SWAT (Soil and Water Assessment Tool) simulation of forest interventions on stream discharge and sediment yield in the Western Area Peninsula, Sierra Leone

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This document provides an overview of available data sets and methodology used to assess potential impacts of land management and proposed forest related interventions for the Freetown Water Fund. A primary barrier to using the Soil and Water Assessment Tool (SWAT; http://swat.tamu.edu/) in many regions of Africa is the lack of current hydrological and meteorological data and there are no known stream discharge data available for the Western Peninsula Area. Similarly, other than average monthly precipitation in the city of Freetown, there are no other known monthly or daily precipitation data available.

What is SWAT

SWAT was originally designed to use in large ungauged agricultural basins to assess the relative impact of land management decisions on a variety of water quality and quantity parameters (Neitsch *et al.*, 2011; Arnold and Fohrer, 2005). While originally intended for use in the United States, the model has been adapted for use worldwide, including throughout Africa. Strengths of the SWAT model are that it can be set up using available global data and then be used to rapidly assess and develop an understanding of long-term impacts on annual or seasonal water balance resulting from potential climate or management changes. With SWAT, we can model a wide variety of surface and channel processes and gain insight into how they are affected by changes in land management (Figure 1).

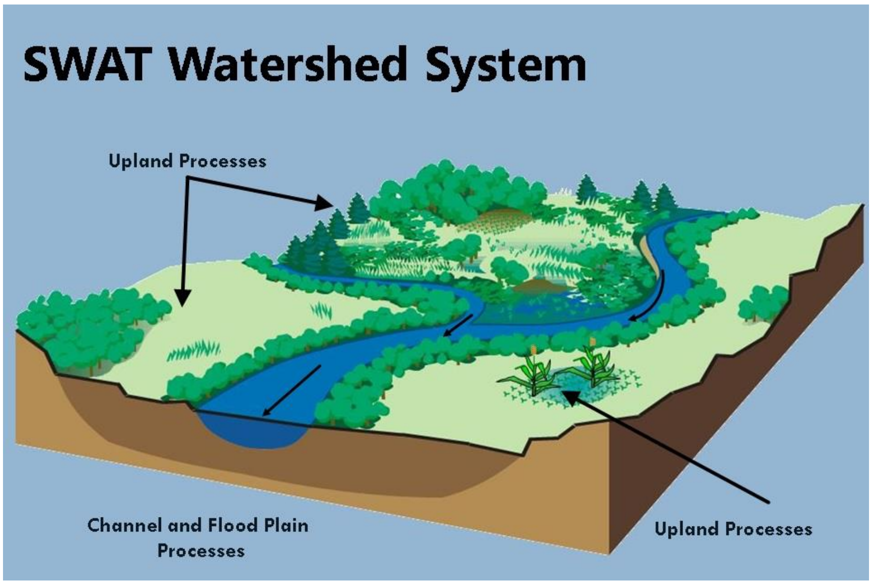

Figure 1. SWAT can model upland and channel processes, allowing users to also assess processes such as erosion (using the Modified Soil Loss Equation), flood routing, sediment routing, evapotranspiration, crop growth, and others.

SWAT is a physically-based, empirical, semi-distributed hydrologic model that can operate at annual, monthly, and daily time steps. What this means is that:

1) *Physically-based and empirical:* SWAT is based on known physical processes depicting hydrology and other processes such as soil erosion, plant growth, and evapotranspiration among others.
2) *Semi-distributed:* The model subdivides a landscape, such as the Western Area Peninsula into smaller units based on topography. Common language used in describing a SWAT watershed is

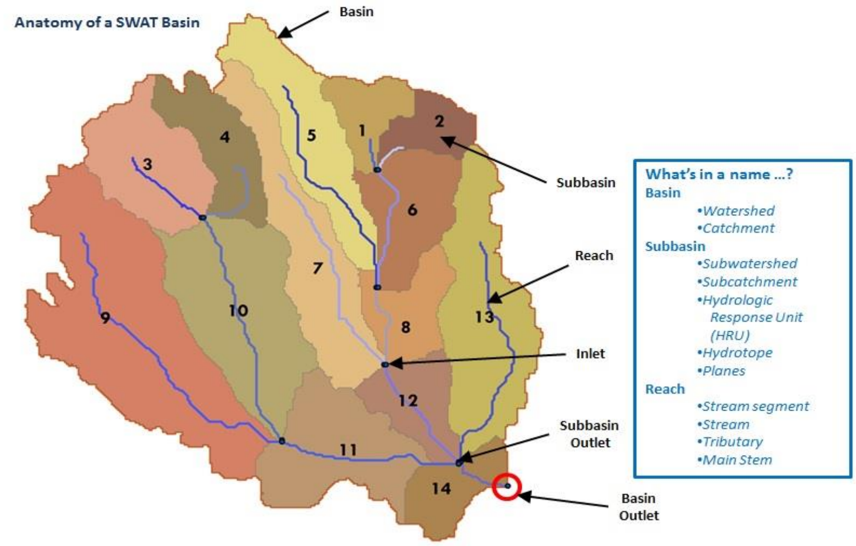

Figure 2. Common terminology used in describing parts of a basin. SWAT divides a basin into subbasins, which can be further divided into individual hydrologic response units (a unique combination of land cover, soils, and topography). Sometimes you may hear alterative names (bullet points) used.

illustrated in Figure 2. SWAT subdivides a basin into smaller subbasin units, each consisting of one reach and a single inlet and outlet. SWAT can further subdivide subwatersheds into hydrologic response units (HRU), having common soils, land cover, management. A subbasin can consist of one or many HRUs.

SWAT is a complex hydrological model with hundreds of parameters that implements numerous physical equations or other models to calculate a variety of water quantity and quality parameters. Some examples of SWAT's main governing equation are detailed here.[1]

SWAT implements the well-established Soil Conservation Service Curve Number (SCS – CN; SCS, 2004) method to calculate runoff using an empirical water balance relationship:

$$Q = \frac{(P-0.2S)^2}{P+0.8S} \qquad \textit{Eqn. 1}$$

Where, Q is the direct runoff (mm); P is the total rainfall (mm); and S = 1000/CN, with CN (curve number) related to soil and land cover conditions, and commonly estimated from published tables (or tables generated by experienced hydrologists for specific locations).

When the spatial data are combined (Figure 3) and used in conjunction with the SCS-CN (Eqn. 1), this information can be used to calculate a water balance for each unit, which in its simplest form is defined as:

$$P = Q + ET + \Delta S \qquad \textit{Eqn. 2}$$

Where, P is the total rainfall (mm); Q is the direct runoff (mm); ET is evapotranspiration, and ΔS is the change in storage (groundwater).

Erosion and sediment yield in SWAT are calculated using the Modified Universal Soil Loss Equation (MUSLE; Williams, 1975) at the smallest spatial unit defined in the model, the HRU. The benefit here, particularly in data scarce regions, is that MUSLE relies on runoff rather than erosive energy of rainfall. MUSLE is given by:

$$sed = 11.8(Q_{surf} \times q_{peak} \times area_{hru})^{0.56} \times K_{USLE} \times C_{USLE} \times P_{USLE} \times LS_{USLE} \times CFRG \qquad \textit{Eqn. 3}$$

Where, sed is the sediment yield on a given day (metric tons); Q is the surface run off volume (mm H_2O ha^{-1}); q_{peak} is the peak runoff rate (m^3s^{-1}); $area_{hru}$ is the area of the HRU (ha); K_{USLE} is the USLE soil erodibility factor [0.013 metric ton $m^2h/(m^3$-metric ton cm)]; C_{USLE} is the USLE cover and management factor; P_{USLE} is the USLE support practice factor; LS_{USLE} is the USLE topographic factor; and $CFRG$ is the coarse fragment factor.

[1] Full theoretical documentation on SWAT can be found at https://swat.tamu.edu/media/99192/swat2009-theory.pdf and https://swat.tamu.edu/docs/.

Basic water balance elements, along with other variables related to both water quality and quantity are derived through its application and may be output as daily, monthly, or annual information. This information may be transformed in a variety of ways useful to land management activities, such seasonal analyses at the basin level or smaller units, such as subbasins and HRU.

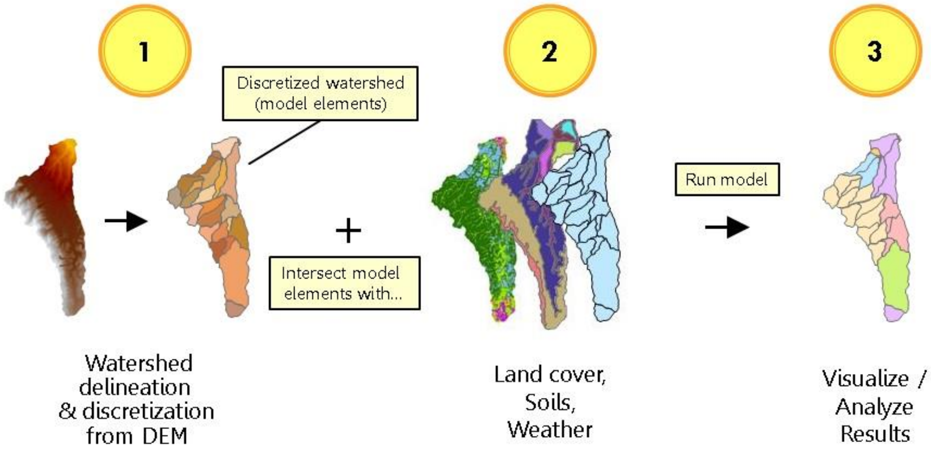

Figure 3. A visual representation of how topography, land cover, soils, and weather intersect.

Due to its deterministic nature, each successive SWAT run that uses a given set of inputs will produce the exact same outputs each time the model is run. If a user modifies an input, such as climate or land management, however, the output may change. This allows users to isolate the response to that specific given change. In this way, SWAT is an excellent model for exploring alternative land management scenarios or interventions and how they are likely to modify the water balance, and this is the most basic function of the SWAT model.

In addition, SWAT is able to derive more complex information about a basin when detailed site specific data are available and combined with stream discharge, sediment, or other water quality information collected in the field and used to calibrate key model parameters to achieve improved agreement between the model outputs and the real world. In the absence of field data for calibration, parameter regionalization or remotely sensed data, such as soil water content or evapotranspiration, may be used in model calibration. Modelers may work with published literature on local hydrological processes, regionalize model parameters by looking at a nearby gauged watershed with similar biophysical characteristics (*e.g,* land cover, topography, and climate), or local experts and use their knowledge as a foundation to improve model calibration.

Data

An overview of datasets used to set up and run scenarios in SWAT for the Freetown Water Fund is provided in Table 1 and described further in subsequent sections.

Table 1 Data sources used in this assessment

Data	Spatial Resolution	Temporal Resolution	Source
DEM	12.5m	-	https://asf.alaska.edu/data-sets/derived-data-sets/alos-palsar-rtc/alos-palsar-radiometric-terrain-correction/
2016 Land Cover	20m	-	http://2016africalandcover20m.esrin.esa.int/
Canopy Density	30m		https://www.terrapulse.com/terraView/
AfSIS Soils		-	http://africasoils.net/
Precipitation	0.1° x 0.1°	Daily	https://gpm.nasa.gov/data/imerg
Other weather variables	0.5° x 0.5°	Daily	https://globalweather.tamu.edu/
Evapotranspiration	1km	Monthly	https://www.ntsg.umt.edu/project/modis/mod16.php

Digital Elevation Model and Delineation

Project watersheds were delineated in ArcGIS 10.5.1 using the ArcSWAT2012 interface (https://swat.tamu.edu/software/arcswat/). The ALOS PALSAR resampled 12.5m radiometric terrain corrected DEM (https://asf.alaska.edu/data-sets/derived-data-sets/alos-palsar-rtc/alos-palsar-radiometric-terrain-correction/) was used for delineation, resulting 325 subbasins (Figure 4). Each subbasin contains one inlet (or beginning channel if the subbasin is the headwater or start of channel; *c.f.* Figure 2), one outlet, and one stream segment. As part of the delineation process, two dam sites – Guma and Kongo – were manually added as outlets and used to define the corresponding stream segment and contributing source area[2]. The average subwatershed size is <1km^2.

As part of the HRU development, the DEM was used to generate a slope map. SWAT allows multiple slope classes and the slope map was divided into five classes using natural breaks, resulting in the following percent slope classes: 0-5, 5-18, 18 – 33, 33-53, and >53 (Figure 5).

[2] Dam, actual or potential, specifications are unknown at present and not incorporated into the model, focusing instead on changes in discharge at the locations only as a proxy for how this may impact future planning.

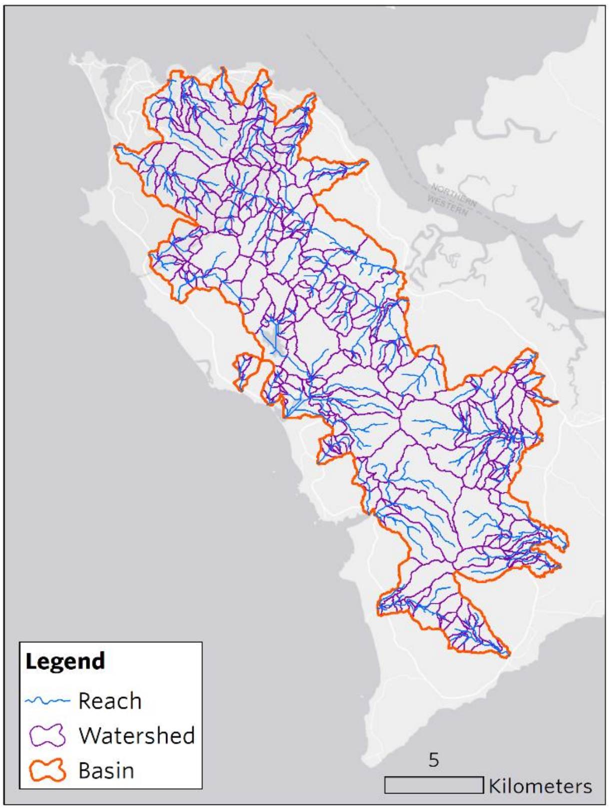

Figure 4 Final subbasins and reaches configuration.

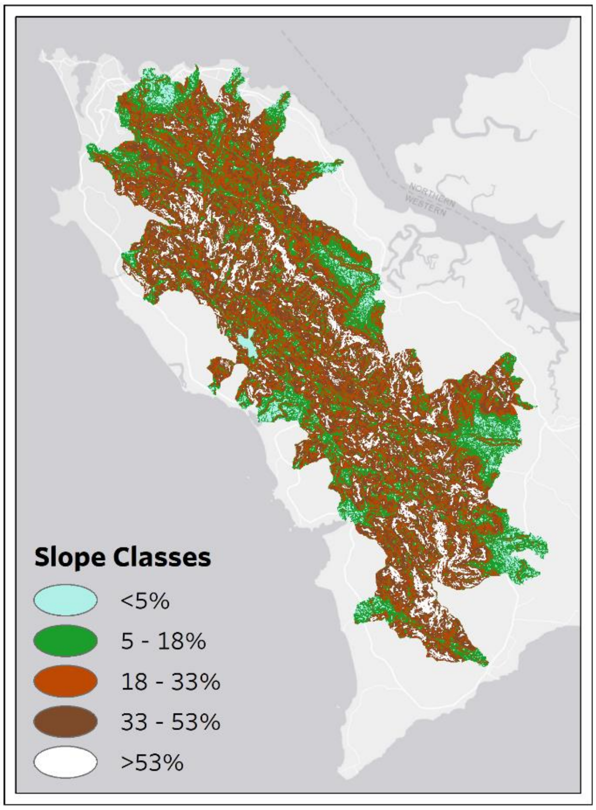

Figure 5 Slope classes used.

Land cover and land use

Land cover and land use (LCLU) is an essential input for SWAT. Three publicly available LCLU data sets were reviewed for use in SWAT and applicability for the Water Fund interventions at a spatial scale that allows the modification of land management activities to be assessed across scenarios. The 20m Sentinel S2 Prototype 2016 data product was selected for us in the current assessment.[3]

Seven land cover classes are defined in the Sentinel land cover map for the Water Fund project area: tree cover, shrub, grassland, cropland, wetland, urban, and water. These classes were further refined to reflect different levels of forest density from 10% - 84%. In addition, pixels within 30 meters of the riparian zone were refined to indicate their land class as occurring in a riparian zone (e.g., riparian-cropland, riparian-urban, etc.). A final land cover adjustment that was made within SWAT to the land cover was to designate 40% of the Urban areas to have higher overland flows, as might be found in more industrial areas where little infiltration occurs. Other urban areas are considered medium to high density residential where people may have kitchen gardens for domestic purposes and there may be some spaces where higher infiltration occurs, such as parks or football pitches, and overland flow processes are slowed. These refinements were made to accommodate conservation interventions on degraded forests and within riparian zones.

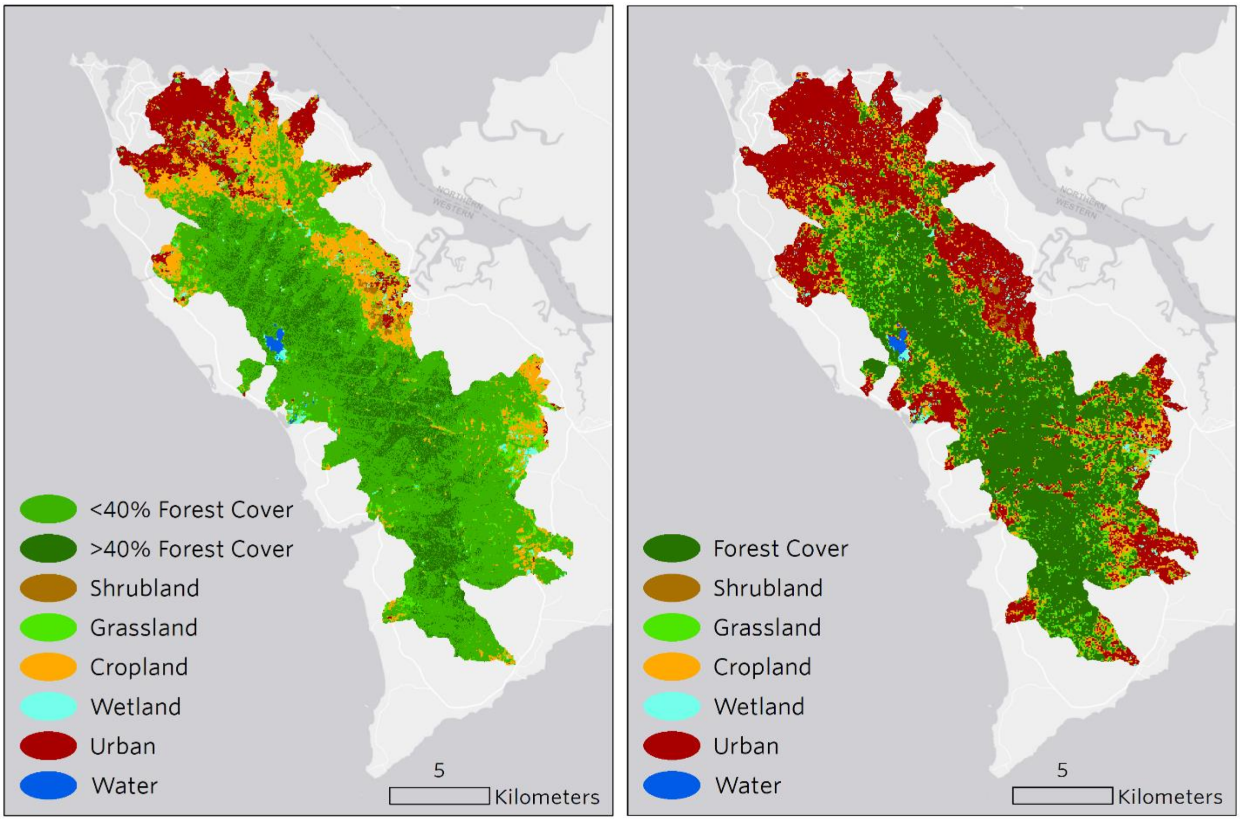

Figure 6 Baseline land cover and land use (left) and potential land cover and land use in 2050 based on past trajectories of change[4].

[3] For further details on how the land cover datasets were assessed, please see "Notes on available land cover and land use data sets for use in SWAT modeling for the Freetown Water Fund" previously shared on the CRS Teams site for the Freetown Water Fund.

[4] See Villanova report for details in development of Business as Usual scenario https://tnc.app.box.com/s/0nw5wx3578fxkwp1ztft8aka2idxtqmd/file/729384045286

Soils

Soil characteristics are a critical component to understanding the movement of water through soil profile in SWAT. SWAT requires an extensive database of soils properties, which are not often widely available and so until recently the most available solution was to use the 1km Harmonized World Soil Database and parameters developed for SWAT. For this work, the raster dataset did not fully cover the Western Peninsula and so the recently developed AfSIS 250m grid and database developed for SWAT were used (Ayana *et al.*, 2019).

Weather

Spatial variability in rainfall is often the greatest source of uncertainty in any hydrological model. For the Freetown Water Fund modeling, only monthly rainfall data were available from the Sierra Leone Meteorological Agency (Table 2) and the coordinates for the rainfall collection site are unknown. SWAT requires daily rainfall inputs so two alternative satellite-based precipitation products were considered: Tropical Rainfall Measuring Mission (TRMM) and Integrated Multi-satellite Retrievals for the Global Precipitation Measure Project (IMERG).

Table 2: Monthly rainfall provided by staff at Catholic Relief Services.

FREETOWN MONTHLY RAINFALL(MM) DATA												
YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEPT	OCT	NOV	DEC
1990	0.3	3.7	0	0	82.2	297.8	893.1	826.7	533.4	317.5	79.2	0.9
1991	0	0	26.7	53.3	168.8	266.3	354.4	738.8	316.5	337.7	87.1	0
1992	0	1	1.1	204.4	323.1	399.4	448.2	752.7	489.5	280.8	131.6	0
1993	0	8.8	70.6	336.4	228.8	336.5	487.6	510	630.8	442.3	116.4	13.6
1994	22.6	6.2	30.5	62.3	202.6	259.2	1524.6	1100.3	1478.6	394.3	85.9	13.9
1995	0	4.1	9.1	1.2	162.2	240.3	226.1	1297.1	819.8	187	35.2	9.8
1996	3.9	0	9.6	25.2	314.7	521.9	1385	1031.7	1219.5	424.5	119.6	7.9
1997	4.1	6.4	10.1	11.1	152.2	264.3	567.8	936.3	323.8	142.9	39.5	1.7
1998	12.2	12	53.3	1.9	86.2	441.1	1635.4	1690.5	1589.8	560.6	148.2	0
1999	0	30.7	82.8	0	241.7	275.8	1154.1	1526.3	563.8	960.1	107.3	4.2
2000	55.1	0	0	52.4	208.3	368	662.2	727	395.8	228.4	88.7	0
2001	0	0	5	55.4	124.9	419.8	756.2	679	704.7	279.4	146	0
2002	83.5	0	49.6	2.5	183.5	376.6	706.1	646.7	587.3	356.6	98.5	0
2003	0	0	0	23.7	140.8	509.8	125.6	896.3	659.9	140.3	122	0
2004	0	0	13.8	72.9	197.1	294.2	874.7	1019.5	307.9	54.4	69.8	19.8
2005	0	0	0	-	-	-	206.5	965.4	774.5	257.4	84.3	15.2
2006	0	0	0		110.2	281.5	-	-	-	-	-	-
2007	0	0	0	0	110.3	381	874.7	1009.5	307.9	254.4	158.8	109.9
2008	0	0	0	23.7	140.8	509.8	1005.6	915.4	774.4	257.5	84.3	25.3
2009	1.5	0	0	22.7	54.8	110.3	901.5	601.3	715	243.7	75.2	26.4
2010	15.9	22.5	9.3	34.5	108.6	313.7	366.2	489.4	624.9	245.5	97.7	36.1
2011	4.5	16.6	12.9	91.1	213.5	495.9	423.7	579.2	394.9	327.8	61.1	73.2
2012	5	11.6	16.6	56.7	236.3	543.5	457.1	557.6	413.2	307.8	221.5	74.7
2013	7.3	7.7	10	55.3	220.4	625.4	877	990.8	696.7	473.9	249.6	99.5
2014	13.5	2.5	14.5	22	339.3	828.3	861.3	1085.5	964.8	538.5	194.7	63.6
2015	8.6	6.8	5.4	55.3	202.8	459.7	1102.8	949.4	832.3	576.9	309.1	10.1
2016	0	0	0	0.2	79	146.5	106.5	350.9	374.2	386.5	7.3	21.4
2017	2	1.7	17.3	35	176	352	940.3	1219.3	754.3	258.7	104.3	8
2018	3.3	3	13	20.7	34.3	290.3	691	548.3	588.3	285.4	115.2	14.4
2019	0	0	14.4	18.6	97.3	332.8	1025.5	927.9	216.2	107	49	0

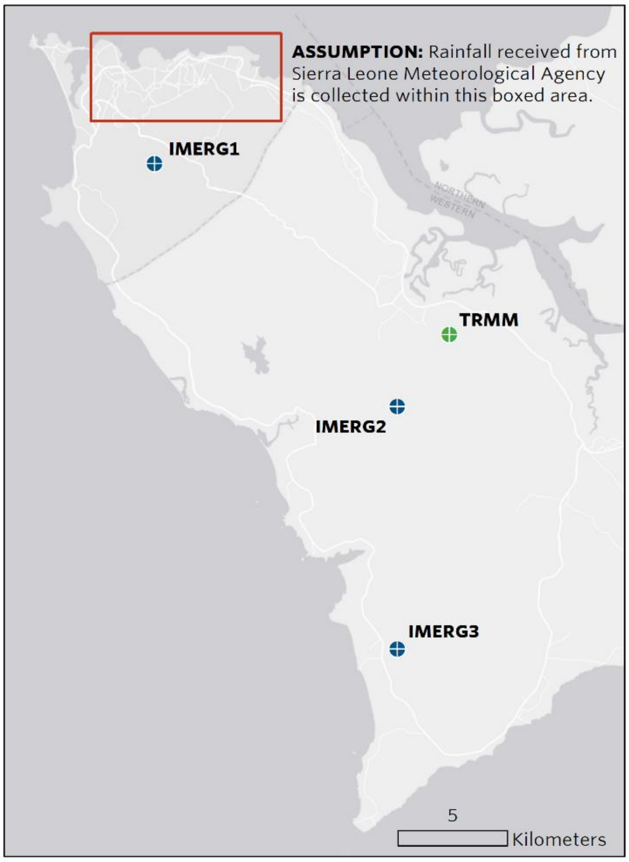

Figure 7 Locations for rainfall data options for use in SWAT alongside the assumed area of observed rainfall collection in Freetown

Rainfall across the Peninsula is known to be highly variable and so using a rainfall data set that most closely reflected the monthly rainfall statistics nearest to the one known rainfall collection area and provided daily data was needed.

TRMM resolution is 0.25° and so there is only one point where data are derived (Figure 7). TRMM data are daily; however, the satellite derived data point is located over the watershed divide from where monthly rainfall is assumed to be collected in Freetown. Given this, it is likely that rainfall recorded will be lower at that satellite location.

IMERG data are daily and due to the higher resolution (0.1°) offer three points for deriving data (Figure 7). One of the points, IMERG1, is located within the same vicinity assumed for the observed monthly rainfall.

It is important to note that the TRMM and IMERG data represent an average rainfall over their raster grid space. They do not represent a point location such as a rainfall gauge.

Basic descriptive statistics were analyzed to assess the suitability of the observed rainfall versus TRMM and IMERG for use in SWAT. TRMM and IMERG were also assessed against one another. While all rainfall datasets were well correlated (Table 3), IMERG1 was more highly correlated to the observed rainfall in Freetown than the other IMERG or TRMM data points. This is to be expected, as it is assumed the closest spatially to the observed rainfall. TRMM and IMERG 2 were also highly correlated, which was also to be expected given their proximity to one another and the areas they represent. IMERG 3 was better correlated to the observed rainfall and this may have to do with is proximity to the ocean side of the Peninsula.

Because IMERG1 is located nearest to the observed rainfall, this is the one of the three IMERG data sets that were compared against the observed data. There is only one TRMM location, so it was the only available option for comparison against the observed data (

Table 4). What we found was that the available TRMM data only has 65% of the total rainfall during the period of record, while IMERG1 has 97% of total observed amount. In terms of average monthly rainfall (Table 5), TRMM more severely underrepresents rainfall during the monsoon than IMERG. IMERG showed a tendency to overpredict precipitation at the beginning and end of the monsoon and moderately underpredict, though less than TRMM, during the peak months of the monsoon.

Table 3 Rainfall data correlation.

	OBSERVED	*TRMM*	*IMERG 2*	*IMERG 1*	*IMERG 3*
OBSERVED	1				
TRMM	0.799538517	1			
IMERG 2	0.833868924	0.936393505	1		
IMERG 1	0.838190632	0.891107327	0.944381174	1	
IMERG 3	0.825953393	0.923396994	0.991425743	0.938944005	1

Table 4 Descriptive statistics for available monthly data options.

OBSERVED		*TRMM*		*IMERG 1*	
Mean	263.9040179	Mean	164.1047009	Mean	246.2531
Standard Error	20.92781447	Standard Error	11.97698843	Standard Error	14.67116
Median	110.25	Median	98.65	Median	200.367
Standard Deviation	313.2188464	Standard Deviation	183.2126931	Standard Deviation	224.4256
Sample Variance	98106.04577	Sample Variance	33566.89092	Sample Variance	50366.85
Kurtosis	0.217589223	Kurtosis	0.58116347	Kurtosis	-0.91935
Skewness	1.163707011	Skewness	1.18091621	Skewness	0.499385
Maximum	1219.3	Maximum	809.4	Maximum	953.9843
Sum	59114.5	Sum	38400.5	Sum	57623.22
Count	224	Count	234	Count	234

Table 5 Average monthly rainfall with monsoon season highlighted in blue.

MONTH	**OBSERVED**	**TRMM**	**IMERG**
JANUARY	7.6	5.3	21.4
FEBRUARY	3.8	5.5	11.4
MARCH	9.6	9.0	21.4
APRIL	34.7	38.58	47.7
MAY	153.9	113.0	204.5
JUNE	402.1	279.5	445.7
JULY	682.3	366.4	543.0
AUGUST	797.8	436.1	568.6
SEPTEMBER	583.1	354.9	464.8
OCTOBER	293.7	212.7	347.9
NOVEMBER	123.0	94.7	180.7
DECEMBER	33.2	13.6	41.6

Next, IMERG2 was compared against TRMM, as these two sites represent similar areas and are nearest to one another. The two sites are highly correlated (0.92). Because no observed data are available for this area of the Peninsula, it is impossible to know which of the two datasets more accurate represents rainfall in this area of the Peninsula. We can see that IMERG shows a higher overall rainfall amount (Table 6) and while the two datasets are more similar in the dry season, IMERG predicts significantly more rainfall during the monsoon season (Table 7).

IMERG data were selected for use in SWAT given they meet the criteria of being daily and IMERG1 showed the highest general agreement with observed rainfall. Daily precipitation data were generated from IMERG for direct input to SWAT using https://github.com/nasa/NASAaccess/blob/master/R/GPMswat.R. SWAT does require other weather parameters (minimum temperature, maximum temperature, solar radiation, windspeed, and relatively humidity) and these were statistically generated using data from the CFSR World Weather Database (https://globalweather.tamu.edu/).

Table 6 Descriptive statistics for TRMM and IMERG 2 datasets.

TRMM		*IMERG 2*	
Mean	164.1047009	Mean	226.4689092
Standard Error	11.97698843	Standard Error	15.59528248
Median	98.65	Median	146.7805442
Standard Deviation	183.2126931	Standard Deviation	238.561949
Sample Variance	33566.89092	Sample Variance	56911.80351
Kurtosis	0.58116347	Kurtosis	0.346668166
Skewness	1.18091621	Skewness	1.027725923
Maximum	809.4	Maximum	1089.319672
Sum	38400.5	Sum	52993.72476
Count	234	Count	234

Table 7 Average monthly rainfall with monsoon highlighted in blue.

MONTH	**TRMM**	**IMERG 2**
JANUARY	5.3	6.2
FEBRUARY	5.5	10.7
MARCH	9.0	14.6
APRIL	38.6	43.9
MAY	113.0	170.0
JUNE	279.5	419.4
JULY	366.4	538.3
AUGUST	436.1	607.9
SEPTEMBER	354.9	438.7
OCTOBER	212.7	257.3
NOVEMBER	94.7	128.2
DECEMBER	13.6	28.1

Evapotranspiration

Because no stream discharge data are available on the Peninsula, satellite-derived evapotranspiration (ET) was used for model calibration. In data scarce regions, this approach has become widely accepted in hydrological modeling (Dile *et al.*, 2020; Weerasinghe *et al.*, 2020; Esayas *et al.*, 2019; Ha *et al.*, 2017; Ramoelo *et al.*, 2014). While there are numerous ET products available, the time available for carrying out analyses of the individual products was beyond the scope of the Business Case project. For this reason, MOD16 ET data were selected given they have been most successfully used in Africa (Dile *et al.*, 2020; Esayas *et al.*, 2019). MOD16 represents monthly average ET at 1 km^2. This was too coarse to adequately generate average values at a subwatershed scale, so pixels were resampled to 500m to calculate the average monthly mean ET per subwatershed. Resampling did not result in any significant change to average monthly values but allowed more subwatersheds to be captured in a zonal statistics analysis.

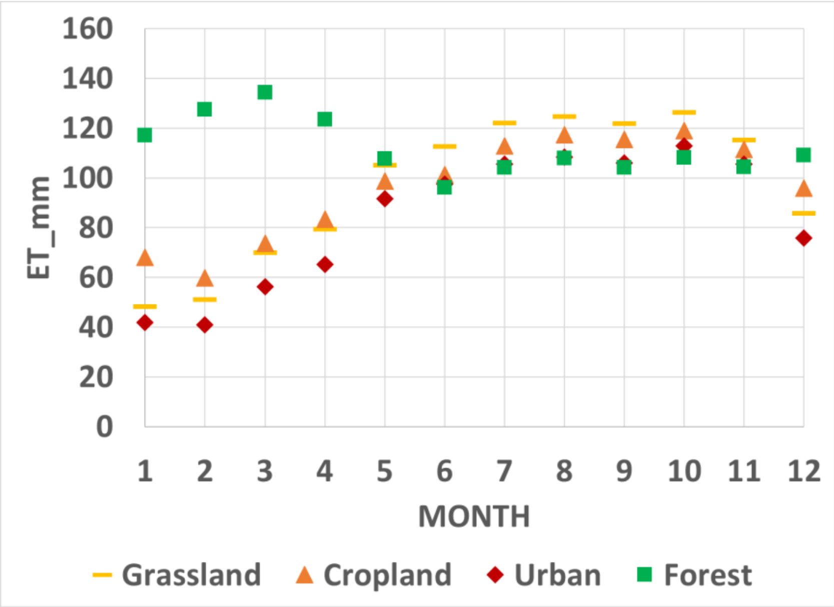

Figure 8 Example of average ET derived over four main land use classes.

We found that MOD16 ET had higher than would be expected average monthly values for overall ET and this was later confirmed when assessing bias as part of the model calibration exercise. The bias was uniform and consistent and so was not addressed in the current analysis. Another issue noted in the ET data was that subwatersheds dominated by forested exhibited elevated ET during the dry season (Figure 8), however, ET in tropical forests does not typically vary as such and should remain within a narrow range throughout the year. Both issues were attributed to proximity to the open ocean, which has been noted in other studies, including along African coastlines.

Model Set-up and Simulation

ArcGIS 10.5.1 was used to parameterize the SWAT2012 model for the Freetown Water Fund. HRUs were then developed with no thresholding for land cover and 20% thresholding each for soils and slope. This resulted in 11,224 HRUs distributed across the 325 subwatersheds.

Model outputs were generated for 2003 – 2019. Precipitation data spanned from 2000 – 2019 and SWAT requires a 3 – 5-year spin-up period to reach equilibrium in the soil water content. A 3-year model spin-up was used for this model.

Land management parametrization

Only simple land management operations were applied as indicated below.

Urban - To account for the variation in urban types with only one class defined in the land cover, medium density urban parameters were selected but FIMP (fraction of impervious area) and FCIMP (fraction directly connected impervious area) were both increased to reflect high density values of 0.6 and 0.44, respectively. It was noted that across the urban areas, density of people decreased, and the landscape began to appear as medium density residential areas where there may be some “green spaces” in the form of kitchen gardens, small fields, or parks and some riparian zones moderately intact. To account for this, 60% of urban areas were given no land management operations, while 40% of the area had land management operations applied to account for activities such as kitchen gardens. To do this, overall urban parametrization was maintained but these areas also received a generic crop at the end of April that were harvested in October. This served to provides some distinction between areas that are highly urban and industrial versus areas that may be considered urban but lack the characteristics of tarred roads, parking lots, and other large buildings.

Cropland - Because this area shows a typical tropical rainfall pattern, plant growth is rainfall driven and not temperature driven. A simple cropland management operation was set up that repeated annually whereby no crop is growing in January and then a generic row crop (maize) is planted on May 1st, fertilized on May 7 with

20 kg/ha of elemental nitrogen, and then harvested on October 15. No irrigation was applied, as based on the MOD16 data, there did not appear to be a strong signal that would typically be seen in agriculture dominated subwatersheds. It was therefore assumed irrigation is minimal.

Forests – In this modeling exercise, it was important to indicate different canopy densities to represent areas where people may be encroaching into forests. It is assumed that at the edges where forest density is low, that people are encroaching. This also has an impact on hydrological response and so some plant growth parameters were scaled to represent changes across canopy densities. All forest areas were initialized in SWAT to be fully grown at the start of the model simulation. This was done by setting the initial leaf area index to 2, the initial dry weight biomass (kg/ha) to 1,000, and the heat units (growing degree days) required to bring a plant to maturity to 3,500.

Model Calibration

Model calibration was carried out using SWAT-CUP and implementing the SUFI2 algorithm. Due to the bias in the ET data, we accepted that we could not capture a model result within the 95% probability distribution of the observations. This would require first a bias correction of the ET data, which was beyond the scope and time available of the immediate Business Case work. To this end, we were seeking to capture shape and timing of the ET curve throughout the year and therefore used R2 as the objective function. The PBIAS statistic also indicated a consistent 50 – 60 % bias across all land uses and all sampled watersheds, which is in line with the overestimation found in the MOD16 data as described previously.

Because the model was calibrated using satellite-derived ET, the calibration was carried out by land use type. The process was carried out in two steps. First, 50 random watersheds were selected to explore parameter sensitivity over 480 model iterations. Parameter ranges were then targeted and eight subwatersheds, two for each dominant land use class (cropland, forest, urban, grassland), were identified with relatively homogeneous land covers.

Calibration was further refined by running two SWAT-CUP runs consisting of 480 iterations per run. Between runs, parameter ranges were further adjusted to restrict the search area for each parameter. Two distinct sets of fitted parameters were derived and are indicated in Table 8.

R2 values for Forest, as expected, were the lowest when assessing across all months, ranging from 0.2 – 0.25. When excluding dry season months, where there earlier noted an abnormal increase in ET detected in the MOD16 data, R2 values increase to 0.7 – 0.75. R2 for urban areas ranged from 0.7 – 0.8, and over cropland ranged from 0.4 – 0.7 and on grasslands from 0.75 – 0.8. A noted challenge in calibrating cropland areas is that we could not capture increasing agricultural intensification over the modeling period and little is known about the extent of any irrigation or actual agricultural practices. During the assessment we also noted that we could quickly detect areas that had been converted from forest to cropland because there was a dramatic change in the ET signal. This also decreased the R2 for some agricultural areas, as during the modeling period they have a static land cover (cropland) but may have been forest for the first part of the simulation. This was also noted in forest areas but was less pronounced in impacting R2 results. Final fitted parameters used for calibration are given in Table 8.

Table 8 Final calibration parameters.

	BRIEF DESCRIPTION	Default	Forest Fitted	Other LCLU Fitted
CN2.mgt	Curve Number for moisture condition II	varies	74.06[5]/varies 0.917292	Varies 0.941458
SOL_AWC.sol	Available water capacity of the soil layer (mm/H_2O/mm soil)	varies	0.766146[6]	0.799479
ALPHA_BF.gw	Baseflow alpha factor (1/days)		0.01335	0.03005
GW_DELAY.gw	Groundwater delay time (days)	0.048	97.875	27.875
GWQMN.gw	Threshold of water in shallow aquifer for return flow to occur (mm)	31	1135.416626	1797.916626
RCHRG_DP.gw	Fraction of water from root zone that recharges deep aquifer (unitless)	0.05	0.036354	0.000521
REVAPMN.gw	Threshold of water in shallow aquifer for revap or percolation to deep aquifer (mm)	750	701.5625	689.0625
GW_REVAP.gw	Movement of water from shallow aquifer to root zone (unitless)	0.02	0.052437	0.039313
ALPHA_BF_D.gw	Alpha factor for groundwater recession curve for deep aquifer (1/days)	0.01	0.163542	0.830208
ESCO.hru	Soil evaporation compensation factor (unitless)	0.95	0.57375	0.532917
CANMX.hru	Canopy storage (mm)	0	49.947914	36.09375
SLSOIL.hru	Slope length for lateral surface flow (m)	0	149.375	0.208333
LAT_TTIME.hru	Lateral flow travel time (days)	0	100.15625	125.78125

[5] This was set as initial Daily CN. SWAT varies CN for each HRU based on the land cover, soil, and slope and then modifies daily CN based on precipitation after the model reaches equilibrium. Many CNs for forest are much lower than this and there may be some that are higher depending on other conditions.

[6] For spatially varying parameters in SWAT, values are modified by multiplying by a fitted factor.

Table 9 Plant database parameters used to simulate plant growth varying canopy density. See https://swat.tamu.edu/media/69341/ch14_input_plantdb.pdf for detailed parameter descriptions.

	CANOPY DENSITY %									
SWAT PARAMETER	**10**	**20**	**30**	**40**	**50**	**60**	**70**	**75**	**80**	**85**
BIO_E	1.59	3.17	4.74	6.32	7.90	9.48	11.06	11.84	12.63	13.42
HVSTI	0.09	0.17	0.25	0.33	0.40	0.48	0.56	0.60	0.64	0.68
BLAI	0.54	1.06	1.59	2.11	2.64	3.16	3.69	3.95	4.21	4.47
FRGRW2	0.45	0.41	0.37	0.33	0.28	0.24	0.20	0.18	0.16	0.14
CHTMX	0.64	1.27	1.90	2.53	3.16	3.80	4.42	4.74	5.05	5.37
RDMX	0.46	0.82	1.17	1.53	1.89	2.25	2.61	2.78	2.96	3.14
T_OPT	25.53	26.05	26.58	27.10	27.63	28.16	28.68	28.95	29.21	29.47
T_BASE	11.79	11.58	11.37	11.16	10.95	10.73	10.53	10.42	10.32	10.21
CNYLD	0.02	0.02	0.02	0.02	0.01	0.01	0.01	0.01	0.00	0.00
CPYLD	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BN1	0.05	0.05	0.04	0.04	0.03	0.02	0.02	0.02	0.01	0.01
BN2	0.02	0.02	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.00
BN3	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00
BP1	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00
BP2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BP3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
WSYF	0.81	0.71	0.62	0.52	0.43	0.34	0.24	0.20	0.15	0.10
GSI	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
WAVP	9.79	9.58	9.37	9.16	8.95	8.73	8.53	8.42	8.32	8.21
BIOEHI	1.69	3.38	5.06	6.74	8.43	10.11	11.79	12.63	13.48	14.32
RSDCO_PL	0.45	0.41	0.36	0.31	0.26	0.22	0.17	0.14	0.12	0.10
OV_N	0.14	0.13	0.13	0.12	0.12	0.12	0.11	0.11	0.11	0.10
CN2A	72.68	68.37	64.05	59.74	55.42	51.10	46.79	44.63	42.47	40.32
CN2B	83.26	80.53	77.79	75.05	72.32	69.58	66.84	65.47	64.11	62.74
CN2C	89.11	87.21	85.32	83.42	81.53	79.63	77.74	76.79	75.84	74.89
CN2D	92.42	90.84	89.26	87.68	86.11	84.53	82.95	82.16	81.37	80.58
ALAI_MIN	0.08	0.16	0.24	0.32	0.39	0.47	0.55	0.59	0.63	0.67
BIO_LEAF	0.03	0.06	0.09	0.13	0.16	0.19	0.22	0.24	0.25	0.27
MAT_YRS	5.26	10.53	15.79	21.05	26.32	31.58	36.84	39.47	42.11	44.74
BMX_TREES	105.26	210.52	315.79	421.04	526.32	631.56	736.84	789.47	842.11	894.74
EXT_COEF	0.96	0.93	0.89	0.85	0.82	0.78	0.74	0.72	0.71	0.69

Table 10 Plant database parameters used to simulate plant growth for two forest types under the BAU scenario. See https://swat.tamu.edu/media/69341/ch14_input_plantdb.pdf for detailed parameter descriptions.

	Crop/Woodland Mosaic	Forest
BIO_E	24.25	15
HVSTI	0.61	0.76
BLAI	4	5
FRGRW1	0.1	0.15
LAIMX1	0.05	0.7
FRGRW2	0.45	0.25
LAIMX2	0.95	0.99
DLAI	0.82	0.99
CHTMX	3.5	10
RDMX	2.75	3.5
T_OPT	30	30
T_BASE	10.5	0
CNYLD	0.0107	0.0015
CPYLD	0.0018	0.0003
BN1	0.025	0.006
BN2	0.0092	0.002
BN3	0.0072	0.0015
BP1	0.0034	0.0007
BP2	0.0013	0.0004
BP3	0.0011	0.0003

	Crop/Woodland Mosaic	Forest
BMX_TREES	n/a	1000
EXT_COEF	0	0.65
BM_DIEOFF	0	0.1
WSYF	0.13	0.6
USLE_C	0.101	0.001
GSI	0.004	0.002
VPDFR	4	4
FRGMAX	0.75	0.75
WAVP	8.25	8
CO2HI	660	660
BIOEHI	26	16
RSDCO_PL	0.05	0.05
OV_N	0.12	0.1
CN2A	51.5	25
CN2B	68.5	55
CN2C	78	70
CN2D	83	77
FERTFIELD	1	0
ALAI_MIN	0	0.75
BIO_LEAF	0	0.3
MAT_YRS	0	10

Scenarios

Of the interventions described in the Anchor report, only four intervention impacts that can be measured using SWAT. Four scenarios were developed based on a level of implementation to assess intervention potential impacts:

- Scenario 1: 25% implementation
- Scenario 2: 50% implementation
- Scenario 3: 100% implementation
- Business as Usual

Area covered for each intervention under each conservation scenario is listed in sections below.

4.2.2

This intervention is fully implemented in all three scenarios. It entailed converting any cropland within the national park boundary to Forest with full canopy closure.

- Scenarios 1 – 3 = 147.6 ha.

To simulate 4.2.2 in SWAT, all cropland within the National Park was converted to forest by removing all cropland operations parameters as well updating key parameters in Table 8.

4.2.3

In selected National Park watersheds, all forests were converted to 90% canopy density from their current canopy density.

- Scenario 1: 3,156 ha
- Scenario 2: 6,153 ha
- Scenario 3: 12,406 ha

To simulate 4.2.3 in SWAT, low density forest areas or low-density forests were converted to a more closed canopy, which involved updating plant/crop parameters in Table 9.

4.2.4

For this intervention cropland areas within a 1km buffer zone of the park are converted to agroforestry. Areas selected are based on slope class with first preference given to cropland on slopes <5% and second preference given to slopes between 5% and 18%.

- Scenario 1: 329 ha
- Scenario 2: 577 ha
- Scenario 3: 1,151 ha

To simulate 4.2.4 in SWAT, 50% of cropland areas within a 1km buffer zone of the park were converted to forest by modifying parameters in Table 1 as done for 4.2.2. SWAT cannot simulate more than one crop in an HRU. Areas for conversion to forest were selected based on slope class with first preference given to cropland on slopes <5% and second preference given to slopes between 5% and 18% (Mwangi *et al.*, 2016).

4.3.1

This involves adding a generic filter strip to riparian zone areas. Filter strips were simulated by implementing the FILTERW parameter with a setting of 30m.

How considered in SWAT: "*Filter strips are vegetated areas that are situated between surface water bodies (i.e. streams and lakes) and cropland, grazing land, forestland, or disturbed land. They are generally in locations where runoff water leaves a field with the intention that sediment, organic material, nutrients, and chemicals can be filtered from the runoff water. Filter strips are also known as vegetative filter or buffer strips. Strips slow runoff water leaving a field so that larger particles, including soil and organic material can settle out. Due to entrapment of sediment and the establishment of vegetation, nutrients can be absorbed into the sediment that is deposited and remain on the field landscape, enabling plant uptake.*"[7]

- Scenario 1: 4 ha
- Scenario 2: 26 ha
- Scenario 3: 53 ha

Business as Usual (BaU)

This scenario looks at a potential future landscape based on past trends, becoming more urbanized and with increased forest loss and degradation. To simulate the BaU in SWAT, new HRUs were parameterized using land cover representing the year 2050 based on past land cover change trends. Because this map has only one forest class, the land cover split tool in SWAT was used to convert 20% of forest cover to a degraded mixed cropland/woodland class (Table 10).

[7] https://swat.tamu.edu/media/57882/Conservation-Practice-Modeling-Guide.pdf

Results

SWAT was run on a monthly timestep from 2000 – 2019 with a three-year model spin up. Stream discharge and sediment yield results can be downloaded at https://tnc.box.com/s/6rlufvyythhybcw3iufmqoegs0sncrlp.

Deforestation has a significant impact on hydrological processes in watersheds. Significant deforestation has occurred since on the Western Area Peninsula (Figure 9) and Figure 10 and Figure 11 illustrate the isolated hydrological response to this significant change in both the dry season and monsoon. Because the urban watersheds had little forest in 2000, they will not show a pronounced response when highlighting the influence of forest loss only. Dry season flows are significantly reduced for many key communities identified as being of interest and monsoon season flows increase by up to 26% in Lumley Creek.

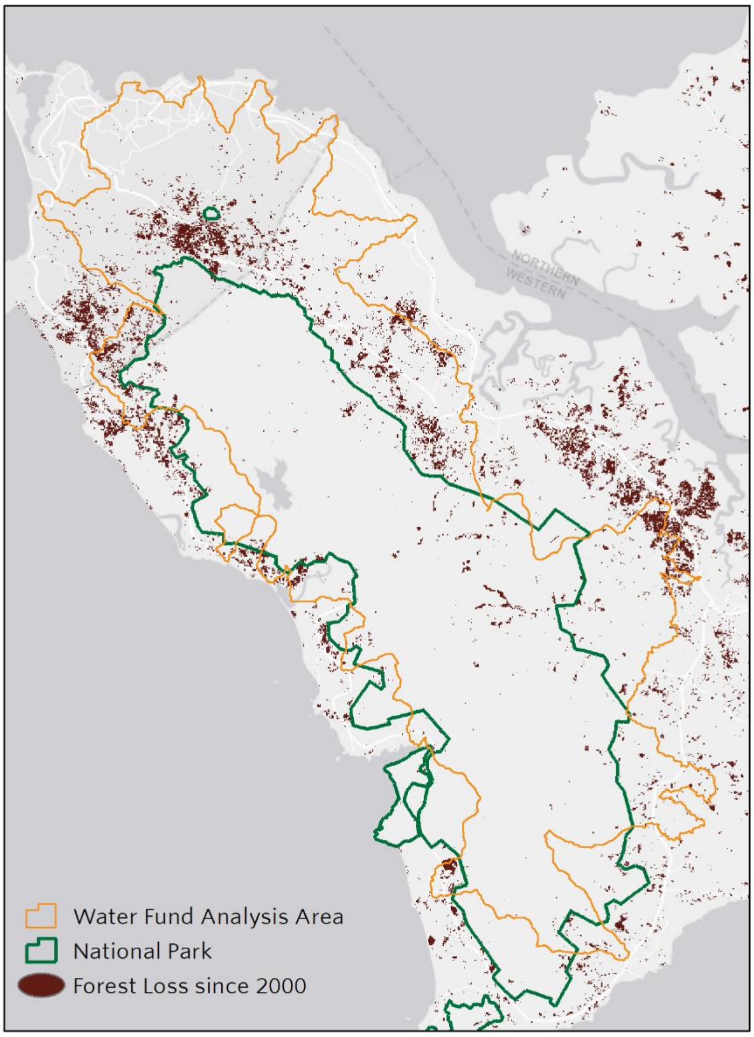

Figure 9 Forest loss since 2000 on the Western Area Peninsula. Source: https://www.globalforestwatch.org/.

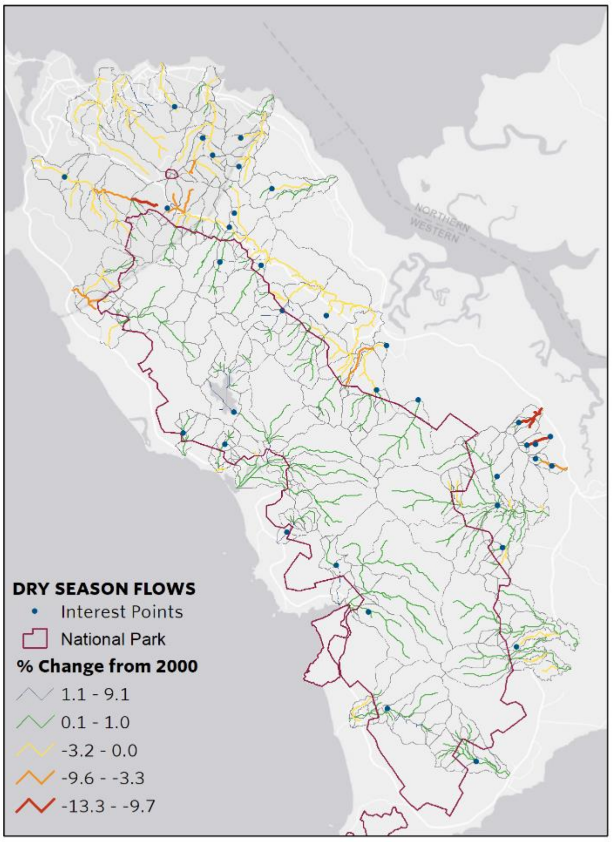

Figure 10 Percent change from 2000 to 2019 in average dry season streamflow.

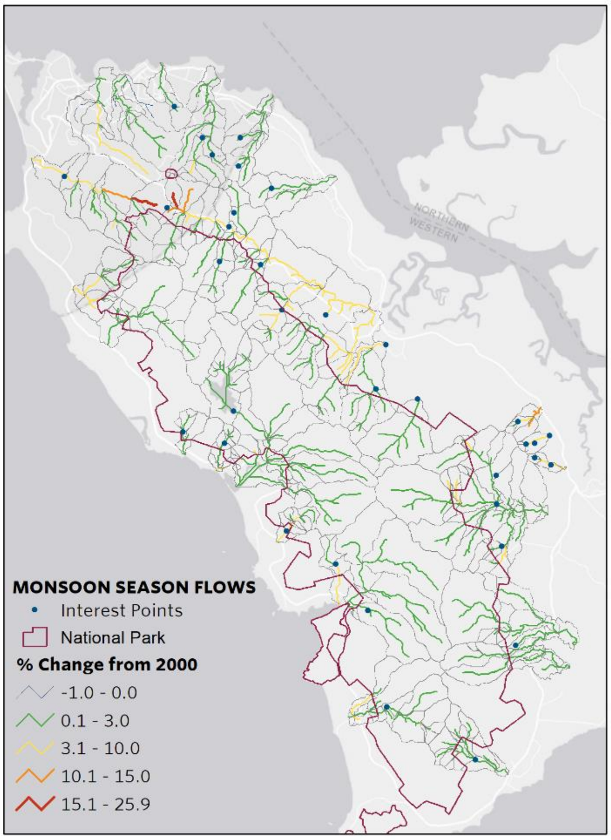

Figure 11 Percent change from 2000 to 2019 in average monsoon season streamflow.

From the scenarios originally proposed, only Scenario 3, henceforth called Conservation, and the Business as Usual are considered in the final analysis. The spatial distribution of interventions implemented in SWAT under the Conservation scenario, as described in the scenarios section above, are illustrated in Figure 12.

Under the BAU, streamflow is predicted to be impacted significantly such that many areas will see up to a 20% decrease in flows (Figure 13) indicating that baseflow contributions from groundwater are reduced. This is a consequence of decreased recharge over time as compared to the Conservation scenario where dry season flows will remain more stable. Some areas, particularly those that become more urbanized, are anticipated to see an increase in flows during the dry season but this is a consequence of increased flows – and potentially increased flooding – throughout the year. This can be noted when comparing the response of streamflow in urban areas across Figure 13 and Figure 14. Nearly all reaches in the Water Fun area are anticipated to see an increase in monsoon season flows under the BAU scenario as compared to the Conservation scenario (Figure 14), which can lead to increased flooding and reduces the opportunity for groundwater recharge, the latter of which results in greatly reduced water security for most communities in the Water Fund area. Finally, under the BAU scenario as compared to the Conservation scenario, there is predicted to be much higher annual sediment yields across the Water Fund area (Figure 15), with some locations having well over 25,000% increase.

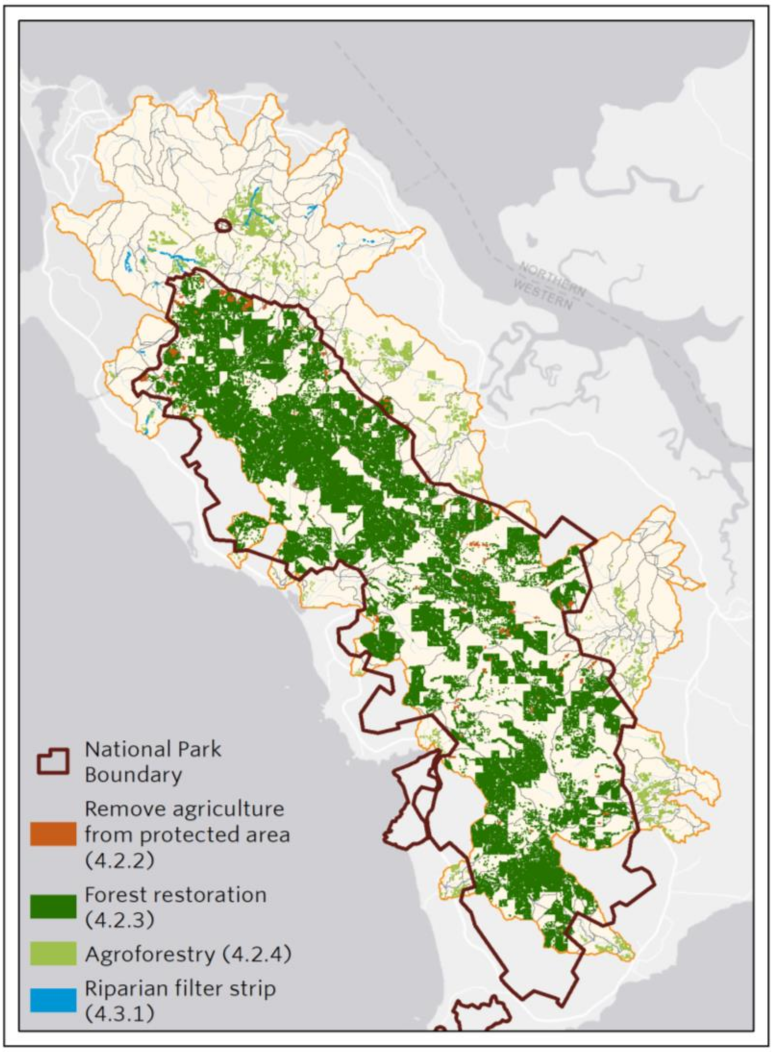

Figure 12 Spatial distribution of interventions applied in SWAT for the Conservation Scenario.

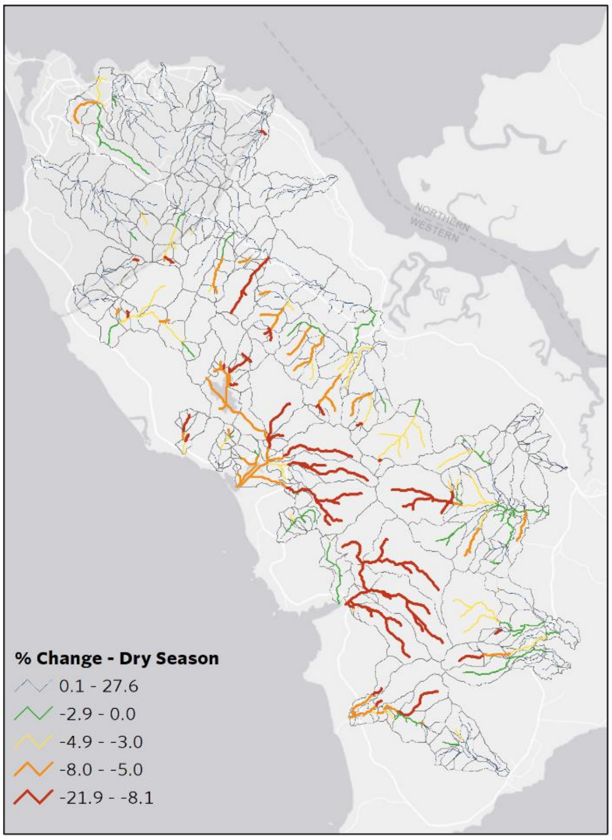

Figure 13 Percent change in dry season flows under the BAU as compared to the Conservation Scenario.

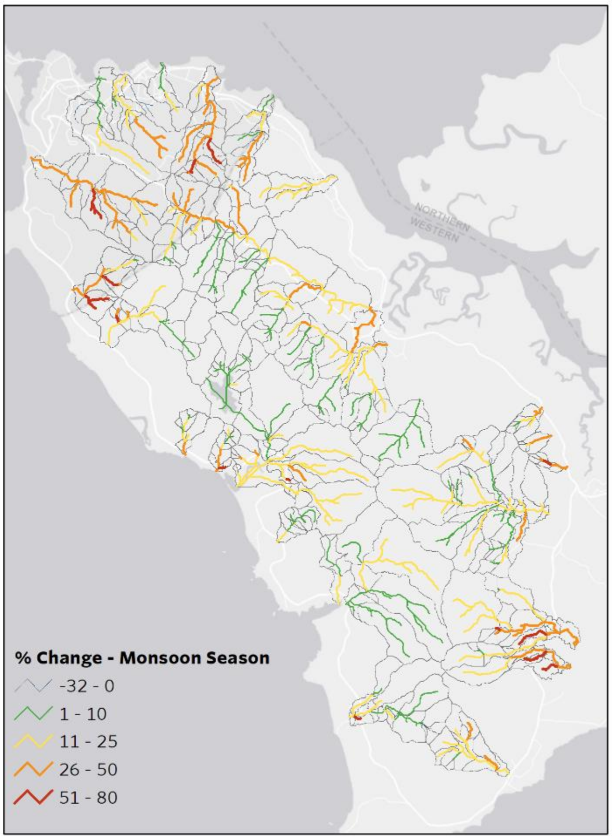

Figure 14 Percent change in monsoon season flows under the BAU as compared to the Conservation Scenario.

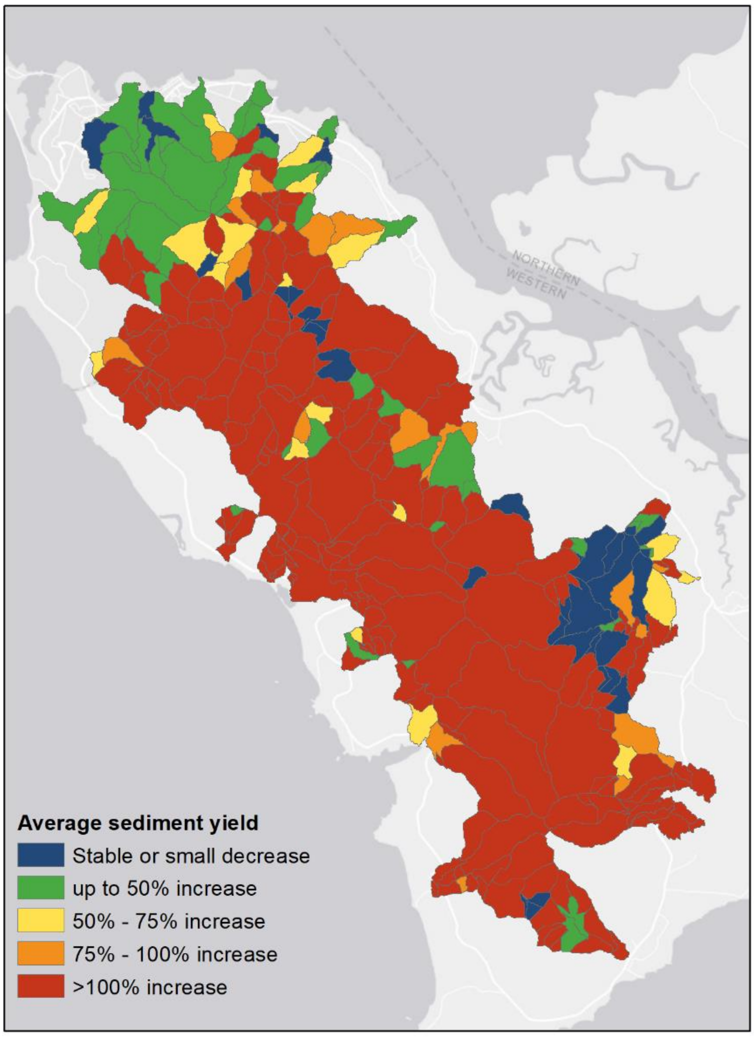

Figure 15 The percent increase in sediment yield under a Business as Usual scenario versus the proposed Conservation Scenario.

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