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Abstract: The assessment of the performance of (semi)distributed hydrological models has traditionally depended on parameters monitored at a gauging station usually located at the lowest end of a basin regardless of the size, complexity and spatial- temporal variations. The result of such an approach is that the processes in the basin are lumped by composting the catchment processes over time and space. The Soil and Water Assessment Tool (SWAT) model gives various outputs which are distributed all over the basin by use of the hydrologic response units (HRU). However, due to lack of physical location for the hydrological response unit, and their possible large number in a single watershed or even subbasin, it is physically impossible to monitor the flow, nutrients and sediments at all the outlets of these HRUs. The use of geographic information system (GIS) to overlay datasheets and the availability of gridded remotely sensed data for biomass, evapotranspiration, leaf area index (LAI) and yields in real time makes it possible to perform a dynamic quasi-distributed model validation. The SWAT model is used to test the applicability of remotely sensed variables on a 2905 Km^2 basin. The watershed is data challenged, geologically difficult, with dynamic land management practices, elevations from 800m to 3000m above sea level, and drastically changing climatic conditions from semi- arid to humid tundra/montane conditions. The concept of land use soil units (LUSU) created from overlaid soil and land use classes makes it possible to spatially compare outputs. Results indicate that under unfertilized soil conditions, simulated yields for annual agricultural crop types are underestimated due to water and nutrient stresses. Under stress conditions, soil type plays a big role due to the available water retention capacity and hydraulic conductivity parameters. With reduced nutrient stress the type of agricultural crop is the major determinant of the yields in the LUSU. Although remotely sensed Leaf Area Index values are higher than the simulated LAI, it mirrors to a great extent the timing and shape of the simulated LAI, and depicts comparable seasonality characteristics..

Keywords: LAI, yields, SWAT, remote sensing

1 INTRODUCTION

The calibration and validation procedures play an important role in watershed modeling. Utilization of a model without calibration may result in predictions substantially different from observed data (Arabi et al. 2006). Literature is awash with model applications where calibration has been performed using objective function either at a single or multiple monitoring sites in the watershed. Calibrations of most hydrological models have mostly been performed by comparing the simulated surface runoff, sediment yield, and nutrient concentration against observations at the watershed outlets (Luo et al. 2007). The major shortcoming of rainfall-runoff modeling, particularly in ungauged basins, is the lack of both long-term rainfall observations with sufficient spatial coverage and corresponding runoff observations that would allow for adequate model calibration and validation (Miller et al. 2002). The International Association of Hydrological Sciences (IAHS) defined an ungauged basin as "one with inadequate records of hydrological observations to enable computation of hydrological variables of interest at the appropriate spatial and temporal scales, and to the accuracy acceptable for practical applications" (Sivapalan et al. 2003). The quantification of the hydrological budget is extremely difficult over large spatial domains and over large time periods through direct observations, as insitu observations are labour intensive and expensive (Lakshmi, 2004). According to Sivapalan et al. 2003, and Srinivasan et al. 2010 different methods have been used to build hydrologic modeling systems in ungauged basins, including the extrapolation of response information from gauged to ungauged basins, measurements by remote sensing, the application of process-based hydrological models in which climate inputs are specified or measured, and the application of combined meteorological-hydrological models that do not require the user to specify precipitation inputs. Other parameters that have gained increased use in spatial model calibration include the Evapotranspiration (ET), biomass, the leaf area index (LAI), and the crop yield. LAI represents the size of the interface between the plant and the atmosphere for energy and mass exchanges. It is thus of prime interest for energy balance, photosynthesis, transpiration and litter production. LAI could be used to validate canopy photosynthesis models which simulate growth and canopy development based on climate and environmental factors (Baret et al. 2006). Crop yield or biomass generally accounts for both evapotranspiration and soil moisture required for vegetative growth, and can therefore be used as an alternative for evaluating combined actual evapotranspiration (AET) and soil moisture within the hydrological budget (Srinivasan et al. 2010). These indices are either measured in the field or generated from remote sensing. Lakshmi (2004) noted that Satellite data represent a wealth of information, which can bridge the gap between point measurements and computer-based simulations, and that larger basins (100–10 000 km^2) are perfect locations for the use of satellite and radar data, as they will have multiple pixel coverage. Satellite remote sensing is an attractive tool for crop area and Net Primary Productivity (NPP) estimates because it provides spatial and temporal information on the location and state of crop canopies (Moulin et al.1998). There are few published studies on the calibration of SWAT model using vegetation parameters, the two most notable applications are by Luo et al. 2007 and Srinivasan et al. 2010. Luo et al. 2007 assessed the performance of the soil water module in simulating the water stress to crop growth by comparing the observed and simulated LAI amongst other things. They concluded that, overall, the crop growth and soil water modules of the SWAT2000 performed well in simulating wheat LAI, biomass, and soil water moisture. Srinivasan et al. 2010 evaluated the performance of SWAT hydrologic budget and crop yield simulations in the Upper Mississippi River basin (UMRB) without calibration. They compared uncalibrated SWAT model predictions of streamflow and crop yield with observed data from 11 streamflow locations and 14 four-digit hydrologic unit codes (HUC) basin level for crop yield. Their results showed that, except for only two HUCs, the SWAT model predicted observed yield well with a small percent bias (PBIAS).

The need to perform a distributed validation was necessitated by the fact that the 2905 km^2 watershed has a complex hydrographic and agroclimatic profiles making the use of one monitoring site ineffectual. Furthermore, the three river gauging stations available within the stations have data of questionable quality (Kilonzo et al. 2012). The objectives of this article are therefore to; (1) Perform SWAT calibration for streamflow while maintaining parameter values within realistic ranges and preserving the annual water balance for the major components of the hydrologic cycle, (2) validate the streamflow calibrated SWAT model using other watershed parameters like LAI and crop yields obtained from both remote sensing and field observation data.

2 MATERIALS AND METHODS

2.1 Study Area Description

The study area covering 2905 Km^2 is delimited by escarpments to the north, and the protected reserves of the Masaai Mara ecosystem to the south, figure 1. Rainfall varies with altitude with mean annual rainfall ranging from 1600 mm in the Escarpment to 800mm in the plains. Economic activities roughly follow the elevation aggregation with grazing and subsistence agriculture in the low areas, forest and plantation tea growing in the mid-section and mixed farming in the upper sections. The area is underlain by undifferentiated pyroclastic materials consisting mainly of poorly consolidated volcanic tuffs and volcanic ashes, which are widespread in the area and are frequently altered into clay in the upper escarpment area.

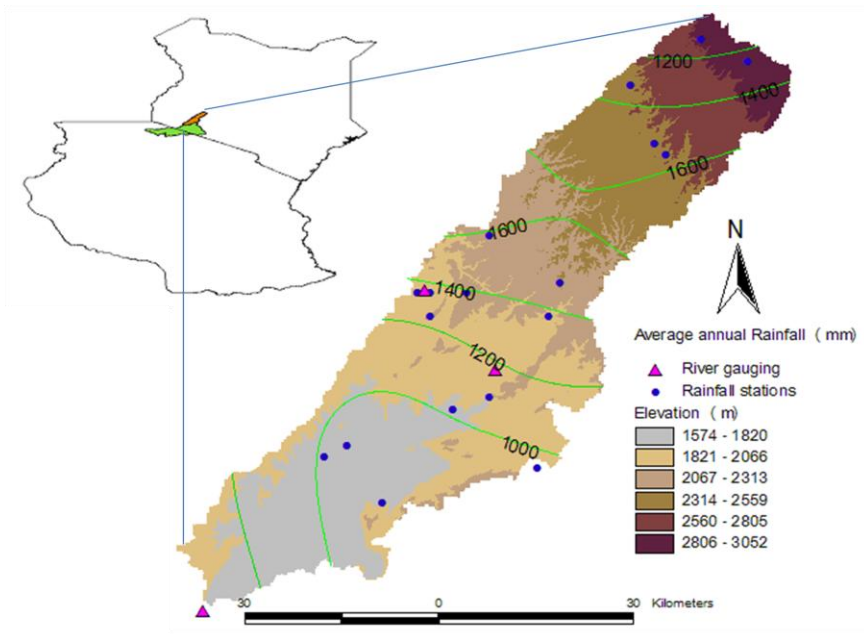

Figure 1. The study area as part of the larger Mara river basin

2.2 SWAT Model Description

The Soil and Water Assessment Tool (SWAT) is a dynamic, long-term, distributed parameter model (Arnold et al. 1998) with applications in watersheds having agriculture as the primary land use (Manguerra and Engel, 1998). SWAT uses the Erosion Productivity Impact Calculator (EPIC) crop model (Williams et al. 1989) concepts of phenological crop development based on daily accumulated heat units, harvest index for partitioning grain yield, Monteith approach for potential biomass, and water and temperature stress adjustments. A single model is used for simulating all the crops considered and SWAT is capable of simulating crop growth for both annual and perennial plants. Annual crops grow from planting date to harvest date or until the accumulated heat units equal the potential heat units for the crop. Perennial crops maintain their root systems throughout the year, although the plant may become dormant after frost (Arnold et al. 1998). The LAI is simulated as a function of heat units and biomass, while the crop yield is estimated from the series of model operations in the growth cycle and the optimal growth. Crop yield is estimated in each HRU from the above ground biomass and a harvest index (HI).

2.3 SWAT Model Inputs

Input data for the SWAT model setup was accessed from different sources. The daily stream flow data were obtained for the Water Resources Management Authority, Kenya. Climatic data were obtained from the Kenya meteorological department. Two types of remote sensed databases were used to identify both cropped areas and wells as type of crops in the study area. Landsat Enhanced Thematic Mapper Plus (ETM+) imagery for February 2006 (considered the driest month in the area and hence the best to separate annuals from perennials) were obtained from the Glovis website of the U.S. Geological Survey. The SPOT-VEGETATION (VGT-S10) ten day maximum value composite (MVC), normalized difference vegetation index (NDVI) images for 04/2007-03/2010, and the Leaf area index (LAI) for 08/2007-03/2011 were accessed from the Flemish Institute for Technological Research (Vito) website. Soil data and digital elevation models (DEM) were accessed from global databases.

2.3.1 Land Use/Land Cover

Both unsupervised and supervised classification procedures were performed on the Landsat ETM+ image to derive land cover map. A Level-1 land cover map recommended for Landsat images in the Anderson Classification system (Anderson, 1976) featuring four Land Cover classes was developed. The classes definitions used included: Forest, Shrubland, Cropland, and Grassland. The Iterative Self Organizing Data Analysis (ISODATA) technique in ERDAS was used to perform initial unsupervised classification of the SPOT-VEGETATION NDVI data. The land cover map developed from Landsat was used to mask the natural and semi natural vegetated areas which represented the forest and shrubland cover classes. Once masked, time series data for the remaining areas representing cropland and grassland were extracted using the TIMESAT tool (Jönsson and Eklundh, 2002). Output from the TIMESAT program is a set of files containing seasonality parameters; beginning of season, end of season, amplitude, integrated values, derivatives, etc, as well as fitted function files containing smooth renditions of the original series. The phenological parameters derived from the TIMESAT program for different clusters were compared with both the crop calendar for the common crops and suitability maps to arrive at a land use map of the area. The NDVI derived landuse map which features a level 2 crop related landuse classification is a more detailed upgrade of the Landsat derived land cover map enabling the comparison of simulated data with field measured/observed data. The developed land use map had an overall accuracy of 76% and Kappa = 0.68.

2.3.2 Watershed Decomposition

The SWAT model delineates a watershed to subwatersheds, subbasins and Hydrologic response units (HRUs). HRUs are portions of the subbasin that possess unique landuse/management/soil scenarios (Nietsch, 2002). HRU have no spatial location, as they are a result of lumping of similar soil and landuse areas into a single response unit. A new term referred to as land use soil unit (LUSU) is proposed in this study to represent a physical location on the ground with a soil layer overlaying a given land use layer. The differences between the LUSU and the HRU are; 1). A given point in the watershed has a unique landuse and soil type. 2). there are fewer LUSUs than HRUs in a watershed since HRU is defined in the subbasin, while LUSU is basinwide (ie repeat HRU are not considered in LUSU). The purpose of the LUSU is to make it possible to assess the vegetation response to hydrological processes at any point by use of measurable and available metrics like yield, biomass and LAI. For this study all the 12 land use and 19 soil classes were used in the overlaid map with 0% threshold resulting into 75 HRUs and 50 LUSUs. Four crop related land use classes resulted into 17 LUSUs which are used in this study for the comparison of the measured and simulated yield and LAI.

2.4 Model Set Up

The model was run using the AVSWATX interface. Autocalibration for streamflow was performed with the ParaSol method in SWAT2005 for the most sensitive parameters, including the CN, ESCO, Rchrg_DP, SOl_AWC, GWQMN, and CH-K.

2.5 Model Evaluation

2.5.1 Streamflow

Hydrological models can be assessed either by their goodness of fit to statistical measures based on an objective function or by comparison to the water mass balance in the watershed. For this study the model is calibrated more for physical agreement to the watershed characteristics than for numeric fitness ie optimized for water balance than statistical parameters so as long it meets the threshold for acceptability. The goodness-of-fit measures used were the Nash-Sutcliffe efficiency (ENS) value (Nash and Sutcliffe, 1970), the percent bias (PBIAS) and the Root Mean Square Error-observations standard deviation ratio (RSR).

2.5.2 Crop Yield

Crop yield data was collected from a stratified multistage cluster designed field study conducted in the months of July and August 2011. The study involved interviewing of 102 farmers spread over 17 (out of 55) locations.

2.5.3 Leaf Area Index (LAI)

LAI is the one sided area of green elements per unit leaf horizontal soil, and represents the quantity of foliage in the pixel area, LAI=0 corresponds to bare soil; LAI=5 or 6 characterizes a dense canopy. The SPOT-VEGETATION LAI is supplied by the VGT4Africa project at a 10-day temporal frequency, and a 1km spatial resolution (Baret et al. 2006). The time series for the LAI were extracted using the TIMESAT tool ((Jönsson and Eklundh, 2002), and the digital number values divided by 30 to get physical (real) LAI values (hereafter referred to as RS-LAI).

3 RESULTS AND DISCUSSION

3.1 Streamflow

Tables 1 show the annual water balance and monthly statistics for the calibrated SWAT model. The water balance components of total yield and baseflow are within ±5% of the observed fractions. The statistical indices ENS and PBIAS are within the "satisfactory" and "Good" rating respectively according to Moriasi et al. 2007 criterion of ENS > 0.5, PBIAS <±25 and RSR > 0.7 for stream flow.

Table 1. Model performance for annual water balance

	Mass balance (mm)						Goodness of fit parameters		
	Water yield	GW flow	Lateral flow	Baseflow	Surface flow	Baseflow Fraction,%	ENS	PBIAS	RSR
Observed (O)	234.2			167	67	71			
Simulated (S)	240.8	124.6	33.84	158.5	81.79	66	0.51	-12.34	0.73
% diff= (O-S)/O	-3			5	-22				

3.2 Crop Yields

The performance on the SWAT model was assessed using both default yields without and also with fertiliser application at a rate of 100kg/Ha. From sampled farmers, the commonly used fertilizer was Di-Ammonium Phosphate(DAP) (18:46:0), with application rate ranging from 9 to 247 Kg/Ha, a mean of 116 Kg/Ha and Standard deviation of 65 Kg/Ha. Since fertilizer in Kenya is packaged in 50kg bags, 100kg (2 bags) was selected as the nominal rate. Table 2, shows the comparison of the results for both crop and the soil types. For unfertilized yields, there is no statistical difference (p=0.95) between the different agricultural classes. However there is a significant difference in yields between soil types. The simulated yields are lower than the measured yields. The unfertilised scenario has water stress (W_STRS) for as many as 50 days and upto 144 days of Nitrogen stress (N_STRS). There was significant increase in yields with fertiliser application. All LUSUs had higher simulated yields than the observed, which is understandable since the model assumes optimum management practices like pest control and temperature conditions. The nitrogen stress was reduced by half for all agricultural classes. There is no marked difference between the soil types after fertilizer application, meaning that some soils are naturally more N-stressed than others.

3.3 Leaf Area Index

The LAI time series for the different agricultural LUSUs corresponding to the period when the land use maps were made 2008-2010 were extracted from the remote sensed VGT4Africa LAI maps, and compared with the LAI values obtained from the SWAT simulation (figure 1). The remote sensed values are higher than the simulated SWAT values but resonate well with literature values obtained in the region (Mburu et al. 2011). RS-LAI captures all the green activity on the ground unlike the SWAT model which simulates plant growth for only a single crop at a time. The shape of the graphs for both remote sensed and simulated LAI has a clear seasonality correctly representing the phenological profile of agricultural crops. The SWAT model is able to predict the timing of the start and the stop of the growing season. The model was able to correctly lag the growing profile for the upland corn crop (MAIZ) in a way similar as predicted by the RS-LAI.

Table 2. Average annual yields mton/Ha for both soil type and agricultural type

	Yields, mton/Ha				Yields, mton/Ha		
	observed	Simulated			observed	Simulated	
Soil type		Unfertilized	Fertilized	Soil type		Unfertilized	Fertilized
Ps7	3.24	0.74	3.91	F4	1.95	0.81	5.25
Pn7	2.90	0.73	4.17	Pn4	1.82	0.77	4.72
Pc6	2.73	0.83	2.25	L25	1.67	1.07	4.73
F10	2.67	0.85	4.05	Pn6	1.66	0.78	4.1
F17	2.58	2.48	4.12	Pn11	1.64	0.78	4.7
H16	2.49	0.49	3.34	A14	1.53	0.74	4.48
Up2	2.26	2.33	4.49				
Agric type	**Observed**	**Unfertilized**	**Fertilized**	**Agric type**	**Observed**	**Unfertilized**	**Fertilized**
AGRL	3.5	0.65	2.8	CORN	2.78	1.09	4.2
MAIZ	2.85	0.97	5.7	AGRG	0.67	0.82	3.7
Key							
MAIZ=Upland maize,		AGRG=Row crops		AGRL=Closely grown crops		CORN=Lowland Maize	

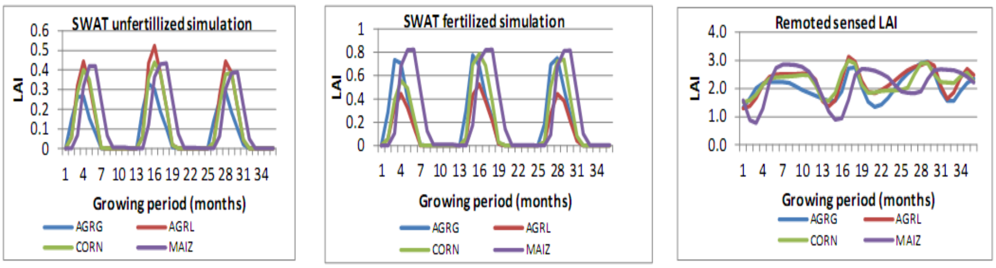

Figure 2. Leaf area index (LAI) values for a three year simulation period and corresponding remotely sensed LAI

4 CONCLUSIONS

The availability of remotely sensed data of adequate spatial and temporal resolution makes their use possible in the calibration and /or validation of hydrological models. Hydrological model which have been satisfactorily calibrated in a lumped way by use of a point monitored parameters like flow, sediment or nutrient, maybe validated further in distributed fashion by of use readily available remotely sensed or observed data. The SWAT hydrological model has been successfully used to demonstrate the application of combined remotely sensed and field observed data for validation of especially agricultural land use classes. The results suggests that the SWAT model may therefore be used to indicate and isolate some of the environmental and management stresses. By allowing for the comparison of optimized scenarios and actual recorded outputs, the model identifies management parameters which influence the crop productivity, thus helping in implementation of interventional management measures. Since SWAT is not a crop model per se, the results obtained should however be collaborated with other sources and expertise.

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