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Sub-Catchment Water Balance Analysis in the Thika-Chania Catchment, Tana Basin, Kenya

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Abstract:

Water scarcity is a growing issue in the Thika-Chania catchment, Kenya. Water allocation planning is used to manage water resources fairly, equitably and to avoid over abstraction. Water allocation planning depends on quantitative information on water availability. Unfortunately there is a lack of data available on water yield due to an inadequate monitoring system. This thesis aims to provide quantitative information on water availability through use of the Soil and Water Assessment Tool (SWAT), using water balance analysis to determine availability and demand. The SWAT model provided acceptable representation of stream flow, calibrated to a Nash Sutcliffe 0.58. The Environmental flow was found to vary across the catchment, ranging between 0 and 1.75 m^3/s. The north edge of the downstream area was found to have the greatest issue with water scarcity due to higher levels of water demand, higher evaporative loses and less rainfall.

Key words: Hydrological Modelling, Data Scarcity, Water Availability, SWAT

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1. Introduction

1.1 Background

Water is crucial for sustaining human life and wellbeing worldwide. It is required for drinking, sanitation, food security and maintaining a wide range of ecosystem services (Aurecon AMEI Limited, 2019). The importance of securing sustainable water use for human development is highlighted in the Sustainable Development Goal (SDG) 6: Ensure availability and sustainable management of water and sanitation for all (UN General Assembly, 2015). However, water scarcity remains a problem in the global south, with population growth and climate change exerting pressure on already strained water resources (Krasovskaia et al, 2006; Hunink et al, 2017; Muthuwatta et al, 2018). Sustainable management of water resources can help leverage the maximum available water for productive use, to avoid water being wasted and deal with scarcity (Akivaga, 2011; Speed et al, 2013; Rural Focus Ltd, 2018). To effectively manage water resources, quantitative data on water availability is of great importance. Unfortunately, areas under the most pressure from water scarcity, which would benefit the most from sustainable water management, often also suffer from data scarcity (Ndomba et al, 2008).

Kenya is situated in East Africa, with the equator running through the centre of the country (JICA, 2013). The Kenya Vision 2030 (Government of the Republic of Kenya, 2008) recognizes that the country is struggling with a water deficiency, with a water per capita of 647 m^3 compared to the United Nations recommendation of 1000 m^3 per capita per year (Government of the Republic of Kenya, 2008). Population growth and climate change are likely to increase this deficit (JICA, 2013). Population growth peaked at 3.865% annual growth in 1982 and continues to grow at a rate of 2.3% (World Bank, n.d). The projections for Kenya suggest that temperatures will rise up to 2.5 degrees C from 2000 to 2050 (Ministry of Foreign Affairs, 2018). Rainfall is projected to become more intense and less predictable, which will increase the prevalence of droughts (Ministry of Foreign Affairs, 2018; Aurecon, 2019). This will present major challenges for water availability and food security across the whole of Kenya (Ministry of Foreign Affairs, 2018).

Sustainable water management of the Tana basin in Kenya is of particular importance for water security in Kenya. The Tana basin network is the longest river network in Kenya at 1000km long, and has a catchment area of over 120, 000 km^2 (Aurecon AMEI Limited, 2019). Along with maintaining its varied ecosystem and supplying its population with water, the Tana River network is relied on for municipal water supply in Nairobi from Nairobi City Sewerage and Water Company (NCSWC) (Knoop et al, 2012). Rapid urban growth has therefore put particular strain on the Tana basin, and most notably the Thika- Chania system in the Upper Tana basin which has two reservoirs which supply Nairobi with water (Aurecon AMEI Limited, 2019).

The Constitution of Kenya 2010 states that every person has ‘a right to clean and safe water in adequate quantities’ (The Republic of Kenya, 2010). To uphold this right despite the challenges faced by the water sector, the Water Resource Authority (WRA) was established to facilitate localized management of water resources for sustainable use (GIZ, 2019). The headquarters are in Nairobi, and there are six regional offices for each major catchment area, which are further divided into 26 sub regional offices (GIZ, 2019). They are responsible for catchment-based planning, and specifically water allocation plans (WAPs) (Rural Focus Ltd, 2018). Water allocation is the process of sharing the available water resources between various water demands, such as domestic, agricultural and industrial (Rural Focus Ltd, 2018). Water allocation plans are of particular importance in areas that are dealing with scarcity (Speed et al, 2013, Rural Focus Ltd, 2018). When water resources are insufficient to meet all demands, distribution of the available water is based on priorities and public benefit (Rural Focus Ltd, 2018). The highest priority is maintaining the reserve flow, which is the flow required to maintain basic ecological functioning, and basic human needs of 25L per person per day (Rural Focus Ltd, 2018). After the reserve, the additional flow is the allocable yield to be distributed over the various demands. The development of a Water Allocation Plan relies heavily on quantitative information on water demand, water availability, permitted abstractions and actual abstractions, as well as quantification of the reserve flow (Speed et al, 2013; Rural Focus Ltd, 2018). Ideally, extensive monitoring of streamflow and water levels as well as meteorological monitoring would give the most accurate description of water availability in a catchment. However in practice monitoring is often poorly implemented due to lack of human and financial resources (Ndomba et al, 2008, GIZ, 2019).

To address these issues, World Waternet partnered with Dutch water authorities Aa & Maas and Hoogheemraadschap de Stichtse Rijnlanden to work with the Water Resource Authority to improve quantitative water management in the Upper Tana in Kenya (WorldWaternet, 2019). The specific focus of the project is on two sub basins of the Thika-Chania catchment in the Upper Tana known as Thika Upper and Thika Mid. These two sub basins are areas of focus since they are known to differ substantially with respect to climate and water availability. Furthermore, there are different irrigation intensities across the two catchments. Water providers rely on the Thika-Chania catchment for large scale abstractions. Thika Upper in particular is an area of focus for the Blue Deal Programme because it contains Ndaikani dam, which supplies Nairobi with the majority of its domestic water (Aurecon AMEI, 2019). World Waternet are also involved in the WaterWorX program, partnered with Nairobi City Sewerage and Water Company (NCSWC) which aims to strengthen sustainable water for Nairobi and therefore has a particular interest in Thika Upper (World Waternet, 2019).

1.2 Problem Definition and Aim

Population growth and climate change have put additional pressure on already strained water resources in the Thika- Chania catchment, Kenya (JICA, 2013). Rapid urban growth of Nairobi has contributed to this problem, as Nairobi receives 80% of its domestic water from the Ndakaini and Sasumua dams, located in the upstream catchment (JICA 2013, GIZ 2019). Furthermore, there are large amounts of agricultural activities in the catchment; a large proportion of which requiring irrigation. Climate change has increased the water demand as droughts and floods have become more prevalent (Muthuwatta et al, 2018). The main water resource is surface water, accounting for over 80% of the available water (World Water Assessment Programme, 2006) and the majority of allocated water is from surface water resources. Since there is little storage capacity in the system and natural flow dominates, the changing climate exacerbates water scarcity issues. To improve water resource management and address water scarcity more efficiently, the Water Resource Authority needs to develop Water Allocation Plans at a sub catchment level (Rural Focus Ltd, 2018). To do so effectively, it is necessary to have both spatially and temporally distributed information on water balance components at a sub catchment level, along with demand and abstraction rates (Rural Focus Ltd, 2018). This prevents over allocation and therefore over abstraction of the water resource which can have detrimental effects on the ecological functioning of the river (Rural Focus Ltd, 2018). The most straightforward indication of surface water availability is streamflow data, accessed through hydrological monitoring. However, there is a lack of hydrological data availability within these sub catchments. Many monitoring stations are completely un-operational, and the operational ones contain large temporal gaps (GIZ, 2019).

Therefore the aim of this project was to provide quantitative, spatially distributed information on water demand and availability despite an inadequate catchment wide monitoring network. It was determined that the most effective way to achieve this was through hydrological modelling; closing the water balance with available data. The spatially distributed water balance can be used as a proxy for water availability, and also be used to determine water demand, which depends heavily on water balance components such as soil water and potential evapotranspiration. Furthermore, the Environmental Flow (E-flow) will be determined in order to provide insight into the reserve flow. The Kenyan Water Act (2002) defines the reserve flow as the ‘quantity of water required to a) satisfy basic human needs for all people who may be supplied by the water resource; and b) to protect aquatic ecosystems in order to secure ecologically sustainable development and use of the water resource’ (The Republic of Kenya, 2002). This is the amount of water which must be left in the river; the additional flow is considered allocable yield. 25L per person per day is straightforward to calculate if you have access to the population density across the catchment, and it does not depend on the river flow. The remaining flow needed to protect aquatic ecosystems and sustain ecological functioning of the river is referred to as the ‘Environmental flow’ or ‘E-flow’. This E flow is more difficult to calculate, and there are several methods used worldwide to estimate it. In depth, holistic methods combine analysis of environmental indicator such as biodiversity, with hydrological analysis (LVBC & WWF-ESARPO, 2010). However a more simple benchmark, ‘hydrological’ method is to equate the E-flow to the Q95 flow of the naturalised system (Rural Focus, 2018). This is the base flow which is exceeded 95% of the time in the naturalised system. The naturalised system is a description of what the catchment behaviour would be if there were no abstractions (Wurbs et al, 2006). The naturalised flow therefore tends to be higher than the observed flow of the actual system since there is a higher volume of water left in the stream. Currently, the WRA determine the Q95 of the naturalised system by creating a flow duration curve of historic flow data (Rural Focus Ltd, 2018). This technique is based on the assumption that there were fewer abstractions and human interference with the river system in the past, so historic observed flow data can be used as a representation of a current naturalised system. This method contains a lot of assumptions and uncertainty, as it doesn’t take into account the changing climate, different land use and changing flow patterns (Wurbs et al, 2006). Therefore creating a model which can simulate a more accurate scenario of the current naturalised system is a key aim of this project.

An additional aim of the project was to provide insight into the water demand of the catchment. Irrigation demand, unlike domestic water, varies widely with climate and land cover, meaning it is difficult to rely on general, country wide estimations. Water balance analysis on the catchment can provide a more accurate estimation of irrigation demand which is targeted to the catchment in question.

1.3 Main Aim and Research Questions

The main aim of the research is as follows:

Determining the annual and monthly spatially distributed water availability in the Thika-Chania catchment.

To help meet this aim, and to provide WRA with additional information for creating WAPs the following three research questions were devised:

1) What are the annual and monthly water balances in Thika Upper and Thika Mid and how do they vary during a drought year, a normal year and a flood year?
2) What is the reserve flow of the naturalized system?
3) What is the spatially distributed irrigation demand of the catchment, and how does it vary during a drought year, a normal year and a flood year?

2. Methods

2.1 Site Description

The Thika-Chania catchment is located in central Kenya approximately 50km north of Nairobi (Aurecon AMEI Limited, 2019). The river system is part of the Tana river basin, which drains into the Indian ocean (Knoop et al, 2012). Originating in the Aberdare mountains, the two main channels running through the catchment are the Thika and Chania rivers which coalesce on the North Western edge of the town Thika (Knoop et al, 2012). The outlet for this catchment is located at 37.382 latitude -1.104 longitude, aligning with the monitoring station 4CC07. The associated watershed is 134227 ha and contains a population of over 900,000 (World Resources Institute, 2007, World Bank, n.d). The catchment largely lies in Muranga and Kiambu counties and the Water Resource Authorities have divided the catchment into Catchment Management Units (CMUs) to facilitate local water management. It should be noted that the catchment delineation and subsequent division of CMUs from the Water Resource Authority does not fully incorporate the catchment which drains through the outlet for this study, since the outlet is situated slightly further downstream in this research. The location of Thika Upper and Thika Mid with respect to the project catchment can be seen in Figure 1.

The topography of the catchment is varied, with steep slopes in the mountainous Aberdare forest and an elevation of 3873m in the highest point, to flatter downstream areas around Thika with an elevation of 1238m (NASA JPL, 2013).

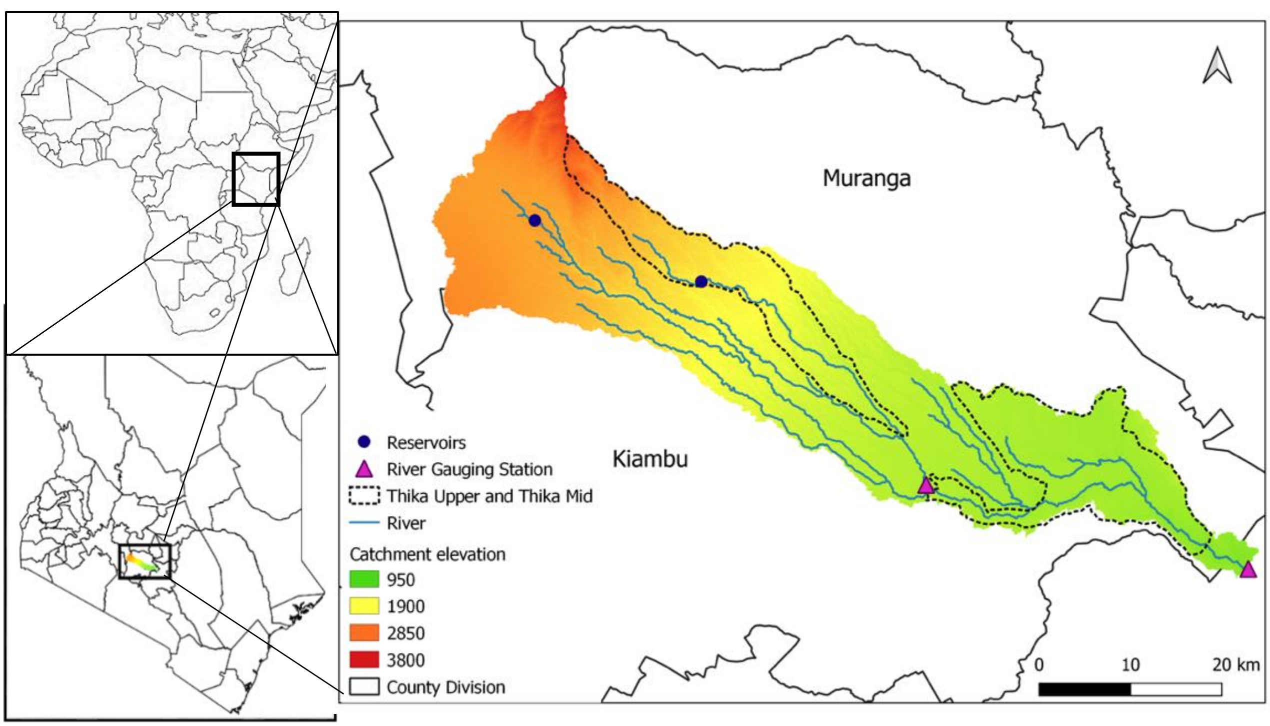


Figure 1: Location of the watershed in Kenya (left), topographic map of the watershed with the location of Thika Upper and Thika Mid included (right).

The catchment contains 20 distinct soil types (Dijkshoorn et al, 2011). The dominant soils are Humic Nitisols, which are clay rich and red coloured. These soils are found in the centre of the catchment, and are generally cultivated for tea and coffee and are resistant to erosion (Dijkshoorn et a, 2011). Humic Andosols are also widely prevalent, which were formed on volcanic ash and can be found in the mountainous areas of the catchment (Dijkshoorn et al, 2011). Rhodic Nitisols, Eutric Vertisols and Rhodic Ferrasols are more prevalent in the downstream catchment. The majority of soils have a high clay content, associated with less infiltration and higher levels of run off (Aurecon AMEI Limited, 2019). Erosion is more of an issue in the upper catchment where the soils have a higher ash content, though this is also dependent on land use (Hunink et al, 2017).

Land use in the catchment primarily consists of agriculture, including coffee, tea and pineapple plantations (Thika Upper WRUA & WRMA, 2013). There is a large forest area upstream of the catchment. Urban areas cover only a small percentage of the land cover. Many of the agricultural areas are irrigated, with a higher intensity of irrigation in the lower catchment (WRI, n.d).

The flow regime comprises of a low base flow with high flood peaks in the rainy season (Knoop et al, 2012). Much of the catchment is unregulated and the natural flow pattern dominates the system, with small scale abstractions from local tributaries and reaches being common place (JICA, 2013). However, there are two dams in the upper catchment, which serve not only to help regulate flow, but to supply Nairobi with the majority of its water (Aurecon AMEI Limited, 2019). Water from the reservoirs is transported through kilometres of tunnels to a treatment plant south of the catchment, and then on to Nairobi (JICA, 2013).

2.1.1 Climate

As the catchment lies extremely close to the equator, the climate is characterized by high temperatures and monsoonal seasons (Maina & Messo, 2017). The climate varies across the catchments, with cooler areas at higher altitudes experiencing more humidity and rain, while the lower altitude areas are characterized as semi arid (Maina & Messo, 2017). There is a large difference in rainfall from areas of higher to lower altitude in the catchment. Annual rainfall varies from about 800mm at an altitude of about 1525m to about 2200mm at an altitude of 2600m (Maina & Messo, 2017). Similarly, the average daily maximium temperature varies across the catchment, ranging from 25 C to 30 C at the lower altitudes of Thika Mid, to between 18C and 20C towards the higher altitudes of 3500m (Maina & Messo, 2017). However the catchment as a whole experiences one long rainy season between March and May, with a shorter, less intense rainy season from late October to December. El Nino and El Nina also have effect on the climate system, leading to large scale flooding on certain years (Muthuwatta et al, 2017). The figures below demonstrate the differences in precipitation and average temperature upstream and downstream in the catchment.

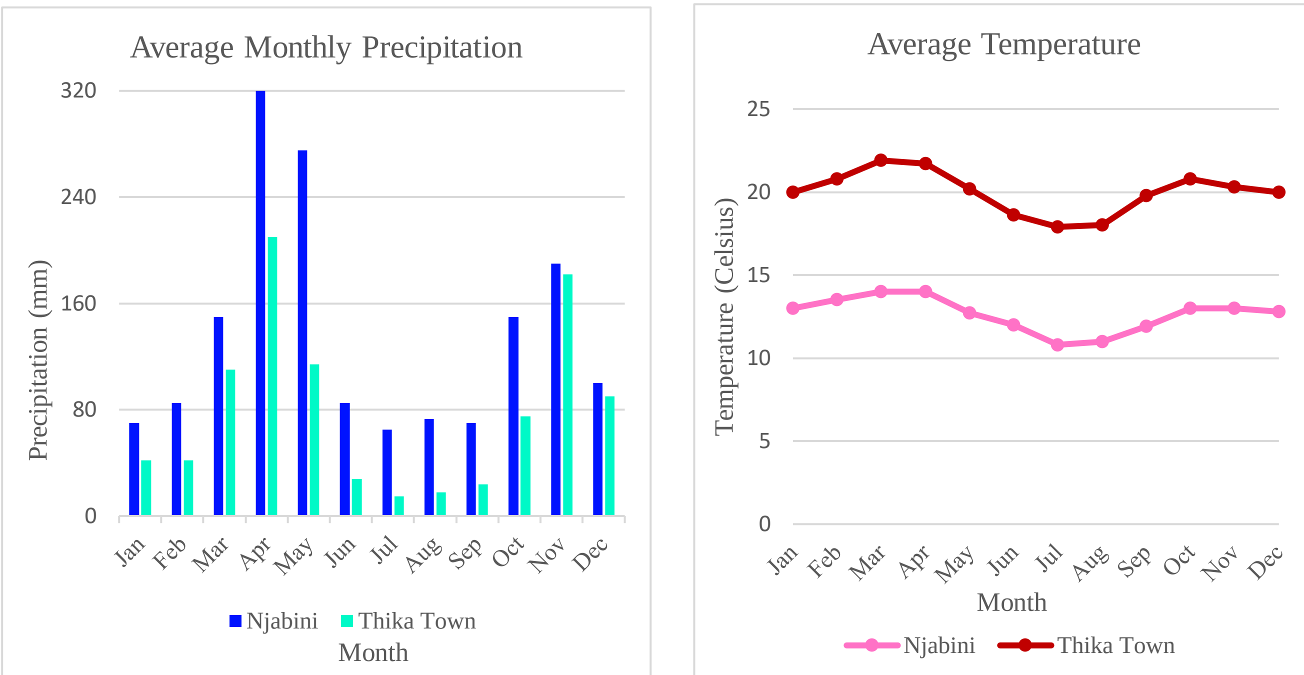


Figure 2: Graphs showing the precipitation (left) and average temperature (right) in Njabini (upstream) and Thika Town (downstream). Graphs created using data retrieved from: https://en.climate-data.org/africa/kenya/kiambu/thika-5812/#climate-graph

2.2 SWAT model

2.2.1 Model justification

Due to a lack of financial resources and time constraints, the catchment has an inadequate monitoring system and hence can be defined as data scarce (GIZ, 2019). A large variety of hydrological models have been developed for the purpose of simulating hydrological processes, and several studies focus on overcoming the challenges of data scarcity (Ndomba et al, 2008; Tegegne et al, 2017; Mengitsu et al, 2019). Different models require different data inputs. The most commonly required data inputs include meteorological data such as precipitation and temperature, topography data such as land cover, elevation and soil type and stream flow data to calibrate (Tegegne et al, 2017). As one of the most important inputs in the water balance of a catchment, precipitation data is required for all hydrological models. The availability of precipitation data varies widely based on geographical location. The spatial heterogeneity of precipitation in a study area will affect the reliability of the model; highly varied rainfall across the study area will require more rainfall gauging stations for a reliable model (Ruelland et al, 2008). To supplement spatially scarce precipitation data, interpolation can be used (Ruelland et al, 2008). Generally, distributed hydrological models can provide realistic simulations despite gaps in input data (Tegegne et al, 2017). Furthermore, hydrological models such as SWAT (Soil and Water Assessment Tool) contain in built statistical programs to generate temporal gaps in precipitation data (Gassman et al, 2007), or options for using generated climate data such as Climate Forecast System Reanalysis (CFSR) (Saha et al, 2010).

There are several comparisons of the performance of different models in areas of data scarcity which provide insights into the suitability of models for areas of differing data availability (Ragettli et al, 2013; Tegegne et al, 2017). Simple lumped hydrological transport models such as Hydrologiska Byråns Vattenbalansavdelning (HBV) do not require detailed land use and soil cover making them suitable for data scarce catchments (Bergström & Forsman, 1973). However lumped models do not provide detailed spatially distributed information on the water balance and only provide detail on discharge at the outlet. Policy making with regards to water allocation within a water scarce catchment requires water balance information with high levels of spatial resolution across the catchment (Speed et al, 2013, Rural Focus Ltd, 2018). For this purpose, physically based distributed models such as the SWAT, MIKE and Water Balance Simulation Model (WaSiM) are more suitable than lumped models (Gassman et al, 2007; Ma et al, 2016;. Idrissou et al, 2020). However, data requirements can be an issue. Land cover, soil and digital elevation maps can be obtained from global databases derived from satellite imagery or remote sensing, which can be used in more data intensive hydrological models. Daily meteorological data is often required for physically based distributed models. This can either be observed data or weather generations based of satellite when there is limited data available (Mengistu et al, 2019). Models that run with a GIS interface are particularly useful for insights into catchments with high levels of spatial heterogeneity, due to the ability of GIS to capture, analyse and visualise vast amounts of georeferenced data (Singh & Fiorentino, 1996).

Due to its capabilities of using freely accessible data and the benefits of using a GIS interface, it was determined that the SWAT model was most suitable for this project. Furthermore, QSWAT uses the QGIS interface which is open source, meaning it can be used for free on site in Kenya. Several hydrological studies in the Tana Basin have used SWAT modelling to good effect (Hunink et al, 2013; Hunink et al, 2017). Furthermore, due to its popularity worldwide, there is an extremely large user group providing support and excellent training documentation (Dile et al, n.d). This is incredibly valuable for the Blue Deal programme, since employees of the WRA who do not have much experience with hydrological modelling can use and develop the model in the future.

2.2.2 Model methodology

SWAT is a semi-distributed physically based hydrological model which can be used to simulate a variety of physical processes in a watershed (Neitsch et al, 2011). The watershed is divided into several sub catchments which allows the spatial distribution of hydrological processes to be analysed. The sub catchments are further divided into Hydrological Response Units (HRUs), the smallest computational unit of SWAT (Neitsch et al, 2011). They are areas of land within a sub catchment which respond similarly to weather inputs, such as precipitation and temperature. Each HRU within a sub catchment has a unique combination of soil, land cover and slope class, and they are created by overlaying the respective maps (Neitsch et al, 2011). The HRUs vary in size and shape, and can range from the size of the whole sub catchment if the land, soil and slope class is the same, to the size of a pixel, which will depend on the resolution of the rasters used. The figure below demonstrates the conceptual process of building HRUs in the model, using this projects watershed as an example.

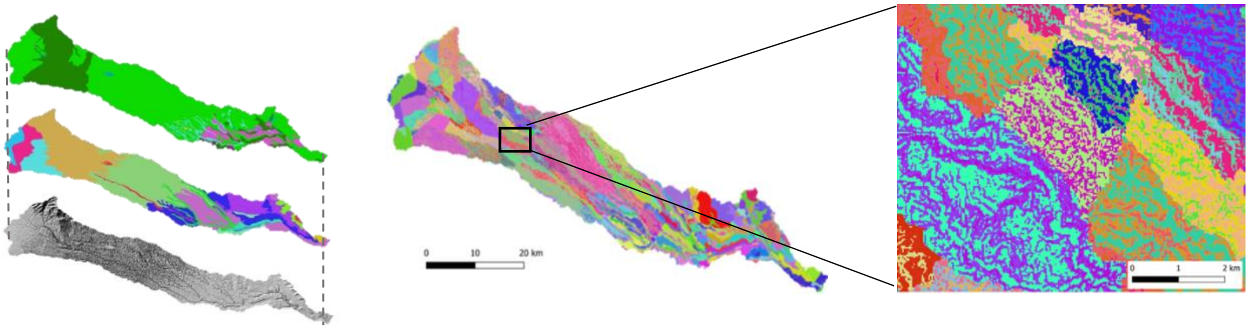


Figure 3: Visual representation of HRU generation in the watershed. From top to bottom are land cover map, soil map and slope (left) with the centre and right images showing the resultant HRUs.

For each HRU the hydrological cycle is simulated using the following soil water balance equation:

$$SW_t = SW_0 + \sum_{i=1}^{t}(R_{day} - Q_{surf} - E_a - w_{seep} - Q_{gw}) \qquad \text{(Neitsch et al, 2011)}$$

Where SW_t is the final soil water content (mm), and SW_0 is the initial soil water content (mm). The following variables are defined over a fixed daily time step: R_{day} is the precipitation (mm), Q_{surf} is the surface flow (mm), E_a is the actual evapotranspiration (mm), w_{seep} is infiltration the and Q_{gw} (mm) is the return flow from groundwater to the reach. While the internal timestep of the model is days, often results are printed on a monthly timestep to minimise the size of the output files (Neitsch et al, 2011).

Potential Evapotranspiration (PET) is defined as the rate at which evapotranspiration would occur from a large area uniformly covered with grass which has unlimited access to water (Neitsch et al, 2011). The SWAT model offers three potential methods for calculating PET: Hargreaves (Hargreaves et al, 1985), Priestly Taylor (Priestly & Taylor, 1972) and Penman Monteith (Monteith, 1965). The radiation based Priestly- Taylor method has relatively few data inputs, only requiring air temperature and solar radiation (Weiß & Menzel, 2008). In the critical analysis of the performance of various PET estimation methods, Zhao et al (2013) noted that when using SWAT, the Priestly- Taylor method was more suitable for wet, humid surfaces. Similarly, the energy based Hargreaves method has climatic restrictions on the suitability of its application; it yields far better estimations when applied to arid catchments (Zhao et al, 2013). The Penman- Monteith method is widely regarded as the most suitable under varying climatic conditions (Weiß & Menzel, 2008; Zhao et al, 2013) but is data intensive, requiring windspeed and relative humidity in addition to the temperature and radiation. The Penman-Monteith method was used in this study with details of the climatic data required in Section 2.3.2.

SWAT provides two methods to simulate run off: the SCS Curve Number (CN) method, and the Green Ampt Mein Larson (GAML) technique (Neitsch et al, 2011). The GAML is a physically based method which requires sub daily rainfall data, making it unsuitable for a data scarce catchment. The CN method was developed by the USDA in 1950s and is incredibly widely used in hydrological modelling due to its simplicity, and its relatively low data requirements (Gassman et al, 2006; White et al, 2010). In SWAT, a CN value is assigned for each HRU, which is then used to determine the theoretical daily storage capacity of the watershed (White et al, 2010). This technique is a statistically based, empirical method so therefore does not have a theoretical basis for use outside of the USA (White et al, 2010). However, it has been widely used across the globe, including in East Africa with good results (Hunink et al, 2013; Ndomba et al, 2016; Hunink et al, 2017). Furthermore, it has been used in the Upper Tana, in catchments overlapping with the study area of this project with good results (Hunink et al, 2013, Hunink et al, 2017). Due to data restraints, its capability of running with daily precipitation data, and its verification in the Upper Tana, the CN method will be used in this project.

2.2.3 Model Parameterisation and Set up

The input parameter values for SWAT were obtained from online databases, satellite data, literature and surveys provided by WRA. This section provides an overview of this parameterisation, and the preparation of the data for the SWAT model. The model was set up using the QGIS interface.

2.2.3.1 Model parameterisation for HRU generation

To delineate the catchment, a digital elevation map (DEM) was downloaded from the USGS website, using the NASA Shuttle Radar Topography Mission (SRTM) (NASA JPL, 2013). A 30x30m raster was used, which is the equivalent of 1 arc second. SRTM is generally accepted to have a minimum vertical accuracy of 16 m absolute error at 90% confidence (Root Mean Square Error (RMSE) of 9.73 m) world-wide (Mukul et al, 2017). This DEM was then projected to UTM zone 37S. A sub basin threshold of 27km^2 was used giving 39 sub basins.

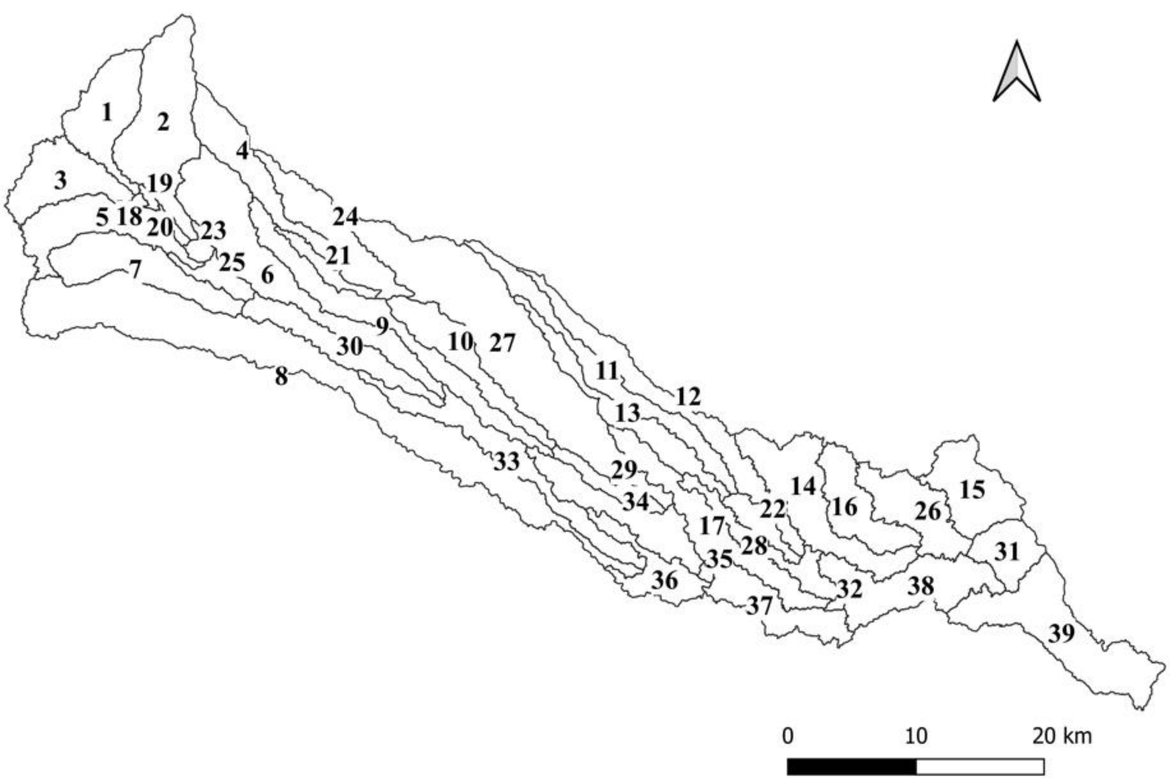


Figure 4: Sub catchment divisions. The sub catchment numbers were assigned automatically by SWAT during catchment delineation. The number of catchments was determined by user determined the sub basin threshold size of 27km^2. This was to achieve enough sub basins such that they were smaller than the Water Resource Authority's Catchment Management Units, to allow for more detailed analysis. Conversations with WRA confirmed that 39 sub catchments of this rough size was the correct level of detail for the project aims.

The catchment was divided into 3 slope classes; 0-20%, 20-50% and 50-100%.

A soil map was downloaded from ISRIC SOTER project (Dijkshoorn et al, 2011), and the associated soil parameters such as available water capacity and clay/silt/sand ratios were obtained from the SOTWIS database (Batjes et al, 2011). The SPAW program was used to determine hydraulic conductivity based on the organic carbon content and the clay/silt/soil ratios. These parameters were used to build a soil database of up to 5 layers of soil, since the SWAT database did not contain the necessary soils. The soil map was converted to rasters with a resolution of 30x30m and projected to UTM zone 37S. The soil map can be seen in Figure 5

Land cover data was obtained from the World Resources Institute (World Resources Institute, 2007). The SWAT parameters dependent on the land cover include SCS Curve number, leaf area index and other parameters which effect evapotranspiration. SWAT contains a database of crop cover so a look up table was created to link the land cover map to the SWAT database. The land cover map can be seen in figure 5

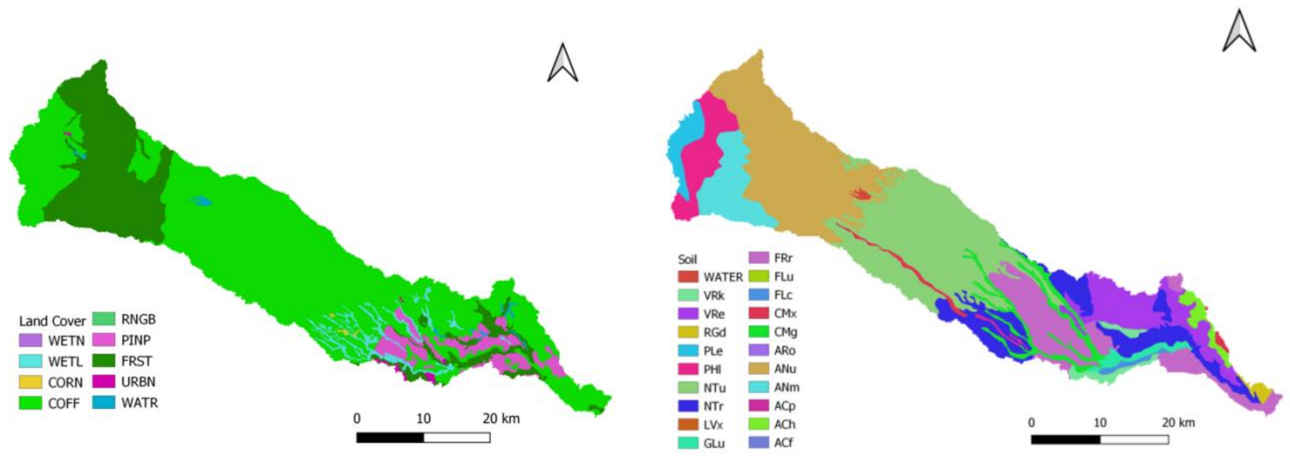


Figure 5: Land cover raster (left) and soil raster (right).

From input data of 39 sub basins, 20 soil types, 9 land cover types and 3 slope classes, 797 HRUS were generated.

2.2.3.2 Climate Data

The weather data required for SWAT to run is daily precipitation, maximum and minimum temperatures, wind speed, relative humidity and solar radiation. There were two possible sources of this data; observed data from the Ndakaini Dam meteorological station, or the Climate Forecast System Reanalysis (CFSR) data , which is freely available online (Saha et al, 2010). The CFSR is processed data which is based on satellite inputs. These two climate data sets were available for different time periods; so selecting which data to was determined by which had the greatest overlap with streamflow data with which to calibrate. An overview of the data availability is presented below.

Figure 6: Overview of observed data. Red indicates there was no data available and green indicates that data was available. 4CB04 is the name of the monitoring station near Thika town at the outlet of sub catchment 34. 4CC07 is the name of the monitoring station in Thika Mid at the outlet of sub catchment 39.

As is clear from the figure, there was very little stream flow data available for calibration during the same period as the observed weather data from the Ndakaini dam. There was a far greater amount of overlapping data available for the CSFR data, so this is the climate data that was used in the project. Furthermore, the CSFR was available at four locations across the catchment, providing the spatial variation in climate. This data is in a daily time step. A map with the locations of the climate stations can be found in the appendix.

2.2.3.3 Reservoirs

Although the natural flow pattern dominates, there are important human activities which affect the flow regime and water availability. There are two reservoirs in the upstream of the catchment. The Ndakaini Dam and the Sasumua Dam both regulate the stream flow, as well as provide water to Nairobi through large scale abstractions (Aurecon AMEI Limited, 2019). The model requires reservoir dimensions to calculate storage and losses through evaporation and infiltration (Neitsch et al, 2011). The reservoir data was obtained from the dam manager for Ndakaini Dam and from NCSWC online information (NCSWC, n.d). The monthly abstraction rates were estimated as a function of the maximum capacity of the tunnels, based on demand from Nairobi city, with the dry months having the highest demand (NCSWC, n.d). The abstractions from the reservoirs were modelled as consumptive water use since it is removed from the catchment. They are not included in the table below, which is an overview of the abstractions from stream flow.

2.2.3.4 Surface water abstractions

Water is also abstracted from tributaries across the catchment to be used for a variety of purposes, such as domestic use, irrigation and industry. The WRA has records of abstraction permits, including information on the amount of water taken, the location of the abstractions and its use. The WRA also provided an abstraction survey, which contained details on illegal abstractions as well as permitted ones. Generally, illegal abstractions were for small scale irrigation. Below is a summary of the different uses of abstraction:

		Volume Abstracted from Channels (10^5 m^3/day)		
Water Use	**Number of permits**	**Legal**	**Illegal**	**Total**
Public	15	6.72	0	6.72
Domestic	16	1.27	0.030	1.30
Irrigation	64	0.237	0.33	2.70
Industry	13	0.0603	0.00527	0.0654
Hydropower	2	5.65	0	5.65
Total	110	1.61	0.365	**16.4**

Table 1: The volumes of permitted water abstractions for different sectors

2.3 Sensitivity Analysis and Calibration

2.3.1 Sensitivity Analysis

A one at a time sensitivity analysis and a global sensitivity analysis were performed using the program SWAT Calibration and Uncertainty Program (SWAT-CUP) (Abbaspour, 2015). The purpose of the ‘one at a time’ sensitivity analysis was to determine visually the most sensitive parameters to use for calibration. Before conducting the one at a time sensitivity analysis, 9 parameters were pre selected to test the sensitivity based on literature (Abbaspour et al, 2015). In particular, the parameters which affected the magnitude of the peaks and base flow were focused on. Parameters which were different in each HRU were changed ‘relatively’, meaning it was multiplied by (1+x) where x is the value given in the range (Abbaspour, 2015). Replace was used if the value was a catchment wide parameter or was likely to have an initial value of 0. The range of the parameters was chosen by consulting the SWAT theoretical documentation (Neitsch et al, 2011). If the parameters were changed relatively, +/- 25% was used after being verified in the SWAT manual that this range remained in the acceptable bounds for the value of that parameter. If the parameter was ‘replaced’ then the limits in the SWAT manual were used. The following parameters were tested in the sensitivity analysis, with a description of the parameters given below:

Parameter	**Definition**	**Type of change**	**Range**
ALPHA_BF	Baseflow alpha factor (day)	Replace	$-1\rightarrow1$
CH-K1	Effective hydraulic conductivity of the tributary channel (mm/hr)	Relative	$-0.25\rightarrow0.25$
CN2	SCS Curve Number (-)	Relative	$-0.25\rightarrow0.25$
ESCO	Soil evaporation compensation factor (-)	Relative	$-0.25\rightarrow0.25$
ESPO	Plant uptake compensation factor (-)	relative	$-0.25\rightarrow0.25$
GW_DELAY	Groundwater delay (day)	Replace	$0\rightarrow1000$
GW_REVAP	Groundwater ‘revap’ coefficient (-)	Relative	$-0.25\rightarrow0.25$
GWQMN	Threshold depth of water in the shallow aquifer (mm H_2O)	Replace	$10\rightarrow450$
SOL_AWC	Soil available water capacity (mm H_2O/mm soil)	Relative	$-0.25\rightarrow0.25$
SURLAG	Surface runoff lag time (-)	Replace	$0\rightarrow30$

Table 2: The model parameters used in the one at a time sensitivity. All were then used in the global sensitivity analysis and calibration other than the CH-K1. The baseflow alpha factor (APLHA_BF) is an indicator of groundwater flow response to changes in recharge. The effective hydraulic conductivity of the tributary channel (CH-K1) controls transmission losses from surface run off in tributaries. The curve number (CN2) directly affects the run off. The soil evaporation compensation factor affects the depth distribution used to meet the soil evaporative demand. This accounts for soil cracks and crusting. The lower ESCO, the deeper evaporation can take place. The plant uptake compensation factor affects the depth of the soil profile that can be used to meet the plants evaporative demand with soil water. The groundwater delay factor (GW_DELAY) describes the lag between the time that water exits the soil profile through percolation and enters the shallow aquifer. It is affected by the physical geology of the vadose and groundwater zones. The threshold depth of water in the shallow aquifer (GWQMN) describes the depth in the aquifer that if exceeded then water can return to the streamflow. The ground water 'revap' coefficient (GW_REVAP) affects the movement of water from the shallow aquifer to the root zone of plants. As it approaches 0, the movement of water is restricted. The soil available water capacity (SOL_AWC) limits the amount of water which can be stored in the soil, which varies by soil type. Finally, the surface runoff lag time (SURLAG) controls the fraction of total available water that is able to enter the channel during one day.

The manual, 'one at a time' sensitivity analysis confirmed that all of the parameters affected the peak and base flow enough to include in calibration other than CH_K1, where no substantial visible change could be seen. This parameter was neglected from the calibration and the global sensitivity analysis. The global sensitivity analysis was then done as part of the SUFI-2 program at the same time as the calibration for 50 iterations. This determines parameter sensitivities using a multiple regression system against the objective function which is used in the calibration. In this case, the Nash Sutcliffe efficiency was used as the objective function, and will be described in more detail in the following section.

A t test and a p test are used to measure the relative significance of each parameter. The sensitivities are a measure of how much the objective function is changed from changing each parameter. The larger the absolute value of the t-stat and the smaller the p value, the more sensitive the parameter (Abbaspour, 2015).

2.3.2 Calibration

2.3.2.1 SUFI-2

Model calibration was performed using the Sequential Uncertainty Fitting v2 (SUFI-2) autocalibration in SWAT-CUP (Abbaspour, 2015). This program allows calibration with a large number of parameters to be performed simultaneously, in a stochastic calibration procedure. The 9 most sensitive parameters from the one at a time sensitivity analysis were used for calibration, and the model was run for 500 iterations.

The model performance is measured using an objective function; in this case the Nash Sutcliffe efficiency factor was used, which is commonly used in testing the performance of a hydrological model. The formula below measures the 'goodness of fit' of the simulated discharge to the observed discharge at the monitoring stations:

$$NSE_1 = 1 - \frac{\sum_{t=1}^{T} |Q_m^t - Q_o^t|}{\sum_{t=1}^{T} |Q_o^t - \overline{Q_o}|} \qquad \text{(Nash \& Sutcliffe, 1970)}$$

Where Q_o is the mean of observed discharges, and Q_m is modeled discharge. Q_{ot} is observed discharge at time t. The time step depends on the time step of the model simulation and of the observed data. In this research a monthly time step was used.

A NS value ranges from $-\infty$ to 1. A NS > 0 indicates that the model predictions are more accurate than the mean of the observed data, and a NS = 1 indicates a perfect model fit (Nash & Sutcliffe, 1970). Generally, NS values of > 0.5 for the calibration period are deemed acceptable, with measures of >0.65 deemed 'good' (Waseem et al, 2017).

The uncertainty of the model is measured in two ways, the P- factor which describes the percentage of measured data which falls within the 95PPU (95% prediction uncertainty), and the R factor which is a measure of the thickness of the 95PPU band. The R factor ranges from 0- infinity and closer to 0 indicates a better model performance.

2.3.2.2. Determining calibration and validation periods

As mentioned in Section 1.2, the project catchment can be characterised as having severe data scarcity. Below is a figure displaying the data availability from both monitoring points. The longest available period from 4CB04 with gaps of less than a year was chosen as the calibration period (07/1991-09/2002). It is worth noting that since the land use in the catchment has evolved in the last 2 decades, calibrating during this time period poses some issues with reliability of the model to predict current stream flow. Several smaller validation periods from 4CC07 were used to provide insight into the performance of the model outside of the calibration period, and in a different location.

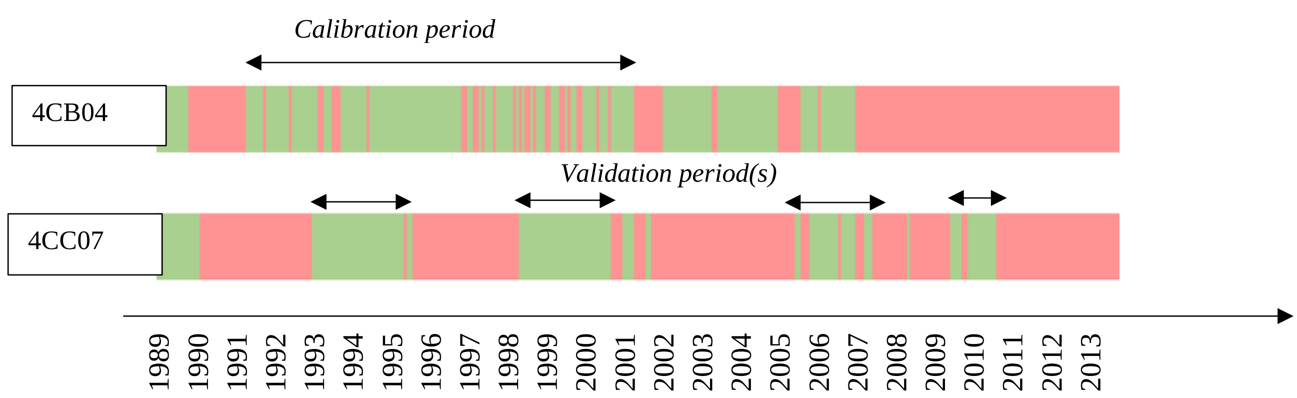


Figure 7: Data availability. Green indicates there was data available, red indicates there was no data available. The code 4CB04 refers to the monitoring station near Thika Tow at the outlet of sub basin 34. 4CC07 refers to the monitoring station at the watershed outlet.

2.4 Environmental flow calculations

The Kenyan Water Act (2002) defines the reserve as the 'quantity of water required to a) satisfy basic human needs for all people who may be supplied by the water resource; and b) to protect aquatic ecosystems in order to secure ecologically sustainable development and use of the water resource' (The Republic of Kenya, 2002). Basic human need is defined as 25L per person per day (Rural Focus Ltd, 2018). To determine the environmental flow, otherwise known as the E flow, the Q95 flow from a naturalised flow duration curve was used (Rural Focus, Ltd, 2018). This is the low flow that is exceeded 95% of the time.

Naturalised flow is the modelled flow which would take place in the catchment if there were no abstractions. Therefore, to create the naturalised flow duration curve, first abstractions in the model from both the dams and the reaches were set to 0.

SBU	Sub - catchment
Thika Mid	39
	37
	32
	31
Kabuku	35
	34
Thika Upper	21
	27
Chania	36
	8

To create the flow duration curve at different points of the river, the simulated discharge for the whole period of the simulation (1989-2013) was analysed at the outlet of each sub catchment listed in the table to the left.

The flow magnitudes were then ranked from lowest to highest, with a rank number M assigned to each value with 1 being the lowest and n being the number of events. A visualisation of the drainage area for each location given can be found in the appendix.

Table 3: Sub catchments where the naturalised flow duration curves were analysed

2.5 Irrigation Demand

Water demand in the catchment is divided by WRA into domestic, industrial, irrigation (JICA, 2013). The National Water Master Plan 2030 (JICA, 2013) provides a framework on calculating water demand of these various sectors. The ‘water demand’ focus of this project was on the irrigation demand, since the majority of the catchment is used for agriculture. Furthermore, the irrigation demand is based on water balance components which can be simulated with the model, which is a great improvement on the alternative technique which involved relying on generalised, country wide estimations.

Irrigation is the technique of adding water to the soil to apply the essential water for plant growth (Ministry of Water and Irrigation, 2007). It is particularly necessary in areas where stored soil water from rainfall does not adequately meet the crop water demand. Crop water demand is directly related to the amount of water that is lost through evapotranspiration, and therefore depends on the climatic conditions such as temperature and solar radiation, but also on the type of crop and its individual water requirements (Ministry of Water and Irrigation, 2007).

To estimate water demand, first the potential evapotranspiration must be determined. Potential evapotranspiration (PET) is a measure of the evaporative power of the atmosphere and is therefore only dependent on climatic conditions (Ministry of Water and Irrigation, 2007).

As discussed in Section 2.1, SWAT contains three options to calculate Potential Evapotranspiration, and the Penman-Monteith method was deemed most appropriate for this catchment. The PET is calculated by SWAT for each HRU, based on the input climate data (Gassman et al, 2011). The Penman-Monteith formula can be found in the appendix.

The water requirements for each individual crop under similar climatic conditions vary, due to the 'water efficiency' of that crop. To calculate the crop water demand for each specific crop, the following equation was used:

$$ET_c = K_c * ET_0 \qquad \text{(Zou et al, 2018)}$$

Where ETc = crop water demand (mm/d), Kc is crop coefficient (-) and ETo is the PET (mm/d). The Kc values were taken from FAO for the 'middle' growth stage. For the crop cover used in the model, the following values were utilised.

Crop Type	**Kc**
Coffee	0.95
Maize	1.2
Pineapple	0.5

Table 4: Kc values of different crops. Retrieved from: http://www.fao.org/3/x0490e/x0490e0b.htm

To determine the irrigation water demand, the water balance simulated in SWAT was used to determine the net difference between the crop evapotranspiration demand and the available water. The available water is also known as the 'effective precipitation' and can be determined using components of the water balance simulated by SWAT. It is equal to the precipitation that is not lost through run off or infiltration.

$$P_e = R_{day} - Q_{surf} - W_{seep} \qquad \text{(Zou et al, 2018)}$$

Where P_e is the effective precipitation, R_{day} is the daily rainfall, Q_{surf} is the surface flow and W_{seep} is the percolation into the aquifer.

Therefor the irrigated water demand is:

$$Irrigation\ Demand = ET_c - P_e \qquad \text{(Zou et al, 2018)}$$

This was calculated each month for each sub catchment over three different years; a drought year (2004), a normal year (2010) and a flood year (2013).

Finally, the water availability for irrigation was determined as the Water Yield – Irrigation Demand. This was calculated for the system when the large scale abstractions for public water supply were in place, under the assumption that this accounted for domestic water supply.

3. Results

3.1 Sensitivity Analysis and Calibration

3.1.1 Global Sensitivity analysis

The global sensitivity analysis results can be seen below.

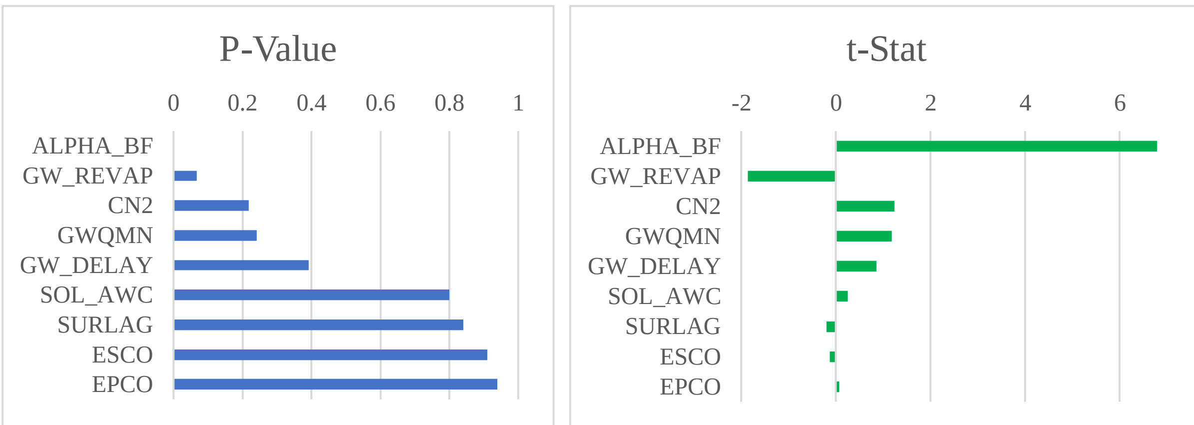


Figure 8: Hydrological parameters used in the sensitivity analysis. They are presented in descending order from most sensitive to least sensitive. The absolute value of the t-Stat indicates how sensitive the parameter is. The P value is a test of significance; the larger the value the less significant the parameter.

The Alpha baseflow factor had the largest effect on the model output, as it has the lowest P value and highest absolute t-stat value. The negative t-Stat value for GW_REVAP, SURLAG and ESCO simply mean the fitted value is on the left of the mean. The last four parameters had almost equal sensitivities.

3.1.2 Calibration and Validation

Below are the results from the calibration between 1991 and 2002. The green band is the 95PPU band, which indicates the 95% prediction uncertainty.

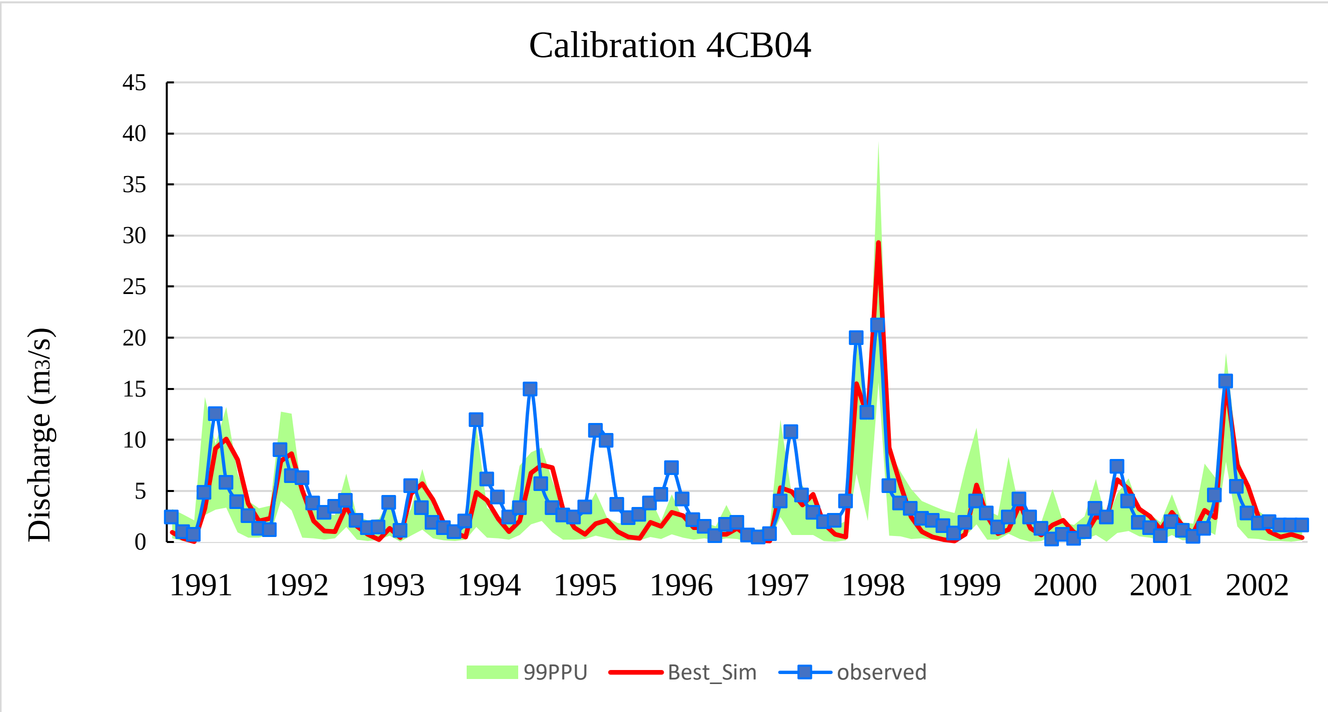


Figure 9: The calibration at 4CB04 between 1991 and 2002. The blue markers indicter observations and the red line is the simulated value. The green band indicates the 95% PPU band.

The Nash-Sutcliffe value for the calibration period was 0.58 with an R_2 of 0.66, indicating an 'acceptable' model performance. The P factor was 0.55, r factor was 0.52. Generally the observed data and the simulation had a fairly close fit, other than the period from 1994-1996 where the peak flows were far lower in the simulated version. Since CFSR data was used rather than observed data, it is possible that the simulation simply missed a few precipitation events. A plot of the observed data against the simulated data can be seen below. The red line indicates a perfect model fit.

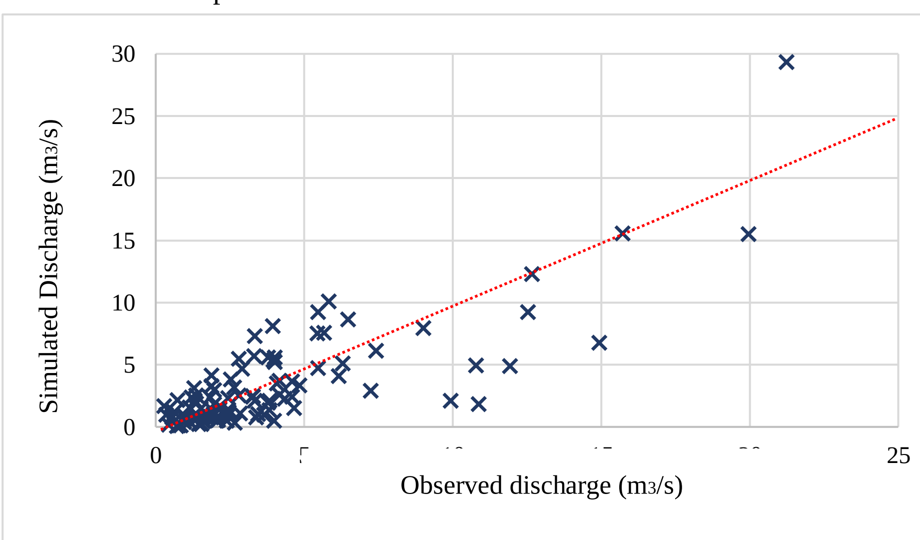
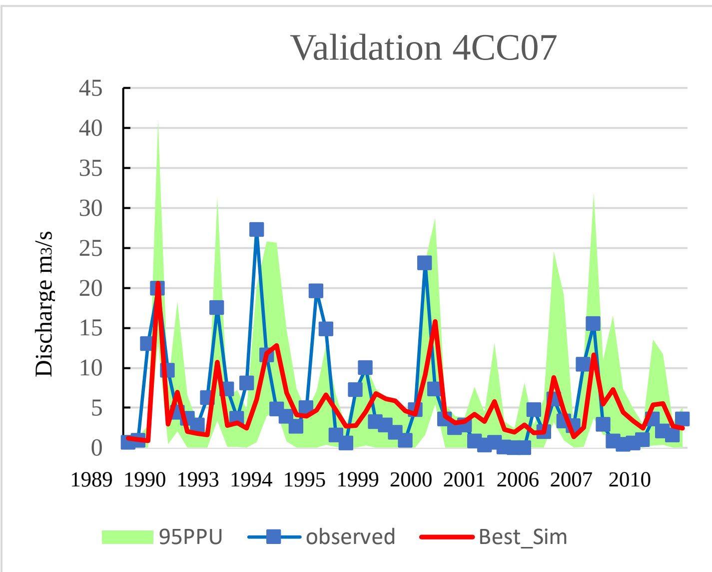


Figure 10: Observed discharge against simulated discharge for 4CB04 during the calibration period 1991-2002.

The model validation can be seen below. Overall, the validation returned a Nash Sutcliffe of 0.19 which is fairly low. Since this monitoring station is further downstream than 4CB04, this includes flow from the Chania which does not pass through 4CB04 meaning there is more chance of variation. Furthermore, the period of time where the simulated model misses the peak flow in 4CB04 is also present in 4CC07. Because there was less data to validate with at 4CC07, these missed peaks account for a proportionally higher time period than in the calibration, so it will have a greater negative effect on the NS value.



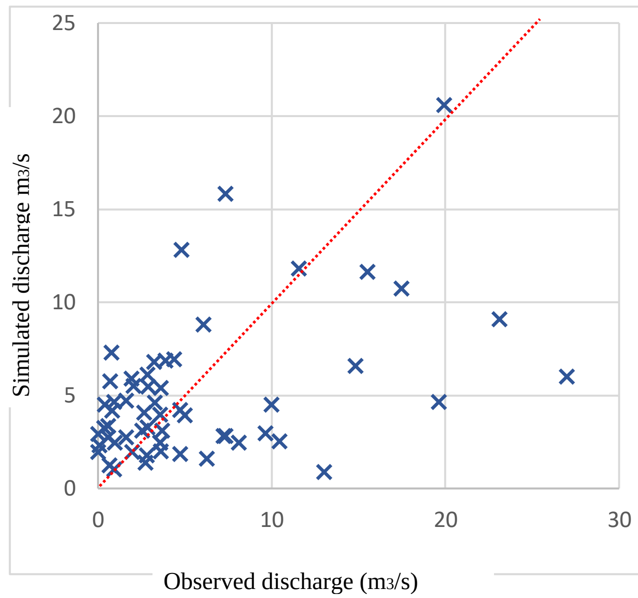


Figure 11: Validation at 4CC07 (left). It should be noted that there are jumps in time along the x axis where the missing data was left out. Figure 12 (right) displays the observed values against model simulation for all the data points included in the validation between the years 1989 and 2010. The dotted red line indicates a perfect fit.

3.2 Water balance

The water balance over the year is presented below for three years: 2004, 2010 and 2013. These years in particular were selected to represent a drought year, a normal year and a flood year.

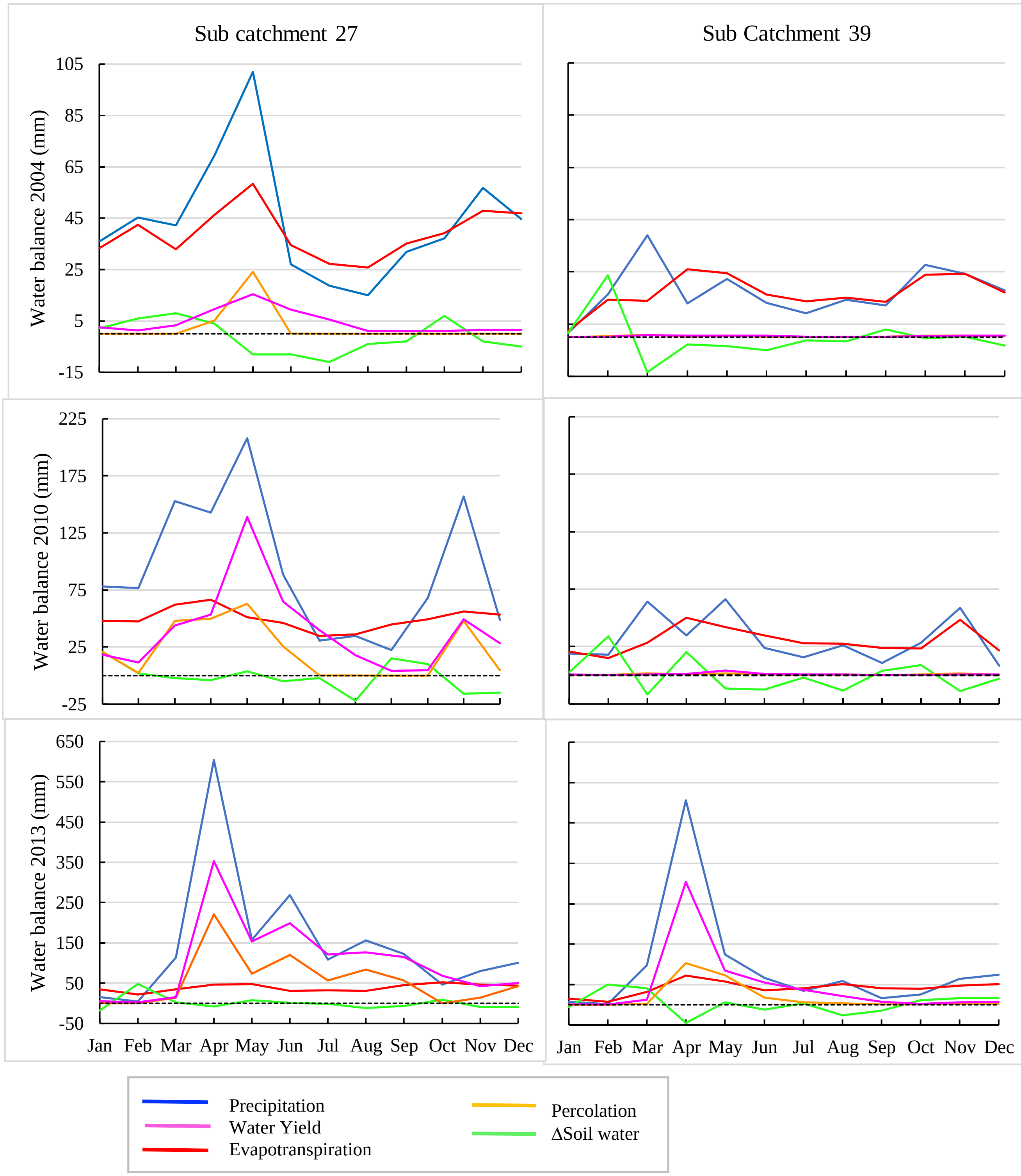
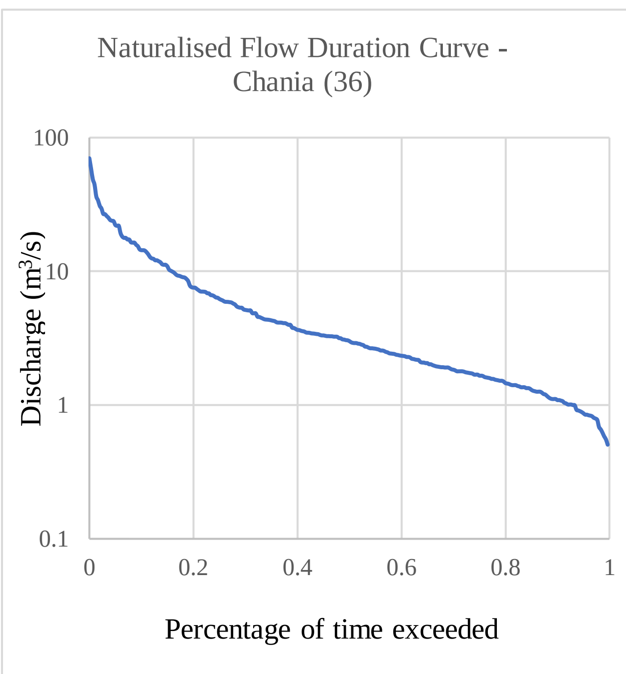


Figure 13: Graphs showing monthly water balances in sub catchment 27 and 39 in a drought, normal and flood year (descending). Note the different scales on the y axis for each year.

Clear differences can be seen between the two sub catchments. In all three years, sub catchment 27 experiences more precipitation, and correspondingly higher volumes of water yield. In 2004, the drought year, there is very little yield generated by either sub catchment. Evapotranspiration is roughly equal to precipitation in both sub catchments. The soil water is refilled and discharge bi annually in sub catchment 39 but remains more steady in sub catchment 27. Total initial soil water values can be found in the Appendix. In 2010, the water balance for sub catchment 39 is similar to the drought year, since there was little precipitation in this area. Sub catchment 27 experiences much higher levels of precipitation. Only slightly more water is stored in soil and lost through evapotranspiration than in the drought year so more yield is generated, although percolation rates also increase. This is water which travels down to the aquifer. Finally, in 2013 the two sub catchments behave much more similarly to each other. There is ample rain in both sub catchments to saturate the soil and meet potential evapotranspiration, and so large amounts of runoff are generated in both sub catchments.

3.3 Naturalised Flow Analysis

The naturalised system was simulated for the model assuming no abstractions from the reaches or the reservoirs. The flow duration curves for sub catchments 36 and 34 are presented below, since these are the outflows of the two main reaches in the watershed; Thika and Chania. These flow duration curves are fairly steep, meaning there is low base flow for the majority of the time, but a high peak flow.



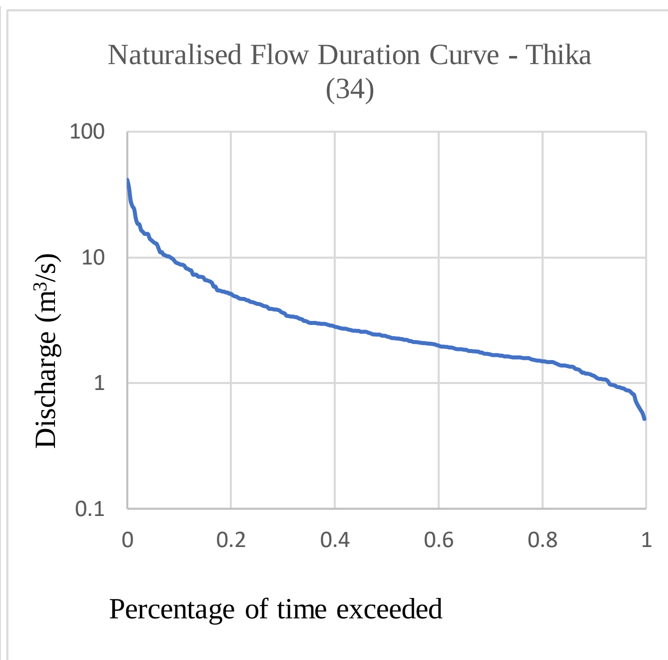


Figure 14: Flow duration curves for the outflow of sub catchments 36 (left) and 34 (right).

Naturalised flow duration curves were made at 10 different locations over the catchment. The Q95, Q80 and Q50 flows, which correspond to the flow which is exceeded 95%, 80% and 50% of the time respectively, were calculated using these flow duration curves. The results are presented in the table below:

SBU	Sub catchment	FLOW (m^3s^{-1})		
		Q95	Q80	Q50
Thika Mid	**39**	**0**	**0.169**	**2.81**
	37	**0.021**	**1.03**	**3.51**
	32	0.342	0.562	0.806
	31	0	0.00372	0.0448
Kabuku	**35**	**1.75**	**2.96**	**5.44**
	34	**0.923**	**1.49**	**2.35**
Thika Upper	21	0.169	0.255	0.423
	27	**0.871**	**1.3**	**1.97**
Chania	**36**	**0.869**	**1.46**	**3.01**
	8	0.778	1.21	1.69

Table 5: Q95, Q80 and Q50 flow at various locations over the watershed. The bold values indicate the main channels, while the rest are tributaries. See Figure 20 in the Appendix for a visualisation of the drainage areas of each location where the Q95, Q80 and Q50 flows were calculated.

The flow duration curves and corresponding Q95, Q80 and Q50 values differ across the watershed. The Q95 flow, or the 'environmental flow' is fairly low, between 0 and 1.75 m3/s depending on the location in the watershed. As expected, tributaries to the main stream in Thika Mid experience very low base flow, in some cases drying completely. Interestingly, sub catchment 39 which contains the main reach at the outlet of the watershed also has a Q95 of 0, meaning the river dries completely at times, even when there are no abstractions.

3.4 Irrigation Demand

The results on the irrigation demand of the basin are presented in this section, along with comparisons with water yield to gauge the overall water availability. Similarly to the water balance results, the years 2004, 2010 and 2013 were used to be representative of a drought year, a normal year and a flood year respectively. First, the total annual irrigation demand was calculated per sub catchment for each of these years. It should be noted that this irrigation demand is for plants to grow 'optimally' such that all the water demand that they could potentially evaporate is applied. In reality it is not necessary to supply the crops with this total amount for them to survive.

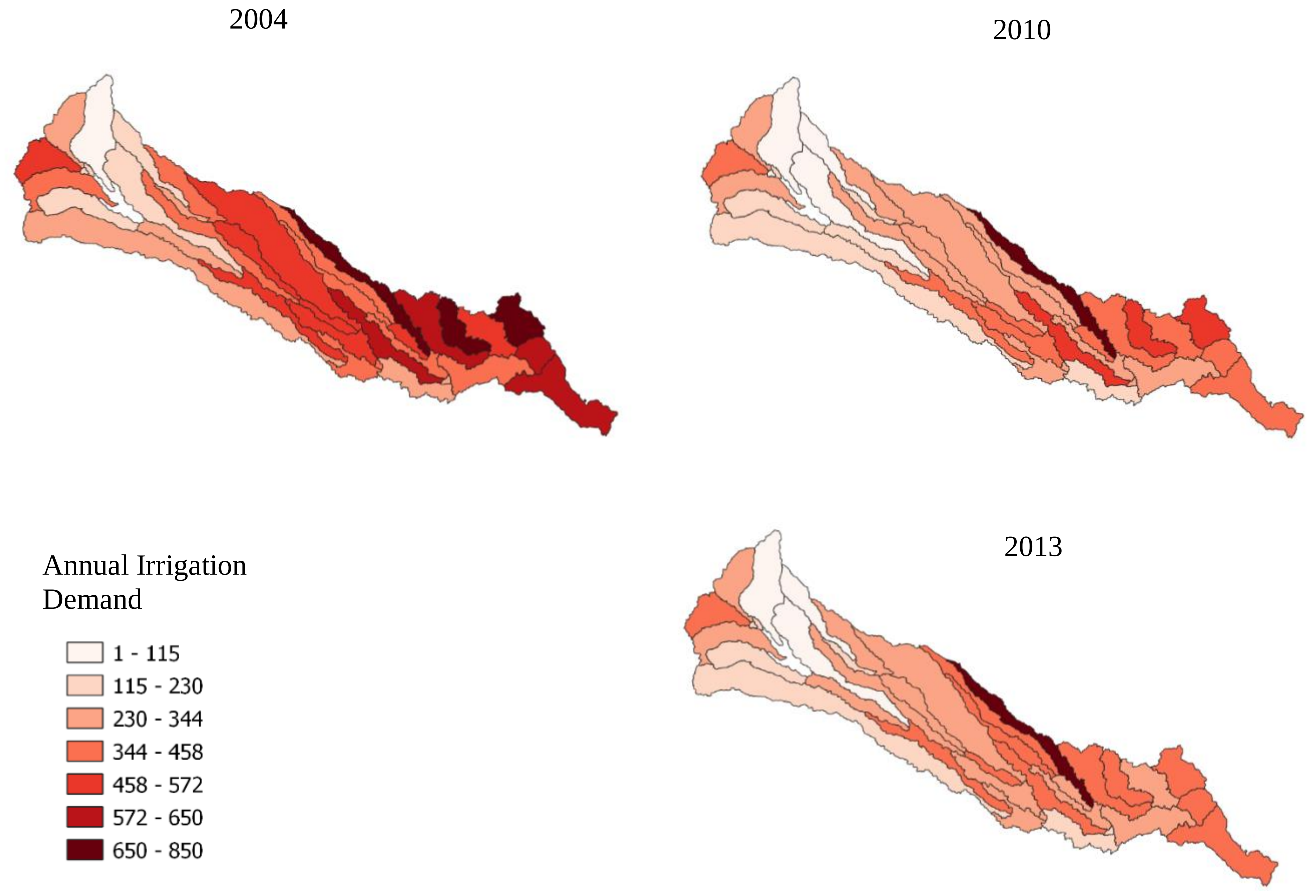


Figure 15: The irrigation demand per sub catchment. Drought year 2004 (top left) Normal year 2010 (top right) and flood year 2013 (bottom right).

As expected, the irrigation demand is highest during the drought year, and lowest in the flood year. There is a more pronounced difference between the normal and drought year than the normal and the flood year. During 2010, several sub catchments, particularly in the upper basin have low irrigation demand. The spatial difference in irrigation demand is largely as expected based on surveys and discussions with WRA. The lower half of the catchment is known to be more arid, and therefore is highly irrigated.

Along with the total annual irrigation demand, the seasonal pattern of irrigation demand was analysed and compared to the water yield in order to gauge how water availability varies throughout the year. The figure below shows the monthly irrigation demand and yield for 2004, 2010 and 2013 for the whole catchment.

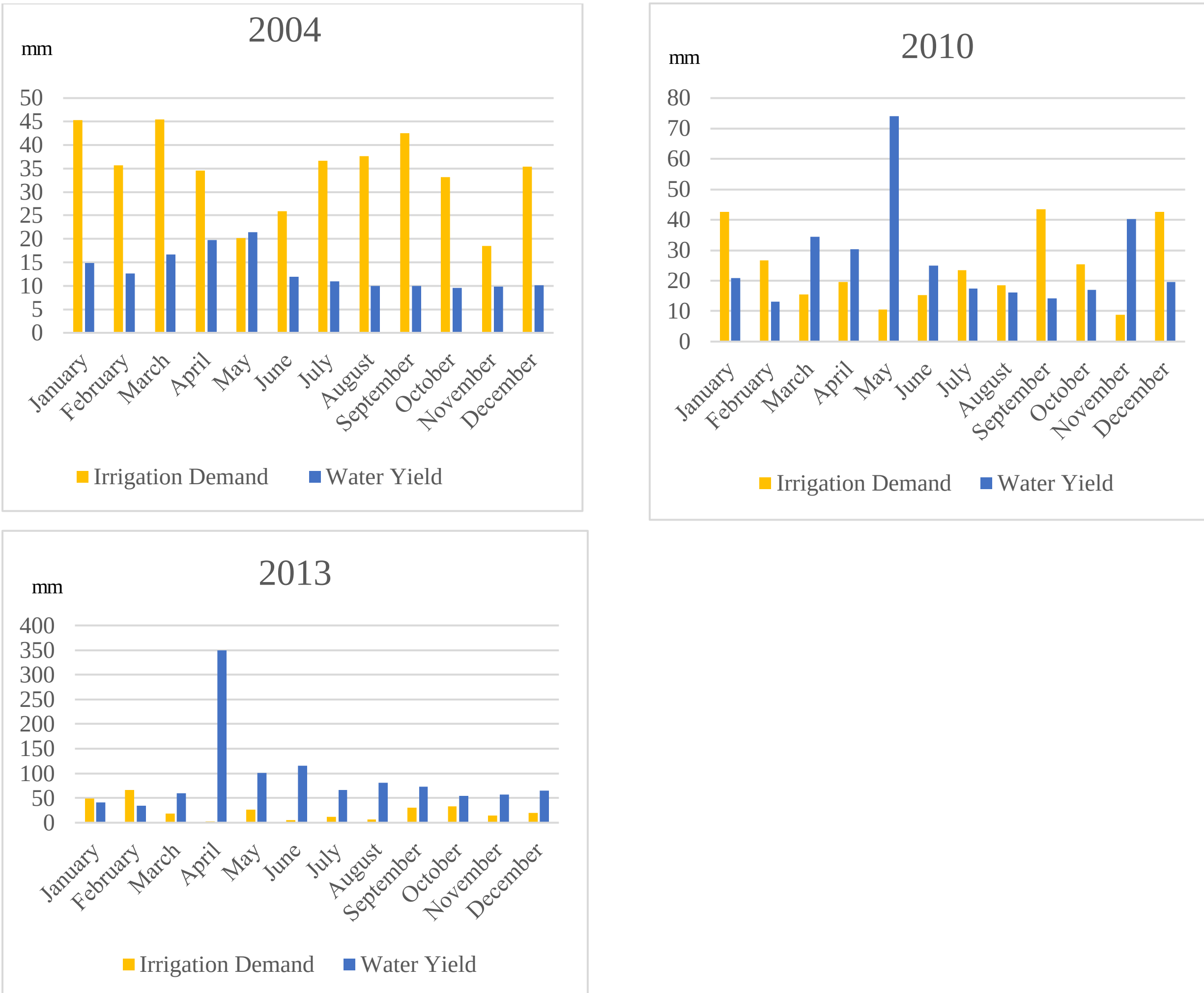


Figure 16: Monthly irrigation demand and yield for the whole watershed. Note the difference in scales on the y axis in each of the three years.

It can be seen that during the drought year, the irrigation demand is higher than the yield for the majority of the year, indicating water scarcity. In 2010, overall the volume of water yield is higher than the demand, however during the drier months the yield does not meet the demand. Furthermore, there is a ‘peak’ in water yield in May. During the flood month there are extremely high volumes of yield compared to the demand. This indicates that there are large monthly differences in water availability.

3.5 Water Availability Overview

These results were combined to show the seasonal water availability for all three years. Water availability was defined as Water Yield – Irrigation Demand. Therefore the graph below is a summary of the results of the three previous charts in Section 3.4.

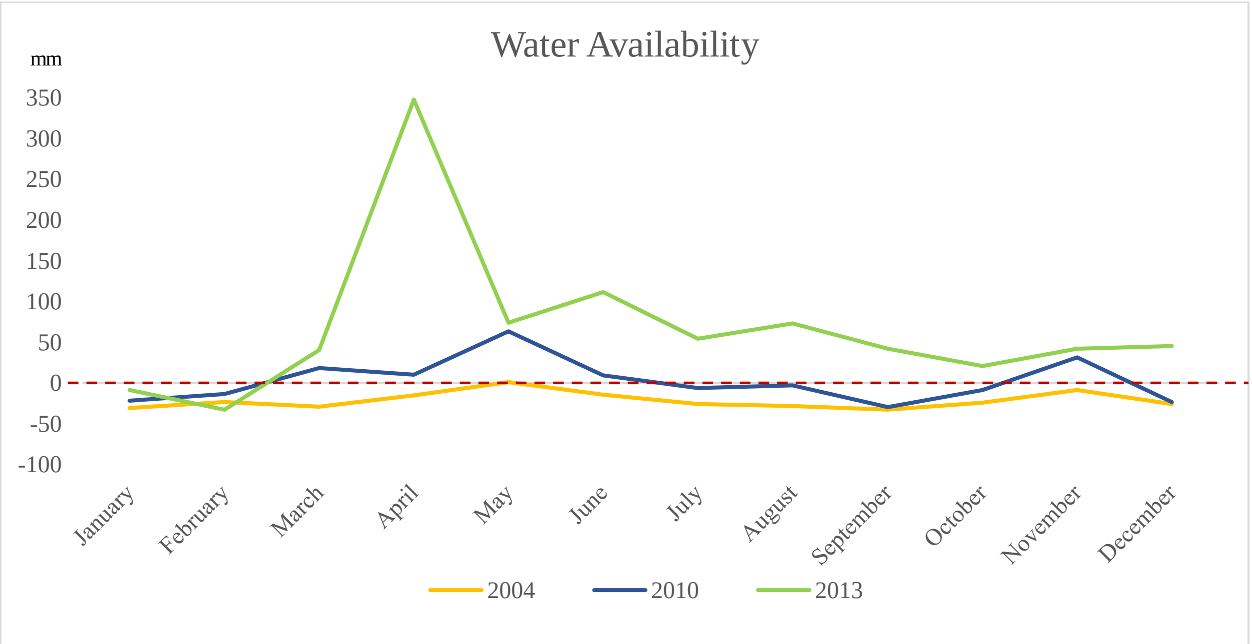


Figure 17: Monthly water availability for the whole watershed during 2004, 2010 and 2013.

During 'normal' years with two rainy seasons such as 2010, it can be seen that during certain months there is surplus water (indicated by water availability >0), and during certain months there is water scarcity (water availability <0). This suggests that generally, although there is enough water annually to meet demand, water abstracted and stored during the rainy seasons could help alleviate water stress during the drier months.

The results show that there are differences in both spatial and temporal distribution of water availability within the water shed. These differences are presented together in the following table, which allows the monthly water availability to be seen for each sub catchment, in order to advise WRA which months would be best for encouraging more abstractions and storage from for different areas over the water shed.

Sub catchment	Month												
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
1	-8	6	31	29	85	32	17	17	-8	17	47	1	266
2	29	18	56	56	119	40	18	18	10	23	69	20	476
3	-33	-5	10	12	67	23	12	13	-24	9	31	-16	99
5	-17	3	23	17	75	27	16	16	-12	14	38	-4	196
18	25	25	81	56	166	43	21	21	5	32	93	21	589
19	14	19	67	43	139	35	18	18	0	26	77	13	469
20	36	20	57	58	121	40	20	19	16	24	70	26	507
7	2	9	38	28	92	29	17	17	-1	18	50	7	306
23	36	20	57	58	120	41	20	20	16	24	69	26	507
4	22	14	55	58	120	38	11	11	-1	18	70	11	427
25	38	20	61	63	127	41	18	18	15	23	74	25	523
6	17	13	48	50	112	36	14	14	0	18	64	11	397
24	-4	8	44	48	112	35	7	8	-21	15	64	-12	304
21	4	11	50	53	119	38	9	10	-16	17	69	-1	363
8	-1	7	37	32	98	30	14	14	-7	16	52	2	294
30	-3	6	41	43	107	32	8	8	-17	13	60	-5	293
9	-17	2	35	37	101	28	3	4	-29	9	56	-16	213
10	-25	-1	28	28	97	25	5	6	-31	8	51	-19	172
27	-24	-1	30	31	97	25	4	5	-31	9	52	-19	178
33	-26	-26	12	12	36	12	-19	-12	-44	-24	30	-40	-89
11	-25	-1	30	29	96	23	4	6	-30	9	51	-20	172
13	-22	-1	41	33	103	15	-5	4	-31	11	58	-28	178
12	-78	-72	-51	-66	2	-40	-49	-43	-79	-71	-47	-74	-668
29	-27	-26	9	12	35	12	-18	-12	-44	-24	29	-40	-94
34	-23	-24	25	7	35	9	-17	-10	-39	-21	30	-36	-64
36	-18	-17	34	5	36	11	-9	-4	-29	-14	31	-27	-1
17	-56	-52	-17	-37	-1	-30	-38	-28	-61	-52	-13	-62	-447
35	-36	-33	-9	-24	4	-19	-24	-17	-39	-33	-7	-40	-277
28	-39	-36	-9	-24	3	-20	-26	-18	-44	-35	-7	-45	-300
22	-45	-41	-12	-28	0	-23	-30	-21	-49	-41	-9	-50	-349
14	-53	-49	-17	-36	-1	-29	-36	-27	-57	-50	-13	-59	-427
37	-20	-18	-1	-12	9	-10	-13	-8	-23	-18	-1	-23	-138
32	-30	-28	-7	-20	4	-16	-21	-15	-33	-28	-6	-34	-234
16	-66	-61	-23	-45	-5	-37	-45	-34	-71	-62	-17	-72	-538
26	-44	-41	-14	-29	0	-24	-30	-22	-48	-41	-10	-49	-352
15	-64	-59	-22	-44	-4	-36	-44	-33	-68	-60	-16	-70	-520
38	-35	-32	-8	-21	2	-17	-24	-16	-39	-31	-6	-41	-268
31	-55	-50	-18	-37	-2	-30	-37	-28	-59	-51	-13	-60	-440
39	-55	-51	-17	-36	-1	-29	-37	-27	-60	-51	-13	-61	-438
Catchment	-21	-13	19	11	64	10	-6	-2	-29	-8	31	-23	33

Figure 18: Water availability in 2010 (mm). Blue indicates surplus water is available, and red indicates there is a deficit. The intensity of the colour varies with the quantity of water. The sub catchments are ordered from upstream to downstream.

From this figure it is clear that during a 'normal' year certain sub catchments downstream experience water scarcity year round, highlighting the need for water allocation and distribution. There is a general trend of decreasing water availability from upstream to downstream. During both rainy seasons, there is surplus water in the catchment. Upstream sub catchments such as 1-8 generally experience a positive water balance year-round. Furthermore, from the 'totals' row and column it can be seen that overall, annually there is a positive water availability (of 33mm).

4. Discussion

4.1 Implication of results

The results of the water balance comparison between Thika Upper and Thika Mid (Section 3.2) confirmed discussions with WRA that there is much greater water availability in the upper catchment, with Thika Mid experiencing the most intense water scarcity. The water balances presented in section 3.2 show that during a drought year the soil water flux varies throughout the year in both catchments, generally filling during the later half of the year after the big rainy season. Interestingly, it seems there is a delay in the soil recharge after the large rainy season. During 2010, which reflects a 'normal' year, the water yield follows the precipitation pattern closely while the soil stored water remains fairly constant, particularly in sub catchment 27. In 39 where there is less precipitation and less yield, again the soil water re fills and subsequently discharges after the rainy season, however there is a delay. The delays in refill from the rainy seasons are likely due to the high clay content of the soil; run off from precipitation is fairly high, and the movement of water through clay rich soils is much slower than soil with a high sand or silt content (O'Geen, 2013). This also explains the residual soil storage during the drought, as the high clay content makes soil water loss more difficult (O'Geen, 2013). Agricultural techniques can be used to take advantage of the high clay content in Kenyan soils such as tillage, ripping and subsoiling to increase infiltration and soil storage (Biamah, 2005). During the flood year the soil storage reaches its saturation extremely quickly during the rainy season; the total stored soil water peaks at 165mm in sub catchment 27 and 158mm in sub catchment 39. This maximum stored soil is comparable to soil storage seen in similar studies in East Africa, with recent estimations for the higher bound of water storage in Kenyan soils during a flood year between 120-260mm depending on the hydrological model used (Rateb & Hermas, 2020). Since maximum capacity is reached in the soil during the flood year, high levels of runoff are seen in both sub catchments. It is also interesting to note that despite the differences in land use, soil and slope over the catchment, when there is ample rain all over the whole catchment, the sub-catchments behave fairly similarly to each other. This suggests that it is the differences in precipitation over the catchment that has the greatest effects on the water balance, while the differences in soil had less of an effect than expected. During a drought year the sub catchments behave fairly similarly to each other, with most water from precipitation lost through evapotranspiration.

The naturalised flow analysis confirms these differences in water availability across the catchment and provides further insight into the distribution of cumulative discharge, which is particularly useful for Water Allocation Planning. In the WWF analysis of the Mara River basin, which lies in both Kenya and Tanzania, the quantification of the reserve flow provided greater insight into the behaviour of the river system than simply measuring the average stream flow (LVBC & WWF-ESARPO, 2010). Analysis indicated that the ecology of the river basin could thrive with low base flows and high peaks, with a Q95 flow of 0.9m^3/s in the main channel (LVBC & WWF-ESARPO, 2010). Similar patterns were observed in the Thika-Chania catchment. The E flow of the river was low throughout the whole catchment, ranging from 0m^3/s to 1.75m^3/s. Interestingly, the Q95 flow of Thika Mid's main channel, the outlet of sub catchment 39 had a Q95 flow of 0 m^3/s, suggesting that the river dries completely at this point 5% of the time in the naturalised system. This is slightly surprising since it is the furthest point downstream, meaning has the largest drainage area and therefore should have more water flowing through. The respective drainage areas can be seen in the Appendix. The Q95 flow of 0 can be explained by high levels of water loss through evaporation at this part of the channel, which at low flows could lead to the river completely drying. The fact that the river dries completely out at this point has been confirmed by the WRA in meetings, although several large scale abstractions occur in Thika-Mid which would account for a shortage of water downstream in the observed scenario. However in the naturalised system there are no abstractions so it is expected that the Q95 flow would be slightly higher than 0, since generally the naturalised system has proportionally higher flows than the actual system, which can be seen in the graphs of the flow comparison in the Abstract. It is likely that abstractions were underestimated in the model, for reasons that will be elaborated on in Section 6.3.1, which means that the model will have been over calibrated. This means during the naturalised model run when the volume of abstracted water is ‘re included’ in the model, there is a certain volume of water missing. For this reason it is fairly likely that the Q95, Q80 and Q50 values determined from the model are a slight underestimation of the true naturalised flow. Additional data on abstractions would lead to a more accurate estimation of the naturalised system.

The results on irrigation demand suggest that the necessity for irrigation is far greater downstream in the catchment. In particular, the sub catchments on the northern border of Thika Mid experience the greatest demand. The areas with the highest intensity experience an irrigation demand of up to 840mm per year in the drought season. Although this may seem a high demand, a study using similar methods of analysing the Potential Evapotranspiration and effective precipitation in the Taita Hills in Kenya yielded comparable results (Maeda et al, 2011). This study also found a bimodal irrigation demand, with the highest monthly demand of around 110 mm and lowest monthly demand of around 30mm (Maeda et al, 2011). By comparison, the results from this study found a similar bimodal pattern, with the average monthly catchment irrigation demand in 2010 demand ranging from 45mm to 10mm, and the sub catchment with the highest total irrigation demand (sub catchment 12) ranging from 78mm to 0.1mm. These irrigation demand results are therefore representative of the irrigation demand for maximum growth if no drought resistant agricultural techniques were applied. The overall results on water availability confirm that areas downstream are under far more water stress than the rest of the catchment. In fact, areas around the centre of the catchment and the Abedare forest have surplus water almost all year round. The results confirm the hypothesis that there is enough water annually in the catchment, but the seasonal fluctuations and differences in availability upstream and downstream means that water scarcity is an issue in Thika Mid for much of the year and for much of the catchment in July, August and November.

This suggests that distributing water would be particularly advantageous for water management in this catchment. Large scale abstractions from public water providers take place in Thika Mid, which leaves less for small scale irrigation and domestic use. Ideally, this public water could be abstracted further upstream which would minimise loss through evapotranspiration. Furthermore, rainwater harvesting to provide water during the drought is also a viable option. The 2019 paper on rain water harvesting in Kiambu, Kenya confirms that rainwater harvesting would be beneficial, and suggests using larger scale storage in areas which minimise the impacts downstream (Mugo & Oderal, 2019).

4.2 Contributions to Society and improvements on current practice

This research contributed to sustainable development in Kenya most notably through providing the Water Resources Authority with a hydrological model of a catchment which is heavily relied on for water supply, for the city of Nairobi as well as local areas (Knopp et al, 2011). Urbanisation, population growth and climate change mean that sustainable management of this catchment is crucial to water security in Kenya (Aurecon AEMI Limited, 2019). The specific contribution to each Sustainable Development Goal (SDG) is summarised in the table below:

Sustainable Development Goal	**Description**	**Contribution**
2: Zero Hunger	End hunger, achieve food security and improved nutrition and promote sustainable agriculture	Quantification and analysis of irrigation demand helps promote sustainable agriculture. Generally, effective management of water promotes food security,

		particularly in countries like Kenya which rely heavily on local agriculture.
6: Clean Water and Sanitation	Ensure availability and sustainable management of water and sanitation for all	Hydrological modelling provides insights into water availability and demand, allowing for water allocation planners to distribute water fairly and equitably with the greatest benefit to human life and the environment.
14: Life below water	Conserve and sustainably use the water resources to maintain life and ecosystems below water	Quantification of the environmental flow allows water allocation planners to protect the reserve and avoid over abstraction, allowing life below water to thrive.
15: Life on land	Promote sustainable use of terrestrial ecosystems, and halt and reverse land degradation and halt biodiversity loss	Quantification of the environmental flow allows water allocation planners to protect the reserve and avoid over abstraction, avoiding biodiversity loss in the river catchment.

Table 6: Contributions to the Sustainable Development Goals. SDGs and description from (UN General Assembly, 2015)

A hydrological model is particularly useful in providing information on the water availability all over the catchment rather than only at the monitoring points, allowing for insight into water availability even when there's no measured data (Ndomba et al, 2008). Scenario analysis is also facilitated by the model, which is valuable for water planners to see how the system will react to different situations, such as increased abstractions, no abstractions (naturalised flow) and climate and land use changes (Githui et al, 2009; Hunink et al, 2017). Within this project, the analysis of the naturalised scenario is of particular importance to sustainable water management. As discussed in section 1.1, determination of the Q95 flow of the naturalised system is used to determine the reserve flow and consequently the allocable yield. Furthermore, the Q80 and Q50 flows give insight into the normal and flood flow respectively. The development of a hydrological model in this catchment for this research has allowed for a far more insightful analysis of the naturalised system than was previously possible. The previous technique of creating a flow duration curve of the naturalised system was to create a flow duration curve using historical stream flow data (Rural Focus Ltd, 2018). This method was used under the assumption that there were fewer abstractions in the past, therefore this historical measured data could be representative of the current naturalised system. In the 2006 paper on methods for developing naturalised flows, the need to simulate flows that would have occurred historically with respect to human interference, but with present river basin conditions is highlighted (Wurbs, 2006). Simply using historical data is therefore an issue. The assumption that there were fewer abstractions in the past is valid; population growth means there is a higher overall water demand, and agricultural activities have intensified meaning it follows logically that there will be more abstractions for irrigation in the recent years than in the past Although it is difficult to quantify exactly the increase in abstractions from historical data since it was largely unregulated in the past, the steady population increase of 2.5% annually from the 1940s along with a significant increase in agricultural intensity (Heald, 1999) indicate that the change in abstractions is significant. However, the fact that less abstractions were taking place in the past does not mean that the discharge data will be representative of the current naturalised system (Wurbs, 2006). Although there were fewer abstractions in the past it is unlikely there were absolutely no abstractions, meaning the system is not completely naturalised. Furthermore the catchment has experienced significant land use change and climate change, which both have strong effects on the flow pattern (Knoop et al, 2011). The average temperature change from 1976 is 2.14 degrees Celsius, which has had significant affects on the flow regime (Maina & Messo, 2017). On average, this higher temperature has increased the Potential Evapotranspiration, meaning more water is generally lost from stream flow. As well as the average temperature rising, the weather has become more variable with higher instances of both flooding and drought in the more recent years (Maina & Messo, 2017).These differences in the current physical system and the historic physical system means that historic data is a poor representation of the current naturalised system. Since historical data was available at 4CB04, the Q95 flow was calculated between 1945-1950 as a comparison, giving a value of 0.78m^3/s, which is lower than the value from the naturalised flow simulation of this model at the same location, 0.92m^3/s. In addition to these methodological issues, there is the practical issue that historic data only exists where there are gauging stations. Since the monitoring system in this catchment is not extensive, there is not sufficient data to give an overview of the naturalised system. Therefore, the naturalised flow analysis in this model gives far more reliable and complete results to use in a Water Allocation Plan.

The results on irrigation demand also provide a valuable contribution to the sustainable management of the water system. The framework used by the Water Resources Authority for the calculation of irrigation demand is provided in the Kenyan National Water Master Plan (JICA, 2013), and is calculated based on an average, 'Tana wide' irrigation demand, multiplied by the area of the catchment. Using a general irrigation demand for the Tana basin is not particularly useful since the Tana basin is extremely large, and covers several agro-climatic zones which range from the Abedare mountains to the coast on the Indian ocean. The land use varies widely along with the climate. It is much more appropriate to have an irrigation demand calculated directly from water balance components in the particular sub catchment in question, which is provided in this thesis. Calculations from this study indicate large local differences of 10mm to 840mm annually between sub catchment 1 and 39, indicating the need for spatially distributed irrigation demand calculations.

4.3 Limitations

4.3.1 Methodology

Despite these contributions to sustainable development in Kenya, there are several limitations to the research. There are limitations with the methodology; hydrological modelling is never a true representation of reality (Refsgaard, 1997). Perhaps the most crucial issue in realism in the methodology of this research is the use of the CN number to calculate runoff (White, 2010). This is an empirical method which is based on statistical data rather than using a true reflection on physical reality. This is especially problematic when using in areas outside of the study area it was developed in; the USA (White, 2009). The Curve Number method relys on the statistical relationship between the CN and the soil moisture, and this relationship has not been tested in areas where intense rain leads to soil saturation (White, 2009). This could help to explain why the Nash-Sutcliffe only fell into the 'acceptable' category rather than 'good' during calibration. A physically based run off calculation would be more appropriate, and generally this would be achievable if there was more frequent precipitation data available; for example if sub daily rainfall data is available the Green-Ampt method can be used in SWAT (King, 1999). This is an infiltration excess model which is physically rather than statistically based, but due to its data requirements its rarely used in data scarce catchments (King, 1999). However, the SCS Curve Number method has been used in East Africa in several studies with promising results (Ndomba et al, 2008; Githui et al, 2009; Hunink et al, 2013; Hunink et al, 2017). The SWAT model using SCS Curve Number method was used in a data scarce catchment in central

Tanzania to determine its suitability, and returned a Nash Sutcliffe of 0.85, indicating a very good model performance (Ndomba et al, 2008). It was noted that the SCS curve number underestimated the discharge in the transition from a dry to a rainy season, and overestimated discharge in other areas (Ndomba et al, 2008). Hunink et al (2013) used SWAT in the Upper Tana basin, which includes the Thika-Chania catchment to study the effects of climate change on sedimentation throughout the basin. The SCS Curve number was used to calculate run off, and the model had a 0.75 Nash Sutcliffe efficiency in calibration of stream flow, indicating a good performance, and there was a slight systematic over prediction of discharge (Hunink et al, 2013). These close model fits suggest that the SCS curve number is a good option for hydrological modelling in data scarce catchments if money and resources are lacking since it provides good predictions of stream flow. However it is important to bear in mind that it is not a true reflection on the physical processes involved.

Despite yielding comparable results to the literature, there were assumptions made during the irrigation demand calculations which affect the reliability of the results. The model did not take into account growing seasons, assuming that agriculture intensity was constant all year round. In reality, the Kc value which affects the crop demand varies throughout the stages for a plants growth. For example, the Kc of pineapple can range from 0.3-0.5 depending on its stage of growth (FAO, n.d). Since the intensity of the cropping in the study area was not known, the mean value had to be taken. Furthermore, the irrigation demand was defined as the amount of water needed to meet the crop water demand of the plant to allow for optimal plant growth. In reality crops are able to grow with less water than this (Bodner et al, 2015), and 'irrigation deficit techniques' can be applied to minimise the loss of yield. For example, managing the irrigation supply such that the later stages of the growth cycle experience water stress minimises the overall loss of yield (Kipkorir et al, 2002). Furthermore, there are growing techniques which can increase drought resistance. For example, intercropping coffee and bananas helps to partly shield the coffee from sunlight reducing the crop water demand; a technique that is often implemented in small scale coffee farms in East Africa (Wairegi et al, 2015). The irrigation demand results therefore reflect what the demand would be if no drought resistant management practices occurred.

4.3.2 Data availability

In general, data availability proved a large limitation on the reliability of the model; even more so than was initially anticipated. During the proposal stage of this research it was expected that it would be possible to use observed climate data as a model input. Unfortunately due to the COVID-19 situation, there were delays in accessing data which meant that only observed data from the Ndakaini dam was accessed during the project time frame. There was only a small overlap with discharge data downstream with which to calibrate, and it was determined that this would not provide enough detail on the reliability of the model, particularly in areas further away from the dam. Furthermore, using data from only one location would mean that the spatial variability in the model would be reduced, which was one of the key focuses of the project. For these reasons climate forecasting data was used from 4 locations. However it is expected that obtaining more observed climate data from additional stations over a longer period would likely improve the reliability of the model substantially. The CFSR data used provided a NS of 0.58, which indicates that when there is no access to observed data, climate forecasted data is still useful input to the model to provide acceptable results. However from a brief comparison with observed precipitation data at the dam, it seemed that the forecasted data missed certain large precipitation events. As well as climate data, there was other data scarcity that lead to uncertainties within the model. The soil map was fairly recent and robust, with most soil parameters measured in the field under a high resolution. However the land use map, leveraged from the WRI was fairly coarse. In particular, the 'agricultural areas' were generally indistinct on which crop was growing. From the literature, it was known that the majority of the agriculture in the middle of the catchment was used to grow coffee. For this reason, and also due to the fact that coffee has a crop factor close to 1 (which was used to determine irrigation demand) coffee was used as a proxy for undetermined agricultural areas in the model. However from discussions with WRA and from reviewing existing Water

Allocation Plans, it is clear that this is a large generalisation (Thika Upper WRUA & WRMA, 2013). In reality, there are large tea farms in the middle of the catchment, upstream of the coffee farms and downstream of the Abedare forest. There is a large variety of different small scale agriculture throughout the catchment such as horticulture, bananas, passionfruit, cassava, potatoes, beans and tomatoes and grassy areas (Thika Upper WRUA & WRMA, 2013). These all have different crop factors, which effect the crop water demand. Cassava, bananas and tomatoes all have crop factors of 1.15, and tea has a crop factor of 1.0, which means the actual crop water demand will be higher than that of coffee (FAO, n.d).

4.3 Future research

One way to improve and refine the data inputs to the model is to conduct field work. Driving to random locations over the catchment to verify and determine different land covers would refine the land use map and provide more confidence in the model. Furthermore, field work to complete a survey on water use would certainly improve the reliability of the model. The survey which was used to input abstractions into the model was only taken in Thika Mid and Thika Upper. However it is likely that illegal abstractions take place throughout all agricultural areas and indeed in any populated areas for domestic use. Estimates suggest that over 50% of abstractions could be illegal (World Water Assessment Programme, 2006). A thorough and systematic survey to determine the volume of illegal abstractions across the whole catchment would improve the model. The expected effect on the model of the naturalised system would be that the streamflow would be higher than the values in this research, since the 'missing' abstractions would be re included in the model.

For additional research, it would be interesting to do a model run with more observed climate data and compare the NS values to the forecasted data used in this research to gain an insight to the extent of the effect that additional observed climate data has on the reliability of the model. A similar study was conducted in China comparing several precipitation input options including observations, satellite data and simulations (Yi et al, 2018). It was concluded that all provided acceptable results, however the best Nash Sutcliffe of 0.658 was achieved with observed data, and the lowest value of 0.464 from the Weather Research and Forecasting model (Yi et al, 2018), which supports the hypothesis that while the CSFR provides acceptable model results, it would be improved with observed data.

In addition to improving the model through refining and supplementing data inputs, there are further research topics that follow on from this research. Since the results on the variability of water availability throughout the seasons suggest that storage would be a good option for the catchment, it would be interesting to explore this further and deduce what effects storage upstream has on the flow downstream. It would also be interesting to use the model to predict the effect of population growth and by extension land use change, and climate change on the catchment. Future land use change could be modelled by increasing the size of urban areas and including more abstractions. The effect of climate change on the catchment can be analysed by using the Relative Concentration Pathways (RCPs), which are future climate change scenarios based on likely emission trajectories and coupling them with the input weather data. A similar study has been conducted in the lower Thika catchment, finding that all of the RCPs increased the extremity of the weather experiences in the catchment; more intense rainy periods but longer droughts (Kiptum, 2014). Naturally, the reliability of predictions of future scenarios using the model from this study would increase with the reliability of the model at predicting current stream flow. Observed climate data and additional abstraction data would improve this reliability.

5. Conclusion

The Soil and Water Assessment Tool provided significant insights into water availability and demand in the Thika Chania catchment. Climate Forecast System Reanalysis data was used as meteorological inputs to compensate for data scarcity. The model was calibrated to Nash Sutcliffe efficiency of 0.58 at monitoring station 4CB04 which lies on the Thika River, indicating an acceptable model performance. However, the validation at the catchment outlet at monitoring station 4CC07 was lower, at 0.19. Water availability results suggest that during a normal year, in total there is enough water to meet demand however there is seasonal scarcity and large spatial differences. The water availability was found to be lower in the downstream areas of the catchment, with areas in Thika Mid experiencing water scarcity all year round. Even during the flood years areas in Thika Mid experienced overall scarcity annually, since high volumes of rain falling during one month does not alleviate the high irrigation demands during the rest of the year. Generally, irrigation demand was found to have a bimodal pattern, and was highest during the drought year with certain sub catchments in Thika Mid experiencing an irrigation demand of 800 mm per year. The seasonality of the water availability suggest rainwater harvesting and storage could be viable options for alleviating water stress during the dry season. Finally, the Environmental Flow was found to vary over the catchment, ranging from 0-1.75 m^3/s. The Environmental flow was found to be lower in Thika Mid than Thika Upper, and was 0 m^3/s at the catchment outlet.

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7. Appendix

7.1 SCS Curve Number Method

In SWAT, a CN value is assigned for each HRU, which is then used to determine the theoretical daily storage capacity of the watershed using the following equation:

$$CN = \frac{1000}{10 + S/25.4}$$

(United States Department of Agriculture, 1986)

Where CN is the curve number assigned by SWAT, and S is the watershed storage (mm). The run off volume is calculated using the equation below:

$$Q = \frac{(P - I_a)^2}{(P - I_a) + S}$$

(United States Department of Agriculture, 1986)

Where Q = daily surface runoff (mm), P is daily precipitation (mm), I_a js the initial abstraction (assumed to be 0.2*S)

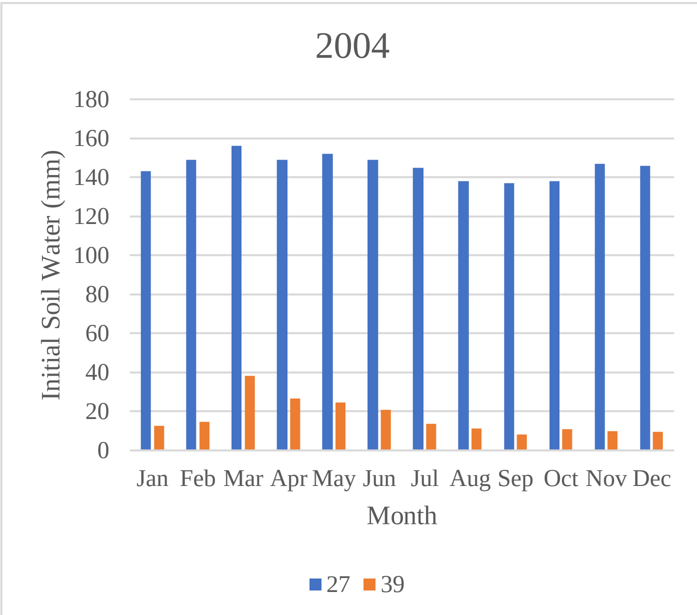
7.2 Penman Monteith

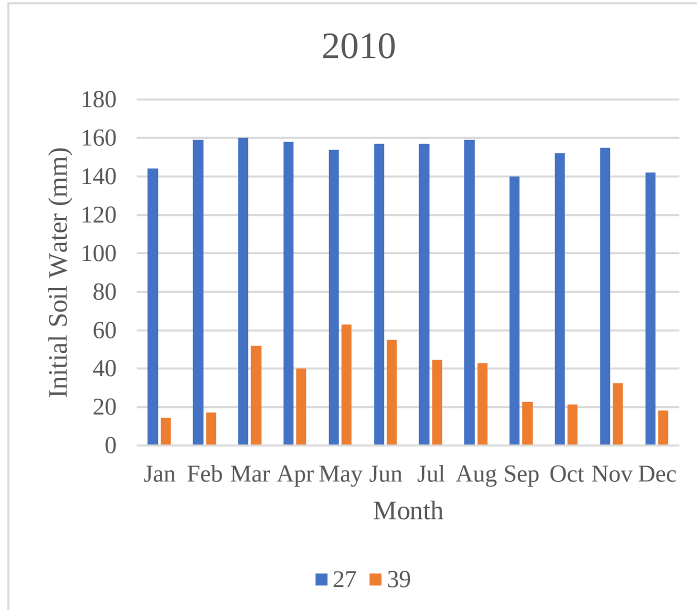
The Penman- Monteith equation, used to calculate Potential Evapotranspiration, is given below:

$$\lambda ET = \frac{\Delta(R_n - G) + \frac{86400\rho_a C_P(e_s - e_a)}{r_a}}{\Delta + \gamma(1 + \frac{r_s}{r_a})} \qquad \text{(Monteith, 1965)}$$

Where λ (MJkg^{-1}) is the latent heat of vaporization, Δ (kPaC^{-1}) is the gradient of the vapor pressure-temperature, R_n (MJ m^{2}day^{-1}) is net radiation, G (MJm^{2}day^{-1}) is the soil heat flux, ρ_a (kgm^{-3}) is the moist air density, C_p (MJkg^{-1} C^{-1}) is the specific heat capacity of air, e_s and e_a (kPa) are saturated and actual vapour pressure respectively, γ (kPaC^{-1})is the psychometric constant; r_s (s m^{-1}) is the water vapour resistance from plants, soil or water surfaces and r_a (sm^{-1}) is aerodynamic resistance (Monteith, 1965)

7.3 Initial Soil Water





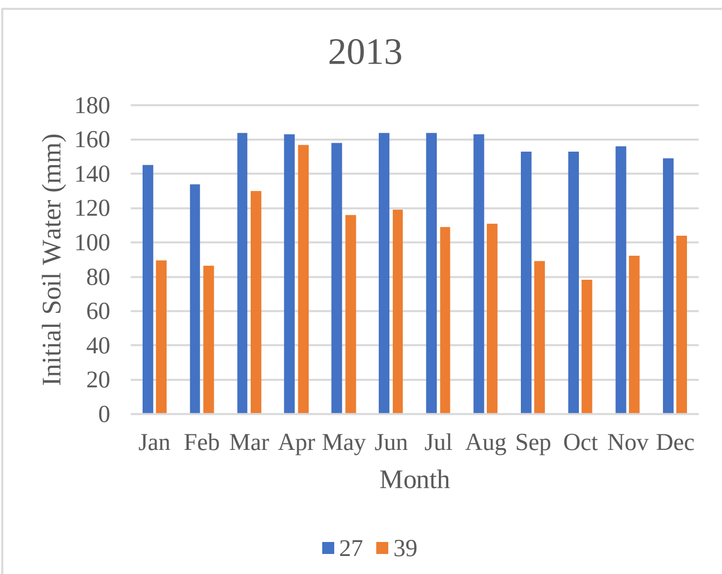
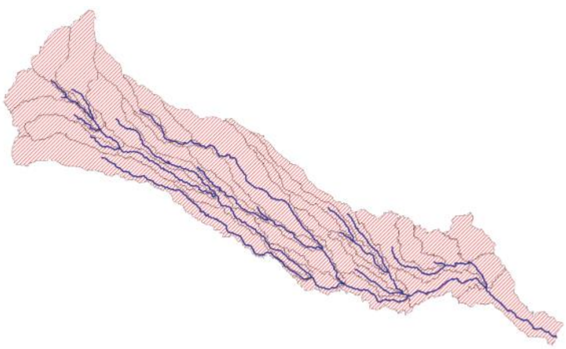


Figure 19: Total initial soil stored water in subcatchments 27 and 39 during the years 2004, 2010 and 2013.

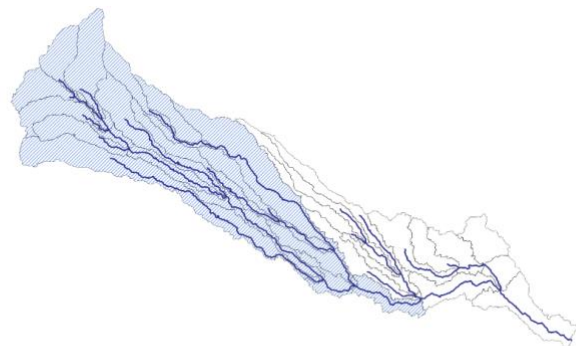
7.4 Drainage Areas for Naturalised Flow Analysis (Section 3.3)

Below is a visualisation of the drainage areas of each sub catchment outlet for which a Q95, Q80 and Q50 flow was simulated in the naturalised system.

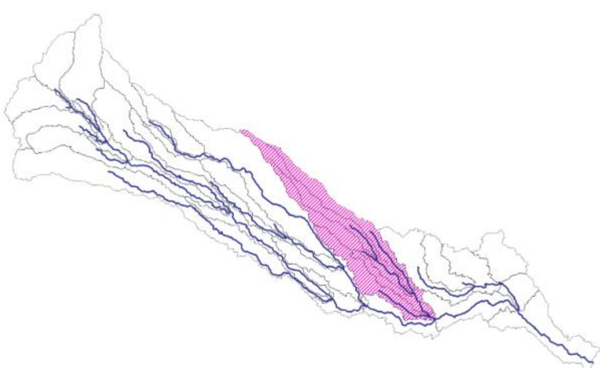
39



37



32



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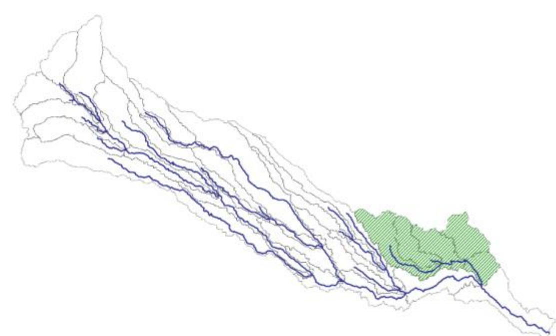

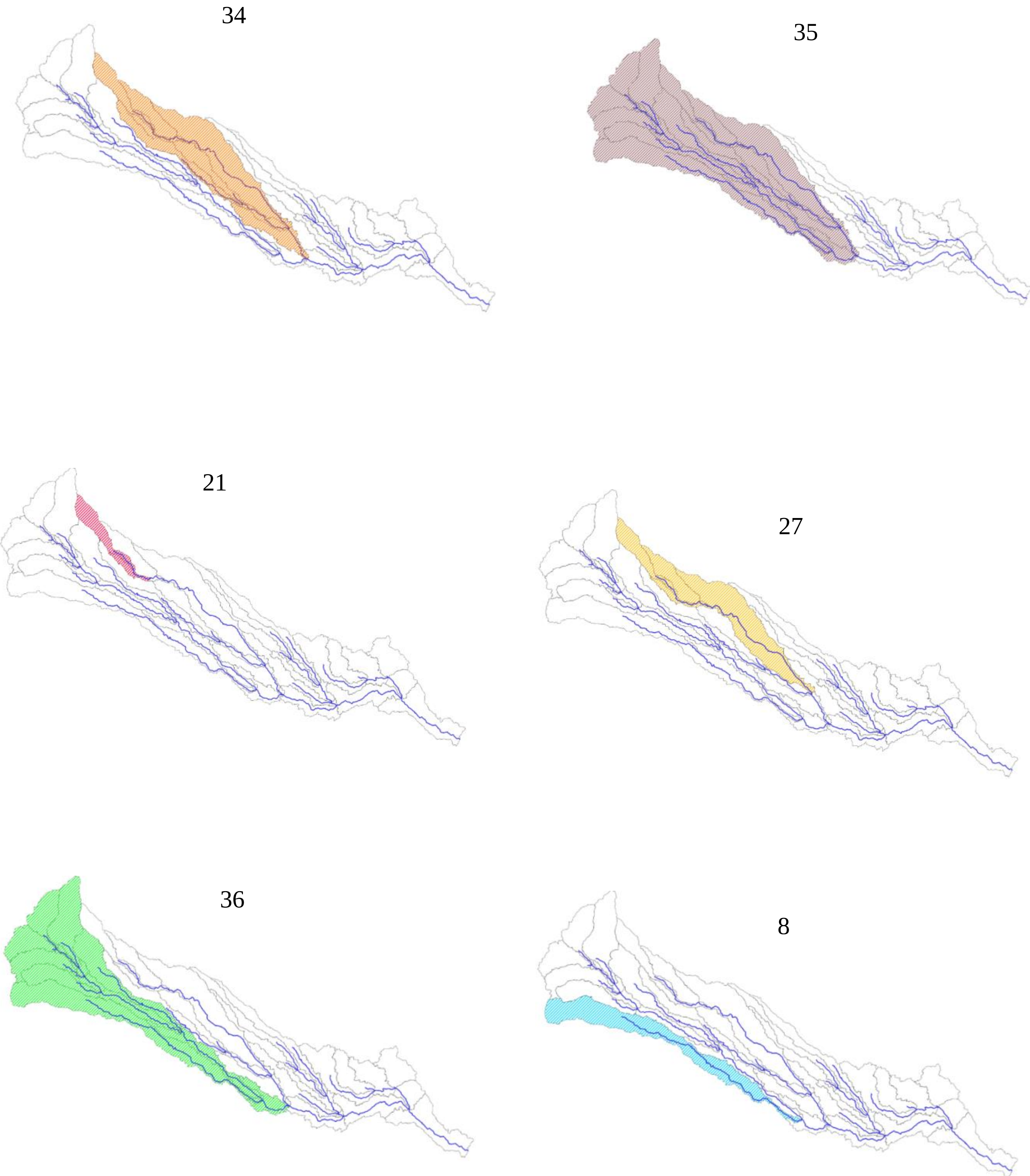

Figure 20: Drainage areas of each sub catchment outlet used in the naturalized flow analysis

7.5 Naturalised flow and regular flow comparison

Below are graphs of the naturalised flow and the regular flow to demonstrate the affect abstractions have on the discharge.

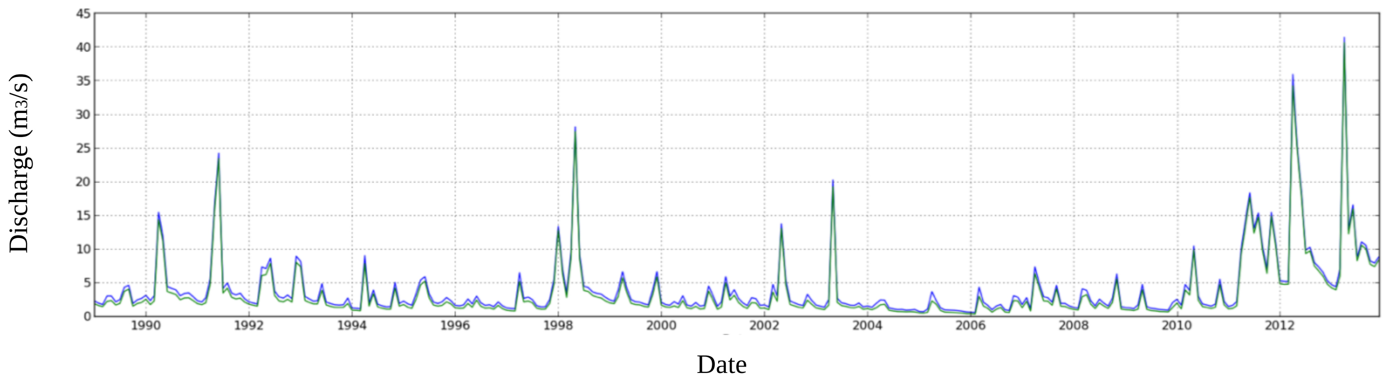

Figure 21: Hydrograph at the outlet of sub catchment 34. Naturalised flow is blue and regular flow green.

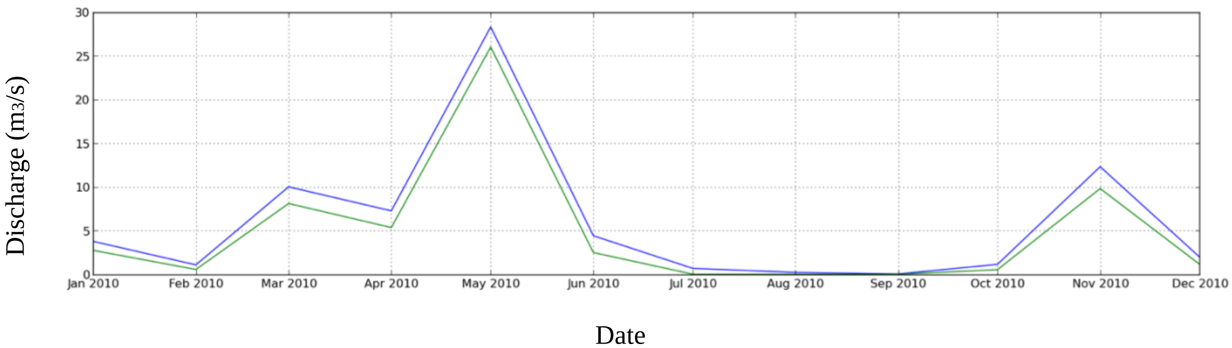

Figure 22: Naturalised flow (blue) and regular flow (green) at the outlet of sub catchment 39 in 2010.

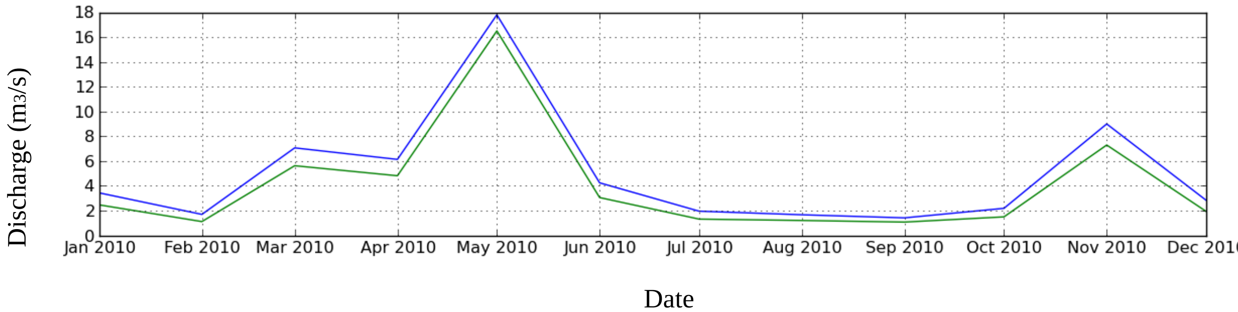

Figure 23: Naturalised flow (blue) and regular flow (green) at the outlet of sub catchment 36 in 2010.