Estimating Water Consumption Through Hydrological Modelling In Mara River Basin

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ESTIMATING WATER CONSUMPTION THROUGH HYDROLOGICAL MODELLING IN MARA RIVER BASIN

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Abstract

The Mara River Basin (MRB), is transboundary shared between Kenya and Tanzania. The basin covers a total area of 13,834km$^2$, with the larger upper part of the basin (65%) in Kenya while 35% of the basin lies in Tanzania. The Upper Mara Basin in this study refers to the Amala, the Nyangores and some part of the Emarti sub-catchments in the MRB, on the Kenyan side. It covers an area of 3400km$^2$, which is approximately 26% of the total area of the MRB. The natural habitat of the Mara-Serengeti ecosystem depends heavily on the Mara River.

The MRB has attracted many researchers because of its ecological and biodiversity importance. However, many studies show that there are significant environmental challenges due to land-use changes in the basin. Irrigation agriculture is expanding in the MRB to increase food productivity. As a result, the river flows, especially during low flows and the ecosystem at large in the entire basin, have been affected. In the long run, there might exist a conflict between the livelihood and the ecosystem due to limited water resources.

This research, therefore, aimed at using the modified Spatial Tool for River basin Environmental Analysis and Management (STREAM) model to quantify irrigation water abstraction in the Upper MRB for planning resource development and management in the context of multiple users for sustainability purposes. In addition to this, ETblue, which refers to the portion of evapotranspiration not from direct precipitation in the soil zone, contribution to total evapotranspiration was analysed for different land cover existing in the basin. Also, intercomparison of the original STREAM model to the modified STREAM model in simulating the hydrograph of the Upper MRB was compared. Finally, the use of the remote sensing derived precipitation in modelling was assessed.

The modified STREAM model was scripted using the PCRaster Python modelling framework at a spatial and temporal resolution of 90m and 10-day (dekadal) respectively. The model utilised remote sensing products from the WaPOR database as spatial input data. Calibration and evaluation of the model were done using historical data and field data.

From the rainfall intercomparison, TAHMO (point measurement) and WaPOR (remote sensing products) R$^2$ value of 0.9 was obtained. This suggested that there is a strong correlation between the two precipitation datasets.

The model simulated the basin irrigation water abstraction well with an error margin between 16-28% relative to in situ. These results are reasonable, considering the losses that are experienced in irrigation systems. Also, a comparison of individual irrigation farms’ ETblue to the data obtained from the irrigation fields was assessed to provide more insights in irrigation abstraction in the upper MRB. For the individual farms' intercomparison, the model results were even better as it was done on a seasonal scale. The model was able to reasonably reproduce irrigation amounts. The model was also able to reasonably reproduce flows with NSE values in the range of 0.5 during both calibration and evaluation.

ETblue (blue water use) contribution to total evapotranspiration varied among different land-cover types in the basin. Dense agriculture recorded the highest average ETblue of 55% of the total evapotranspiration. Sparse agriculture and forest ETblue contribution were 30% and 25% respectively. Woodlands, grasslands, bushlands and plantations had ETblue contribution of <10%. 2015 and 2018 recorded the maximum and minimum ETblue values for all land-cover types.
Keywords Upper MRB, modified STREAM, blue and green water use, irrigation water abstraction.

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Abbreviations

MRB………………………… Mara River Basin
NSE …………………………… Nash- Sutcliffe coefficient
STREAM………………………Spatial Tool for River Environmental Analysis and Management.
DEM………………………….. Digital Elevation Model.
ASAL…………………………...Arid and semi-arid lands.
IWRM………………………….. Integrated Water Resources Management.
TAHMO……………………….. Trans-AfricanHydroMeteorological Observatory.
KMD…………………………….. Kenya Meteorological Department
WRA………………………….. Water Resources Authority
WRUAs………………………… Water Resources Users Association.
1.1 Background introduction

Many regions in the world are experiencing freshwater resource shortages. Overexploitation of water resources is increasing, and the situation will worsen if the current consumption and water use pattern persist (Mati et al., 2008). Population increase, climate change, and economic growth are the main drivers of water scarcity. Thus water managers are facing a challenge of balance between human water demands and ecological needs (Kiptala et al., 2014).

The Mara river basin (MRB), which is a sub-basin in the large Nile Basin, is not an exception. The situation in the MRB becomes more pronounced as sustaining the water demand of the increasing population and meeting the ecological requirements of the Mara-Serengeti ecosystem is becoming a big challenge in the basin. In addition to that, wildlife demands, pressures from large-scale irrigation, increasing livestock population and large-scale mining activities are straining the river (Hoffman et al., 2009). All the water users in a basin are dependent on each other, and therefore, the activities of the upstream users will affect the activities of downstream users (Kiptala et al., 2014).

The MRB is experiencing environmental threats such as land-use change and accelerated vegetation reduction in the upper catchment, which impacts river flows (Mutie et al., 2006). The rising pollution is also threatening wildlife in the basin. In the lower catchment, deforestation of the hills has resulted in increasing fast runoff generation, resulting in erosion and thus affecting the riparian wetlands (Mati et al., 2008).

According to Mati et al. (2008), the water resources in Mara are inefficiently utilised mainly in the downstream reaches. There is limited information on blue and green water consumptive use in the basin. Due to this, the management and coordination of the water resources in the basin are not well documented. Therefore, this calls for Integrated Water Resources Management (IWRM) in the entire MRB. To achieve the three pillars of the IWRM principles, i.e. economic efficiency, ecological integrity and equity in the resource allocation, there is a need to understand how much water is available, the quantity needed, the duration and the purposes (Gürlük and Ward, 2009).

Disputes over the shared water resources in the MRB will continue to rise as long as there are no linkages and cooperation among water users. In the MRB, there is Water Management Authority (WMA) and Water Resources Users Associations (WRUAs) who are responsible for the management of the water resources at the basin and sub-basin level. But besides this political framework, quantification of water resources is needed for the planning of water resources.

The planning for water resources development, management, and allocation for multiple users in the basin, depends on water availability and economic efficiency. To achieve this objective in a river basin with scarce hydrological data, such as the Mara, it is crucial to apply a methodology that utilises open data, including free remote sensing data. The issues described above, highlight the importance of adopting a hydrological model that will provide tools for the
management of the basin focusing on water availability and estimation of water use within the river basin.

1.2 Problem statement and justification

The natural habitats of the Mara-Serengeti ecosystem depend heavily on the Mara River. In addition to this, the river is essential to other land uses in the basin. However, a recent report by LVBC & WWF-ESARPO (2010), shows that there are significant environmental changes due to land-use changes in the basin. This includes, among others, accelerated reduction of vegetation cover due to increased agricultural activities and population growth. This land-use changes has impacted the river flows and the ecosystem at large in the upper catchment.

In the middle reaches, there is increasing livestock water use, as it is occupied by the Maasai community. Originally, these areas used to be dominated by both rangelands and pastoralists sustainably. According to Hoffman et al. (2009), the livestock population has increased in the area because of the growing pastoralists’ population resulting in overgrazing in the rangelands. The reported increase in drought is also a challenge in the basin resulting in extremely low flows. As a result, there exists a conflict between the livelihood and the ecosystem due to limited water resources. This increasing demand for scarce water resource calls for urgent mitigation planning.

In the lower catchment, around the Mosirori wetland, the dominant economic activity is the small scale farming of subsistence and cash crops such as maize, sorghum, and cassava. The surrounding hills in this region have undergone deforestation. As a result, the runoff pattern has changed, resulting in fast runoff which in turn causes soil erosion and siltation in the wetland area (Mango et al., 2011). These problems call for the need for understanding the available water and water use in the entire basin to quantify the hydrological impacts of the upstream activities on the downstream water uses.

In recent hydrological studies, many researchers have focused on using physically-based distributed models for the analysis of water use problems in the basin due to land-use change. This is because the researchers have drawn much attention to the basin because of its ecological and biodiversity importance. However, there is no single study that has been conducted to quantify the total consumptive water use in the basin. According to Kiguchi et al. (2014), Kenya is projected to reach a water-scarce country status in less than 25 years as well as Tanzania being water-stressed within the projected period. Therefore, it is very crucial to quantify the availability of surface water in the basin for planning resource development and management in the context of multiple users for sustainability purposes.

The MRB has been mentioned to have limited hydrological data (Hoffman et al. 2009). To achieve the objective of this study, which aims at analysing the consumptive water use in the basin, a methodology that applies freely available remote sensing data is used to assess water use through hydrological modelling in the upper MRB. However, for the calibration and parameterisation of the model, field and in situ data is used.

1.3 Research objectives

1. The main objective of this study is to adapt the modified STREAM model for estimating the water use on the river flows in data-scarce areas. The modified model will be applied and evaluated in the MRB.
1.3.1 Specific objectives
The specific objectives of this study are:

1. To evaluate existing models and identify the gaps in the estimation of water consumption.
2. To adapt the modified STREAM model to estimate better water use in data-scarce areas by incorporating open data, including remote sensing products.
3. To apply, calibrate and evaluate the adapted STREAM model in the MRB.
4. To compare the model results of the original STREAM model to the adapted STREAM model in simulating Upper MRB flows.

1.3.2 Research questions
The following are research questions linked to specific objectives.

1.1 What are the current research gaps for modelling water use in data-poor river basins?
2.1 How can the STREAM model be improved to estimate water use in data-poor areas better?
2.2 How can the STREAM model be improved to use available open data sources, including remote sensing products?
3.1 What data is needed to parameterize, calibrate and evaluate the model?
3.3 How accurate is the adapted STREAM model in simulating flow in MRB, in particular for the impacts of water use?
4.1 How is the modified STREAM model results different from the original STREAM model in simulating the upper MRB flows?


Chapter 2  Study Area

2.1   General characteristics of the study area

The MRB is a transboundary basin shared between Kenya and Tanzania. It is located approximately between latitudes 0°38’ S and 1°52’ S and longitudes 33°47’ E and 35°47’ E. The basin covers a total area of 13,834 km², with the larger upper part of the basin, 65% in Kenya while 35% of the basin lies in Tanzania (Mati et al., 2008).

The 395 km long Mara River flows from its source in the Mau forest at an altitude of 2932m and discharges into the Lake Victoria at Musoma Bay at an altitude of about 1134m. The main tributaries of Mara are the rivers Amala and Nyangores which rise from the Mau escarpment and converge to form Mara River. Other branches of Mara River, which are found on the Kenyan side include rivers Talek, the Engare Engito and Sand River which join the Mara River at the border of Kenya and Tanzania at the Serengeti plains. Rivers Mori, Kenyo, Tambura and Nyambire drain the basin on the Tanzanian side (Mango et al., 2011). Figure 1 shows the location of the Upper Mara basin.

![Figure 1: Upper Mara catchment](image-url)
2.2 Climate

According to Pruijssen (2015), precipitation in the basin varies throughout the catchment depending on the local topography. The highest amount of rainfall is received in the upstream catchment ranging from 1000 to 1750mm per year. Rainfall amounts in the middle and downstream of the catchment range from 900 to 1000mm per year and 300 to 850mm per year, respectively. The basin receives two rainy seasons. The long rains occur from March to May while short rains are received from October to December.

The mean annual temperature varies between 23°C to 25°C. The maximum temperature is 28°C while the minimum temperature is 17°C. In the highlands, the temperatures are much cooler. Potential evaporation is high ranging from 1800 mm to 2000 mm/year. Areas near Lake Victoria record the highest potential evaporation. Figure 2 and Figure 3 shows monthly precipitation of five rainfall stations in the upper Mara for the years 2018 and 2019, from The Trans-African Hydro-Meteorological Observatory (TAHMO) stations. The graphs agree that the rainy season in the Upper Mara is between March and May, and September to December. Figure 2 shows that in 2008, the heavy rainy season was experienced from March to May. In contrast to Figure 3, the heavy rains were experienced between September to December.

![Figure 2: Monthly precipitation data for five rainfall stations in upper Mara (Source: TAHMO)](image_url)
Figure 3: Monthly precipitation data for five rainfall stations in upper Mara (Source: TAHMO)

### 2.3 Physical geography

The dominant soils in the upper and middle Mara are cambisols, while vertisols are predominantly found in the lower MRB. According to Murunga (2017), land cover can be defined as the materials covering the earth's surface while land use is defined as the human activities on the land cover. The major land-cover types in the basin are agriculture, grass, shrubs, and forests, as shown in Figure 4. Grassland dominates the middle part of the catchment, while in the north and south of the basin, croplands are the main land-cover types. The Mau forest occupies the northern part of the catchment (Mati et al., 2008). The Upper Mara is occupied by the Kalenjin community, which is known for cropland agriculture. Maasai Mara National Reserve occupies the better part of the middle reaches dominated by savanna grassland. The Maasai community which borders the Kalenjin community practices pastoralism.

Figure 4 shows the major land-cover classes in the Mara basin.
2.4 Socio-economic characteristics

The total population of the Mara basin is estimated to be 1.28 million. The highest population densities are in Kenyan highlands with low population densities in Tanzanian lowlands. The low lands have the lowest population densities due to its semi-arid nature (LVBC & WWF-ESARPO, 2010).

The main dominant economic activities are subsistence agriculture and livestock production. About 60% of households are practising smallholder subsistence farming. Subsistence farming is mainly practised by the Kalenjin community, which is known best for this. Maasai community, borders the Kalenjin and they are known for pastoralism. Other economic activities in the basin include tourism, cash crop production, mining, trade and industry and forestry (UNFCCC, 2018).
3.1 Blue and green water flows in a catchment

In hydrological studies, the term blue and green water flows are used and defined differently by many researchers. The concept of green water was first introduced by Falkenmark (1997). Jewitt (2006) defined green water as flows of water vapour from soil and vegetation, while blue water is the combination of runoff and groundwater recharge. Schuol et al. (2008) defined green water as the estimated sum of evapotranspiration and soil water content. Falkenmark (2013) defined green water as rainwater storage in the unsaturated zone and sometimes rainwater evaporation. In other studies, green water flows are defined as evaporative flows from the land (Schyns et al., 2015). Green and blue water are sometimes used in the context of water resources availability or water resource use (Falkenmark, 1997).

Hoekstra (2019), defined blue and green water in terms of consumption. He further referred to the consumption term as evapotranspiration (ET). According to him, ETblue refers to evaporation of abstracted blue water resources, which is linked to irrigation water consumption. ETgreen refers to evaporation from direct precipitation in the soil zone. In this study, this definition was adopted.

In arid and semi-arid areas (ASALs) where both actual and potential evapotranspiration is high, green water flows tend to dominate the water cycle. Therefore, any change in green water flows will result in significant impacts on blue water flows in the downstream of the catchment. Historically, the management of the water resources has focused on the blue water component neglecting the green water flows. According to Jewitt (2006), the difficulties in consideration of this green water in policy is as a result of challenges in the estimation of evapotranspiration and difficulties in understanding the linkage between these two types of flows.

In the recent past, many studies have been focused on estimating the climate change impacts and land-use change on total water flows (Calder et al., 2008; Schulze, 2005). This proved to be an essential tool in green water management since it illustrated the potential impacts of land-use change. However, this was a limitation to address the downstream flow requirement. Mwangi et al. (2016), argued that to have integrated catchment management, both blue water and green water have to be taken into consideration. Jewitt (2006), suggested that to have effective water resources management and planning, there is a need for incorporating the connection between these two flows. Figure 5 indicates the concept of blue-green water flows (Bestelmeyer et al., 2017).
3.2 Hydrological modelling

3.2.1 Overview of hydrological modelling

Models are used in hydrological studies for the prediction of catchment responses to a precipitation event. The information generated from models is used by water managers to make sound decisions regarding the management of the water resources at the watershed level. Due to the complexity of the hydrological cycle, the modelling of the rainfall-runoff process has proved to be an important tool in understanding hydrological processes.

For many decades, hydrological studies have focused on the development and application of hydrological models in modelling rainfall-runoff processes (Jakeman et al., 1993). Furthermore, models are used in investigating the relationship between natural and human impacts on water resources.

According to Breuer et al. (2009), fully distributed models are suitable for simulating land-use change effects. In contrast, semi-distributed models represent these changes more accurately since only a small portion of land-use changes in a catchment. Sivakumar (2008), argued that MIKE SHE has evolved in the recent past and is being used by many researchers in hydrological studies. However, parameter estimation is challenging when using these kinds of models. This led to an alternative development of semi-distributed models such as Soil and Water Assessment Tool (SWAT) which simulates hydrological processes in a catchment (Legesse et
al., 2004). However, a SWAT model requires substantial data input and a large number of parameters that are difficult to acquire.

Further simplification of the hydrological models was made to simulate hydrological fluxes at the sub-catchment level. An example is the HBV model. Many researchers (Jakeman et al., 1993; Legesse et al., 2004; Mango et al., 2011; Mutie et al., 2006) have proved that data scarcity in many river basins has limited the applicability of physically-based models. Also, the uncertainty of input data and error propagation in models is a challenge that can be addressed with stochastic models.

Decisions on water resources management can be made appropriate only if there is sufficient information on future scenario changes. In the recent past, modelling has proved to be a suitable tool in predicting future changes. According to Mango et al. (2011), modelling future runoff regime is a challenge in African catchments because of limited historic runoff data. They further suggested that remote sensing data can be useful in modelling hydrology of a basin. However, they emphasized that care should be taken when interpreting the results. Winsemius et al. (2006), found out that at a finer spatial scale, open data such as from remote sensing can be used to parameterize relevant hydrological processes in a catchment.

Figure 6 represents a general classification of hydrological models (Refsgaard et al., 1995).

![Figure 6: General classification of hydrological models (Refsgaard et al., 1995)](image-url)
3.2.2 Modelling of blue and green water resources

In the recent past, many researchers have focused on spatial and temporal modelling of green and blue water resources. The aim of most of these studies was to form a basis for the proper decision of management and allocation of available water resources. Since the introduction of the blue-green concept by Falkenmark (1997), the research in this field has become diverse especially after the conceptualisation of the green-blue flows approach for planning and management of water resources by Rockström (1999).

Zang et al. (2012), modelled the green, and blue water flows under natural conditions for the Heihe basin using the SWAT model. The results showed that there was both a decrease of blue and green water from upstream to downstream reaches. However, they emphasised that there is a need to include human intervention in modelling green-blue water flows since the distribution of water resources on a spatial and temporal scale is influenced by anthropogenic activities in the entire catchment.

Again, many novel research methods have been applied. For instance, Rost et al. (2008), used the LPJmL model for assessment of global green and blue water use in irrigated and rain-fed agriculture over a long period of about three decades, while Zang et al. (2015), assessed the global blue-green water consumption of cropland using GEPIC model. The SWAT model was used to model the green-blue water flows of Mara catchment (Mango et al., 2011). Similarly, Schuol et al. (2008), used the SWAT model to simulate the green-blue water resources of Iran.

In arid and semi-arid regions facing water scarcity challenge, a green-blue water concept is a fundamental tool in water resources management. According to Janssen and Heuberger (1995), this concept can assist in the sustainable allocation of water resources.

3.2.3 Modelling in the Mara River Basin

The MRB has attracted many researchers in the recent past in modelling of the Mara flows. Mango et al. (2011), investigated the impact of land-use change scenarios on the streamflow of the MRB using the SWAT model. The results projected that with increased deforestation in the basin, the flows in the Mara River would significantly decrease.

According to Mutie et al. (2006), modelling of the Mara basin is facing a challenge of limited historic hydro-meteorological datasets. This has resulted in a limited understanding of the hydrology of the MRB.

Mati et al. (2008), used the United States Geological Survey Geospatial Stream Flow Model (USGS Geo SFM) to investigate the effects of land-cover changes on the Mara River flows between 1973 and 2000. The results of the simulation showed that the impact of land-use pressure in the basin has resulted in high flood peaks and faster travel time since the basin has experienced land-use changes from decreased forest cover to increased agriculture.

In addition to this, Abwoga (2012) applied the original STREAM model that was developed for the Zambezi catchment by Winsemius et al. (2006) to model the Upper Mara flows and the impacts of land-use change on the flows. He also compared the efficiency of the STREAM
model to that of SWAT and GeoSFM that had been used before in other studies. The results revealed that the STREAM model performed better as compared to SWAT and GeoSFM.

3.2.4 Research gap
From the results of the modelling of the Mara hydrograph using the SWAT model by Mango et al. (2011), it is clear that the model developed simulated the hydrograph to unsatisfactory level, low NSE and R-value for both the calibration and validation of the model. The NSE values for Amala and Nyangores were during calibration were 0.076 and -0.53, respectively. The R² values were <0.5.

The results of modelling the flows of the Mara using the STREAM model Abwoga (2012) proved that the model performs better with flow simulation as compared to the SWAT and USGS geo stream model. During the calibration of Amala and Nyangores, NSE values of 0.56 and 0.59 respectively. R² values were above 0.6.

From the above discussion, it is clear that there has been some effort of modelling in the Mara catchment, especially using the SWAT model, even though the model evaluation results are moderate. The STREAM model has proved to be a powerful modelling tool to simulate flow in the MRB. However, there is a need to improve the existing STREAM model to account for extensive irrigation water abstraction in the catchment, because it is the major water user in the basin.

Since the STREAM model has proven to perform better than the previous models that were applied, it has been used in this particular study. The choice of this model is based on the argument that even though several researchers have simulated the blue and green flows in the MRB using different models, there is no single study that has attempted to quantify the combined blue and green water use in the basin. Blue water consumption over the irrigation fields is linked to irrigation and thus this study aims at quantifying the irrigation water use.

Most of the physically-based models that have been used in the past focused on simulating the blue and green flows (discharge and evapotranspiration). Furthermore, these models required a large amount of data which is a challenge to get in poorly gauged river basins such as the Mara.

The STREAM model, which is a physically based conceptual model, is developed in the PCRaster modelling environment (Aerts and de Moel, 2004). PCRaster is a library and framework within python that is used in dynamic environmental modelling (Van Deursen, 1995). It can be used in the development of distributed rainfall-runoff simulation models.

PCRaster is a raster-based software that supports the construction of dynamic spatial-temporal models (Schmitz et al., 2009). In PCRaster, users can develop new models through its scripting model development environment. The PCRaster modelling environment allows for the development of new models depending on the objectives of the model.

The original STREAM model was developed in PCRCalc. PCRaster is now a python library with a framework for static, dynamic and stochastic modelling. It uses the dynamic framework to analyse the hydrology of a catchment in space and time. Furthermore, it has several advantages, such as being flexible, thus easily incorporating remote sensing data. In addition to this, it is a free source model. Therefore, it has been applied in data-scarce regions in Africa
(Abwoga 2012; Gerrits, 2005; Kiptala et al., 2014; Winsemius et al., 2006). The model’s spatial character enables users to analyse water availability patterns due to human influences such as deforestation and irrigation.

Due to the flexibility of the STREAM model, Kiptala et al. (2014), modified the original STREAM model (Winsemius et al., 2006) by including an extra bucket to account for blue water use as a result of extensive irrigation agriculture in the upper Pangani basin. The results of the streamflow simulation proved to be sufficient with NSE values above 0.6.

Since the MRB is also a data-scarce catchment with growing irrigation agriculture, there is a need to adapt the modified STREAM model developed for upper Pangani to the MRB. The reason for this is to account for the blue water use by irrigation agriculture in the MRB. This will provide sound information to decision-makers for proper management of the water resources of the shared MRB.
Chapter 4  Research methodology

4.1 Introduction

The STREAM model was scripted in the PCRaster Python library. PCRaster is a raster-based software that supports the construction of dynamic spatial-temporal models (Van Deursen, 1995). In PCRaster, users develop new models through its scripting model development environment. Figure 7 illustrates the STREAM model schematization and structure.

Figure 7: The STREAM model schematization and structure (Gerrits, 2005).

4.2 Hydrological model description

Blue and green water use of the upper Mara River Basin was modelled using the modified STREAM model (Kiptala et al., 2014). The modified STREAM model was applied to simulate the Upper Mara River flows for five years (2015-2019). A 10-day time step and 90m temporal and spatial resolution were used respectively. The choice of 90m resolution is linked to the DEM, which is used as a clone map in the model. In PCRaster, clone map is a map in PCRaster format, with the model extent and spatial resolution. All other spatial maps used in the model should have the same properties as the clone map. Furthermore, small-scale irrigation that is dominant in the upper Mara is representative of this scale. The 10-day temporal resolution is due to the temporal resolution of the interception and evapotranspiration maps that were
obtained from the WaPOR database. This temporal resolution is also sufficient for agricultural water use that ranges from 10-30 days (Notter et al., 2007).

4.3 Model mechanism

The hydrological cycle of the catchment is described as a series of storage reservoirs in the STREAM model. The model, which is based on raster maps, calculates the water balance of each grid cell of the catchment. The digital elevation model (DEM) determines the direction of the water flow. In the model, surface runoff is routed to the rivers through a series of reservoirs that are in the model structure. The calculation of water balance in the STREAM model is based on the simple Thorn Waite (1957) equation, in which the major input variables are precipitation and temperature. The major output from the model after running for a monthly period includes; runoff, groundwater storage and snow cover (Aerts and de Moel, 2004). The model’s spatially explicit character enables users to analyze water availability patterns due to human influences such as deforestation and irrigation. All input data into the model is in the form of raster maps. Figure 8 illustrates the flow direction in the STREAM model.

![Figure 8: Flow direction in the STREAM (Gerrits, 2005).](image)

4.4 The adapted STREAM model structure

In the modified STREAM model, (Figure 9) two zones: saturated and unsaturated zones represent the model structure. For this particular case, the green water use represents evapotranspiration from direct precipitation in the unsaturated zone while the blue water use represents the evapotranspiration of blue water resources in the unsaturated zone. In the model, an additional bucket (Sb) was added to account for supplementary blue water use that is not accounted for in the original STREAM model. The additional blue water use could be in the form of river abstraction or capillary rise from the groundwater. Bluewater consumption in the basin is linked to irrigation and therefore this study aims at quantifying irrigation water use. The rationale of adapting this model is based on the argument that the MRB is experiencing
intensive irrigation in the upper reaches, which abstracts water from the streams and groundwater. Figure 9 shows the modified STREAM structure (Kiptala et al., 2014).

Hydrological processes in the STREAM model from precipitation to runoff generation is described in chapter 4.5.

![Figure 9: Modified STREAM model (Kiptala et al., 2014)](image)

### 4.5 STREAM model processes

#### 4.5.1 Interception

The part of the intercepted precipitation that evaporates in the atmosphere after falling is called interception. Interception components are canopy interception and shallow soil interception (Winsemius et al., 2006). In this case, interception data was available from the WaPOR database, which was included as input data in the model. In the original STREAM model, interception is modelled using threshold value \( D \), and it depends on land-use types. The properties of the land use that is utilized in the model include the leaf area index. The timescale for interception is a day. Equation 1 below illustrates how interception is modelled in the STREAM model. However, in this case, the equation was not applied.

\[
I_d = \min(D_d, P_d)
\]  

Equation 1
Where,

\[ I_d = \text{daily interception [LT}^{-1}] \], \ D_d \ \text{is the daily interception threshold and it depends on the land use. The values of D were obtained from the literature (Zang et al., 2015) and } \ P_d \ \text{is the observed precipitation [LT}^{-1}] \].

**4.5.2 Net precipitation (P_e)**

Net precipitation is obtained after subtracting interception from the total precipitation received. The \( (P_e) \) in the model is calculated as shown according to Equation 2. The dekadal interception is subtracted from the dekadal precipitation to obtain net precipitation.

\[
P_e = P_d - I_d \quad \text{Equation 2}
\]

Where \( P_e = \text{net precipitation [LT}^{-1}] \), \( P_d = \text{observed precipitation [LT}^{-1}] \) and \( I_d = \text{interception [LT}^{-1}] \).

**4.5.3 Evaporation depletion (E + T)**

This component is derived by subtracting the dekadal interception from the dekadal actual evapotranspiration at each time step. Equation 3 illustrates this calculation.

\[
E+T = (ET_a(10) - I_d(10)) \quad \text{Equation 3}
\]

Where \( E+T = \text{evaporation depletion [LT}^{-1}] \), \( ET_a = \text{total actual evapotranspiration [LT}^{-1}] \), and \( I_d = \text{interception [LT}^{-1}] \).

**4.5.4 Unsaturated zone**

The net precipitation is partitioned into the unsaturated zone and saturated zone by a calibration parameter \( cr \). This separation coefficient is dependent on land use type and soil texture. In this zone, available water for evapotranspiration includes water infiltrated from precipitation (\( cr \cdot P_o \)) and blue water use (\( Q_b \)), which consists of capillary rise (\( C \)) from the groundwater and river abstractions (\( Q_d \)) (Kiptala et al., 2014). The maximum soil moisture storage (\( S_{u, \text{max}} \)), was derived depending on land use types. The model assumes a minimum soil moisture level (\( S_{u, \text{min}} \)), which varies for different land use. \( (S_i) \) is the soil moisture status at each time step and therefore it controls water and energy fluxes in the soil according to the equations Equation 4, Equation 5 and Equation 6 below.
$$Q_b = E + T \rightarrow \text{if } (S_u \leq S_{u,\text{min}}) \quad \text{Equation 4}$$

Where $Q_b =$ blue water use [LT$^{-1}$], $(S_{u,\text{min}}) =$ minimum soil moisture level [LT$^{-1}$], $S_u =$ soil moisture status at each time step [LT$^{-1}$].

$$Q_b = 0 \rightarrow \text{if } (S_u \geq S_{u,\text{min}}) \quad \text{Equation 5}$$

To account for green water use, the following equation is used,

$$Q_g = E + T - Q_b \quad \text{Equation 6}$$

Where $Q_g =$ green water use, [LT$^{-1}$].

### 4.5.5 Saturated zone

The saturated component receives water from both the net precipitation ($(1-c_t)P_e$) and excess overflow ($Q_u$) from the unsaturated zone after field capacity is reached. This overflow is then routed to ground flow using recession factor, K. This zone consists of saturation overland flow ($Q_{of}$), slow flow ($Q_{sf}$) and quick flow ($Q_{qf}$), which are routed to the river by recession constants $K_o$, $K_s$ and $K_q$ respectively.

Saturated groundwater flow occurs when groundwater storage ($S_s$) exceeds $S_{s,\text{max}}$ according to equation 7 below. This normally occurs when the groundwater table reaches the surface under saturated soil condition. The situation whereby the groundwater table reaches the surface is determined by the DEM and the bottom of the draining river ($GWS_0$) (Gerrits, 2005).

$GWS_{\text{dem}}$ is defined as the distance between the surface and the bottom as showed in Figure 10.
Due to porosity, the space GWS_{dem} is not completely available for water, therefore to determine the actual space, GWS_{max}, an empirical equation in Figure 11 is used to show the relationship between GWS_{dem} and GWS_{max}.

\[
Q_{of} = \frac{\max(S_s - S_{s,\max}, 0)}{K_o}
\]

Equation 7

Where \( Q_{of} \) = saturated overland flow \([LT^{-1}]\), \( S_s \) = groundwater storage \([LT^{-1}]\), \( S_{s,\max} \) = threshold value for saturated overland flow \([L]\), \( K_o \) = timescale of \( Q_{of} \) \([T]\).

The quick groundwater flow component \( (Q_{qf}) \), groundwater flow through macropores and cracks, depends linearly on \( S_s \) and quick groundwater flow threshold \( S_{qf} \) according to Equation 8.
\[ Q_{qf} = \max(S_s - S_{s,q}, 0)/K_q \]  

Equation 8

Where \( Q_{qf} \) = quick groundwater flow [LT\(^{-1}\)], \( S_s \) = groundwater storage [LT\(^{-1}\)], \( S_{s,q} \) = threshold value for quick groundwater flow [L], \( K_q \) = timescale of \( Q_{qf} \) [T].

The slow groundwater component depends on groundwater storage levels as described in equation Equation 9.

\[ Q_{sf} = (S_s)/K_s \]  

Equation 9

Where \( Q_{sf} \) = slow groundwater flow [LT\(^{-1}\)], \( S_s \) = groundwater storage [LT\(^{-1}\)], \( K_s \) = timescale of \( Q_{sf} \) [T].

Therefore blue water in the model is calculated as shown in Equation 10 below.

\[ \text{Bluewater} = Q_{of} + Q_{qf} + Q_{sf} \]  

Equation 10

### 4.5.6 Interaction between unsaturated and saturated zones

When groundwater storage is above \( S_{c,min} \), capillary rise will occur. Estimation of capillary rise above this value depends on the balance between water available in the saturated zone and water use needs in the soil zone (Kiptala et al., 2014). Actual capillary rise is therefore calculated using the maximum capillary rise, \( C_{max} \) calibration factor, evaporation depletion and available groundwater storage as shown by Equation 11 below.

\[ C = \min (C_{max}, (E+T), S_s) \rightarrow \text{if } S_s \geq S_{c,min}. \]  

Equation 11

Where \( C_{max} \) = calibration factor [-], \( S_s \) = groundwater storage [LT\(^{-1}\)], \( S_{c,min} \) = variable threshold for groundwater storage [L].

However, for some land-use types, the capillary rise is low compared to water use. Therefore, supplementary blue water from rivers (\( Q_d \)) is required to fill this gap in the system. River abstraction includes supplementary irrigation, open water evaporation from lakes and rivers including wetlands (Kiptala et al., 2014). Equation 12 shows the process.

\[ Q_d = (Q_b - C) \rightarrow \text{if } (S_b \leq Q_b) \]  

Equation 12
\[ Q_d = 0 \rightarrow \text{if } (S_b > Q_b) \quad \text{Equation 13} \]

Where \( Q_d \) = supplementary blue water [LT\(^{-1}\)], \( Q_b \) = blue water required to fill evaporation gap [LT\(^{-1}\)], \( S_b \) = groundwater storage threshold [L]. \( Q_d \) is modelled as irrigation water abstraction in the basin.

### 4.5.7 STREAM variables

Table 1 shows the STREAM model variables as adapted from Winsemius et al. (2006).

**Table 1:** STREAM variables as adapted from (Winsemius et al., 2006)

<table>
<thead>
<tr>
<th>STREAM variable</th>
<th>Determination method</th>
</tr>
</thead>
<tbody>
<tr>
<td>( I )</td>
<td>Interception[mm/10 day]</td>
</tr>
<tr>
<td>( P )</td>
<td>Precipitation[mm/10 day]</td>
</tr>
<tr>
<td>( P_e )</td>
<td>Net precipitation[mm/10 day]</td>
</tr>
<tr>
<td>( S_{u,\text{max}} )</td>
<td>Field capacity[mm]</td>
</tr>
<tr>
<td>( S_u )</td>
<td>Initial saturated zone storage[mm]</td>
</tr>
</tbody>
</table>

### 4.5.8 STREAM parameters

Table 2 below summarises the STREAM model parameters.

**Table 2:** STREAM model parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Determination method</th>
</tr>
</thead>
<tbody>
<tr>
<td>( S_{u,\text{ini}} )</td>
<td>calibration</td>
</tr>
<tr>
<td>( K )</td>
<td>Recession curve</td>
</tr>
<tr>
<td>( K_q )</td>
<td>Recession curve</td>
</tr>
<tr>
<td>( K_s )</td>
<td>Recession curve</td>
</tr>
<tr>
<td>( GWS_{\text{ini}} )</td>
<td>calibration</td>
</tr>
<tr>
<td>( GWS_{\text{max}} )</td>
<td>calibration</td>
</tr>
<tr>
<td>( C_r )</td>
<td>calibration</td>
</tr>
<tr>
<td>( C_{\text{max}} )</td>
<td>calibration</td>
</tr>
</tbody>
</table>

Source: (Winsemius et al., 2006)
4.6 Data collection and field observation

The data used in this modelling exercise is shown in Table 3 below.

*Table 3: Model input data.*

<table>
<thead>
<tr>
<th>Input data</th>
<th>Type of data</th>
<th>Source of the data</th>
<th>Data type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Climatological data</td>
<td>1. Rainfall data</td>
<td>From WaPOR data</td>
<td>Raster</td>
</tr>
<tr>
<td></td>
<td>2. Evapotranspiration</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Basin maps</td>
<td>1. Landuse/land cover map</td>
<td>1. WaPOR data</td>
<td>Raster</td>
</tr>
<tr>
<td></td>
<td>2. DEM</td>
<td>2 SRTM</td>
<td></td>
</tr>
<tr>
<td></td>
<td>3. soil map</td>
<td>3. Digital soil map of the world.</td>
<td></td>
</tr>
<tr>
<td>Literature review data</td>
<td>Parameters relating to soil and vegetation.</td>
<td>Publications on the STREAM model.</td>
<td>vector</td>
</tr>
<tr>
<td>Discharge data</td>
<td>For calibration and evaluation of the STREAM model.</td>
<td>Water Resources Authority in Kenya.</td>
<td>vector</td>
</tr>
</tbody>
</table>

4.7 STREAM model spatial input data

For running the STREAM model, six spatial input dataset layers were used. This includes: land-use map, soil map, precipitation maps, interception maps, total evapotranspiration maps, and digital elevation model.

4.7.1 Digital elevation model

A digital elevation model (DEM), 3-Arc Second Product, was obtained from the Shuttle Radar Topography Mission (SRTM) with 90 m resolution. The catchment boundary chosen is in line with the other researchers who modelled the upper Mara. This was selected for the sake of comparison purposes. The DEM was used as a clone map of the catchment. In this sense, all the spatial data layers were resampled to have the extent, cell size, number of rows and columns and coordinate system as the DEM. Figure 12 shows the elevation in the Upper MRB.
4.7.2 Land-use maps
The land cover map was derived from WaPOR data (2015-2019) at a spatial resolution of 250m. At this spatial resolution, eight LULC classes were identified. Most of the model parameters such as separation coefficient (cr) and quick flow coefficient (qc) depend on the land-use type. Figure 13 shows the Upper MRB land-cover classes.
4.7.3 Soil map
The soil map was obtained from the Digital Soil Map of the World. The soil classification is according to FAO classes. The main soil classes identified include clays, clay-loam, sandy clay and sandy clay loam. The dominant soil type is clay loam, covering about 50% of the total study area. The soil map of the Upper MRB is displayed in Figure 14 below.

![Figure 14: Upper Mara soils](image)

4.7.4 Precipitation, interception and evapotranspiration maps
Spatially distributed rainfall maps were obtained from WaPOR data at a spatial and temporal resolution of 5km and 10-day, respectively. Interception and evapotranspiration maps were obtained from the WaPOR database too. Unlike the precipitation maps, these two were obtained at a spatial resolution of 100m. The source of the precipitation dataset is CHIRPS (Climate Hazards Group Infrared Precipitation with Station). According to Cheema et al. (2011), CHIRPS products are one of the most reliable remote sensing products. Furthermore, CHIRPS products perform well on dekadal temporal resolution (Dembélé and Zwart, 2016).

In addition to this, monthly rainfall data were obtained from 10 Trans-African Hydro-Meteorological Observatory (TAHMO) stations and 7 Kenya Meteorological (KMD) stations, which are located in the Mara basin. The point rainfall dataset ranges from the year 2014-2019, though some stations have fewer data. Data from TAHMO stations were used in the intercomparison with the WaPOR precipitation datasets, for evaluation purposes.

4.8 Pre-processing model input data
Since the STREAM model was scripted in the PCRaster Python environment, all the input data is in the form of raster maps. Therefore, one of the major tasks was to prepare the raw data into
the PCRaster maps. In PCRaster Python, all the maps used should have the same properties. In this case, the first step was to make a clone map. Thus, the digital elevation model was set as a clone map.

The second step involved creating a flow direction map, which in PCRaster is called local drain direction map (ldd map). This map determines the flow of water in all the cells. Other raster maps including soil map, land-use map, catchment outlet maps were processed in QGIS, imported to PCRaster and resampled to the clone map to have the same properties whereby the number of rows/columns, cell size, extent, the coordinate system should be the same as that of the DEM.

For precipitation, evapotranspiration, and interception maps, a short script was made to convert them from the tiff format into time-series format. As other PCRaster maps, they were also resampled to the DEM.

### 4.9 Modelling procedure

Modelling of the MRB involved a series of steps as listed below.

1. Conversion of the adapted script from old pcrcal to PCRaster python. The adapted STREAM model Kiptala et al. (2014), was developed before the PCRaster was a library and used the PCRaster native language (pcrcal). Since the two modelling languages differ in different ways, there was a need to change operations and applications from the old model to the new one.

2. Integration of Kiptala’s script (Pangani River Basin) and Abwoga 2012 script (Mara River Basin). The reason is that they used two different approaches, especially in modelling green water use (see section 4.5.4).

3. Testing the new model using available files and analyzing the results.

4. Preparation of the input data for the adapted Mara model. This included preparation of precipitation and evapotranspiration maps, land cover and soil maps into PCRaster format.

5. Running the Upper Mara model

6. Calibration of the model

7. Evaluation and comparison of the results.

Figure 15 represents the general procedure using the STREAM model.
4.10 Model calibration and validation

The model calibration was done manually. For the discharge calibration, water level data from Amala and Nyangores Rivers were converted to river discharges by the use of the rating curve equation (Hulsman and Hulsman, 2016) (see annex E). Even though there are four gauging stations in the upper MRB, two gauging stations were used in the calibration and validation process. These stations include gauging stations at Bomet Bridge and Kapkimolwa Bridge on Nyangores and Amala Rivers respectively. The choice for this decision was limited to the available historical data from the Water Resources Authority (WRA).

The daily discharges were summed up to a 10-day time scale to match the output of the simulated discharges. The calibration period was between 2015-2016. The validation of the model was done for the period 2017-2019. Figure 16 below shows the gauging stations in the upper MRB.
4.11 Rainfall intercomparison

Precipitation datasets from TAHMO stations were downloaded from their portal. Since all the model input data is from remote sensing and modelled at grid-scale, the in situ precipitation datasets were used for intercomparison with remote sensing precipitation. Since only one rainfall station out of the total ten stations mapped in MRB was available for the upper Mara, the intercomparison was done at the basin scale for the year 2019. Since most TAHMO stations were installed between periods of 2017-2018, by 2019, all the stations were installed and had reliable data, thus determining the choice of 2019 as the year of comparison.

Daily precipitation dataset from TAHMO stations was accumulated to dekadal scale, for easier intercomparison with WaPOR precipitation, which has a temporal resolution of 10 days. The first two dekads of each month comprise of 10 days while the last dekade of each month consists of 8 days for February and 11 days for the months with 31 days. In total, 36 dekads were used for the comparison.

To determine the average amount of rainfall received in the MRB at a dekadal scale, the Thiessen polygon method was used as an interpolation method. The in situ rainfall time-series was then compared with the WaPOR rainfall time-series at the same temporal resolution. The coefficient of statistical determination method was then used to determine the level of
correlation between the two-time series rainfall sets. Figure 17 displays the TAHMO rain station at Senchura secondary school in Narok County.

![Figure 17: TAHMO rainfall measurement station](image)

4.12 Irrigation water use

Irrigation water use information was also collected from the farmers in the MRB. In the MRB, irrigation agriculture is dominant in the Amala and Nyangores sub-catchments, as shown on the land-use map (see Figure 13). This data was compared with modelled irrigation water abstraction on a basin scale. Besides, individual farm’s ETblue was compared to irrigation water abstraction. Figure 18 shows the irrigation farms in the Upper MRB visited during field data collection in December 2019.
4.13 Model evaluation

Generally, the hydrological model is evaluated for its performance. This is done by comparing the hydrographs of simulated and observed discharge. The process of model evaluation is essential during the calibration of the model and also during the communication of the model results to the water resources managers (Mwangi et al., 2016).

Common methods used in the evaluation of hydrological models include Nash-Sutcliffe Efficiency (NSE) and the coefficient of determination ($R^2$). According to Zang et al. (2012), the choice of the appropriate method to use can be very challenging since each approach emphasizes differently on different types of observed and simulated behaviours. In this particular study, the STREAM model will be evaluated using NSE and $R^2$. (Nash Sutcliffe, 1970).

Equation 14 below (Nash and Sutcliffe, 1970) is used to calculate the NSE coefficient.

\[
NSE = 1 - \frac{\sum_{t=1}^{N} [q_{obs}(t) - q_{sim}(t)]^2}{\sum_{t=1}^{N} [q_{obs}(t) - q_{sim}(t)]^2} \tag{14}
\]
From the equation above, the NSE value ranges from -1 to 1. NSE values close to 1 indicate the best model performance. NSE values < 0 shows that the model simulation doesn’t match the observed data.
Chapter 5  Results and discussion

This chapter describes the results of the research questions. It includes rainfall intercomparison, model parameters calibration, calibration and evaluation of the model results, blue-green water use, irrigation water abstraction, and model intercomparison in this order.

5.1 Rainfall intercomparison

In this analysis, TAHMO was taken as a reference. From the analysis of rainfall intercomparison, it can be concluded that on a basin scale, the coefficient of determination ($R^2$) of 0.90 suggests that remote sensing precipitation is almost similar to the measured rainfall. Figure 19 and Figure 20 shows the plot and scatter diagram for the intercomparison analysis. However, the NSE value obtained was -1.4, which implies that the WaPOR precipitation was overestimated.

Figure 19: TAHMO-WaPOR cumulative dekadal areal rainfall intercomparison
The STREAM model was run in PCRaster python on a dekadal scale for five years (2015-2019) resulting in 180-time steps. The simulated discharge was then compared to the observed discharge.

For this research, model calibration was done manually. This involved varying a certain model parameter at a time while the other parameters were held constant. Table 4 below shows the parameters that were varied during the calibration process and a range of suitable values obtained. However, not all the model was sensitive to all parameters. The most sensitive parameters include the $S_{u,\text{max}}$ and the $q_c$ which are related to the size of the unsaturated and saturated zones. In the next sections, the calibration of the parameters in Table 4 is explained.

### Table 4: STREAM model parameter values used in the model

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Description</th>
<th>Units</th>
<th>Values</th>
<th>Optimization</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S_{u,\text{max}}$</td>
<td>Maximum unsaturated zone storage</td>
<td>mm/10day</td>
<td>240-470</td>
<td>Calibration</td>
</tr>
<tr>
<td>$S_{u,\text{ini}}$</td>
<td>Initial unsaturated zone storage</td>
<td>mm</td>
<td>50</td>
<td>Calibration</td>
</tr>
<tr>
<td>K</td>
<td>Overtop timescale</td>
<td>10-day</td>
<td>0.5</td>
<td>Manual</td>
</tr>
<tr>
<td>$K_q$</td>
<td>Quick flow timescale</td>
<td>10-day</td>
<td>21</td>
<td>Recession curve</td>
</tr>
<tr>
<td>$K_s$</td>
<td>Slow flow timescale</td>
<td>10-day</td>
<td>15</td>
<td>Recession curve</td>
</tr>
<tr>
<td>$GWS_{\text{ini}}$</td>
<td>Initial groundwater storage</td>
<td>mm</td>
<td>50</td>
<td>Recession curve</td>
</tr>
</tbody>
</table>
5.2.1 Maximum unsaturated zone storage ($S_{u,\text{max}}$)

This parameter determines the amount of water that percolates to the groundwater reservoir. Sometimes, it is called field capacity of the soil and it depends on the type of land cover and soil. In the STREAM model, $S_{u,\text{max}}$ is estimated according to the equation below.

$$S_{u,\text{max}} = 1000(\theta_{\text{FC}} - \theta_{\text{WP}})Z_r$$

Where, $S_{u,\text{max}}$ is the water available in the root zone, [L], $\theta_{\text{FC}}$ is the water content at field capacity, [$L^3L^{-3}$], $\theta_{\text{WP}}$ is water content at the wilting point, [$L^3L^{-3}$] and $Z_r$ is the rooting depth, [L].

Annex 1 shows all the parameters adapted from the WetSpa Extension and user manual relating to the determination of the field capacity of the soil. Table 5 and Figure 21 show the estimated values of the $S_{u,\text{max}}$ as used in the adapted STREAM model for upper Mara.

**Table 5: Estimated values of $S_{u,\text{max}}$**

<table>
<thead>
<tr>
<th>Soil type</th>
<th>$S_{u,\text{max}}$(mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clay</td>
<td>470</td>
</tr>
<tr>
<td>Sandy clay loam</td>
<td>350</td>
</tr>
<tr>
<td>Silt Loam</td>
<td>300</td>
</tr>
<tr>
<td>Loam</td>
<td>320</td>
</tr>
<tr>
<td>Clay loam</td>
<td>370</td>
</tr>
<tr>
<td>Sandy loam</td>
<td>240</td>
</tr>
</tbody>
</table>

**Figure 21: Field capacity, ($S_{u,\text{max}}$)**
5.2.2 Initial unsaturated zone storage ($S_{u, ini}$)
This refers to the initial state of the soil moisture storage before the analyses. The value arrived at 50mm after a series of trial and error.

5.2.3 Recession constants for the saturated zone
The residence time for the groundwater flow of the upper mara catchment was determined using the recession curve method by use of the observed discharge values. These constants include the K, ko, kq, and ks as described in the methodology section. These parameters are obtained by plotting the natural logarithm of the discharge data and the steepness of the curve represents these time scales. These values were obtained visually.

5.2.4 Maximum groundwater storage in the saturated zone ($GWS_{max}$)
Maximum groundwater storage is determined as a function of DEM and bottom of the draining river ($GWS_0$) as shown in Figure 22.

![Figure 22: schematization of GWSdem (Gerrits, 2005)](image)

$GWS_{max}$ was calculated as shown in the equation below;

$$GWS_{max} = 25 \ln (GWS_{dem})$$

This implies that when $GWS_{max}$ is exceeded by the groundwater table, then the water will flow directly into the river.

5.3 Model Results
In this section, the results of the final calibrated model are presented. The calibration of model parameters was presented in section 5.3.

The adapted STREAM model was calibrated against daily discharges that were obtained from the measured water levels by the use of the rating curve equation. The reason for using the rating curve equation is limited to the discharge data obtained from the Water Resources Authority in Kenya. The discharge data had missing gaps and was only for two years, therefore not sufficient for the model calibration.
Calibration was only done for the Amala and Nyangores rivers. Calibration for the remaining two stations (Emarti and Mara) was not possible due to lack of observed discharge. The calibration period for both rivers was from 2016 to 2017. The year 2015 had a lot of missing data; therefore, it was not used in the calibration.

The evaluation period for both the two rivers was from 2018-2019. Model performance was evaluated using the (NSE) and the $R^2$. Equation 11 above was used for calculating the NSE values for the two rivers. The $R^2$ value was obtained from the linear regression.

### 5.3.1 Calibration of Amala and Nyangores

Figure 23 and Figure 24 shows the hydrograph of Amala and Nyangores Rivers during the calibration of the model. The NSE values for calibration are 0.59 and 0.50 for Amala and Nyangores respectively. Figure 25 and Figure 26 show the $R^2$ values for the two rivers. For Amala River, the $R^2$ is 0.75 while for Nyangores, 0.6 was obtained. The NSE values are satisfactory, since NSE values >5, indicates good model results performance. Even though the model results are satisfactory, visual inspection of the hydrograph shows that the model underestimated the peak flows.

![Amala hydrograph during calibration](image)

*Figure 23: Amala calibration at 10-day temporal resolution (2016-2017)*
Figure 24: Nyangores calibration at 10-day temporal scale (2016-2017)

Figure 25: $R^2$ value for Amala River during the calibration period (2016-2017).
Both Amala’s and Nyangores’ simulated peak flows (Figure 23 and Figure 24) were underestimated. For the Amala, there are no noticeable delays between the hydrographs, but for Nyangores, this is evident. Analysis of maximum high flows for Amala river indicates that the flows respond to rainfall seasons that are experienced (March to May) and (September to December). In contrast, for the Nyangores, this trend is not seen. Amala’s highest flow was recorded in June 2017. This is the period of high rainfall season in the basin. For Nyangores River, the highest flows were experienced during September 2016 during the short rainy season in the basin. Based on the rainfall-runoff relationship, it is clear that the hydrograph responds well to rainfall seasons. Based on the gradient of the trendline, which is less than one, it can be concluded that the model underestimated the discharges of both the Amala and Nyangores.

5.3.2 Evaluation of Amala and Nyangores

Evaluation of the model was done for the years 2018 and 2019. NSE values for both the rivers were 0.52 (Figure 27 and Figure 28). The $R^2$ for the Nyangores was 0.75 as opposed to that of Amala of 0.61 (Figure 29 and Figure 30). The NSE values are fair and it can be concluded that the model evaluation was better. As seen from both the hydrographs, the peak flows are underestimated. It is not clear whether it is due to uncertainties in observed discharge or the estimation of the model parameters. Both the river’s low flows were fairly simulated with a better match between the two hydrographs. There are no noticeable delays between the hydrographs in both cases. In both cases, the flows respond well to the rainfall events in the basin.
Figure 27: Amala evaluation at 10-day temporal resolution (2018-2019).

Figure 28: Nyangores evaluation at 10-day temporal resolution (2017-2019).
This section presents the model results on the ETblue and ETgreen. Here, blue water use (ETblue) is defined as water abstracted from the rivers, groundwater and capillary rise for supplementing soil moisture in the unsaturated zone. This water then becomes ETblue if it is consumed in the evapotranspiration process (for example after application to a field through irrigation). Green water use is defined as precipitation component that evaporates back to the atmosphere as evapotranspiration from the soil zone. The two components make up the total evapotranspiration in the unsaturated zone.

From the model, both the ETblue and ETgreen for different land-cover types in the basin were analysed annually from 2015-2019. Also, ETblue of some irrigation farms was compared to the irrigation water abstraction for those specific farms, to provide more insights into the analysis of the ETblue.
The results presented in Figure 31 represents the averages of the annual blue-green water use for the 5 years. The pie chart represents the total area of each land cover in Figure 32.

**Figure 31:** Bluewater- green water use contribution to Eta averaged over five years.

**Figure 32:** Percentages of land cover classes in the upper Mara.
From the results, agriculture dense ETblue contribution to total evapotranspiration is the highest throughout the year, about 55%. Sparse agriculture and forest’s ETblue contribution is 30%, and 25% respectively averaged over the years. Woodlands, bushlands, and grasslands show ETblue contribution of <10%. For plantations, ETblue contribution to ETA is approximately 10%. In the upper MRB, dense agriculture is the most dominant land-cover class as represented on the pie chart. About 52% of the total area is covered by dense agriculture. Forest and bushlands cover about 20% and 11% of the total area respectively. Grasslands, woodlands, sparse agriculture occupy the remaining 16% of the total area. In general, ETblue was maximum and minimum in 2015 and 2018 respectively.

Figure 33 and Figure 34 shows the results of seasonal ETblue of Mara farming and Mara beef in comparison to river abstraction (Qb), respectively. These two farms are among the major irrigation farms in the MRB, thus assumed the greatest blue water users. The Qb values were obtained from the management of the irrigation farms during fieldwork activities. ETblue over the months during which irrigation is dominant in the basin was summed up. All the months in a year were considered apart from October, November and December, which are harvesting months.
From the graphs, ETblue varies slightly in Mara farming and is less than Qb throughout the whole period. The Qb value was obtained from the management of the Mara farming. It represents the amount of water abstracted for irrigation. ETblue for Mara Beef scheme varies significantly throughout the 5 years. In both farms, the maximum and minimum ETblue values were in 2015 and 2018 respectively. This agrees with the results of the assessment of ETblue values for all land-cover classes. Small-scale irrigation farms show the same trend of varying ETblue as shown in Figure 35, Figure 36 and Figure 37 below. In the upper MRB, both small-scale and large-scale farmers grow the same types of crops, thus similar cropping pattern season.

![Average Seasonal ETblue (m³) against Qb (m³) of Nkinej farms](image1)

*Figure 35: Average Seasonal ETblue (m³) against Qb (m³) of Nkinej farms*

![Average Seasonal ETblue (m³) against Qb (m³) of Longisa farms](image2)

*Figure 36: Average Seasonal ETblue (m³) against Qb (m³) of Longisa farms*
From the graphs above, ETblue ranges from 2000 to 7000 m$^3$ per year. This value varies depending on the sizes of the irrigation farms. For the Nkinej farms, the sizes of the farms are approximately 5ha. Farmers in this region have a universal pump which they use for pumping water from Timbilil River, a tributary for Amala River. They irrigate in shifts and they mostly grow vegetables, watermelons and French beans. They use horse pipes to irrigate their irrigation farms. ETblue in these farms is approximately half of the Qb.

Longisa small-scale farmers abstract water from the Amala River. Their farms are in the magnitude of 10ha. ETblue in these farms is relatively high, above 5000 m$^3$. One farmer had simple drip irrigation but the rest use small horse pipes to deliver water to the crops. Kaboson farms are about 5ha. Farmers here abstract water from the Nyangores River, near the confluence with the Amala. They have formed small cooperative whereby they support each other in terms of financing farm inputs. ETblue in these fields is in the magnitude of 3500 m$^3$.

Based on the analysis of these small-scale farms, ETblue is less than Qb for all the farms. Also, there is a noticeable annual variation in ETblue.

Irrigation efficiency of the existing irrigation schemes was determined by dividing the ETblue over Qb. In this study, irrigation efficiency is defined as the evaluation of irrigation water use (Derpsch, 2003). The efficiency was assessed on each farm annually. For Mara Beef and Mara farming schemes, the irrigation efficiencies was in range of 80%. This implies that only 20% of the abstracted irrigation water is lost from the system. For the small-scale farms, irrigation efficiency was relatively lower as compared to the large schemes. Nkinej farms had the lowest efficiencies in the range of 50%. The Kaboson and Longisa farms recorded irrigation efficiencies of >60%.

### 5.3.3 Irrigation water abstraction (Qb)

The modelled decadal irrigation water abstraction (Qb) over the 4 gauging stations were aggregated to annual. The annual estimate was then compared to the estimated river abstraction, for the existing irrigation schemes in the basin, as documented by the Water Resources Authority (WRA) in Kenya. The annual net irrigation in m$^3$/day was converted to m$^3$/year (annual volume) for easier comparison. Table 6 shows the major irrigation water abstractors in the Upper MRB.
Table 6: Irrigation abstractors in Upper Mara m³/day (source: WRA, Kenya)

<table>
<thead>
<tr>
<th>Irrigation Scheme</th>
<th>Source of Water</th>
<th>Amount m³/day</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kaboson Irrigation scheme</td>
<td>Nyangores</td>
<td>5500</td>
</tr>
<tr>
<td>Shimo Ltd</td>
<td>Amala</td>
<td>70908</td>
</tr>
<tr>
<td>Shimo Ltd</td>
<td>Amala</td>
<td>1818</td>
</tr>
<tr>
<td>Olerai Ltd</td>
<td>Amala</td>
<td>2364</td>
</tr>
<tr>
<td>Olerai Ltd</td>
<td>Amala</td>
<td>2818</td>
</tr>
<tr>
<td>Ndkaini Farm Ltd</td>
<td>Amala</td>
<td>2000</td>
</tr>
<tr>
<td>Ndkaini Farm Ltd</td>
<td>Amala</td>
<td>22273</td>
</tr>
<tr>
<td>Mara WRUA</td>
<td>Amala</td>
<td>524</td>
</tr>
<tr>
<td>Sigor Sec School</td>
<td>Nyangores</td>
<td>46</td>
</tr>
<tr>
<td>James Finlay</td>
<td>Timbilil</td>
<td>3200</td>
</tr>
<tr>
<td>Isinya roses</td>
<td>Ndoinet</td>
<td>56</td>
</tr>
<tr>
<td>Olerai farm</td>
<td>Mara</td>
<td>2368</td>
</tr>
<tr>
<td>James Finlay</td>
<td>Amala</td>
<td>3700</td>
</tr>
<tr>
<td>Tibu limited</td>
<td>Amala</td>
<td>2043</td>
</tr>
<tr>
<td>Lalela Limited</td>
<td>Mara</td>
<td>2636</td>
</tr>
<tr>
<td>Mara farming limited</td>
<td>Amala</td>
<td>1830</td>
</tr>
<tr>
<td>Mara beef limited</td>
<td>Mara</td>
<td>8400</td>
</tr>
<tr>
<td>Total in m³/day</td>
<td></td>
<td>132487</td>
</tr>
<tr>
<td>Total in m³/year</td>
<td></td>
<td><strong>48357755</strong></td>
</tr>
</tbody>
</table>

From the table, it is clear that the most substantial volume of irrigation abstraction is from the Amala River. An estimate of about 83% of the total documented abstraction is from the Amala River. The remaining 17% is from Nyangores and Mara downstream of the confluence of Amala and Nyangores.

Figure 18 shows the major irrigation schemes in the Upper MRB. The largest scheme in size is Lalela limited, which covers 450 Ha. Mara farming and Tibu farms belong to the same management and occupy 350 Ha in total. Mara beef and Olerai covers 200 Ha each. James Finlay and Isinya roses cover 70 Ha each. Other irrigation schemes such as Kabosson, Ndkaini, and Shimo are equally significant basing on the abstraction rate, but the size is not documented.

Modelled irrigation water abstraction is presented in Table 7. The dekadal irrigation water abstraction from the model was summed up to annual for all the four gauging stations for the five years. The model assumed river abstraction is for irrigation use. Since abstraction is
distributed in the upper Mara, in this study, the totals from all the gauge stations were compared to estimated annual abstraction from the entire sub-basin as documented by WRA, Kenya.

From the results in Table 7, we can see that a total of approximately 40 M m$^3$ was abstracted from the basin for irrigation purposes as compared to approximately 48 M m$^3$ that is documented annually by the WRA in 2015. For the subsequent years, the modelled irrigation water abstraction ranged between 34 M m$^3$ to 39 M m$^3$. 2015 and 2019 recorded the maximum and minimum irrigation water abstraction in the basin, respectively.

Table 7: modelled irrigation water abstraction in the upper Mara (m$^3$/year)

<table>
<thead>
<tr>
<th>Year</th>
<th>Amala</th>
<th>Nyangores</th>
<th>Kichwa Tembo</th>
<th>Mara</th>
<th>Total (m$^3$/s)</th>
<th>Total (m$^3$/yr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2015</td>
<td>3.1</td>
<td>3.1</td>
<td>3.5</td>
<td>3.2</td>
<td>12.9</td>
<td>40*10$^6$</td>
</tr>
<tr>
<td>2016</td>
<td>1.6</td>
<td>2.7</td>
<td>4.1</td>
<td>4.1</td>
<td>12.5</td>
<td>38*10$^6$</td>
</tr>
<tr>
<td>2017</td>
<td>3</td>
<td>2.6</td>
<td>3.1</td>
<td>3.5</td>
<td>12.2</td>
<td>37*10$^6$</td>
</tr>
<tr>
<td>2018</td>
<td>2.7</td>
<td>2</td>
<td>3.1</td>
<td>3.4</td>
<td>11.2</td>
<td>34*10$^6$</td>
</tr>
<tr>
<td>2019</td>
<td>2</td>
<td>2.6</td>
<td>3.4</td>
<td>3</td>
<td>11</td>
<td>34*10$^6$</td>
</tr>
</tbody>
</table>

Figure 38 shows the modelled irrigation water abstraction. The gauge stations in this figure do not represent the abstraction points but rather gauge stations that exist in the basin. Due to this, it was not possible to compare the total volume of water abstracted from a certain river to the modelled one.

![Modelled irrigation water abstraction in the Upper Mara Basin](image)

Figure 38: Modelled irrigation water abstraction in the Upper Mara Basin

5.3.4 Model intercomparison
Modelling upper Mara using the modified STREAM model was driven by the fact that the original STREAM model which was developed for the Zambezi catchment (Winsemius et al., 2006) had already been applied in 2012 and did not account for irrigation water abstraction. Since the two model structures differ from each other, it was important to compare and assess
the results of the two models on simulating stream flows of the Upper Mara. These two model structures have been applied to the same catchment but under a different period. Model evaluation results from the original STREAM model (Abwoga, 2012) and the modified STREAM model were compared. The comparison was based on the model structure, model properties, the type of input data and the model evaluation.

Basing on the model structure, an additional bucket was added in the modified STREAM model to account for the supplementary irrigation water abstraction (figure 11). In the original STREAM model, this is lacking. Therefore, irrigation withdrawals cannot be compared.

In both cases, the spatial resolution of the model was 90m. The temporal resolution used in the original STREAM model was one month while in the modified model, dekadal scale was used. The modified STREAM model was run for five years (2015-2019) while the original STREAM was run for nine years (2001-2009).

Insitu precipitation datasets were used in the original STREAM model, the interception was modelled as a threshold D depending on land-use type while evaporation and transpiration were determined using empirical formulas. In the modified STREAM model, both the precipitation, interception, and evapotranspiration were obtained from the WaPOR database.

Evaluation of the model in both cases was performed by calculating NSE and $R^2$ values. Table 8 below shows a summary of model properties and input data sources.

<table>
<thead>
<tr>
<th>DATA TYPE</th>
<th>Original STREAM</th>
<th>Modified STREAM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rainfall</td>
<td>Point measurement</td>
<td>Satellite-based</td>
</tr>
<tr>
<td>Evapotranspiration</td>
<td>Empirical formula derivation</td>
<td>Satellite-based</td>
</tr>
<tr>
<td>Soils</td>
<td>KENSORTER database</td>
<td>Digital soil map of the world database</td>
</tr>
<tr>
<td>Land use</td>
<td>Landsat Thematic Mapper data</td>
<td>WaPOR database</td>
</tr>
<tr>
<td>DEM</td>
<td>SRTM 90m</td>
<td>SRTM 90m</td>
</tr>
<tr>
<td>Discharge</td>
<td>Amala and Nyangores gauge stations</td>
<td>Amala and Nyangores gauge stations</td>
</tr>
</tbody>
</table>

### 5.3.5 Model performance efficiency

Model evaluation was discussed based on the evaluation results that were done separately. The results are shown in Table 9 below.
Table 9: Intercomparison of model evaluation results

<table>
<thead>
<tr>
<th>STATISTICS</th>
<th>MODEL TYPE</th>
<th>Original STREAM</th>
<th>Modified STREAM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Amala</td>
<td>Nyangores</td>
<td>Amala</td>
</tr>
<tr>
<td>NSE(calibration)</td>
<td>0.56</td>
<td>0.59</td>
<td>0.59</td>
</tr>
<tr>
<td>NSE(validation)</td>
<td>0.35</td>
<td>0.52</td>
<td>0.52</td>
</tr>
<tr>
<td>R2(calibration)</td>
<td>0.81</td>
<td>0.8</td>
<td>0.75</td>
</tr>
<tr>
<td>R2(validation)</td>
<td>0.66</td>
<td>0.79</td>
<td>0.61</td>
</tr>
</tbody>
</table>

The results above suggest that the model evaluation is of the same magnitude for both models. In both cases, the NSE values are in the range of 0.5 except during the validation of the Amala River, using the original STREAM model which is below 0.5.
5.4 Discussion of the model results

5.4.1 Rainfall Intercomparison

By comparing the satellite-based precipitation to the in-situ, the NSE value indicates that the two are reasonably correlated even though the coefficient of determination is high. One of the reasons could be a result of a few rain stations that existed. Most of the stations are located in the upper Mara, but the interpolation was for the whole Mara. This could be one source of error. Also, the time step used for intercomparison is a key factor in the intercomparison. Dembélé and Zwart (2016), found out that as evaluation time step increases, the performance of satellite-based rainfall also improves. This suggests that at a monthly or annual time scale, the results would improve.

Doing intercomparison for only one year is not sufficient to prove whether there is a correlation between measured precipitation and satellite-based precipitation. Intercomparison for an extended period and at different time scales is recommended. Dembélé and Zwart (2016) assessed the accuracy of seven satellite-based rainfall in Burkina Faso for 14 years. They found out that the statistical evaluation of the satellite-based rainfall was above average and the NSE value was about 0.7.

Generally, satellite-based precipitation products overestimate rainfall events (Dembélé and Zwart, 2016). This is also true for this case. During intercomparison, it is possible to know which decades were overestimated or underestimated. However, in this study, the comparison was made on the accumulation scale, it was not possible to show which decades were overestimated or underestimated. They further linked the sensor’s inability to discriminate drizzling days to rainy days as the major cause of this overestimation.

According to Cohen Liechti et al. (2012), satellite-based rainfall of smaller grid sizes may perform well due to the reduction of point-to-pixel comparison. However, he argued that the best satellite product depends on the specific use and the time-step chosen. For flood analysis studies, he recommended a daily time step while for agricultural water use, he suggests a dekadal time scale. However, for the analysis of hydrology of a basin, a monthly or seasonal time step is recommended for better results.

When comparing the satellite-based rainfall to the point measurement, identical results are not expected since the point measurement lacks areal coverage. In contrast, the satellite-based only provides spatial averages based on intermittent rain rates. Therefore, Wang et al. (2014), suggested that when making this comparison, the difference between these two estimates should be separated into area-point error variance and satellite-rain estimation variance. Furthermore, point measurement is subject to mechanical errors. Since this analysis did not consider the area-point estimation error, the ground data is not considered a perfect measure.

5.4.2 Simulated flows

The reason for the Amala’s extreme low flows could be a result of deforestation which occurred paving the way for the irrigation agriculture that is dominant in the sub-catchment (see Figure 13). This, as a result, led to decreased groundwater recharge, thus low base flow contribution to river discharge during the dry periods.
Normally, underestimation of the peak discharges always results in the overall underestimation of discharge in the model. Temporal rainfall distribution could be the cause of this. Precipitation falling over a short period results in higher discharges. However, in the model, temporal rainfall distribution is assumed uniform, thus in this case, the model underestimates the rainfall.

Observed discharge datasets for both Amala and Nyangores Rivers are subject to uncertainties. This could be because the rating curve used to obtain these discharges was last updated in 2009 (Hulsman and Hulsman, 2016). River flow regime and the hydrology of the catchment changes over the years. These changes can either be as a result of human influences or natural phenomena. Human influences on river flow may be due to differences in land use such as the conversion of natural forest to agriculture. This land-use change can have an impact on the hydrograph of the river. As a result, using a rating curve that was generated before such changes to the current flows may lead to uncertainties in the generation of discharges from water levels.

Furthermore, water levels in Amala and Nyangores rivers are read manually using a staff gauge that is installed in the river’s cross-section. Sometimes during flooding season in the Amala and Nyangores rivers, the staff gauge is submerged; thus the water levels in such cases are either overestimated or underestimated. This may result in uncertainties.

Another uncertainty would be as a result of model input data which was constrained by satellite images. Errors would arise as a result of clouded images, especially during the rainy seasons. During the model calibration, some parameters were changed freely through a trial and error method until a good match was observed between the simulated and observed discharges. This may also be another source of error that causes a mismatch between the simulated and observed discharges. Using low-resolution precipitation 1000m, as compared to model resolution, 90m might have led to low results too.

**5.4.3 Model Intercomparison**

Model results seem to be of the same magnitude in both cases. The hypothesis was that the model results of the adapted STREAM model would be better than those of the original STREAM. However, there are different reasons as to why this was not the case. First, different rating curve equations were used in both cases. Using the original STREAM model, the rating curve that was used for Nyangores was last updated in 1963 (see appendix C) while that used for Amala was updated last in 1980 (see appendix D). While using the modified STREAM model, the rating curve equation that was used was last updated in 2009 (Hulsman and Hulsman, 2016). It is difficult to tell which rating curve equation is accurate even though from the reports, all the two rating curve equations corresponded well with the discharge series measured during that period.

Differences in the model evaluation result may be the result of different time steps used. Probably, if a bigger time step would be considered (monthly or seasonal), the results would have improved. From the literature, Lama et al. (2015) proposed a monthly or seasonal time step while analysing the hydrology of the catchment using satellite-based data. Therefore, based on this argument, using a 10-day time step was not a good decision for this particular study. However, considering irrigation water abstraction, this time step can produce results that can be regarded as useful (Kiptala et al., 2014).

Another difference maybe as a result of precipitation datasets. Streamflow is generated as a result of precipitation that is received in the area. While modelling using the original STREAM model, a lot of interpolation was done due to the limited rainfall stations installed in the Mara. Due to this, rainfall datasets outside the Mara catchment were also used in the model. This might have exaggerated the results. Looking at the rainfall intercomparison results conducted in this study, it is evident that WaPOR datasets were overestimated. By using these datasets
without any analysis may have also led to overestimated results. The study concluded that the improved STREAM model did not produce different results from the original STREAM model while simulating the flows of the upper Mara Basin.

5.4.4 Blue and green water use
In the Mara basin, the upper part is dominated by irrigation agriculture (see Figure 13). Irrigation abstractions are experienced in the basin. This, in return, supplements soil moisture and contributes to the total actual evapotranspiration. Both dense and sparse agriculture recorded high evapotranspiration over the years as well as high ETblue. Higher ETblue in agricultural fields would be as a result of irrigation use in the basin. High ETblue for the forest maybe as a result of capillary rise from groundwater table by deep forest roots. Bushland, grassland, and woodland had the lowest ETblue stemming mainly from the capillary rise.

ETblue from the Mara farming and Mara Beef irrigation schemes from the model is low as compared to equivalent Qb. One of the reason is the underestimation of irrigated farms during the digitizing process, which in return underestimates ETblue. From the management of the farms, Mara Beef and Mara farming occupy a total area of 200ha and 350ha respectively. In contrast, the digitized farms show a total area of 192ha and 320ha respectively (see appendix G). Considering that WaPOR precipitation was overestimated, maybe the ETblue would be less when using in situ precipitation. For the small-scale farmers, reasons for low ETblue as compared to Qb could be as a result of irrigation water losses. Most of the farmers use horse pipes to irrigate their crops. These might result in percolation losses.

Qb was expected to be higher than the ETblue, which is valid for this study. The reason behind this is that in irrigation farms, mechanical losses are high, especially if the irrigation system is not well maintained. As a result, water maybe is lost before reaching the farms. Sprinkler irrigation is practised in large-scale farms, hence losses due to wind and also through pipe leaking.

5.4.5 Irrigation water abstraction
Sprinkler irrigation is the most common type of irrigation used in the upper Mara basin for large scale farmers. French beans, tomatoes, watermelons, oats, baby corn, local food crops, dairy and fodder production, are the major types of crops irrigated in this region. These large scale farmers include but not limited to Mara farming, Tibu, Mara beef, Lalela farm, Olerai farm, James Finlay, Isinya roses, Shimo, Ndakaini and Kaboson irrigation system. Apart from the Kaboson irrigation scheme and Mara beef irrigation which are situated in Nyangores sub-catchment, the remaining schemes are in Amala sub-catchment. This implies that the Amala River is highly utilised for irrigation water.

Sprinkler irrigation systems are prone to water losses during water applications. These losses are due to wind evaporation. However, in this study, these losses were not quantified due to the lack of evaporation and wind speed losses data. In Mara farming irrigation, 100ha is occupied by the French beans. According to management, during the dry season, irrigation is done at around noon. This is done to prevent the leaves from wilting, which in turn may result in low yields. Irrigating at this time of the day is prone to evaporative losses. Other crops are irrigated at different times of the day, from morning to evening.

During wet seasons, supplemental irrigation is practised by all farmers. The amount of irrigation water is reduced from 15mm to 5mm per day for French beans and oats. Other crops such as avocado trees, tomatoes and apples are not irrigated during this season. Irrigation losses are low during the wet season.
There also exists a large number of small-scale irrigators. Some of which are individual farmers while some have formed small cooperatives. Most of these small scale irrigators are concentrated in Nyangores sub-catchment. Towns in Nyangores sub-catchment are occupied by the Kalenjin community, which is known for crop farming. The majority of the farmers grow cash crops such as butternuts, watermelons, vegetables and French beans. They mostly use water from tributaries that join Nyangores, and almost all of them don’t have water permits from the WRA. This information was collected during a field visit in December 2019.

For the small-scale farmers, irrigation is done during the dry period, i.e. months without rainfall. However, during the wet season, supplemental irrigation is also practised depending on the water requirements of the different types of crops. Horse pipes are used to irrigate the farms, and most farmers have little knowledge of irrigation water efficiency.

Irrigation efficiencies of 80% in the large-scale farms in the Mara is reasonably good. Based on a sprinkler irrigation system, which is prone to water losses, 20% of the losses are realistic. For small-scale farms, the low irrigation efficiencies are mostly due to water losses through pipe leakages, losses in canals and practising irrigation during midday when the evaporative losses tend to be high.

By analysing the modelled irrigation to field data, the modelled irrigation water abstraction is underestimated relative to field data. An error margin of between 16% to 28% is recorded from 2015-2019. The reason could be that from the abstraction records, the authority documents the estimated amount of water applied for during permit application rather than actual pumped amounts. This figure could be high based on the fact that during the wet season, less water is used to crops as a result of rainfall received. Some crops such as bananas, fodder crops, and fruits are not irrigated during this period. Basing on this argument, together with irrigation losses due to both mechanical and due to climate losses, the study concludes that the model gave a realistic estimate of irrigation water abstraction.
Chapter 6  Conclusion and Recommendations

The main aim of this research was to apply the adapted STREAM for simulating the river flows of the Upper Mara River basin. In addition to this, the STREAM model was used to quantify the blue and green water use at the pixel level. The model utilized remote sensing data from the WaPOR website. However, for the evaluation of the model results, field datasets were used. Lastly, a comparison of the model results was done to the previous results of Abwoga (2012) who applied the original STREAM model to the same study area.

The model performed fairly well in simulating the stream flows of the upper Mara for Amala and Nyangores sub-catchments. NSE values of 0.58 and 0.52 were obtained during the calibration and validation of the Amala River. R² values achieved for the same river were 0.75 and 0.61 for calibration and validation respectively. For Nyangores River, NSE and R² values obtained during calibration and validation are 0.50, 0.52 and 0.6, 0.75 respectively.

Generally modelling the flows of Upper Mara using the adapted STREAM model by the use of remote sensing data was successful. The simulated hydrograph responded well to the peak flows and low flows of both the rivers during the rainy period, (March to May). High flows were underestimated by the model especially during the validation of the Nyangores River (See Figure 27). Low flows were fairly simulated for both rivers during the entire modelling period. It is not clear whether the model’s fair performance is due to the uncertainties of observed discharge datasets or due to input variables in the model. Discharge underestimation in this study maybe is as a result of either high evaporation of high storage within the basin, which normally is not taken considered in the model.

Basing on the rainfall intercomparison, a good value of the coefficient of determination was obtained (0.9). This suggests that there is a strong correlation between the two types of rainfall data. Dembélé and Zwart, (2016) found out that remote sensing products mostly overestimate the rainfall. This study agrees with these findings. He further suggested doing the intercomparison for a relatively long time to get reliable results. In this case, intercomparison was done for only one year. This was limited by the available complete datasets since most datasets had missing gaps hence not possible for this task.

Intercomparison of the evaluation of the original STREAM model (Abwoga 2012), to the adapted STREAM model, showed results of the same magnitude. The NSE values for both the model structures during calibration and validation of Amala and Nyangores Rivers were in the range of 0.5, except during validation of the Amala where the NSE value was 0.35. This suggests that the modified STREAM model had no significant impact on the simulation of the Upper Mara flows. (Kiptala et al., 2014)

Blue and green water use for various land-use classes in the upper Mara was analysed for the entire modelling period. 2015 recorded the highest blue water use of about 27% of the total evapotranspiration. This may suggest that that was the driest year which resulted in enhanced
irrigation. The remaining years recorded values of more than 10%. Dense agriculture recorded the highest consumer of blue water use of more than 40% of all the total annual blue water use.

Knowledge of blue and green water consumption is a key factor in the management of water resources on a basin scale. These two types of flows differ in both storage and use. Generally, green water (rainwater) is stored in the soil and used by plants while blue water, on the other hand, is stored in rivers, aquifers, lakes and wetland. Blue water is utilised by many users such as industries, domestic and irrigation. This shows that blue water is highly consumed in the basin.

Knowledge of consumption of blue and green water resources assist in the assessment of blue water scarcity in the basin. By determining the blue water consumption in comparison to blue water availability, the resource managers might come up with sustainable strategies to mitigate this scarcity. Also, the trade-off between the green and blue water use can be achieved through assessment of this study. Irrigation management strategies such as shifting from irrigation agriculture to rainfed agriculture can be adopted to reduce blue water use. Lastly, this knowledge may assist in improving water productivity by adopting high irrigation efficiency measures.

The model simulated fairly the irrigation water abstraction. Here, the annual volume abstracted from the rivers for irrigation in the upper Mara (in million cubic meters) was accumulated and compared to the modelled results. From the results about 48M m³ is abstracted from the rivers annually. Model results show that about 34-40 million cubic meters are abstracted from the rivers. The differences between the modelled and the documented abstraction could be due to the assumption of the Authority that water from rivers is abstracted daily for irrigation use. Normally, there are days when irrigation is not practical in the basin. The differences between the years could be due to different irrigation water demand that changes annually.

STREAM model has proved to be a simple model with limited complexities as compared to other heavily parameterized models such as MIKE SHE and SWAT. The adapted STREAM model simulated well the net irrigation water abstraction, which was the main objective of this study. Having been scripted in the PCRaster python environment, it makes it easier to improve or add structure to suit your objectives.

Even though the adapted STREAM model has shown the potential of simulating better the irrigation water use in a basin using remote sensing data, the following recommendations are made for the improvement of the model results and the management of the basin.

6.1 Model structure

Since the STREAM model is more flexible, I would further recommend the inclusion of groundwater abstraction for irrigation water abstraction. This is motivated by the fact that the adapted STREAM model accounted for irrigation water abstraction by only considering river abstractions. From my field visit study, I found out that some farmers use groundwater for irrigation. This would improve better the results of irrigation water use.

6.2 Model variables, parameters and field recommendations

✓ In the case of the use of satellite-based data in the model, pre-processing of the datasets should be done.
✓ Sensitivity analysis to be done to identify the most sensible model parameters.
6.3 Management recommendations and further research

✓ Illegal abstraction to be monitored through ETblue measurements by the WRA.
✓ A further study on irrigation efficiency as well as water productivity study to be done in the whole basin.
✓ Mapping of evapotranspiration in the MRB which maybe be used in future hydrological and water accounting studies.
✓ The adapted STREAM model to be applied in the whole MRB. This is because, in the downstream part, there is extensive irrigation too.
References

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Murungu, K.W., 2017. Spatio-temporal analysis of land- use and land-cover change in the transboundary Mara River Basin (MSc Thesis).


Schulze, R.E., 2005. Climate change and water resources in southern Africa, Water Resources.


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Appendices

Appendix A. - Research Ethics Declaration Form

Date: 2020-03-16
To: Eunice Shisial Ashiono
MSc Programme: WSE- MWR
Approval Number: IHE-RECO 2020-053

Subject: Exemption for further ethical review

Dear Eunice Shisial Ashiono,

Based on your application for Ethical Approval, your proposal Estimating water consumption through hydrological modelling in Mara River Basin has been exempted from further revision by the Research Ethics Committee (RECO), IHE Delft. You need to notify the RECO of any modifications to your research protocol.

Please keep this letter for your records and include a copy in the final version of MSc. Thesis.

On behalf of the Research Ethics Committee, I wish you success in the completion of your research.

Yours sincerely,

[Signature]

Angeles Mendoza
Acting Ethics Coordinator

Copy to: Academic VP.
Copy to: Reviewer
Appendix B. - Parameters characterizing soil textural classes and land use

### a)

<table>
<thead>
<tr>
<th>Texture classes</th>
<th>Hydraulic conductivity $^{1}$ (mm/h)</th>
<th>Porosity $^{1}$ (m$^{3}$/m$^{3}$)</th>
<th>Field capacity $^{1}$ (m$^{3}$/m$^{3}$)</th>
<th>Wilting point $^{1}$ (m$^{3}$/m$^{3}$)</th>
<th>Residual moisture $^{1}$ (m$^{3}$/m$^{3}$)</th>
<th>Pore size distribution index $^{2}$ (-)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sand</td>
<td>208.80</td>
<td>0.437</td>
<td>0.062</td>
<td>0.024</td>
<td>0.020</td>
<td>3.39</td>
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<tr>
<td>Loamy sand</td>
<td>61.20</td>
<td>0.437</td>
<td>0.105</td>
<td>0.047</td>
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<td>3.86</td>
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<td>0.453</td>
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<td>0.085</td>
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<td>Silt loam</td>
<td>13.32</td>
<td>0.501</td>
<td>0.284</td>
<td>0.135</td>
<td>0.015</td>
<td>4.98</td>
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<td>Silt</td>
<td>6.84</td>
<td>0.482</td>
<td>0.258</td>
<td>0.126</td>
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<tr>
<td>Loam</td>
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<td>0.463</td>
<td>0.232</td>
<td>0.116</td>
<td>0.027</td>
<td>5.77</td>
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<tr>
<td>Sandy clay loam</td>
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<td>0.244</td>
<td>0.136</td>
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<td>Silt clay loam</td>
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<td>Clay loam</td>
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<td>Sandy clay</td>
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<td>0.321</td>
<td>0.221</td>
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<tr>
<td>Silt clay</td>
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<td>0.479</td>
<td>0.371</td>
<td>0.251</td>
<td>0.056</td>
<td>10.38</td>
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<td>Clay</td>
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<td>0.475</td>
<td>0.378</td>
<td>0.251</td>
<td>0.090</td>
<td>12.13</td>
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</tbody>
</table>

### b)

<table>
<thead>
<tr>
<th>Category</th>
<th>Cover</th>
<th>Interception capacity (mm)</th>
<th>Root depth (m)</th>
<th>Manning’s coefficient fraction (%)</th>
<th>Vegetated Leaf area index</th>
<th>Maximum</th>
<th>Minimum</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Evergreen Needleleaf Forest</td>
<td>2</td>
<td>0.5</td>
<td>1.0</td>
<td>0.40</td>
<td>80</td>
<td>60</td>
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<tr>
<td>2</td>
<td>Evergreen Broadleaf Forest</td>
<td>3</td>
<td>0.5</td>
<td>1.0</td>
<td>0.60</td>
<td>90</td>
<td>60</td>
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<tr>
<td>3</td>
<td>Deciduous Needleleaf Forest</td>
<td>2</td>
<td>0.5</td>
<td>1.0</td>
<td>0.40</td>
<td>80</td>
<td>60</td>
</tr>
<tr>
<td>4</td>
<td>Deciduous Broadleaf Forest</td>
<td>3</td>
<td>0.5</td>
<td>1.0</td>
<td>0.80</td>
<td>80</td>
<td>60</td>
</tr>
<tr>
<td>5</td>
<td>Mixed Forest</td>
<td>3</td>
<td>0.5</td>
<td>1.0</td>
<td>0.80</td>
<td>83</td>
<td>60</td>
</tr>
<tr>
<td>6</td>
<td>Closed Shrubs</td>
<td>3</td>
<td>0.5</td>
<td>0.8</td>
<td>0.55</td>
<td>83</td>
<td>60</td>
</tr>
<tr>
<td>7</td>
<td>Open Shrubs</td>
<td>2</td>
<td>0.5</td>
<td>0.8</td>
<td>0.40</td>
<td>80</td>
<td>60</td>
</tr>
<tr>
<td>8</td>
<td>Woody Savannah</td>
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<td>0.5</td>
<td>1.0</td>
<td>0.80</td>
<td>80</td>
<td>60</td>
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<tr>
<td>9</td>
<td>Savannahs</td>
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<td>0.40</td>
<td>80</td>
<td>60</td>
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<td>10</td>
<td>Grasslands</td>
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<td>0.30</td>
<td>80</td>
<td>20</td>
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<td>11</td>
<td>Permanent Wetlands</td>
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<td>0.2</td>
<td>0.5</td>
<td>0.50</td>
<td>80</td>
<td>60</td>
</tr>
<tr>
<td>12</td>
<td>Croplands</td>
<td>2</td>
<td>0.5</td>
<td>0.8</td>
<td>0.35</td>
<td>85</td>
<td>60</td>
</tr>
<tr>
<td>13</td>
<td>Urban and Built-Up</td>
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<td>0.0</td>
<td>0.5</td>
<td>0.05</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>14</td>
<td>Cropland/Natural Vegetation</td>
<td>2</td>
<td>0.5</td>
<td>0.8</td>
<td>0.35</td>
<td>83</td>
<td>40</td>
</tr>
<tr>
<td>15</td>
<td>Snow and Ice</td>
<td>0</td>
<td>0.0</td>
<td>0.1</td>
<td>0.05</td>
<td>0</td>
<td>0</td>
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<tr>
<td>16</td>
<td>Barren or Sparsely Vegetation</td>
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<td>0.2</td>
<td>0.5</td>
<td>0.10</td>
<td>5</td>
<td>20</td>
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<tr>
<td>17</td>
<td>Water Bodies</td>
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<td>0.0</td>
<td>0.1</td>
<td>0.05</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Appendix C. - upper MRB rating curves (source: WRA)

### Historical Amala rating curves

Amala Rating Curve  Source: (WRMA, Kenya)

### Nyangores rating curve

Nyangores Rating Curve  Source: (WRMA, Kenya (valid from 1963 to date))
Appendix D. - Rating curve equations used in this study as adapted from discharge data quality assessment report

2.2. Amala

Table 11: Results for fitting the discharge series at Amala based on method 2, versions 1-8 and method 3 with different reference water levels $h_0$.

<table>
<thead>
<tr>
<th>Method</th>
<th>$h_0 = 0,\text{m}$</th>
<th>$h_0 = h_{\text{max}} = 0.01,\text{m}$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$a$</td>
<td>$b$</td>
</tr>
<tr>
<td>Method 2 V1</td>
<td>12.55</td>
<td>1.98</td>
</tr>
<tr>
<td>Method 2 V2, 5</td>
<td>11.27</td>
<td>1.88</td>
</tr>
<tr>
<td>Method 2 V3</td>
<td>23.61</td>
<td>1.48</td>
</tr>
<tr>
<td>Method 2 V4</td>
<td>19.30</td>
<td>2.33</td>
</tr>
<tr>
<td>Method 2 V5</td>
<td>18.77</td>
<td>2.30</td>
</tr>
<tr>
<td>Method 2 V6</td>
<td>21.39</td>
<td>2.24</td>
</tr>
<tr>
<td>Method 2 V7</td>
<td>18.98</td>
<td>2.31</td>
</tr>
<tr>
<td>Method 3</td>
<td>15.53</td>
<td>1.94</td>
</tr>
</tbody>
</table>

2.1. Nyangores

Table 9: Results for fitting the discharge series at Nyangores based on method 2, versions 1-9 and method 3 with different reference water levels $h_0$.

<table>
<thead>
<tr>
<th>Method</th>
<th>$h_0 = 0,\text{m}$</th>
<th>$h_0 = h_{\text{max}} = 0.07,\text{m}$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$a$</td>
<td>$b$</td>
</tr>
<tr>
<td>Method 2 V1</td>
<td>21.21</td>
<td>1.52</td>
</tr>
<tr>
<td>Method 2 V2</td>
<td>25.73</td>
<td>1.50</td>
</tr>
<tr>
<td>Method 2 V3</td>
<td>21.20</td>
<td>1.52</td>
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<tr>
<td>Method 2 V4</td>
<td>21.77</td>
<td>1.54</td>
</tr>
<tr>
<td>Method 2 V5</td>
<td>19.33</td>
<td>1.62</td>
</tr>
<tr>
<td>Method 2 V6</td>
<td>19.33</td>
<td>1.62</td>
</tr>
<tr>
<td>Method 2 V7</td>
<td>21.20</td>
<td>1.52</td>
</tr>
<tr>
<td>Method 2 V8</td>
<td>21.55</td>
<td>1.54</td>
</tr>
<tr>
<td>Method 2 V9</td>
<td>20.45</td>
<td>1.49</td>
</tr>
<tr>
<td>Method 3</td>
<td>33.71</td>
<td>2.33</td>
</tr>
</tbody>
</table>

Appendix E. - Upper Mara script

```python
def initial(self):
    setclone('maramask.map')
    self.landuse = self.readmap("landuse")
    self.soil = self.readmap("soil")
    self.flowstat8 = self.readmap("flowstat8")
    self.level = self.readmap("homdem8")
    self.myldd = self.readmap("mask12ldd")
    self.mask = self.readmap("maramask")
```
self.blue = self.readmap("blue")  # selected points on landuse map for bluewater use
self.k = scalar(0.5)               # Recession Su 2 GWS constant**********
self.surface = scalar(0.01)        # surface of a gridcell (km2)
self.ConvConst = scalar(0.0000099454) # From mm/10 days to m3/s: *1/1000 * 1/10 *
                        # 1/24 * 1/3600 * 90^2
self.kq = scalar(21)              # Recession constant quick flow **********
self.ks = scalar(15)               # Recession constant slow flow
self.ksf = (10)                   # Recession constant saturated overland flow
self.Su = scalar(10.0)            # soil moisture storage
self.gwsmmax = scalar(0.0)        # parameter controlling the groundwater flow to the river
self.GWS = scalar(20.0)           # groundwater storage
self.cap = scalar(0.0)            # potential capillary rise
self.GWU = scalar(50.0)           # groundwater use

#Lookup tables for STREAM parameters
self.D = lookupscalar("d.tbl",self.landuse)
inter = 1.0 * self.D
self.inter = self.D
self.report(self.inter,"int")

#soil zones
self.Smax = lookupscalar("smax.tbl",self.soil)
self.report(self.Smax,"SM")

#separation coefficient
self.cr = lookupscalar("cr.tbl",self.landuse)
self.report(self.cr,"sepcoeff")

#Quickflow coefficient
self.qc = lookupscalar("qc.tbl",self.soil)
self.report(self.qc,"Qc")

#scenario on transpiration
self.g = lookupscalar("g.tbl",self.landuse)
self.report(self.g,"Trans")

#potential soil moisture recycling factor(landuse)
self.sc = lookupscalar("sc.tbl",self.landuse)
self.report(self.sc,"moist")
#potentail capillaryrise
self.cp = lookupscalar("cp.tbl",self.landuse)
self.report(self.cp,"potcap")
#potentail river abstraction
self.c = lookupscalar("c.tbl",self.landuse)
self.report(self.c,"riverabs")
#minimum soil moisture
self.Sm = lookupscalar("Sm.tbl",self.landuse)
self.report(self.Sm,"moist")

# Reporting Timeseries.

    self.saofTss = TimeoutputTimeseries("saof.tss", self, self.flowstat8, noHeader=False)
    self.qfloTss = TimeoutputTimeseries("qflo.tss", self, self.flowstat8, noHeader=False)
    self.RunoffTss = TimeoutputTimeseries("Runoff.tss", self, self.flowstat8, noHeader=False)
    self.gwsTss = TimeoutputTimeseries("gws.tss", self, self.flowstat8, noHeader=False)
    self.suTss = TimeoutputTimeseries("su.tss", self, self.flowstat8, noHeader=False)
    self.rainbrutTss = TimeoutputTimeseries("rainbrut.tss", self, self.flowstat8, noHeader=False)
    self.runoffBlueTss = TimeoutputTimeseries("runoffBlue.tss", self, self.flowstat8, noHeader=False)
    self.runoff3Tss = TimeoutputTimeseries("runoff3.tss", self, self.flowstat8, noHeader=False)
    self.ETaTss = TimeoutputTimeseries("ETa.tss", self, self.flowstat8, noHeader=False)
    self.totETaTss = TimeoutputTimeseries("totETa.tss", self, self.blue, noHeader=False)
    self.totBWuTss = TimeoutputTimeseries("totBWu.tss", self, self.blue, noHeader=False)

def dynamic(self):
    Rainfall = self.readmap("ppt")
    ETa = self.readmap("ETa")

    #Calculate Net Precipitation and Evaporation depletion
Int = self.readmap("Inc")
#self.report (Int,"inter")

RainNet = Rainfall - Int
self.report (RainNet,"Rn")

ETT2 = ETa-Int # E+T = total eta minus interception
self.report(ETT2,"ETttl")

Ett = ETT2*self.g # scenario on actual evapotranspiration.
self.report (Ett,"Evapdel")

#Unsaturated zone flows.


Overtop = max(0, ((self.Su - self.Smax) / self.k))
self.report (Overtop,'ovtp')

self.Su = self.Su - Overtop

self.Su = self.Su - Ett
self.report (self.Su,"Us")

# Sat. ov. flow

GWSdem = self.level

self.gwsmax = 25 * ln(GWSdem)

self.gwsmax = self.gwsmax
self.report (self.gwsmax,"gwSmx")

ground = self.GWS

self.GWS = self.GWS + (self.cr * RainNet) + Overtop
self.report (self.GWS,"gws")

saof = ifthenelse(self.GWS > self.gwsmax, self.GWS - self.gwsmax, 0)/self.ksf

overland = saof
self.report (saof,"ovflo")

self.GWS = self.GWS - saof

#Quick flow

GWSquick = self.gwsmax * self.qc

qflo = max((self.GWS - GWSquick), 0) / self.kq
self.report(qflo,'qflo2')
self.GWS = self.GWS - qflo
quick = qflo
self.report (qflo,"quickflo")

# Slow flow
sflo = max(self.GWS, 0) / self.ks
self.GWS = self.GWS - sflo
slow = sflo
self.report (sflo,"slowflo")

# Blue water use.
PotentialBlue = ifthenelse(self.Su < self.Smax*self.sc,Ett,0)
Blue2 = PotentialBlue
self.report(Blue2,"Qbl")
caprise = ifthenelse(self.GWS>self.gwsmax/4, min(self.cp,Ett,self.GWS), 0)
self.GWS = self.GWS - caprise #capillary rise
self.GWU = self.GWU + caprise #GWU- groundwater use
Abs1 = ifthenelse(self.GWU > Blue2, Blue2, 0) # Abs =abstraction
self.GWU = self.GWU - Abs1
Abs2 = Blue2 - Abs1
Abs3 = Abs2*self.c # scenario on river abstraction
self.report(Abs3,"bwu")
self.Su = self.Su + Abs1 + Abs2
Blue3 = Abs1+Abs2
self.report(Blue3,"Qb")

# Scenario of calculating blue and green water use for different landuse
totETa = areaaverage(ETa,self.blue)
self.report(totETa,"tETa") # total actual evapotranspiration
totBWu = areaaverage(Abs3 + Abs2,self.blue) # total blue water use

# Reporting runoff
Runoff1 = saof + qflo + sflo
riverflow = Runoff1
self.report (Runoff1,"Runoff")
runoff3 = saof + qflo
self.report(runoff3,"run3")
runoff4 = sflo
self.report(runoff4,"run4")
runoffBlue = Abs3
self.report(runoffBlue,"runB")

# Runoff conversion to discharge.
runoffBlue = accuflux(self.myldd, Abs3)*self.ConvConst
saofTot  = accuflux(self.myldd, saof)*self.ConvConst
qfloTot  = accuflux(self.myldd, qflo)*self.ConvConst
runoff  = accuflux(self.myldd, Runoff1)*self.ConvConst
runoff3  = accuflux(self.myldd, runoff3)*self.ConvConst
runoff4  = accuflux(self.myldd, runoff4)*self.ConvConst

# Reporting
self.saofTss.sample(saofTot)
self.qfloTss.sample(qfloTot)
self.RunoffTss.sample(runoff)
self.gwsTss.sample(self.GWS)
self.suTss.sample(self.Su)
self.runoffBlueTss.sample(runoffBlue)
self.runoff3Tss.sample(runoff3)
self.ETaTss.sample(ETa)
self.totETaTss.sample(totETa)
self.totBWuTss.sample(totBWu)

nrOf time steps=180
myModel = MyFirstModel()
dynamicModel = DynamicFramework(myModel,nrOf time steps)
dynamicModel.run()
import os, glob
import sys

def convert(pattern, outputprefix):
    count = 0
    inputFiles = glob.glob(pattern)
    inputFiles.sort()
    print("Converting files to PCRaster format", end=" ")
    for inputFile in inputFiles:
        count += 1
        sys.stdout.write('.

if count < 10:
    extension = "00" + str(count)
    #print("less than 10")
    #print(extension)
elif count < 100:
    extension = "0" + str(count)
    #print("less than 100")
    #print(extension)
else:
    extension = str(count)
    #print(extension)
    cmd = "gdal_translate -of PCRaster -ot Float32 -mo VS_SCALAR " + inputFile + " " + outputprefix + "." + extension
    #print(cmd)
    os.system(cmd)

convert("*.tif", "ptr0000")
### Estimated ETblue for small-scale farms in the Upper MRB

<table>
<thead>
<tr>
<th>Area</th>
<th>m²</th>
<th>ha</th>
<th>2015</th>
<th>2016</th>
<th>2017</th>
<th>2018</th>
<th>2019</th>
<th>Qb</th>
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