22 and ratio of the root mean square error to the standard deviation of measured data (RSR) = 0.3523 for calibration and NSE = 0.83, RSR = 0.61 and PBIAS = -11 % for validation. The sediment vield for baseline scenario was 117×10^6 tyr⁻¹. The filter strips, stone bunds and reforestation 24 25 reduced the sediment yield at the outlet of the Upper Blue Nile basin by 44%, 41% and 11%, 26 respectively. The sediment reduction at subbasins outlets varied from 29% to 68% by filter strips, 9% to 69% by stone bunds and 46% to 77% by reforestation. This study indicates that 27 28 BMPs are very useful in reducing sediment transport and could be used for reservoirs 29 sedimentation management in the Eastern Nile basin.

1 **1 Introduction**

2 The Blue Nile River, which originates from the steep mountains of the Ethiopian Plateau, is the 3 major source of sediment load in the Nile basin. Soil erosion upstream and the subsequent 4 downstream sedimentation has been an immense problem threatening the existing and future 5 water resources development in the Nile basin. The benefits gained by construction of micro-6 dams in the Upper Nile, have been threatened by the rapid loss of storage volume due to 7 excessive sedimentation (El-Swaify and Hurni, 1996; Tamene et al. 2006). Moreover, the green 8 water storage of the Ethiopian highlands, where rainfed agriculture prevails has been diminished 9 because of top-soil loss and this has caused frequent agricultural drought (Hurni, 1993; El-10 Swaify and Hurni, 1996). On the downstream part of the basin (e.g., in Sudan and Egypt) 11 excessive sediment load has demanded for massive operation cost of irrigation canals desilting, 12 and sediment dredging in front of hydropower turbines. For example, the Sinnar dam has lost 13 65% of its original storage after 62 yr operation (Shahin, 1993) and the other dams (e.g., 14 Rosieres and Khashm el Girba) lost similar proportions since construction (Ahmed, 2004). Both 15 the Nile Basin Initiative and the Ethiopian government are developing ambitious plans of water 16 resources projects in the Upper Blue Nile basin, locally called the Abbay basin (BCEOM, 1998; 17 World Bank, 2006). Thus, an insight into the soil erosion/sedimentation mechanism and the 18 mitigation measures plays an indispensable role for the sustainable water resources development 19 in the region.

20 Literature shows several catchment models that are proven to understand the soil 21 erosion/sedimentation processes and mitigation measures (Merritt et al., 2003; Borah and Bera, 22 2003). Nevertheless, there are a few applications of erosion modelling in the Upper Blue Nile 23 basin. These include Zeleke (2000), Haregeweyn and Yohannes (2003), Mohamed et al. (2004), 24 Hengsdijk et al. (2005), Steenhuis et al., (2009), and Setegn et al. (2010). Zeleke (2000) 25 simulated soil loss using the Water Erosion Prediction Project (WEPP) model and the result 26 slightly underestimated the observed soil loss in the Dembecha catchment (27,100 ha). 27 Haregeweyn and Yohannes (2003) applied the Agricultural Non-Point Source (AGNPS) model 28 and well predicted sediment yield in the Augucho catchment (224 ha). The same AGNPS model 29 was used by Mohamed et al (2004) to simulate sediment yield in the Kori (108 ha) catchment 30 and the result was satisfactory. Hengsdijk et al. (2005) applied the Limburg Soil Erosion Model 31 (LISEM) to simulate the effect of reforestation on soil erosion in the Kushet - Gobo Deguat 1 catchment (369 ha), but the result raised controversy by Nyssen et al. (2005). The SWAT model 2 was applied for simulation of a sediment yield by Setegn et al. (2010) in the Anjeni gauged 3 catchment (110 ha) and the obtained result was quite acceptable. Steenhuis et al. (2009) 4 calibrated and validated a simple soil erosion model in the Abbay (Upper Blue Nile) basin and 5 reasonable agreement was obtained between model predictions and the 10-day observed 6 sediment concentration at El Diem located at the Ethiopia-Sudan border.

Most of the above applications are successfully attempted to estimate sediment yield at small catchment scale or evaluate soil erosion model. Yet literature shows a lack of information on mitigation measures in the upper Blue Nile basin. Therefore, the objective of this study is to model the spatially distributed soil erosion/sedimentation process over the Upper Blue Nile basin at a daily time step and assess the impact of different catchment management interventions on soil erosion and ultimately on sediment yield.

A brief description of the Upper Blue Nile Basin is given in the next section, followed by discussion of the methodology used. The third section presents the model results and discussion of different land management scenarios. Finally, the conclusion summarizes the main findings of the investigation.

17 2 Description of study area

The Upper Blue Nile River basin has a total area of 184, 560 km², and is shown in Fig. 1. The 18 19 Ethiopian Plateau has been deeply incised by the Blue Nile River and its tributaries, with a 20 general slope to the northwest. The elevation ranges from 500 m at Sudan border to 4230 m at 21 the top of highlands. The Didessa and Dabus tributaries, draining the south-western part of the 22 basin contribute about one third of the total flow. The climate over the Blue Nile is governed by 23 the seasonal migration of the Inter Tropical Convergence Zone ITCZ from south to north and 24 back. The annual rainfall varies from 900 mm near the Ethiopia/Sudan boarder to 2200 mm over 25 Didessa and Dabus. Since the rainfall is highly seasonal, the Blue Nile possesses a highly seasonal flood regime with over 80% of annual discharge (~ 50 billion m³) occurring in the four 26 27 months from July to October, while 4% of the flow occurs during the driest period from January 28 to April (Sutcliffe and Parks, 1999). In the basin the minimum and maximum temperatures are 11 °c and 18 °c, respectively. The dominant soil types are Alisols and Leptosols 21%, followed 29 by Nitosoils 16%, Vertisols 15% and Cambisols 9%. 30

1 3 Methodology

2 3.1 SWAT model description

3 The Soil and Water Assessment Tool (SWAT) is a physical process based model to simulate 4 continuous-time landscape processes at catchment scale (Arnold et al., 1998; Neitsch et al., 5 2005). The catchment is divided into hydrological response units (HRU) based on soil type, land 6 use and slope classes. The hydrology computation based on daily precipitation, runoff, 7 evapotranspiration, percolation and return flow is performed at each HRU. The SWAT model 8 has two options for computing surface runoff: (i) the Natural Resources Conservation Service 9 Curve Number (CN) method (USDA-SCS, 1972) or (ii) the Green and Ampt method (Green and 10 Ampt, 1911). Similarly, there are two options available to compute peak runoff rate: (i) the 11 modified rational formula (Kuichling, 1989) or (ii) the SCS TR-55 method (USDA-SCS, 1986). 12 The flow routing in the river channels is computed using the variable storage coefficient method 13 (Williams, 1969), or Muskingum method (Chow, 1959). SWAT includes three methods for 14 estimating potential evapotranspiration: (i) Priestley-Taylor (Priestley and Taylor, 1972), (ii) 15 Penman-Monteith (Monteith, 1965) and (iii) Hargreaves (Hargreaves and Riley, 1985). 16 SWAT employs the Modified Universal Soil Loss Equations (MUSLE) to compute HRU-level 17 soil erosion. It uses runoff energy to detach and transport sediment (Williams and Berndt, 1977).

18 The sediment routing in the channel (Arnold et al, 1995) consists of channel degradation using 19 stream power (Williams, 1980) and deposition in channel using fall velocity. Channel 20 degradation is adjusted using USLE soil erodibility and channel cover factors.

21 3.2SWAT model setup

The SWAT model inputs are Digital Elevation Model (DEM), landuse map, soil map, and weather data, which is shown in Table 1. The ArcGIS interface (Winchell et al., 2007) for the SWAT2005 version was used to extract the SWAT model input files. The DEM was used to delineate the catchment and provide topographic parameters such as overland slope and slope length for each subbasin. The catchment area of the Upper Blue Nile was delineated and discretized into 15 subbasins using a 90 m DEM (<u>http://srtm.csi.cgiar.org</u>).

The landuse map of the Global Land Cover Characterization (GLCC) was used to estimate vegetation and their parameters input to the model. The GLCC is part of the United States Geological Survey (USGS) database, with a spatial resolution of 1 km and 24 classes of landuse representation (http://edcsns17.cr.usgs.gov/glcc/glcc.html). The parameterization of the landuse
classes (e.g. leaf area index, maximum stomatal conductance, maximum root depth, optimal and
minimum temperature for plant growth) is based on the available SWAT landuse classes. Table 2
shows the land use and land cover types and their area coverage in the Upper Blue Nile. The land
cover classes derived are Residential area 0.2%, Dryland Cropland 17%, Cropland 5.8%,
Grassland 2.5%, Shrubland 1.1%, Savanna 68.8%, Deciduous Forest 0.02%, Evergreen Forest
1.6%, Mixed Forest 0.7%, Water Body 2.2%, and Barren 0.4%.

8 The soil types for the study area were extracted from the SOIL-FAO database, Food and 9 Agriculture Organization of the United Nations (FAO, 1995). There are around 23 soil types, at a 10 spatial resolution of 10 km with soil properties for two layers (0-30 cm and 30-100 cm depth). 11 The soil properties (e.g. particle-size distribution, bulk density, organic carbon content, available 12 water capacity, and saturated hydraulic conductivity) were obtained from Batjes (2002).

The USGS landuse, the FAO soil and the slope class maps were overlaid to derive 1747 unique HRUs. Although the SWAT model provides an option to reduce the number of HRUs in order to decrease the computation time required for the simulation, we considered all of the HRUs to evaluate the watershed management intervention impact.

The daily precipitation and maximum and minimum temperature data at 17 stations interpolated spatially over the catchments were used to run the model. Most of the stations were either established recently or had a lot of missing data. Therefore, a weather generator based on monthly statistics was used to fill in the gaps. Solar radiation and wind speed were generated by the weather generator.

Daily river flow and sediment concentration data measured at El Diem gauging station (see Fig. 1) were used for model calibration and validation. The flow observations were available throughout the year, while the sediment concentration was usually monitored during the main rainy season, June to October. The Blue Nile water is relatively sediment free during the remaining months.

The model was run daily for 12 years; the period from 1990 to 1996 was used for calibration whereas the period from 1998 to 2003 was used for validation. The modelling period selection considered data availability and avoided rapid landuse/ cover change that was documented as alarming until the late 1980's by Zeleke et al. (2000) and Zeleke and Hurni (2001). Daily flow and sediment discharge were used to calibrate and validate the model at El Diem gauging station, located at the Ethiopia-Sudan border. Although we know that calibrating the model at subbasins outlet would improve the spatial parameter distribution, we could not perform it due to lack of data. Sensitivity analysis was carried out to identify the most sensitive parameters for model calibration using One-factor-At-a-Time (LH-OAT), an automatic sensitivity analysis tool implemented in SWAT (van Griensven et al., 2006). Those sensitive parameters were automatically calibrated using the Sequential Uncertainty Fitting (SUFI-2) algorithm (Abbaspour et al., 2004; Abbaspour et al., 2007).

8 **3.3 Model performance evaluation**

9 Model evaluation is an essential measure to attest the robustness of the model. In this study three 10 model evaluation methods - (i) Nash-Sutcliffe efficiency (NSE), (ii) percent bias (PBIAS), and 11 (iii) ratio of the root mean square error to the standard deviation of measured data (RSR) - were 12 employed following Moriasi et al. (2007) model evaluation guidelines. The Nash-Sutcliffe 13 efficiency (NSE) is computed as the ratio of residual variance to measured data variances (Nash 14 and Sutcliffe, 1970), see Eqs. (1).

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$$NSE = 1 - \left[\frac{\sum_{i}^{n} (X_{i}^{obs} - X_{i}^{sim})^{2}}{\sum_{i}^{n} (X_{i}^{obs} - X^{mean})^{2}} \right]$$
(1)

Where:
X_i^{obs} = observed variable (flow in m³/s or sediment concentration in mg/l).
X_i^{sim} = simulated variable (flow in m³/s or sediment concentration in mg/l).
X^{mean} = mean of n values.
n = number of observations.
The NSE value ranges between ∞ and 1; a value between 0 and 1 indicates acceptable model
performance whereas values ≤ 0 indicates the mean observed values is better than the simulated

25 values and hence, indicates unacceptable performance (Nash and Sutcliffe, 1970).

26 The Percent bias (PBIAS) measures the average tendency of the simulated data to be larger or

smaller than their observed counterparts (Gupta et al., 1999), see Eqs. (2).

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$$1 \qquad PBIAS = \left[\frac{\sum_{i}^{n} \left(X_{i}^{obs} - X_{i}^{sim}\right) \times 100}{\sum_{i}^{n} \left(X_{i}^{obs}\right)}\right] \tag{2}$$

The optimal value of PBIAS is 0, with low-magnitude values indicating accurate model
simulation. Positive values indicate model underestimation bias, and negative values indicate
model overestimation bias (Gupta et al., 1999).

5 The ratio of root mean square error to the standard deviation of measured data (RSR) is 6 calculated as the ratio of the Root Mean Square Error (RMSE) and standard deviation of the 7 observed data (Moriasi et al., 2007), see Eqs. (3):

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$$RSR = \frac{RMSE}{STDEV_{obs}} = \left[\frac{\sqrt{\sum_{i}^{n} \left(X_{i}^{obs} - X_{i}^{sim}\right)^{2}}}{\sqrt{\sum_{i}^{n} \left(X_{i}^{obs} - X^{mean}\right)^{2}}}\right]$$
(3)

10 RSR varies from zero (optimal) to a large positive value. The lower RSR, the lower is the
 11 RMSE, and hence better the model performance (Moriasi, et al., 2007).

According to Moriasi, et al. (2007) simulation judged as satisfactory if NSE > 0.5, RSR ≤ 0.70 and PBIAS= $\pm 25\%$ for flow and NSE > 0.5, RSR ≤ 0.70 and PBIAS= $\pm 55\%$ for sediment.

14 **3.4Catchment management intervention scenarios**

15 Catchment management intervention involves an introduction of best management practices 16 (BMPs) to reduce soil erosion and sediment transport. The SWAT model was applied to simulate 17 the impact of BMPs on sediment reduction in the USA (Vache et al., 2002; Santhi et al., 2005; 18 Bracmort et al., 2006). The BMPs were represented in the SWAT model by modifying SWAT 19 parameters to reflect the effect the practice has on the processes simulated (Bracmort et al., 20 2006). However, the type of BMPs and their parameter value selection is site specific and ought 21 to reflect the study area reality. Thus, we cautiously selected appropriate BMPs and their 22 parameter value based on documented local research experience in the Ethiopian highlands 23 (Hurni, 1985; Herweg and Ludi, 1999; Gebremichael et al., 2005). The three selected BMPs 24 were (i) filter strips, (ii) stone bunds (parallel terrace locally built from stone along the contour), 25 and (iii) reforestation. Each BMP has a different effect on flow and sediment variables and is represented by distinct parameter(s) in the SWAT model. Table 3 shows the SWAT parameters 26

used to represent BMPs. The parameter used to simulate the effect of filter strip is width of filter
 strip (FILTERW). The effect of stone bund was simulated using Curve Number (CN2), average
 slope length (SLSUBBSN) and USLE support practice factor (USLE_P). The reforestation effect
 was simulated by introducing land use change.

5 A total of four model scenarios were run as depicted in Table 3. In Scenario-0, the basin existing 6 condition was considered. In Scenario-1, filter strips were placed on all agricultural HRUs that 7 are a combination of dryland cropland, all soil types and slope classes. The effect of the filter 8 strip is that it filters the runoff and traps the sediment in a given plot (Bracmort et al., 2006). We 9 simulated the impact of filter strips on sediment trapping by assigning FILTERW value of 1m. 10 The FILTERW value was modified by editing the HRU (.hru) input table. This filter width value 11 was assigned based on local research experience in the Ethiopian highlands (Hurni, 1985; 12 Herweg and Ludi, 1999).

13 In Scenario-2, stone bunds were placed on agricultural HRUs that are a combination of dryland

14 cropland, all soil types and slope classes. This practice has a function to reduce overland flow,

15 sheet erosion and reduce slope length (Bracmort et al., 2006). We modified SLSSUBSN value by

16 editing the HRU (.hru) input table, whereas USLE_P and CN2 values were modified by editing

17 Management (.mgt) input table using the SWAT model interface. The SWAT model assigns the

18 SLSUBBSN parameter value based on the slope classes. In this application the assigned values

19 by the SWAT were 61 m, 24 m and 9.1 m for slope class 0-10%, 10-20% and greater than 20%,

20 respectively. The modified parameters values were SLSUBBSN is equal to 10 m for slope class

21 0-10% and 10-20% classes, USLE_P is equal to 0.32, and CN2 is equal to 59 as is depicted in

22 Table 3. The SLSUBBSN represents the spacing between successive stone bunds at field

condition and the modified value was used as reported by Hurni (1985) and Herweg and Ludi(1999). Similarly, USLE P value was obtained from documented field experience by

25 Gebremichael et al. (2005). The CN2 value was obtained from the SWAT user's manual version

26 2005 for contoured and terraced condition (Neitsch et al, 2005).

27 In Scenario-3, we simulated the impact of reforestation on sheet erosion. The reforestation has a

28 function to reduce overland flow and rainfall erosivity. It was deemed impractical to change

agricultural land into forest completely. Thus we replaced 8% of the area occupied by cropland,

30 shrubland, barren, mixed forest, and deciduous forest into evergreen forest. The evergreen forest

31 was selected since it has a wider coverage area than other types of forest in the study area, see

1 Table 2. The associated parameters (e.g., plant, hydrological and erosion) for the new landuse

2 were changed by the SWAT model from the database. The parameters used to simulate the effect

3 of reforestation on soil erosion were USLE cover factor (USLE C) and curve number (CN2) and

4 their values were assigned by SWAT model.

5 4 Results and discussion

6 The SWAT sensitive parameters and their calibrated values are shown in Table 4. Fourteen 7 parameters were sensitive for flow simulation and eleven parameters were sensitive for sediment 8 simulation. For brevity, three flow and four sediment sensitive parameters are discussed below. 9 The three sensitive parameters for flow are curve number (CN2), baseflow alpha factor (ALPHA BF), and recharge to deep aquifer fractions (RCHRG DP). The fitted parameter value 10 11 for CN2 was adjusted multiplying the typical value from the SWAT database by one plus -0.02. 12 While the fitted value for ALPHA BF, and RCHRG DP were 0.29 and 1.07, respectively. The four sensitive parameters for sediment were linear re-entrainment parameter for channel 13 14 sediment routing (SPCON), USLE cover factor (USLE C), exponent of re-entrainment 15 parameter for channel (SPEXP) and channel erodibility factor, (Ch Erod). The fitted value for 16 USLE C cover factor varies for different land cover and the assigned values were 17 USLE C{Cropland}=0.03, USLE C{Dryland-crop}=0.29, USLE C{Savanna}=0.17, 18 USLE C{Grassland}=0.35, and USLE C{Shurbland}=0.36. The calibrated values for SPCON, 19 SPEXP, Ch Erod were 0.01, 1.20 and 0.63, respectively. 20 The SWAT hydrology predictions were calibrated against daily flow from 1990 to 1996 and 21 validated from 1998 to 2003 at El Diem gauging station (Ethiopia-Sudan border). The model 22 flow predictions fitted the observed flow well as showed by acceptable values of the NSE, RSR 23 and PBIAS. The simulated daily flow matched the observed values for calibration period with 24 NSE, RSR and PBIAS is equal to 0.68, 0.57, and 10%, respectively. For the validation period, 25 the simulated daily flow matched the observed values with NES, RSR and PBIAS equal to 0.63, 0.61 and -8 %, respectively. Aggregated daily flow values into monthly average improved the 26 27 model results. The monthly flow simulation matched the observed for calibration period with 28 NES=0.82, RSR=0.42 and PBIAS=10% and NES= 0.79, RSR= 0.46, and PBIAS= -8% for validation. According to Moriasi, et al. (2007) flow simulation judged as satisfactory if NSE > 29

0.5, RSR ≤ 0.70 and PBIAS= ± 25%. Thus we found the model performance quite satisfactory
 both for calibration and validation periods.

3 A comparison between observed and simulated daily flow for the calibration and validation 4 periods is depicted in Fig. 2. The year 2001 is not presented in validation period since the 5 observed data is missing. The model slightly overestimated rising limb and slightly 6 underestimated recession limb in calibration and validation periods. This could be due to the 7 maximum soil depth (≤ 100 cm) that was obtained from the FAO data does not well represent the 8 soil depth distribution of the basin. In fact, literature shows that the soil depth of the basin is very 9 deep (>150 cm) in the south-west, moderately deep (100-150 cm) in the central, and shallow (30-10 50 cm) in the north-east and east (FAO, 1986; BCEOM, 1999). Thus, the model did not abstract 11 the right amount of precipitation before surface runoff generation. Subsequently, the simulation 12 was overestimated for the rising limb. This in turns caused less water storage in a shallow aquifer 13 and underestimated the base-flow for the receding limb. The model simulated the peak flow 14 during the calibration periods except in the year 1994. However, the model slightly 15 overestimated the peak flow in the validation period. There could be various reasons for the peak mismatch but it is most likely attributed to precipitation data since it had a lot of missing data. 16 17 Literature has also reported that precipitation data is the main constraint for accurate modelling 18 of discharge in the Blue Nile (Steenhuis et al., 2009). It is interesting that the model well 19 captured the rising and the falling limbs of the wet-season flow which is very important for 20 sediment simulation, which is shown in Fig. 3. 21 The SWAT sediment predictions were calibrated against measured data from 1990 to1996 and 22 validated from 1998 to 2003 at El Diem gauging station using daily sediment concentrations. 23 However, sediment concentrations data are available only for the rainy season, which occurs 24 from July to October. The calibration and validation periods model performance for the daily 25 sediment simulation is shown in Table 5. The model sediment predictions fitted the observed 26 concentrations very well as indicated by acceptable values of the NSE, RSR and PBIAS. The 27 simulated daily sediment concentrations matched the observed concentrations for calibration 28 period with NSE, RSR and PBIAS is equal to 0.88, 0.35, and -0.05%, respectively. The daily 29 simulated sediment concentrations for the validation period showed agreement with the observed 30 concentrations with NES, RSR and PBIAS equal to 0.83, 0.61 and -11 %, respectively. 31 Aggregating daily sediment concentrations into monthly average improved the model

1 predictions. The simulated monthly sediment concentrations matched the observed sediment

2 concentrations with NES= 0.92, RSR= 0.29, and PBIAS= -0.21% for calibration and NES= 0.88,

3 RSR= 0.34, and PBIAS= -11% for validation. Furthermore, we found our model performance

4 comparable to the recent results reported by Steenhuis et al. (2009). Their results stated that NSE

5 = 0.75 for the calibration and NSE=0.69 for the validation at El Diem gauging station.

6 The comparison between observed and simulated daily sediment concentrations for the 7 calibration and validation periods is shown in Fig. 4. The model well simulated sediment 8 concentrations on the rising and the falling limbs of the sediment hydrograph during the 9 calibration period. Although the sediment peak was well captured in most of the years, the model 10 slightly underestimated the peaks in 1993 and 1994. In contrast, the validation period 11 overestimated peak concentration except in 1998. The model well simulated the rising limb 12 sediment concentrations for the whole validation period. On the falling limb, however, the model 13 well simulated the sediment concentrations except in 2002 and 2003.

wen sinulated the sediment concentrations except in 2002 and 2005.

14 Assessment of spatial variability of soil erosion is useful for catchment management planning. 15 Fig. 5 shows the relative soil erosion prone areas in the Upper Blue Nile basin. The SWAT 16 model simulation shows the soil erosion extent varies from negligible erosion to more than 150 t/ha. The soil erosion in the basin classified into low (0-20 t/ha/yr), moderate (20-70 t/ha/yr), 17 18 severe (70-150 t/ha/yr) and extreme (\geq 150 t/ha/yr) categories. The low-class represents the 19 erosion extent less than the soil formation rates, which is 22 t/ha/yr in the Ethiopian highlands 20 (Hurni, 1983). The moderate-class represents erosion level less than the average soil loss from 21 cultivated land, which is 72 t/ha/yr (Hurni, 1985). The extreme-class represents one fold higher 22 than the average soil loss and the severe-class represents two folds higher than average soil loss. 23 The extreme erosion was observed in the cultivated land and low erosion was observed in the 24 savannah land. Subbasins 2, 3, and 4 were dominated by extreme soil erosion. Severe erosion 25 was dominant in subbasins 8, 9, 12, 13 and 15. Moderate erosion was dominant in subbasins 1, 5, 26 and 6; and low erosion was dominant in subbasins 7, 10, 11, and 14. These results indicate the 27 erosion variations within a subbasin and the basin that is helpful to prioritise BMPs 28 implementation area. Moreover, results showed that the sediment transport to the main river 29 decreases from the north-east to south-west of the basin. However, emphasis should be given to 30 relative erosion level than the absolute values because the model was not parameterized at outlets 31 of subbasins due to lack of data.

The observed average sediment yield at the outlet of the Upper Blue Nile was 131×10^6 tyr⁻¹. 1 The SWAT model predicted 117×10^6 tyr⁻¹ for the existing condition. This result is quite 2 comparable to 140×10^6 tyr⁻¹ estimate by NBCBN (2005) that includes bed load as well. The bed 3 4 load approximately accounts for 25% of the total load. However, running the model with 5 different catchment management scenarios provided very interesting results. The implementations of filter strips have reduced the total sediment yield to 66×10^6 tyr⁻¹ at El Diem, 6 7 equivalent to 44% reduction. The stone bunds have reduced the total sediment yield to 70×10^6 tyr⁻¹, equivalent to 41% reduction. The reforestation has given the least reduction of sediment 8 load $(104 \times 10^6 \text{ tyr}^{-1})$ at El Diem that is 11% reduction. The least sediment reduction by 9 10 reforestation attributed to smaller implementation area (8% of the total basin area) unlike the two 11 BMPs, which were implemented at 17% of the total basin area as is depicted in Fig. 6. In 12 addition, the effect of reforestation on sediment reduction is masked by higher sediment yield 13 from the agricultural land. The filter strips showed higher sediment reductions than stone bunds 14 for the equal implementation area. We found the BMPs efficiency rate on sediment reduction 15 quite within the range as documented in literature (e.g., Vache et al., 2002). 16 The impact of BMPs at subbasins scale showed a wider spatial variability on sediment reduction as is shown in Fig. 7. The sediment reduction varied from 29% to 68% by filter strips, 9% to 17 18 69% by stone bunds and 46% to 77% by reforestation. The least reduction for filter strips (29%) 19 and stone bunds (10% and 9%) were exhibited by subbasins 3 and 8. Conversely, the 20 reforestation has reduced the sediment yield by 46% in subbasin 3 and 8. It was observed that 21 filter strips and stone bunds effectiveness became greater as the agricultural area decrease and 22 the proportion of the area for slope class $\leq 20\%$ increase. This is expected because a higher 23 overland flow concentration occurs as the steepness and a field size increase. The reforestation 24 effectiveness became greater as the percent of agricultural area decrease in a subbasin. This was 25 expected because the sediment yield from agricultural area is higher, and subsequently, masks 26 the effectiveness of the reforestation on sediment reduction. 27 A comparison of percent of land placed in BMP and their effectiveness for each subbasin is 28 depicted Table 5. Filter strips and stone bunds effectiveness were the highest in subbasins 4, 1 29 and 5, higher in subbasins 6, 11, 13, 10, 12 and 14, and low in the rest of subbasins.

- 30 Reforestation effectiveness was the highest in subbasins 4, 1 and 14, higher in subbasins 9, 13, 5,
- 31 7, 5, 15 and 2 and low in the remaining subbasins. It is interesting that the highest reduction per

1 hectare was seen in the subbasins near the outlet. In general, the effectiveness of filter strips and 2 stone bunds are consistent except subbasins 3 and 8, which are characterized by the steepest 3 slope class. The effectiveness of reforestation is consistent in sediment reduction for the entire 4 subbasins. 5 It is important to note that the reforestation effect is higher at the subbasin level than at the basin 6 level. The reason is that the reforestation implementation area was proportional to filter strips 7 and stone bunds at the subbasin level. For instance, in the subbasin-1, agricultural land covers 8 1.7% and reforestation covers 1% of the total area. In the basin level, however, the reforestation 9 covers 8% and agricultural land cover 17% of the basin area, see Fig. 6. Thus, the effect of 10 reforestation in the basin level was masked by the higher sediment yield from agricultural land. 11 These results corroborate Santhi et al. (2005) findings that showed reductions in sediment and 12 nutrient up to 99% at farm level and 1-2% at the watershed level. 13 Comparison of BMPs sediment reductions to literature in the Ethiopian highlands showed that 14 results were reasonable. Filter strips sediment reductions were comparable to results reported by 15 Herweg and Ludi (1999). These researchers reported 55%-84% of sediment yield reductions by 16 filter strips on plot scale in the Ethiopian and Eritrean highlands. However, filter strips become 17 less effective as the scale increase from plot to field due to flow concentration (Dillaha et al., 18 1989; Verstraeten et al., 2006). For instance, Verstraeten et al. (2006) reported low (20%) 19 performance of filter strips due to overland flow convergence and sediment bypasses of filter-20 strips through ditches, sewers and culverts. However, we expect less overland flow convergence 21 in the Blue Nile since the average farm size is less than $\frac{1}{2}$ ha and the basin is unmanaged (e.g., 22 residential area is <1%). Thus, the low scaling effect observed in this study could be attributed to 23 this phenomenon. Stone bunds sediment yield reductions were quite comparable to results 24 reported in literature (Herweg and Ludi, 1999; Gebremichael et al. 2005). Herweg and Ludi 25 (1999) reported 72%-100% sediment yield reductions by stone bunds at plot scale in the 26 Ethiopian and Eritrean highlands. Gebremichael et al. (2005) reported 68% of sediment yield 27 reductions by stone bunds at field scale in the northern Ethiopia. It is worth noting that the 28 scaling effect between plot and field is minimal even at field observation. The reforestation 29 sediment yield reductions well agrees with Descheemaeker et al. (2005) that showed the 30 complete sediment yield reductions by reforestation of degraded land in northern Ethiopia. The

higher sediment yield reductions observed by Descheemaeker et al. (2005) was due to the
 reforestation areas were located down-slope from cultivated land.

3 5 Conclusions

The SWAT model was applied to model spatially distributed soil erosion/sedimentation process 4 5 at a daily time step and to assess the impact of three BMPs on sediment reduction in the Upper 6 Blue Nile River basin. The model showed the relative erosion prone area that is helpful for 7 catchment management planning. The total sediment yield for the existing condition at the basin outlet was 117×10^6 tyr⁻¹. Implementation of filter strips, stone bunds and reforestation have 8 9 reduced the sediment yield at the outlet of the Upper Blue Nile by 44%, 41% and 11%, 10 respectively. The reduction of sediment yield at 15 subbasins outlets varied from 29% to 68% by 11 filter strips, 9% to 69% by stone bunds and 46% to 77% by reforestation. These results showed 12 filter strips, stone bunds and reforestation are quite useful to reduce sediment yield in subbasins and the basin scales. However, their relative effectiveness are dependent upon the percent of land 13 14 allocated, percent of slope class and implementation location in subbasins and the basin. 15 Furthermore, the maximum benefit could be obtained by implementing the reforestation at a 16 steep areas and others two BMPs at a low slope areas of the catchment. 17 The model results indicate that BMPs are very useful in reducing sediment transport and could 18 be used for reservoirs sedimentation management in the Eastern Nile basin. An implementation 19 of catchment management measures to reduce sediment yield involves use of resources. This 20 type of research is very helpful for decision makers to evaluate the cost and benefits of BMP 21 implementation. Nevertheless, the quantitative results may have some limitation because BMPs 22 deterioration and gully erosion are not adequately represented in the SWAT model. Thus, more 23 emphasis should be given to the relative estimates of the erosion than the magnitude. 24 **Acknowledgements.** The authors thank the EnviroGRIDS@BlackSea project under FP7 call 25 FP7-ENV-2008-1, grant agreement No. 226740 for financial support of this research.

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Table 1. Spatial model input data for the Upper Blue Nile.
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Data type	Description	Resolution	Source	
Topography map	Digital Elevation Map (DEM)	90 m	SRTM	
Land use map	Land use classifications	1 km	GLCC	
Soils map	Soil types	10 km	FAO	
Weather	Daily precipitation and	17 stations	Ethiopian Ministry	
	minimum and maximum		of Water Resources	
	temperature			

Landuse	Description	Area (%)
Dryland Cropland	Land used for agriculture crop	
Cropland	Land area covered with mixture of croplands,	
	shrublands, and grasslands	
Grassland	Land covered by naturally occurring grass	
Shrubland	Lands characterized by xerophytic vegetative types 1.1	
Savanna	Lands with herbaceous and other understory	
	systems height exceeds 2 m height	
Deciduous Broadleaf	Land dominated by deciduous broadleaf trees	0.02
Forest		
Evergreen Broadleaf	Land dominated by evergreen broadleaf trees	1.6
Forest		
Mixed Forest	Land covered by both deciduous and evergreen trees	0.7
Water Body	Area within the landmass covered by water	
Barren	Land with exposed rocks and limited ability to support	
	life	
Residential Medium	Land area covered by structures such as town	0.2
Density		

Table 2. Land use/ Land cover types and area coverage in the Upper Blue Nile.

Scenarios	Description	SWAT parameter used			
		Parameter na	me (input file)	Calibration	Modified
				value	value
Scenario-0	baseline		-	*	*
Scenario-1	buffer strip	FILTERW <mark>(.1</mark>	nru)**	0	1 (m)
Scenario-2	stone-bund	SLSUBBSN	0-10% slope	61 (m)	10 (m)
		<mark>(.hru)</mark>	10-20% slope	24 (m)	10 (m)
			>20% slope	9.1 m	9.1 (m)
		CN2 <mark>(.mgt)</mark>		81	59
		USLE_P <mark>(.m</mark> g	<mark>gt)</mark>	0.53	0.32
Scenario-3	reforestation		-	*	*

Table 3. Scenarios description and SWAT parameters used to represent BMPs.

*Assigned by SWAT model.

** The extensions, .hru and .mgt are input files, where parameter value was edited.

Variable	Parameter name	Description	Fitted parameter
			value
Flow	r_CN2.mgt [*]	Curve number	-0.02
	vALPHA_BF.gw**	Baseflow alpha factor	0.29
	v_GW_DELAY.gw	Groundwater delay time	215.59
	v_GWQMN.gw	Threshold water depth in the shallow aquifer	-596.16
	v GW REVAP.gw	Ground water revap co-efficient	-0.46
	v_REVAPMN.gw	Threshold water depth in the shallow aquifer for revap	233.24
	v ESCO.hru	Soil evaporation compensation factor	0.58
	v RCHRG DP.gw	Recharge to deep aquifer	1.07
	v CH K2.rte	Channel effective hydraulic conductivity	4.22
	r_SOL_AWC.sol***	Available water capacity	0.54
	rSOL_K.sol	Saturated hydraulic conductivity	0.00
	rSURLAG.bsn	Surface runoff lag time	33.6
	rSLSUBBSN.hru	Average slope length	90.68
	v_CH_N2.rte	Manning's 'n' value for main channel	0.16
Sediment	v_USLE_C {Dryland}	USLE land cover factor	0.29
	v_USLE_C{Cropland}	Soil erosion land cover factor	0.03
	v_USLE_C{Savanna}	USLE land cover factor	0.17
	v_USLE_C{Grassland}	USLE land cover factor	0.35
	v_USLE_C{Shurbland}	USLE land cover factor	0.36
	v_SPCON.bsn	Linear re-entrainment parameter for channel sediment routing	0.01
	vSPEXP.bsn	Exponent of re-entrainment parameter for channel sediment routing	1.20
	rUSLE_P.mgt	Universal soil loss equation support practice factor	0.53
	vCh_COV.rte	Channel cover factor	0.71
	v Ch Erod.rte	Channel erodibility factor	0.63
	v_PSP.bsn	Sediment routing factor in main channel	0.12

Table 4. SWAT sensitive parameters and fitted values.

* The extension (e.g., .mgt) refers to the SWAT input file where the parameter occurs.

** The qualifier (v_) refers to the substitution of a parameter by a value from the given range.

*** The qualifier (r__) refers to relative change in the parameter where the value from the SWAT database is multiplied by 1 plus a factor in the given range.

	Agricultural	Filter strips			Reforestation
	HRUs area	effectiveness	Stone bunds	Reforestation	effectiveness
Subbasin	(%)	(%)	reduction (%)	area (%)	(%)
1	2	58	62	0.4	77
2	28	65	42	8	48
3	27	29	10	11	46
4	4	58	57	1	69
5	8	61	63	8	72
6	10	68	69	17	74
7	18	43	48	8	69
8	32	29	9	10	46
9	30	49	33	4	55
10	13	50	45	12	56
11	12	50	43	17	63
12	18	67	62	28	62
13	13	54	50	6	60
14	13	47	43	2	64
15	29	60	43	7	50

Table 5. Percent of land paced in BMPs and their effectiveness.

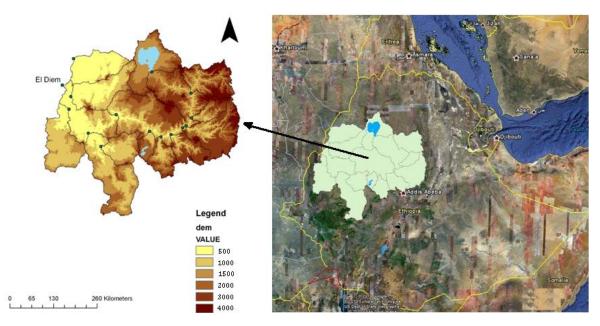


Figure 1. Location map of Upper Blue Nile.

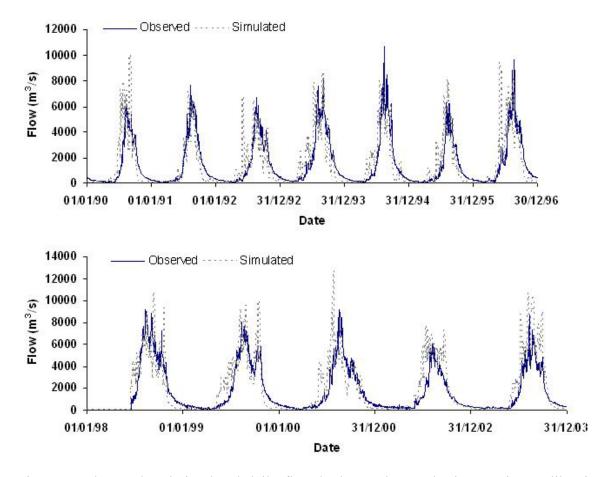
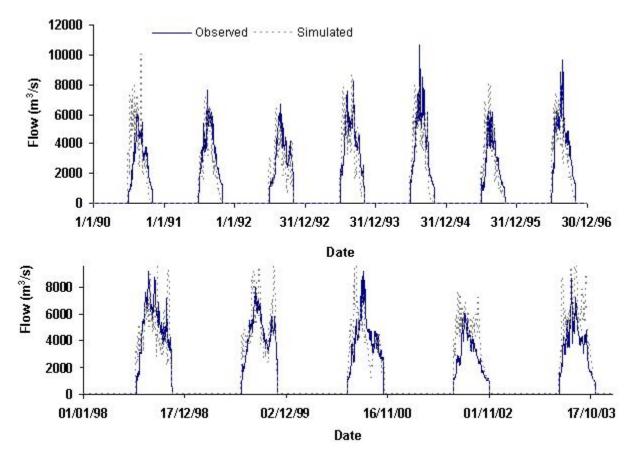


Figure 2. Observed and simulated daily flow hydrographs at El Diem station, calibration (top) and validation (bottom).



1 Fig. 3. Observed and simulated daily wet-season flow hydrograph at El Diem station, calibration

2 (top) and validation (bottom).

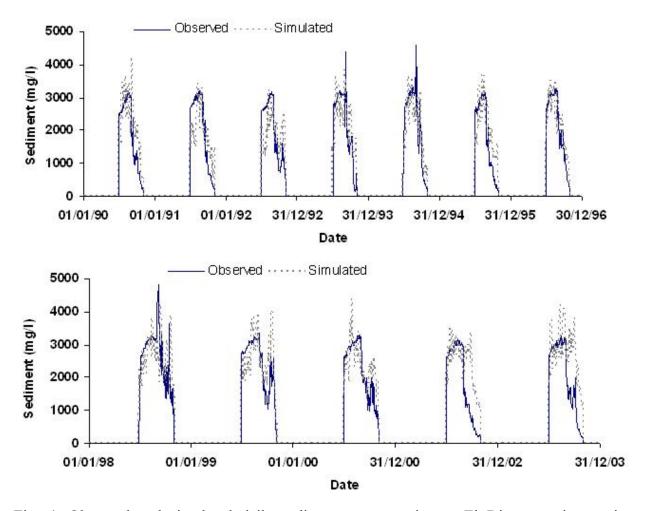


Fig. 4. Observed and simulated daily sediment concentration at El Diem gauging station, calibration (top) and validation (bottom).

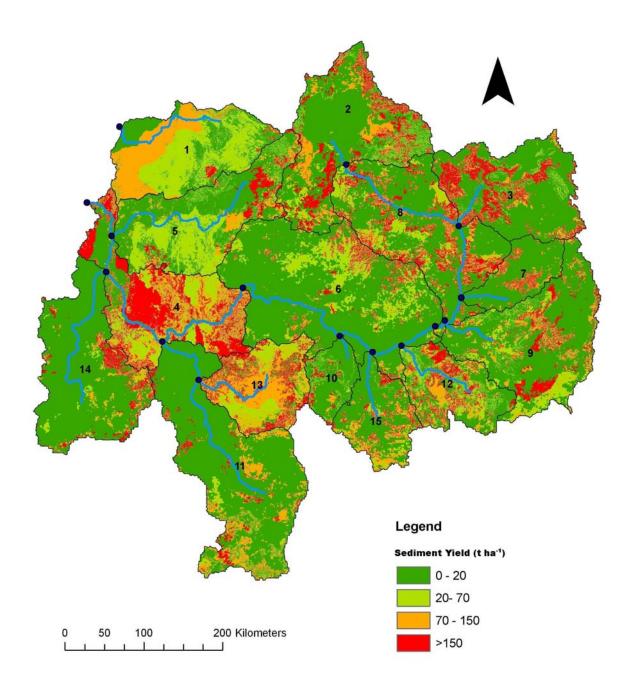


Fig. 5. Relative erosion prone area for existing condition in the Upper Blue Nile.

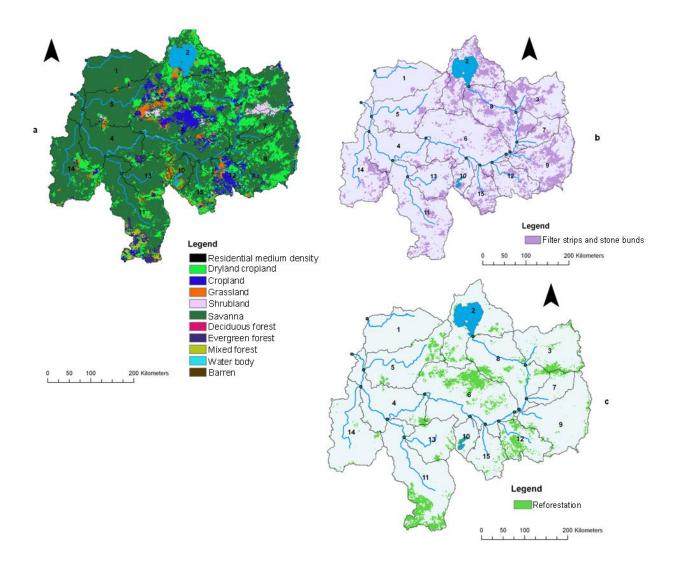


Fig. 6. Landuse (a), filter strips and stone bunds (b) and reforestation (c) maps of the Upper Blue
 Nile.

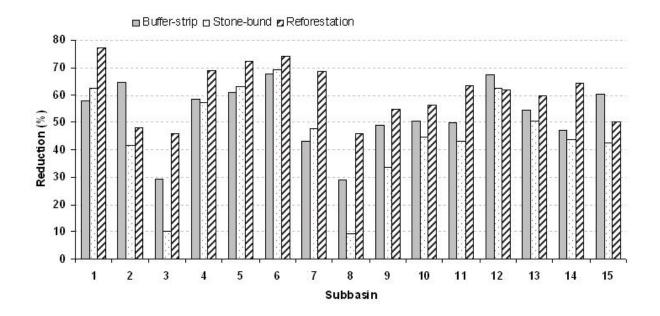


Figure 7. Percent reductions in sediment yield due to BMPs at subbasins level of the Upper Blue Nile basin (the basin outlet is located in the subbasin-4).