SITE SUITABILITY MAPPING OF ROAD WATER HARVESTING IMPLEMENTATIONS

MSc. Thesis Report

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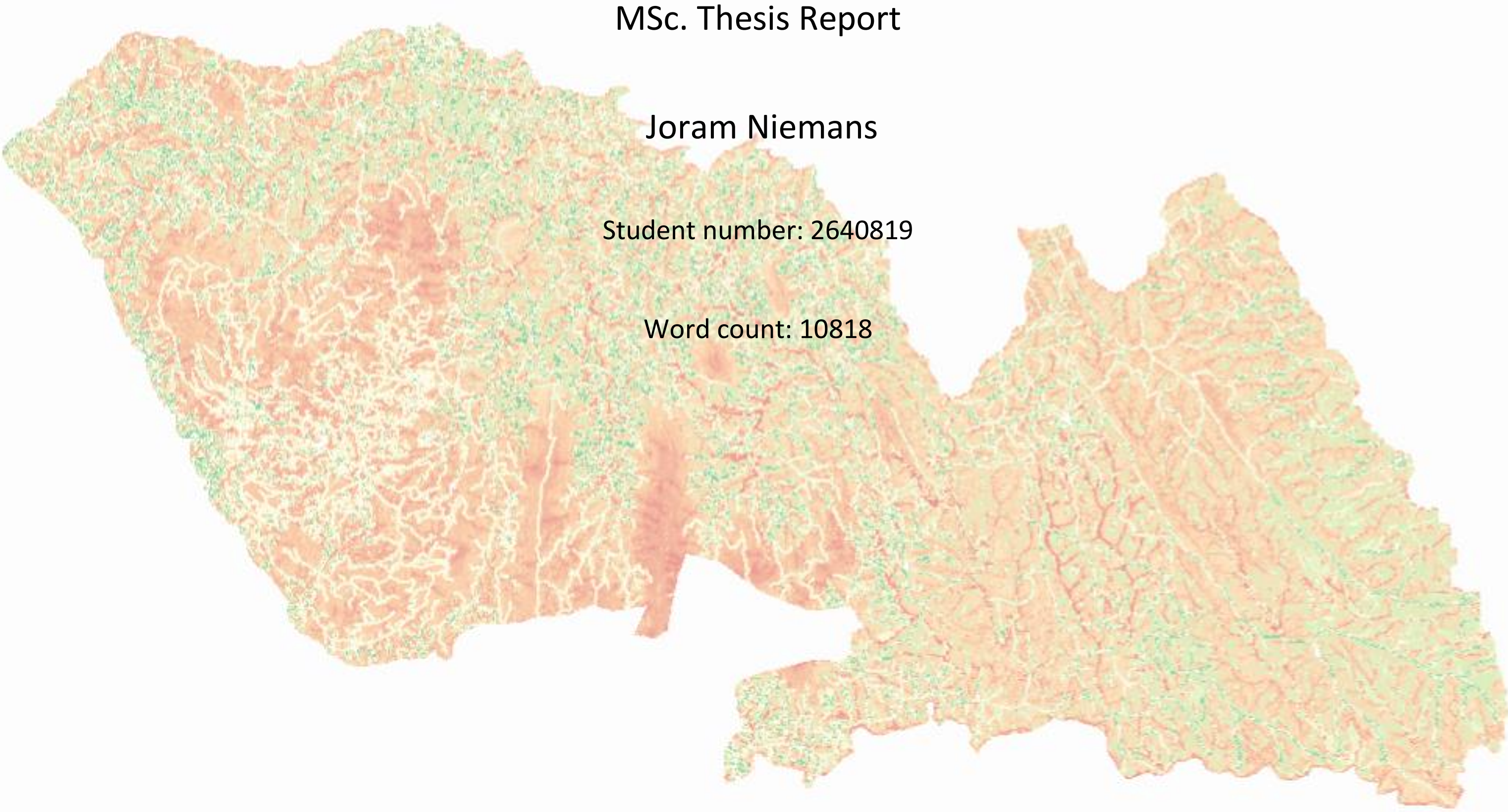

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Abstract

With water scarcity becoming an increasing issue for arid and semi-arid regions under future climate projections, utilizing existing roads in a multi-functional way to capture rainfall and surface runoff can positively impact water resilience, crop production and reduce rain-related damages in the surrounding area. The aim of this study is to improve the implementation of road water harvesting techniques in Makueni County, Kenya, to enhance the effectiveness of water management practices. Selection and ranking of relevant criteria for road water harvesting site suitability is applied within an analytical hierarchy process framework. For this, several biophysical and socio-economic criteria are selected, assigned a weight and combined into several suitability maps. Results show very high suitability for 5,32%, 4,4% and 0,91% of the total study area for mitre drains, farm ponds and sand dams respectively. To quantify the harvestable water after implementing mitre drains, a comparative analysis is conducted within the runoff model SWMM. Mitre drains show a reduction of 62% in runoff losses in water captured by a road body based on a 6 hour 70 mm storm event. However, lack of calibration and validation data does not allow for definite conclusions in absolute volumes of water captured. Nevertheless this framework shows potential in being an effective tool for preliminary site evaluation, by giving an initial overall assessment of potential sites. In turn reducing the fieldwork time needed for selecting implementation locations, leading to a more efficient design and management process.

Contents

1. Introduction

East Africa is among the hotspots with high human vulnerability to climate hazards (IPCC, 2023). Food and water security within Africa are greatly impacted by increased occurrence of extreme events such as droughts and floods (IPCC, 2023). The impacts on water security will likely increase for Kenya under future climate scenarios and affect nearly all sectors of society (Kogo et al.,2021). Thus, obtaining knowledge about factors influencing the management of water resilience is key (Ashokan et al. 2020). The acute necessity of acquiring more insight is reflected in the water targets set by the African Water Vision 2025 (Mutschinski & Coles, 2021), the National Adaptation Program (NAP) and the National Climate Change Action Plan (NCCAP).

Integrated Water Resource Management (IWRM) has been shown to have a positive effect on water systems governance and management effectiveness. Katusiime & Schütt (2020) define IWRM as: ' An approach that aims to ensure a process that promotes the coordinated development and management of water, land, and related resources in a drainage basin to maximize economic and social welfare equitably without compromising the sustainability of vital ecosystems'. However, the success of implementing IWRM requires an informed division of responsibilities, achieved through clear communication between all informed stakeholders (Hamlet et al. 2020). Learning tools used in IWRM prove to be effective in dissemination of knowledge, which indirectly compliment the practical implementation of water management (Katusiime & Schütt, 2020). East Africa and specifically Kenya already implemented the IWRM model. The main driver for implementation was the high level of water scarcity (mainly in the agricultural sector) and the effect of transboundary water resources created by the county system that Kenya implemented (Dirwai et al., 2021).

Water scarcity is a main driver of multi-dimensional poverty experienced among the entire population of Makueni County, Kenya (Kenya National Bureau of statistics, 2020). The indirect effects are mostly felt in the agricultural sector, where production remains low because of a high dependence on rainfed agriculture, underdeveloped irrigation infrastructure and on-farm water harvesting (Government of Makueni County, 2022). Development of water infrastructure and enhanced water governance is prioritized according to the County Integrated Development Plan (CIDP) 2023-27.

In arid and semi-arid regions, such as Makueni county, the capture of rainwater has high potential benefit in improving water resilience (Shadmeri Toosi et al., 2020). Rainwater harvesting has a positive impact on water availability for irrigation of farmlands and lowering the runoff peak flow in an area (Gebru et al., 2020; Hamlet et al., 2020). This reduction in runoff peak flow not only reduces the amount of erosion in an area but also reduces the impact of floods on the surrounding infrastructure (Odhiambo et al. 2021). One way to capture rainwater is through existing drainage networks such as road bodies. When created in collaboration with both local and regional stakeholders, it has the possibility to be an effective measure in improving resilience (Ashokan et al., 2020). Roads fulfill an important role in our modern society, they serve as connecting lifelines between communities and enable transport of essential services and allow access to markets, thus providing many economic benefits (Demenge et al., 2015). However, besides these benefits, roads also have a major impact on ecological and hydrological processes (Roy, 2022). By blocking, dispersing or altering the surface and subsurface waterflows and soil water storge, roads change agro-ecological aspects of the landscape (Garcia-Landarte Puertas et al., 2014). These negative effects may mitigate the benefits of road networks, especially around rural communities where roads alter the landscape used for agricultural production (Demenge et al. 2015).

Water management already is an essential part of road network design. However, design should not only be focused on protecting road infrastructure from water damages, such as erosion and flooding, but utilizing this water for other purposes as well (van Steenbergen et al., 2021). Traditional road designs often focus on the quickest evacuation of water from roads, as water can cause major damages to road infrastructure (Woldearegay et al., 2017). But coincidentally, these practices cause negative impacts on the surrounding geomorphology, through erosion and sedimentation, or affect the local hydrology in a negative way, by increasing surface runoff and thus not allowing infiltration of water (Roy, 2022; van Steenbergen et al., 2021).

The Green Roads for water and climate resilience ('Green Roads' or roads for water) concept proposes the utilization of road networks in a multi-functional way. Serving both as landscape and water management instruments, without losing their transport functions (Maluki et al., 2023). The principles for 'Green Roads' are finding cost effective solutions adapted to local situations, based on multi-stakeholder involvement in all classes of society (van Steenbergen et al., 2021). The adoption of road networks in capturing rainfall can positively impact rural road infrastructure, rain-related road damage reduction and reduction of landscape degradation through erosion, and an improvement in overall climate resilience (Gebru et al.,2020; van Steenbergen et al.,2021; Temmink 2015). In Ketui County, Kenya this approach led to a paradigm shift with more farmers using road runoff as water harvesting methods, and thereby improving the soil moisture content on farms (Mganga et al., 2023). Another effect of the project was an increase in community and government driven initiatives to further improve the dissemination of knowledge (Mganga et al., 2023). Since 2016 the 'Green Roads' project is also implemented in the neighboring Makueni county, in an effort to improve community involvement through learning and implementation of road water harvesting structures (Maluki et al. 2023). To help in this endeavor, the company MetaMeta has set up the 'Drain to Gain' project in Makueni County. This project aims to utilize water harvested from road-runoff to improve nature-based agriculture in the surrounding areas (Kimaiyo, 2023). To achieve this goal an iterative method, including land management strategies, agro-forestry and nature based solutions, are adopted to improve community and landscape resilience (Kimaiyo, 2023).

Since 2013 Makueni county has been active in implementing water management practices, although the county still has difficulty optimizing water management implementations on both technical and social levels (Maluki et al. 2023). Although the amount of rainwater harvesting structures has increased in Kenya over the recent past, its impact has been limited due to insufficient performance of the implementations (Odhiambo et al., 2021). The urgent need of improved water related infrastructure causes a shift towards short term planning in management practices (Hamlet et al., 2020). This may potentially cause infrastructure to become ineffective after a few years leading to low-efficacy within households making use of the infrastructure. Technical factors influencing the performance of rainwater harvesting include: inappropriate design and siltation and evaporation affected by improper maintenance (Odhiambo et al., 2021). Underperformance can also be attributed to socio- economic factors such as ineffective maintenance and improper utilization of the harvested water. Studies performed by Kimani et al. (2015) and Ammar et al. (2016) also concluded that the main reason for failing rainwater harvesting systems was insufficient insight into the socio economic criteria such as gender, literacy, socio-economic status and technological know-how of applicants.

The initial selection of optimal roadside water harvesting sites is currently based on field observations. However, this method is time-consuming and inherently relies on expert judgement which might be prone to subjective interpretation and potential biases. It also does not ensure adequate consideration of potential biophysical or socio-economic criteria for site selection. Thus, improvements in optimizing the water harvesting implementations, both on governance and practical level based on quantitative research, still need to be made to ensure long term benefits of increased water availability and climate resilience. The goal of this study is to improve the implementation of road water harvesting techniques in Makueni County, Kenya, to enhance the effectiveness of water management practices. This will be achieved by setting up a framework that can be applied to assess the optimal location of road water harvesting implementations and assess the benefits of these road water harvesting implementations in a quantitative way.

This research combines the outcomes of hydrological modelling with the practical implementation in water governance. It will do this through the formulation of a general applicable framework that could be applied to aid in the mapping of the benefits of roadside implementations to support policy decisions, creating a framework to turn modelling results into workable policy implementations or direct practical applications. This research project will work in collaboration with the company MetaMeta with a linkage to the 'Drain to Gain' project currently active in Makueni County, Kenya.

2. Methodology

For the first goal of this research a method called the analytical hierarchy process is used. It's application has been used in many other studies to determine site suitability for water harvesting implementations (Ammar et al., 2016). In the analytical hierarchy process, criteria that influence the main goal of determining the optimal site for road water harvesting structures are selected and given a relative weight through a weighting process. Criteria for several alternative road water harvesting techniques and general runoff potential are derived via the weighting process. These criteria are prepared and mapped in geographic information system (GIS) software and combined using python programming (Appendix 1). The resulting maps show the relative potential suitability for water harvesting between areas. The steps to derive the first goal are indicated in warm colors (red and yellow) in the flowchart (figure 1). The first goal results in different suitability maps for the different rainwater harvesting techniques.

Based on the created maps of the first goal, road water harvesting techniques are placed on the most suitable locations along a selected road for model simulation runs. For the model simulation runs, design rainfall and sub-catchments are derived to determine the amount of rainfall the system receives. For the modelling itself, the Storm Water Management Model (SWMM) is used. The model is run for two scenarios, one with the road water harvesting techniques applied and one without any harvesting implementations. The amount of water captured before and after implementing the system is compared and used as a quantitative indication for effectiveness of road water harvesting, which is the second goal of this research. The steps to achieve the second goal are indicated in cold colors (blue and purple) in the flowchart (figure 1).

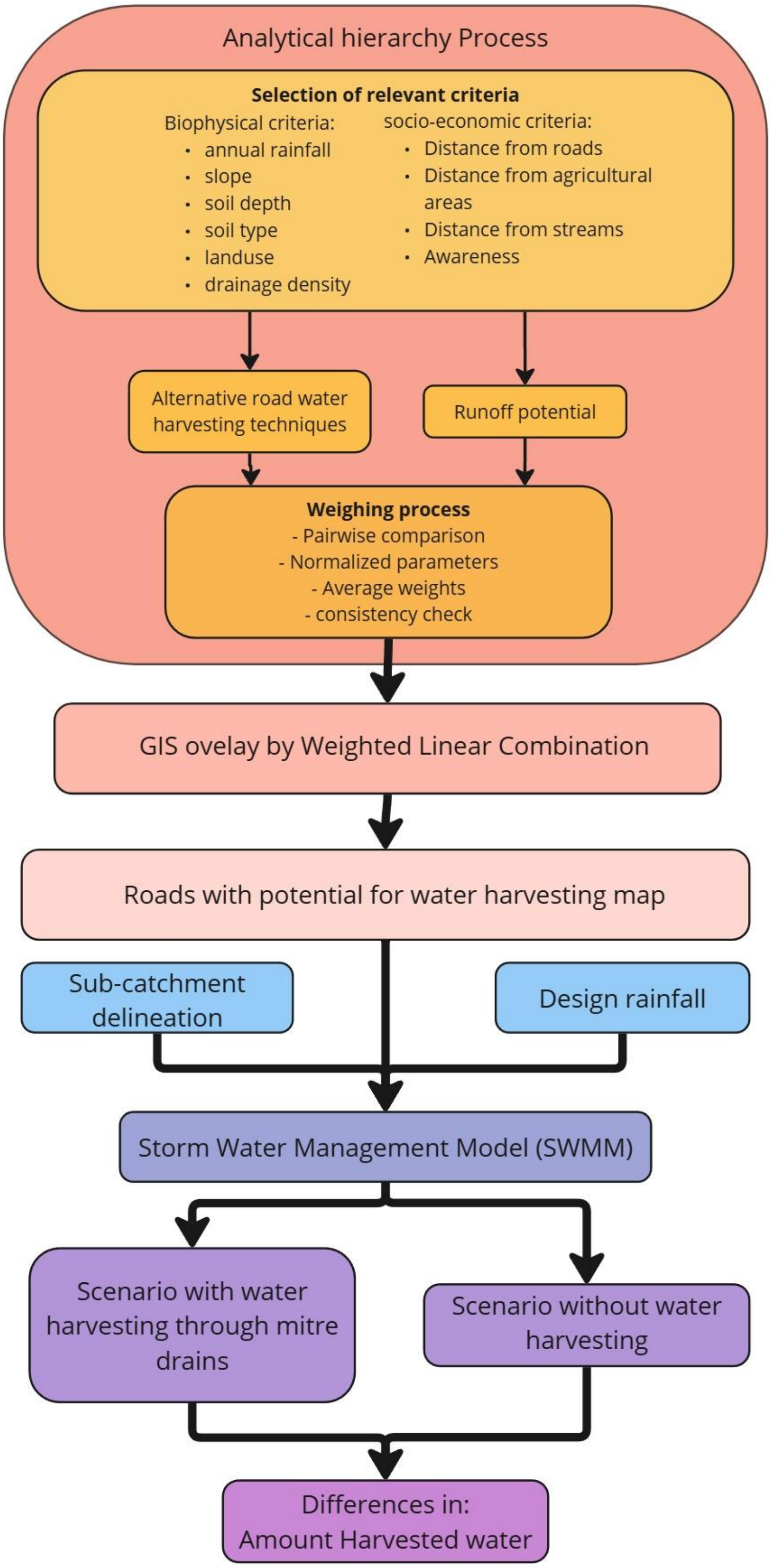

Figure 1: Flowchart of conceptual framework applied in this study

2.1 Study area

Makueni County is situated in South Eastern Kenya. Makueni is subdivided into six sub-counties including Makueni, Kibwezi East, Kibwezi West, Kaiti, Kilome and Mbooni (figure 2). With Agriculture as the main economic activity Makueni is characterized by three main agro-ecological zones. The Upper Middle zone covers Mbooni and Kaiti sub-counties and practice mostly dairy, coffee, avocado, macadamia, maize and beans farming. The Lower High zone covers Makueni and Kilome and produces mostly fruits, grains and root tubers. The Lower Middle zone covering Kibwezi West and East practice mostly cultivation of a variety of legumes and livestock rearing (Government of Makueni County,2022). The Akamba community makes up about 97% of the total number of inhabitants in Makueni County (Government of Makueni County,2022). Changing climate has a huge impact on the livelihoods of people located in Makueni County, Kenya (Maluki et al., 2023). This high vulnerability to climactic stress in Makueni County can be attributed to climate sensitive production systems which are mostly adopted in rural areas (Nthenge, 2016). Within Makueni, Mbooni sub-county is selected for site selection due to the involvement of the 'Drain to Gain' project conducted by MetaMeta within this sub-county. Mbooni covers 957,2 km2 and has a total population size of 200.350 (KNBS, 2019) (figure 2).

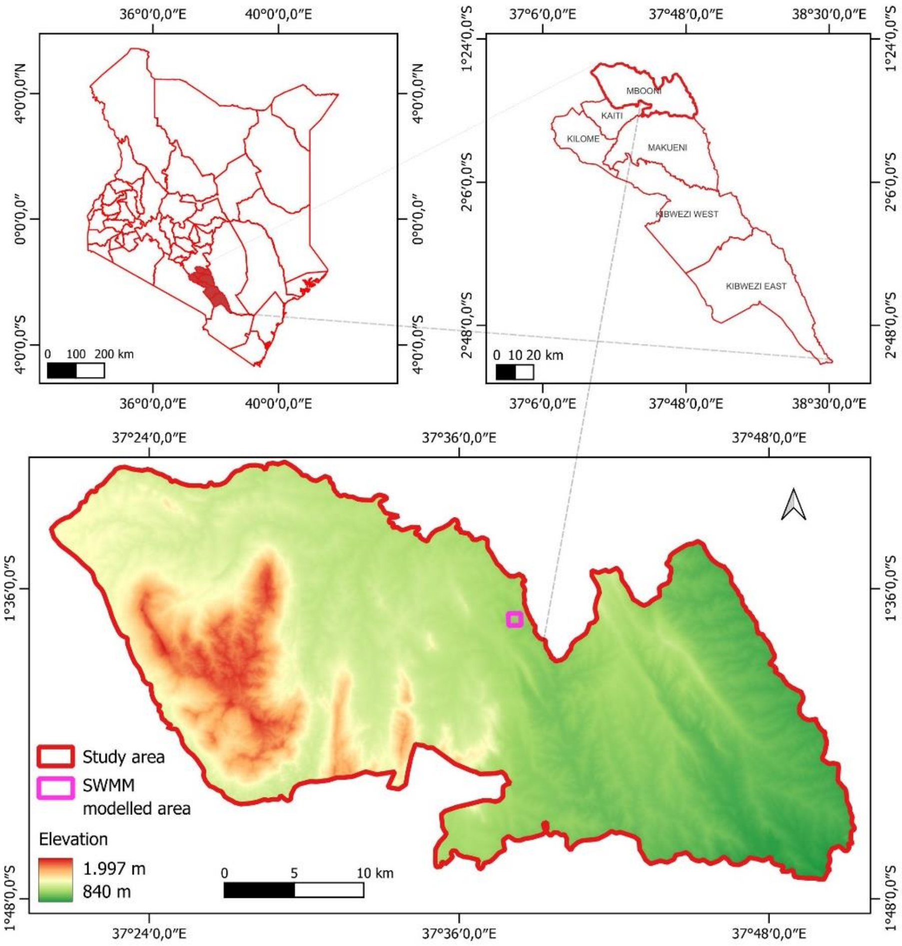

Figure 2: Map showing location of the study area Mbooni sub-county (bottom) with area used for runoff modelling (pink). Upper left map shows location of Makueni County (red) within Kenya, upper right map shows sub-counties within Makueni County.

2.2 Road water harvesting techniques

Three common road water harvesting techniques are chosen for application of site suitability mapping. The selection is based on best practices guidelines from the Guideline: Green Roads for water (van Steenbergen et al., 2021)

<u>Surface storage fed from road drainage: farm ponds</u>

Farm ponds are suitable in most agro-ecological zones that provide enough rain to fill the reservoir, with a preference to areas with higher rainfall (>400 mm/year) (Knoop et al., 2012). Three things are important to consider with farm ponds according to the Green roads for water guidelines (van Steenbergen et al., 2021):

1. Soil: Soils with low hydraulic conductivity and minimum seepage such as sandy clay, sandy clay loam, or clay loam. Soil depth must be >1 m with low pH and low electrical conductivity. Meaning that deep clay soils are the best for storing water. The general depth of a farm pond is 2,5 m as it ensures adequate volume of storage, low evaporation, and ease of access.
2. Topography: Level topography is preferred but implementation with adapted pond shapes can used almost everywhere. Ponds should located near a road catchment area that can generate enough runoff. In unpaved roads, water exiting at bends and low points can be used.
3. Catchment size: Large source areas should be avoided. Particularly if 80 percent of the precipitation occurs in less than two months, ponds might overflow or get damaged when breaching capacity. Ponds with too small a catchment will have difficulty in filling up or the water level may drop too low during extended periods of dry weather.

Farm ponds should not be placed too close to the road area to prevent possible undermining of roads and conflicts with future road development (Shadmehri Toosi et al., 2020). Farm ponds should not be placed on agricultural areas due to interference with agricultural practices, since ponds take up a lot of space. Barren land or land which has no other purpose located near areas where the captured water will be used is preferred for pond placement.

<u>Infiltration along roads: mitre drains and infiltration trenches</u>

Mitre drains and infiltration trenches guide water captured by the road body to areas where the water can be used, such as agricultural areas for direct irrigation of crops.

Mitre drains are typically placed 100m or less apart depending on the slope gradient. Drains should be 50 cm deep and 40 cm wide and rectangular in shape, with an inlet at a position that makes best use of the slope (van Steenbergen et al.,2021). To prevent erosion the drain channel should be less than 3 degrees steep (van Steenbergen et al., 2019). Drains should be placed in areas where there is sufficient overland surface flow, meaning that areas with gentle (4-9%) or moderate (10-15%) slopes are preferred. Soils with a high permeability work best for quicker infiltration of water into the subsurface. Mitre drains should be placed on the downhill side of roads to ensure effective diversion of water away from the road (van Steenbergen et al., 2019).

<u>Road crossings used as sand dams</u>

Roads crossing temporal riverbeds can catch groundwater upstream of the road and increase bank infiltration (van Steenbergen et al., 2021). This can create a small local aquifer that stores water, causing the road body to act as a dam. Sand dams should only be placed on dry riverbeds along narrow sections. Soils should have a high sand or gravel content and have a shallow depth to prevent clogging (van Steenbergen et al., 2021). Sand dams are best placed near areas where the captured water can be used, this includes farmland and locations with a high population density (van Steenbergen et al., 2021).

2.3 Analytical hierarchy process in determining road water harvesting sites.

The analytical hierarchy process (AHP) is a useful mathematical method for making multi-criteria evaluations based on expert knowledge aiding in making informed decisions in management (Abdelkader et al. 2023). The AHP derives a weighting for selected criteria with respect to the overall goal of the study, using pairwise comparison of those criteria (Saaty, 2004). The proposed alternatives of this criteria are compared in the same way resulting in a ranking. The overall goal of the AHP in this project is finding the optimal locations along roads for implementing harvesting systems. This could aid in the design of road drainage systems and the planning of water harvesting and erosion control measures (Shadmeri Toosi et al., 2020; Doulabian et al., 2021; Bera et al., 2023;Abdelkader et al., 2023).

2.3.1 Decision Hierarchy

A decision hierarchy is set up to select criteria affecting the main goal of finding optimal sites per road water harvesting technique (figure 3). On the first level it is determined that two main factors influence the goal. These include: the potential for runoff generation within an area and the suitability of the environment to place different road water harvesting techniques. The selection of level 1 factors is based on assumptions that the amount of runoff affects the water that can be captured on the surface and that different road water harvesting techniques have different optimal sites based on technical specifications. An added constraints map with general areas that are omitted from site suitability selection is used to filter predetermined unsuitable areas. It is assumed that technique suitability is two times as important as the runoff potential with respect to the goal. This assumption causes all level 2 criteria groupings to have the same importance with respect to the goal. For level two factors the Runoff potential is subdivided into several biophysical criteria for which weights were derived using pairwise comparison. The technique suitability is both affected by biophysical criteria and socio-economic criteria that are assumed to have the same amount of influence in determining the technique suitability. For both runoff potential and technique suitability all the level 2 criteria are subdivided into feature classes based on the range of data observed in the study area. These feature classes are assigned a weight as well, based on expert consultation, existing literature and technical guidelines. For the constraints map a Boolean method for the two criteria is applied to omit them in the site selection.

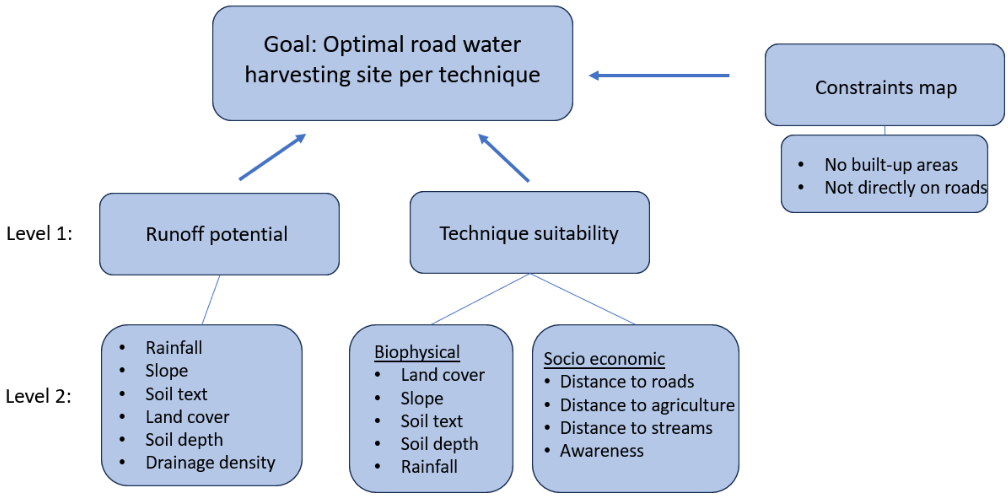

Figure 3: Decision hierarchy

2.3.2 Data collection

Data sources for creating the criteria maps are shown in table 1. All data for the selected criteria, except population awareness, are derived from public data sources. Population awareness could not be derived since no publicly available mappable data could be found, however, after consulting experts having on hand experience in the study area estimated, population awareness were obtained.

Table 1: Data sources

Selected criteria	Data source
Rainfall	Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS). Global rainfall dataset with ~ 5 km resolution.
Slope	Derived from FABDEM, 1 arcsecond (30m) resolution elevation data, in QGIS.
Soil type	iSDAsoil 30 m resolution data
Soil depth	iSDAsoil 30 m resolution data
Land-use	ESA_worldcover_10m_2021
Drainage density	Derived from stream and basin area data calculations in QGIS
Road distance	Open street Map data (Quick OSM tool in QGIS) and matrix distance calculations in QGIS
Distance to agricultural areas	Derived using ESA-woldcover_10m_2021 data and matrix distance calculations in QGIS.
Distance to streams	Derived using stream delineation tools in QGIS and matrix distance calculations.
Population awareness	Expert opinion

2.3.3 Selection of criteria

As per the decision hierarchy, level 2 criteria are selected based on existing literature and expert knowledge. The most common biophysical criteria in identifying rainwater harvesting potential are identified by Ammar et al. (2016) as slope, land-use, soil type and rainfall. However there is no consensus in socio-economic criteria to use in site selection for rainwater harvesting, since this can be case dependent. Input criteria maps for the study area are shown in figure 4.

<u>Rainfall</u>

In order for water harvesting systems to function, the catchment needs to receive sufficient rainfall to create surface runoff that can be harvested. This makes the spatial distribution of rainfall within the study area one of the most important factors to consider in the determination of suitable locations (Ammar et al., 2016). Averaged annual rainfall patterns over a period of 44 years, between 1983 and 2024, show that the rainfall ranges from 1353 mm to 641 mm, with the south western side of Mbooni experiencing the highest amount of rainfall (figure 4E).

<u>Slope</u>

The slope plays a large role in determining the amount of runoff (Ammar et al. 2016). The steeper the slope the higher the speed of the water flow will be, leading to reduced capacity for the water to infiltrate the soil and thus increasing the amount of runoff (FAO, 2014). Another effect of the increased water flow speeds is the increased effect of erosion leading to landscape degradation and more damages to road networks (Shadmehri Toosi et al. 2020). The slope is the most commonly applied biophysical factor in studies related to site selection in arid and semi-arid regions (Ammar et al. 2016). Making it an important factor for the suitability of the different road water harvesting techniques. The study area shows slopes ranging from 0 to 53 degrees with the steepest slopes observed in the southwestern part of Mbooni (figure 4D).

Soil type

The soil type determines the drainage capacity and speed of water within an area (Shadmehri Toosi et al., 2020). More porous soils will show more uptake of water in the subsurface, creating less runoff. For determining the suitability of road water technique, the soil type is a major consideration in choosing techniques that capture runoff or allowing infiltration to recharge groundwater levels (van Steenbergen et al., 2019). Soil type for the study area is shown in figure 4B.

Soil depth

The soil depth determines the water holding capacity within an area. Deeper soils will be able to retain more water than shallow soils. Besides slope and soil type, the soil depth also determines the amount of runoff generated but also determines the depth at which water storage structures can be dug (figure 4F). This is due to the increased effort and costs of digging in bedrock (van Steenbergen et al., 2019).

Land-use

Land-use, just like soil type, has an effect on the amount of surface flow within an area. With built up urban areas, or areas with sparce vegetation having a higher runoff potential than densely vegetated areas. Vegetation captures the rainwater for infiltration in the soils and slows down the surface flow, allowing for more infiltration in the soils (Shadmehri Toosi et al. 2020; Bera et al., 2023). Aside from the effect on runoff potential, land-use in this case can also be used as a socio-economic criteria for site selection of water harvesting implementations along roads. Making roads close to agricultural land more attractive for harvesting since the captured water can immediately be used in the neighboring plots (Gebru et al.,2020). The major land cover types observed in the study area are shrubland, grassland and agricultural areas. Mountainous areas with steeper slopes mainly show tree cover (figure 4C). Due to the rural nature of the study area settlements are small and mostly dispersed having no major influence on land use.

Drainage density

The density of drainage networks helps concentrate runoff generated within an area quicker, this includes valleys, streams, gulley's and existing culvert locations (Bera et al., 2023) (figure 4A). For this specific study, besides existing streams, the road network itself can also be viewed as a drainage network. Roads generate a concentration of runoff along their surface and change the natural drainage pattern within an area (van Steenbergen et al.,2019; Demenge et al., 2015).

Distance to roads

Since this study focusses on water harvesting from road networks it is imperative for the selection of the optimal water harvesting site that runoff generated from and along road networks can be used for capture and subsequent harvesting. As shown by a study performed by Temmink (2015) road alignment has a significant impact on the water harvesting potential. Roads located lower on slopes have more potential for capturing water since more runoff is generated upstream from the road. As a socio economic factor, adoption of water harvesting implementations has a positive relationship with decreased distance from roads (Gebru et al., 2020; Al-Adamat et al., 2010). Because roads act as a drainage channel for water, agricultural areas closer to road networks experience more negative effects of water such as flooding, siltation and erosion(Gebru et al., 2020). Distance to roads is a common socio economic criteria used in the selection of water harvesting sites (Abdelkader et al., 2023).

Distance to agricultural areas

Due to pollutants occurring in road runoff water, untreated water captured using road networks is suitable for agricultural use only (Mutunga, 2018). In order to prevent transport of captured water over large distances causing higher cost and potential losses due to evaporation, agricultural areas near roads are assigned a higher potential for road water harvesting implementations.

Distance to streams

Where roads cross existing water bodies planned retention of water can be created using the existing roadway as a dam (van Steenbergen et al., 2019). The convergence of road and water networks thus provides the capacity to turn water into use in for the surrounding area.

Population Awareness

Knowledge of the existing road water harvesting practices has a positive effect on implementation and correct use of the systems (Demenge et al., 2015). It also allows the people affected by the systems to make a more informed decision about the pros and cons of adopting certain techniques due to past experience (Gebru et al., 2020).

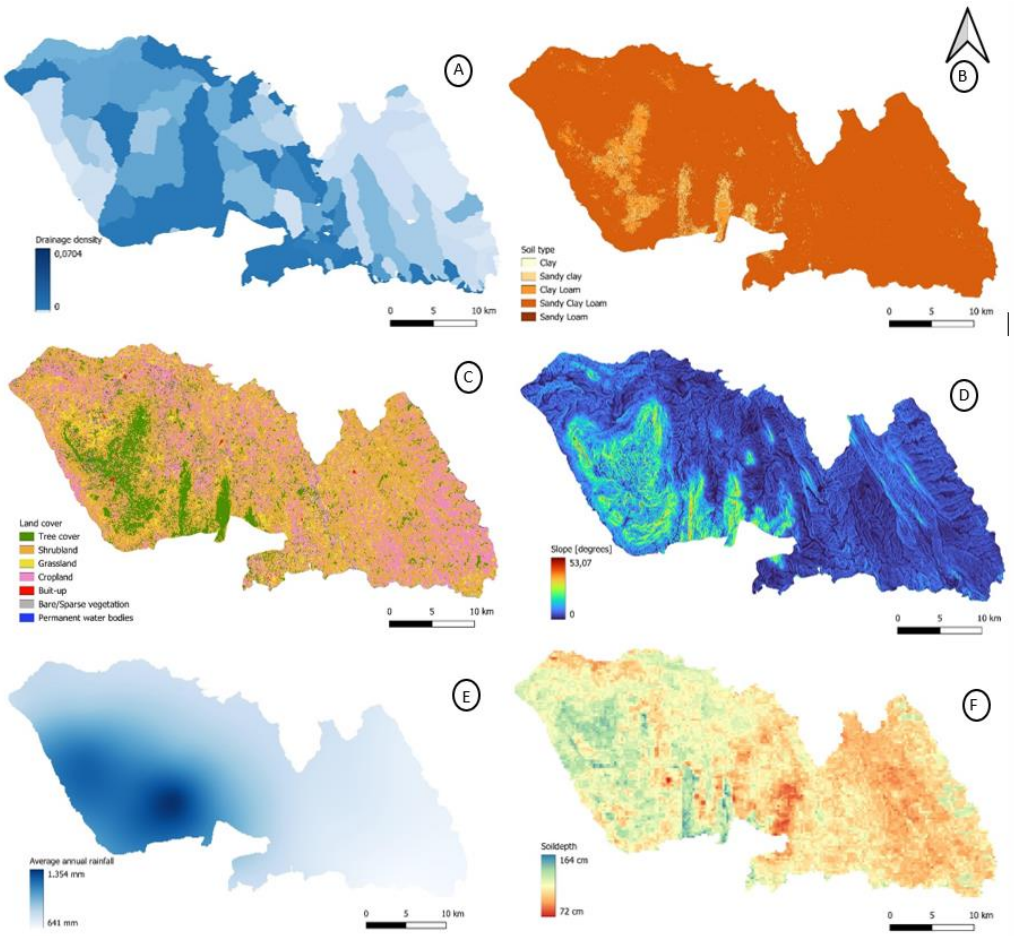

Figure 4: Biophysical criteria maps of the study area used as input for the Weighted Linear Combination.

2.3.4 Pairwise comparison

Relative importance of each level 2 criterion (m) is weighted and assigned a value between 1 and 9 based on the method derived by Saati (2004) (table 2). This is done by creating an (n x n) matrix with n being the amount of selected criteria. Within this matrix the same criteria are put along the x and y axes and compared (table 3). With the value 1 meaning equal importance of both criteria and a value 9 meaning that the criteria in the row is greatly favored above the criteria in the column (table 2). The value assigned to the criteria is based on literature on previous studies adopting multi criteria analysis for site suitability selection and consultation with experts (Bera et al., 2023; Shadmeri Toosi et al., 2020) Doulabian et al., 2021; Abdelkader et al., 2023; Mulualem et al., 2020; Al-adamat et al., 2010).

Table 2: Table showing relative weighting of criteria based on Saati (2004)

Value:	**Definition (with respect to the goal)**
1	Equal importance
2	Slightly more important
3	Moderate importance
4	Moderate plus
5	Strong importance
6	Strong plus
7	Very strong importance
8	Very, very strong
9	Extreme importance

For example, the pairwise comparison matrix with assigned values of importance with respect to the goal: determining the road water harvesting technique suitability is shown in the following table:

Table 3: Pairwise comparison matrix for technique suitability mapping

Pairwise comparison matrix: importance with respect to technique suitability	**Rainfall**	**Slope**	**Soil type**	**Land use**	**Soil Depth**
Rainfall	1	2	3	2	4
Slope	0,5	1	2	1	2
Soil type	0,33	0,5	1	0,5	2
Land use	0,5	1	2	1	3
Soil depth	0,25	0,5	0,5	0,33	1
SUM:	2,58	5	8,5	4,83	12

2.3.5 Normalizing weights

Since each level 2 criteria are pairwise compared with respect to a different level 1 criteria (i.e. technique suitability or runoff potential) and thus assigned different relative weights, the values are normalized to allow for comparison using a common scale (Saaty, 2004; Shadmeri Toosi et al., 2020; Pathak et al., 2024). The normalization process gives equal total weightage to all the criteria and thus allows for integration of all involved criteria in determining potential site suitability (Pathak et al., 2024). The normalized pairwise comparison matrix of all the values per criteria (m_{rc}) is set up using the following formulas derived from Shadmeri Toosi et al. (2020):

$$N = \frac{m_{rc}}{\sum_{l=1}^{n} m_{rc}}$$

Where N is the normalized weight for a value in the matrix, computed by making the sum of the column of each relative weight value (m_{rc}) equal to 1.

Using these normalized weights, a total weight per criteria (cw) is assigned for each criteria by averaging the normalized weights of a criteria on a row.

$$cw = \frac{\sum_{l=1}^{n} N}{n}$$

The normalization process is shown in the following table:

Table 4: Normalized weights of the pairwise comparison matrix

	Rainfall	Slope	Soil type	Land use	Soil Depth	Total Weight/priority vector (cw)
Rainfall	0,38	0,4	0,35	0,41	0,33	0,377
Slope	0,19	0,2	0,23	0,20	0,16	0,200
Soil type	0,12	0,1	0,11	0,10	0,16	0,123
Land use	0,19	0,2	0,23	0,20	0,25	0,217
Soil depth	0,09	0,1	0,05	0,06	0,083	0,081

2.3.6 Consistency ratio

The consistency ratio is derived by first calculating the consistency index (CI), which shows numerically how much the pairwise comparison matrix deviates from perfect consistency (Saati, 2004). A CI value close to zero means that there is a high degree of consistency. The CI uses the principal eigenvalue (x), which is the average of the elements of the vector whose nth element is the ratio of the nth element of the vector (pairwise comparison matrix * weight to the corresponding element of the vector weight) (Shadmehri Toosi et al. 2020). The principal eigenvalue is then used in the following formula to derive the CI:

$$CI = \frac{x - n}{n - 1}$$

After calculating the consistency index it needs to be compared to a reference value called the random index (RI). This RI is the average result of deriving a consistency index by filling in a pairwise comparison matrix where all values (m) are filled in at random 50.000 times (Saati, 2004). This random index is a set value calculated for several matrix sizes (table 5) (Saati, 2004).

Table 5: Random index used in calculating the consistency ratio (Saati, 2004).

n	1	2	3	4	5	6	7	8	9	10
Random Index	0	0	.52	.89	1.11	1.25	1.35	1.40	1.45	1.49

The consistency ratio (CR) is based on the comparison of the consistency index (CI), calculated from the generated pairwise comparison matrix, with a randomly generated matrix (RI) (Saati, 2004). The consistency ratio is derived using the formula below.

$$CR = \frac{CI}{RI}$$

If the consistency ratio is equal to or less than 0.1 the matrix is deemed sufficiently consistent (Saati, 2004). If not, further adjustment of the parameter weightings needs to be considered.

After deriving a normalized weighting of all the criteria and their classes, a weight per feature (fw) of the criteria is assigned for all the observed feature classes. Feature weights are assigned depending on the suitability of the class towards the final goal, the values are based on technical guidelines, literature and expert judgement. Following this method, the AHP was used to identify the weights for the main criteria as well as the features per criteria. All these previously mentioned formulas are calculated and combined in an excel file (Appendix 1).

2.3.7 Weighted Linear Combination

Maps for each criteria are created using GIS and combined in python. Combination is done through the Weighted linear Combination method. Here, the weighting of all the criteria and their features are multiplied per criteria map and summed. The result is shown as a final score for each cell of the map, for the following example the road water harvesting technique site suitability (TSS) is shown. This calculation is formulated in the following way following the example of Shadmehri Toosi et al. (2020):

$$TSS = (Rainfall)_{cw} * (Rainfall)_{fw} + (Slope)_{cw} * (Slope)_{fw} + (Soil\ type)_{cw} * (Soil\ type)_{fw} + (Landuse)_{cw} * (Landuse)_{fw} + (Soil\ depth)_{cw} * (Soil\ depth)_{fw}$$

2.4 Storm Water Management Model (SWMM)

SWMM is a dynamic rainfall runoff simulation model and developed by the U.S. Environmental Protection Agency (EPA). SWMM is mainly used for the planning and design of water drainage implementations (EPA, 2022). The model allows for the inclusion of hydrologic processes and hydraulic modelling, which can model the diversion of runoff generated in a catchment (EPA, 2022). Implementations such as culverts, gutters and water storage units can be included in the modelling process, which makes this applied model suitable for the simulation of different road water harvesting implementations, used in water resource management (Thakuri & Wijesekera, 2022).

Drainage design consists of a series of sub catchment areas that flow into conduits that are connected with junctions. In order to model the amount of rainfall captured within the catchment, the study area was delineated using GIS tools and the 30 m resolution FABDEM data. However, in order to model small scale differences in catchment characteristics, the larger catchment basin was further divided into several sub-catchments using the PC raster tools in QGIS.

Within the setting of road water harvesting we assume that any road network acts as an open conduit. Since flow through open channels from high to low topography has minimal backwater effects, flow reversal or pressurized flow, a kinematic wave routing method was deemed sufficiently accurate for the goal of this study. Kinematic flow routing allows for spatial and temporal deviations in flow and area (EPA, 2022). Within SWMM, flow routing is guided by the conservation of mass and momentum equations for gradually varied, unsteady flow (EPA, 2022). To determine flow rate the Manning roughness equation is used (EPA, 2022).

For modelling specific road characteristics for rural roads, several road design parameters are adjusted. SWMM requires input on total catchment area, catchment width, slope, manning coefficient, and percentage pervious surface area per sub-catchment. Separate road catchments are allocated between each drain location. This is done to ensure that water falling on the road downstream from the drainage inlet is not included in the flow calculations for that inlet. The slope is averaged over the sub-catchment with road gradient calculated as the average slope over the longest flow path, in this case it follows the road elevation pattern. Road width and cross section design are derived from a geometric road design manual by the Ministry of Works and Transport (2010). To determine infiltration rate and the subsequent runoff on the road body, the SCS-Curve number method is used. The Curve number method derives the infiltration capacity from hydrologic soil groups and land cover types.

In this study a single rainfall storm event is modeled by deriving daily rainfall data from Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) for the years 1981 to 2023 (figure 5). CHIRPS is a quasi-global rainfall data set that combines climatological models, high resolution satellite imagery and in-situ rainfall station data to create a gridded time series for rainfall (Funk et al., 2015).

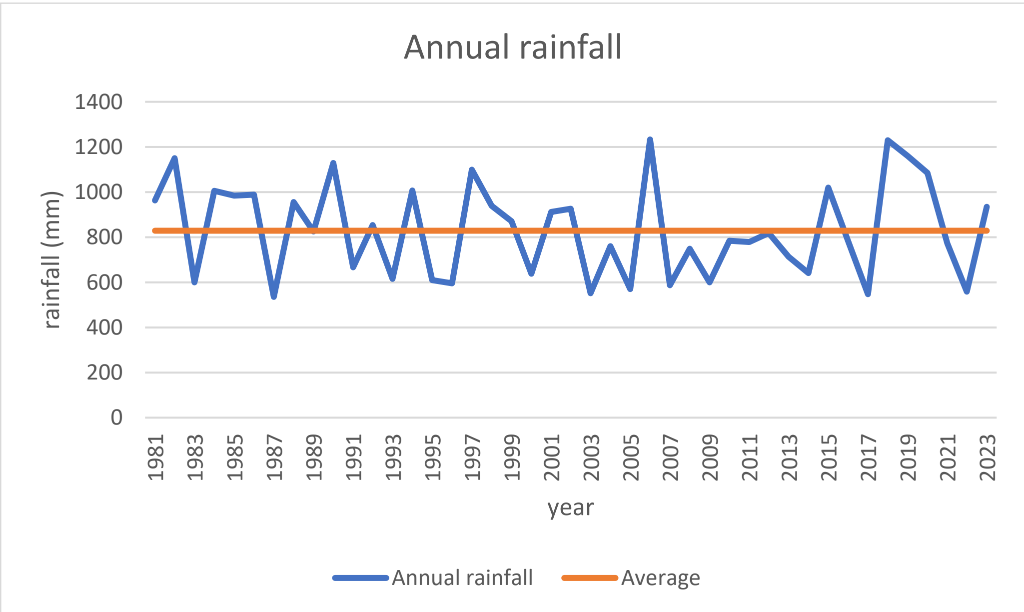

Figure 5: Annual rainfall in study area (CHIRPS)

Since there are no rainfall measurement stations located within the study areas and CHIRPS provides relatively course global rainfall data, the annual rainfall data was compared to results from a study by Nyaga (2016) that implemented the Standard Precipitation Index to identify dry and wet years. Comparison showed that both dry and wet years observed in Mbooni-subcounty by Nyaga (2016) and the CHIRPS data corresponded reasonably well for the whole time series. However classification in wet and dry years by Nyaga (2016) was often seen to be off by one year when compared to the CHIRPS rainfall data. Nevertheless general trends in years with less and more rainfall matched between both datasets.

In order to properly design the number and size of rainfall implementations the FAO (2014) and van Steenbergen et al. (2019) suggest calculating the design rainfall based on historical rainfall records. The design rainfall is a statistically calculated amount of rainfall selected from a precipitation time series to represent a reliable basis for the amount of water received by the harvesting system (FAO, 2014). Modelling based on the design rainfall ensures that the water harvesting implementations are adjusted to receive sufficient water during a rainfall event with a statistically high enough probability.

In order to calculate design rainfall the total annual rainfall amounts are ranked from highest to lowest. Using this ranking the probability of each rainfall amount was calculated with the following empirical formula by FAO (2016):

$$P(\%) = \frac{m - 0{,}375}{N + 0{,}25} * 100$$

P is the frequency of rainfall in percentage, m is the rank order of rainfall series sorted from the lowest to the highest and N is the number of years of the rainfall series. For arid and semi-arid areas a 67% probability of occurrence, i.e. a 33% exceedance probability, is adopted as a recommended parameter for selecting the design rainfall (van Steenbergen et al., 2021).

3. Results

3.1 Site suitability mapping

Pairwise comparison of the level 2 criteria results are shown in table 6 and 7. For both the runoff potential and the technical suitability, the average annual rainfall is assigned the highest criteria weight (cw). However, for technique suitability the land-cover is given small priority over slope, whereas the slope is the second most influential criteria in runoff potential. Soil type and soil depth are assigned the same weight for technique suitability while more weight is given to soil type in runoff potential. Drainage density is omitted as a criteria for technique suitability, since it has no direct effect on technique suitability and is already indirectly included when combining the runoff potential and technique suitability maps in the weighted linear combination process.

Pairwise comparison weightings are deemed sufficiently consistent when results show a consistency ratio below 0,1 (Saaty, 2004). The pairwise comparison of the level 2 runoff potential criteria shows a consistency ratio of 0,058, the level 2 criteria of technique suitability shows a consistency ratio of 0,08 for the biophysical criteria, and a consistency ratio of 0,04 for the socio-economic criteria. Thus, all pairwise comparisons of the level 2 criteria are deemed sufficiently consistent.

Table 6: Table with weights for the level 1 criteria: Runoff potential

Level 2 criteria:	Criteria weight (cw)	Feature class	Feature weight (fw)
Slope (%)	0,24	0-1	4
		1-3	5
		3-5	6
		5-10	7
		10-15	8
		15-30	9
		30>	5
Soil type	0,18	Clay	9
		Silty Clay	8
		Sandy Clay	7
		Clay loam	5
		Sandy Clay Loam	4
		Sandy Loam	2
Land-cover	0,10	Tree cover	5
		Shrubland	7
		Grassland	6
		Cropland	6
		Built-up	9
		Bare/Sparse vegetation	8
		Permanent water bodies	1
		Herbaceous wetland	2
Average annual rainfall (mm)	0,31	<400	5
		400-600	7
		600-800	8
		800-1000	8
		1000>	9
Soil depth (cm)	0,11	<72	9
		72-98	8
		98-124	7
		124-149	5
		149-175	3
		175>	1
Drainage density	0,06	0-0.0015	1
		0.0015-0.0025	5
		0.0025-0.003	7
		0.003-0.0035	8
		0.0035>	9

Feature weights (fw) per criteria for runoff potential are shown in table 6. The feature weights for the technique suitability show different values for farm pond, mitre drain, and sand dam techniques (table 7). It is important to note that the feature weights shown are further normalized before being combined using the weighted linear combination method. All three road water harvesting techniques are suitable in the study area with respect to the amount of rainfall. Since the rainfall within the study area ranges from 600 to 1300 mm per year (figure 4E). Very steep areas with slopes over 15% are considered unsuitable for all three road water harvesting techniques. Farm ponds are considered only suitable for flat areas, sand dams are suitable for both flat and areas with slopes <10% and mitre drains are considered the most suitable in areas with slopes ranging from 10-15%.

Table 7: Table with weights for the level 1 criteria: Technique suitability, for the three selected road water harvesting techniques

Level 2 Criteria:	Criteria weight (cw)	Feature class	Feature weight (fw)		
			Farm pond	Mitre drain	Sand dam
Slope (%)	0,20	0-1	9	0	3
		1-3	8	0	7
		3-5	5	7	9
		5-10	0	9	0
		10-15	0	7	0
		15-30	0	0	0
		30>	0	0	0
Soil type	0,12	Clay	9	0	0
		Silty Clay	9	1	1
		Sandy Clay	9	3	3
		Clay loam	5	5	5
		Sandy Clay Loam	2	9	9
		Sandy Loam	1	9	9
Land-cover	0,22	Tree cover	3	0	0
		Shrubland	8	0	8
		Grassland	8	0	6
		Cropland	0	9	8
		Built-up	0	0	0
		Bare/Sparse vegetation	9	0	9
		Permanent water bodies	0	0	0
		Herbaceous wetland	0	0	0
Average annual rainfall (mm)	0,38	<400	5	5	5
		400-600	7	7	7
		600-800	8	8	8
		800-1000	8	8	8
		1000>	9	9	9
Soil depth (cm)	0,08	<72	0	0	9
		72-98	1	1	8
		98-124	5	5	7
		124-149	7	7	5
		149-175	8	8	1
		175>	9	9	0
Distance to roads (m)	0,46	<3	0	9	9
		3-10	0	9	9
		10-50	9	9	5
		50-100	8	0	0
		100-250	5	0	0
		250-500	3	0	0
		500>	1	0	0
Distance to agriculture (m)	0,28	<100	9	5	9
		100-200	7	9	6
		200-500	5	7	4
		500-1000	3	4	1
		1000-2000	1	3	1
		2000>	0	1	0
Distance to streams (m)	0,15	<10	0	0	9
		10-50	5	1	7
		50-100	9	5	0
		100-200	8	7	0
		200>	7	9	0
Awareness (%)	0,11	7	9	9	9
		4	7	7	7
		3	5	5	5
		2	3	3	3

In this study three criteria layers, subdivided into 6 biophysical criteria, 4 socio-economic criteria and 2 constrains criteria are combined using corresponding weights of each criteria and their feature classes. Three separate technical suitability maps are generated for the three chosen road water harvesting techniques and combined with the runoff potential and constraints map. The maps are down sampled to the criteria input data with the smallest resolution, which is the land cover data with a 10 by 10 m resolution. The resulting maps after combining the runoff potential, technical suitability and constraints map are shown in figure 6. The maps show potential suitable sites for road water harvesting for three different techniques (figure 6).

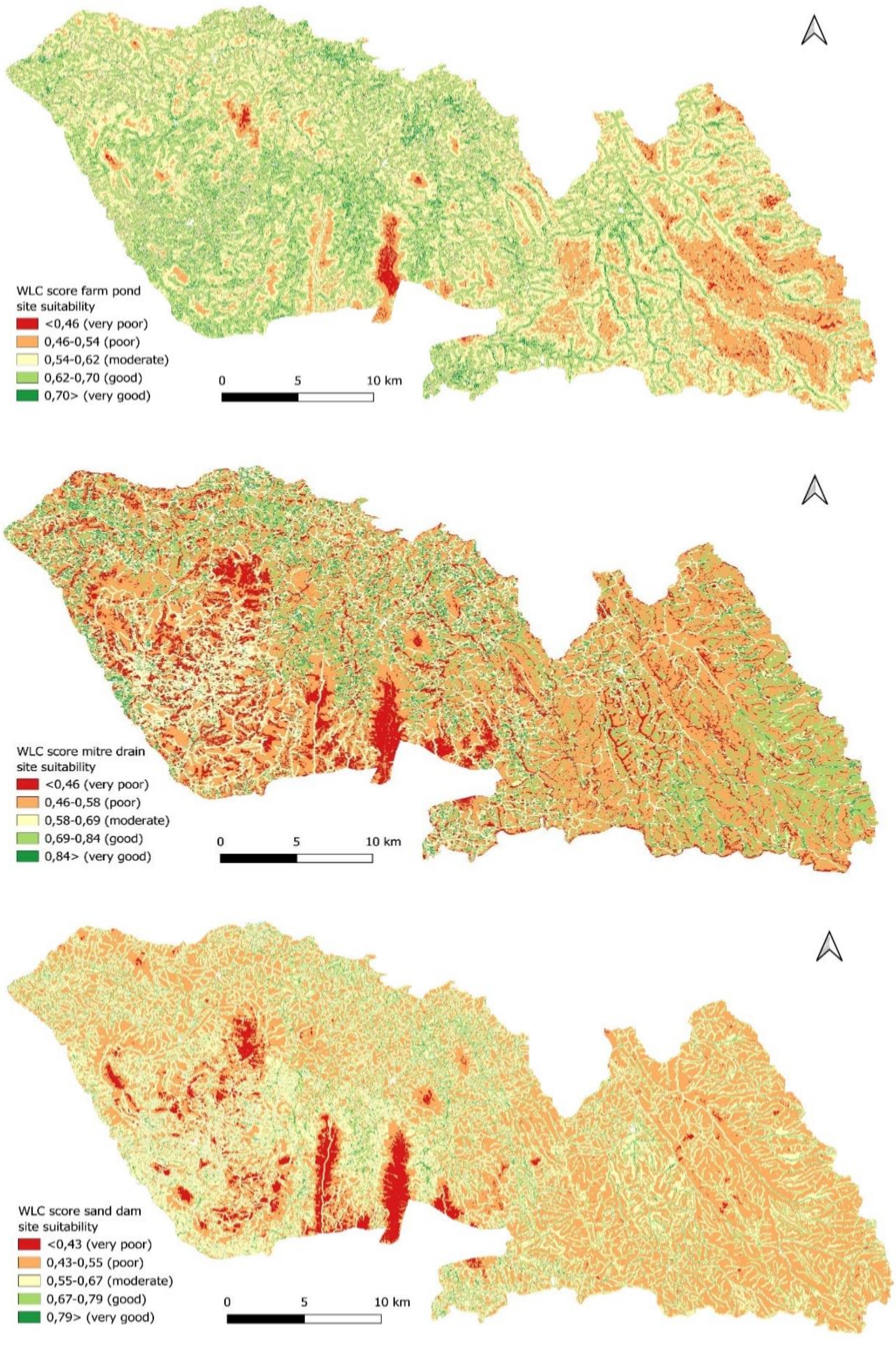

Figure 6: Optimal site suitability farm pond (top), mitre drain (middle) and sand dam (bottom) based on weighted linear combination score

The resulting score after applying the weighted linear combination is a relative rating of suitability. Based on the score, the study area is reclassified according to the equal interval method. The ranges are divided into 5 classes, ranging from 'very poor' to 'very good'. Within the study area 5,32% is deemed 'very good' suitability for mitre drains, 4,4% for farm ponds and 0,91% for Sand dams (table 8). The highest scores are observed next to or in the vicinity of the road network. However, farm ponds are not allowed right next to roads due to possible undermining of the road network, so 'very high' scores were observed some distance from road networks. Areas which received a 'very poor' score were mainly located on mountainous areas with steep slopes or far removed from any road, this trend is the same for all three road water harvesting techniques.

Table 8: Percentage of total area per suitability score for each road water harvesting technique

Suitability score	% of total area		
	Farm pond	Mitre drain	Sand dam
'very poor'	1,89%	13,26%	3,62%
'poor'	21,28%	45,1%	46,81%
'moderate'	42,10%	18,87%	37,23%
'good'	30,30%	17,41%	11,40%
'very good'	4,4%	5,32%	0,91%

3.2 SWMM modelling

3.2.1 Study area

In order to effectively map the small scale implementations along the selected road a smaller area for the SWMM modelling, located within the current study area, is selected. The area is selected based on an ongoing 'Drain to Gain' project for the implementation of road water harvesting structures along a 1 km long section of the Kavingo-Kyamangatu-Ilela road (figure 7). The road is located between 1,63621°S 37,61462°E and 1,60848°S 37,64712°E within a rural area in Mbooni within Kako/Waia ward and has a total length of 3 km. The road crosses a stream at its lowest point and runs along the crest of two hills, causing the road itself to be located on the border of two catchment areas. Since the road surface lies on the border of two sub-catchment areas, it is assumed that the road surface itself acts as a catchment area for rainfall. Since roads can act as drainage paths for runoff generated within a catchment (van Steenbergen 2021). In most cases water is harvested from the entire landscape (not just the road surface) with the help of road embankments and drainage systems. However, in this case the road does not receive any indirect runoff from any hillsides adjacent to the road body due to its placement in the landscape. This means sub-catchment size is equal to the road surface area and catchment width corresponds to the road with (figure 9). The landcover within the study area consist of agricultural area, barren land, grassland and shrubland with some buildings in the vicinity of roadsides.

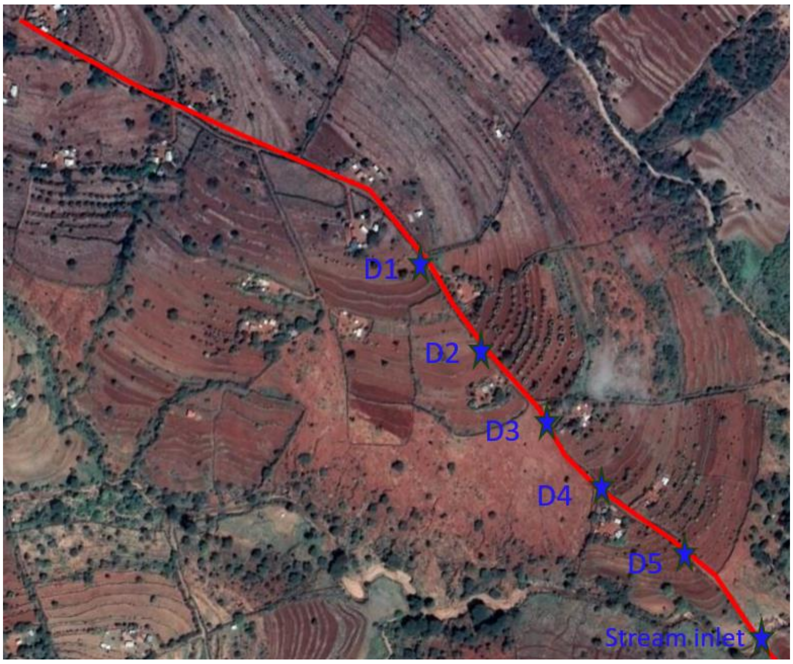

Figure 7: Section of the Kavingo-Kyamangatu-Ilela road (red) with mitre drain locations (blue stars) based on results from the site suitability mapping.

Mitre drains are selected for implementation in SWMM on 5 different locations along the road body, shown in figure 7. Mitre drains are modeled within SWMM as inlets along street sections with a width of 40 cm and height of 50 cm and placed with a 100 meter interval according to van Steenbergen et al. (2021). Inlet locations along the road section are derived from the results of the suitability mapping for mitre drains (figure 6).

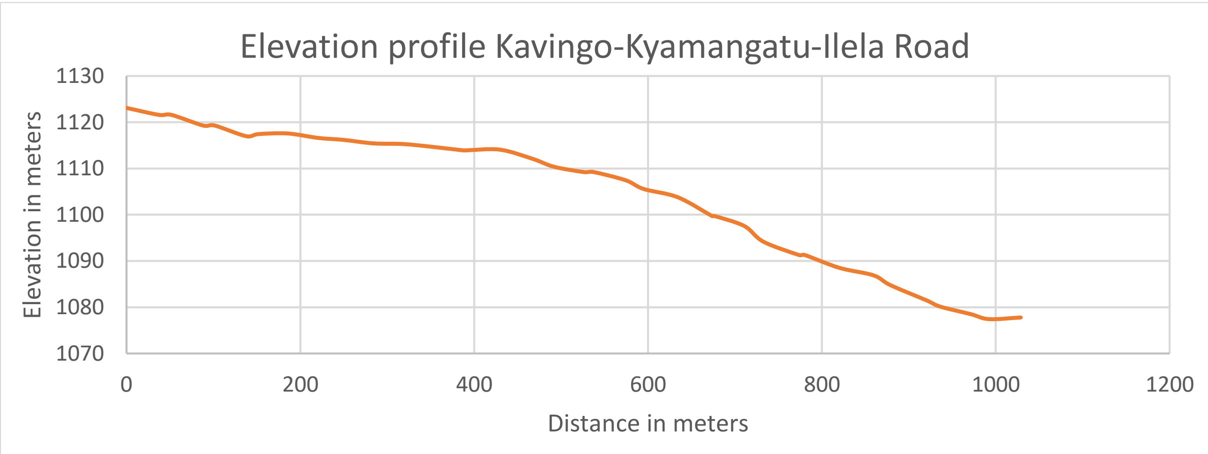

Figure 8: Elevation profile of selected road

3.2.2 Model input for selected road

Figure 8 shows that the road can be divided into a section with an average gradient of 2% up to a distance of 491 meters, and a section of 7% gradient for the rest of the road distance. Manning coefficients for the road segments serving as drainage channels are derived from EPA SWMM 5.2 user guide (2022). A Manning coefficient (N) of 0.02 was given to the selected road assuming the road functions as a clean weathered channel (Chow, 1959). The percentage pervious area of the road body is assumed to be 100% since the road consists of (compacted) dirt. To calculate infiltration losses a SCS runoff curve number of 87 is assigned based on the observed hydrologic soil group and land use value in the study area. The soil type of the road location consists mostly of sandy clay loam belonging to hydrologic soil group ‘C’, which corresponds to a curve number of 87 for ‘dirt roads’ (USDA-SCS, 1986).

The selected road is classified as a rural road with the lowest grade functional class E: minor road (Ministry of Works and transport, 2010). Since no field measurements could be collected within the timeframe of this study, the value of all cross section elements is based on general values for design class ‘Gravel C’ roads, which is the lowest class road available (Ministry of Works and Transport, 2010). This results in a road width of 6,4 meters with a 4% cross section slope (figure 9).

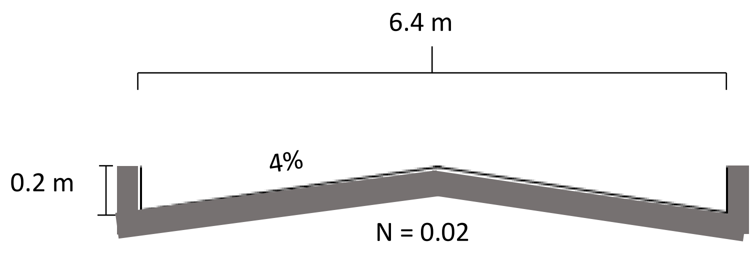

Figure 9: road cross section based on geometric design guidelines, used as conduit design in SWMM.

A Frequency curve for the maximum daily rainfall event for each year is derived for determining the design rainfall (figure 10).

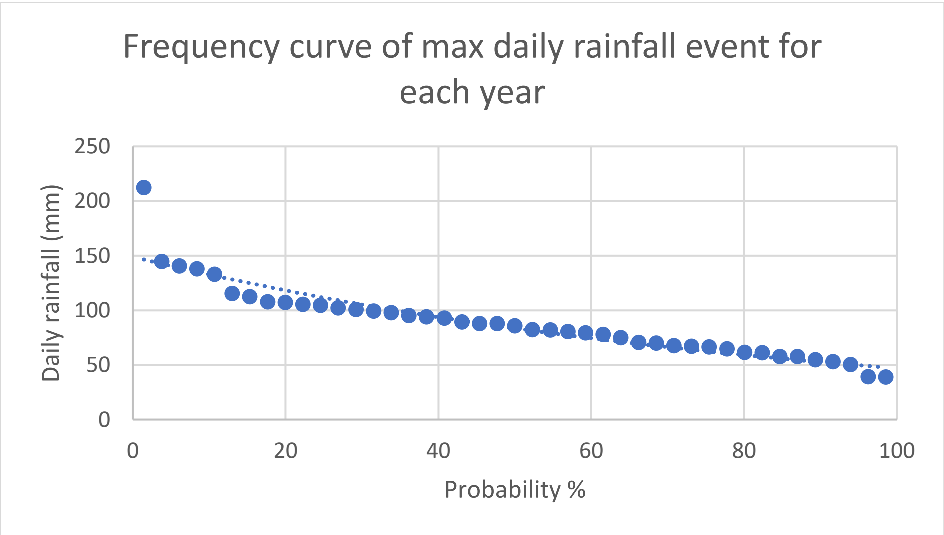

Figure 10: Frequency curve showing probability of occurrence for different rainfall amounts

The resulting frequency curve shows that the 67% probability of occurrence for a max daily rainfall event is a 70 mm in one day (figure 10). It is assumed that total amount of the 70 mm rainfall would occur over a period of 6 hours. Resulting in the timeseries shown in figure 11, used as rainfall input for the kinematic wave routing model.

Figure 11: Rainfall timeseries based on 6 hour 70mm design rainfall event.

3.2.3 Model results

Results for the 6 hour 70mm rainfall event show a runoff coefficient of 0,64 for all road catchments. Table 9 shows the results for the model run for all mitre drains. Drains D1 to D4 and the stream inlet are located from uphill to downhill respectively, with the lowest point at a stream crossing a the 'stream inlet' (figure 7). All drains show maximum inflow after 4 hours. Results show that the percentage runoff captured decreases with an increase of slope steepness. This can be attributed to a higher flow velocity of the road runoff allowing less time for water to flow into the drainage channel.

Table 9: SWMM results for 6 hour 70mm rainfall event for all mitre drains.

	Topographic elevation of drain (m)	Size of connected road catchment (ha)	% road gradient of catchment	Total road section runoff 10^6 ltr	Hour of maximum Inflow (h:m)	Total inflow volume (10^6 ltr)	Total inflow volume (m3)	% runoff captured by drain
D1	1140	0.3142	2	0.14	04:05	0.0534	53	38.1
D2	1160.03	0.06	7	0.114	04:02	0.0313	31	27.4
D3	1098.96	0.06	7	0.11	04:01	0.0301	30	27.3
D4	1084.82	0.06	7	0.104	04:02	0.0293	29	28.1
D5	1091.89	0.06	7	0.106	04:02	0.0287	28	28.1
Stream inlet	1077	0.06	7	0.103	04:01	0.103	103	

Time series plots for flow rates are shown in figure 12. The road body is divided into sections where every section covers the road length between two drains. The model is set up so that runoff that is not captured by the first drain moves to the subsequent lower positioned drain. This causes all street sections above the drains to not only receive water from rainfall falling directly on the road surface, but also all road runoff not captured by the previous drains. When comparing the amount of total road runoff flow being captured by one mitre drain for the different drain placements, figure 12 and table 9 show that the percentage of runoff captured by the drain decreases with an increase of road steepness. Mitre drain D2 positioned on a road with 7% incline captures about 28% of the road runoff flowing past that drain inlet, compared to 38% road runoff captured by drain D1 that has a road gradient of 2% (figure 12).

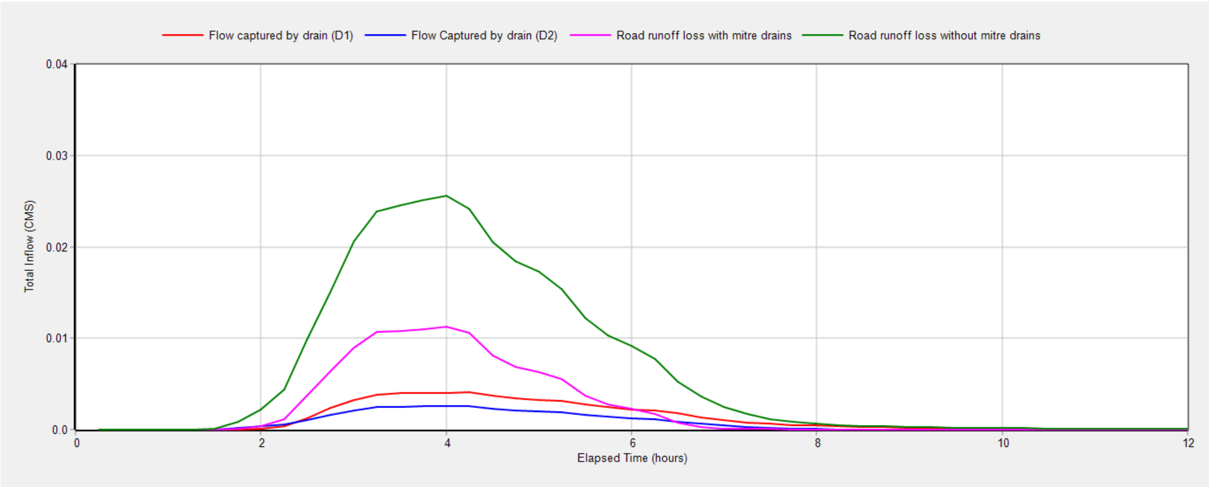

Figure 12: Time series plot showing total road runoff loss in cubic meters per second (CMS) at stream inlet for a model run with 5 mitre drains (pink) and without mitre drains (green). The plot also shows mitre drain (D1) total captured inflow on 2% road gradient (red) and mitre drain (D2) total captured inflow on 7% road gradient (blue).

Comparative analysis of two model runs, one without mitre drains and one with the five mitre drains for the same road section show that implementing mitre drains reduces total water losses due to road runoff by 62% (figure 12). Meaning that over half the amount of the water captured by the road body is distributed along the mitre drains toward neighboring agricultural areas. Without mitre drains the road body has a total outflow volume of 276 m3, compared to a outflow volume of 103 m3 after placing the mitre drains (table 9). This means that with a 6 hour 70 mm rainfall event a total of 171 m3 water is captured over the 5 mitre drains and distributed over several agricultural plots, with mitre drains showing an increased capture of water on lower road inclines. Overall, the results show that the placing mitre drains along the chosen locations is an effective way of reducing losses through road runoff and capturing additional water for agricultural purposes.

4. Discussion

This study derived the potential suitability for road water harvesting implementations by selecting and assigning weights of importance to a multitude of criteria. Both biophysical and socio-economic criteria were taken into account and weights were assigned based on existing literature and expert consultations. Previous research has shown that this approach is a robust method for determining site suitability for rainwater harvesting structures (Ammar et al. 2016). However, no known applications of this method exist in the context of road water harvesting. The aim of this research was to improve the implementation of road water harvesting techniques in Makueni County, Kenya, to enhance the effectiveness of water management practices. This was attempted through the adaptation of an existing analytical hierarch process framework to aid in the mapping of suitable locations for roadside water harvesting implementations and to support policy decisions. It is important to note that the framework results in a relative scale, which shows the difference in potential locations based on subjective criteria. The use of a flexible framework for mapping suitability allows for easy conversion for use in other study areas (Shadmehri Toosi et al., 2020). However, weights will have to be re-calculated, when other criteria are used or the aim of the study changes. This is due to the assignment of weights with respect to the overall aim of the study.

Another benefit of adopting the analytical hierarchy process is that it allows for the selection of site suitability within a flexible range instead of using hard parameters that might not be known or applicable for road water harvesting techniques (Ammar et al., 2016). However, this feature can act as a double edged sword. The lack of knowledge or data on technical or social constraints might cause the resulting suitable areas to be too broad to give a specific location for road water harvesting techniques, which are often implemented on a small scale. The inclusion of socio-economic parameters in water management decision making is essential in ensuring effectiveness (Gebru et al., 2020; Ammar et al., 2016; Kimani et al., 2015). An attempt was made to include socio-economic aspects of water harvesting technique suitability, through the inclusion of population awareness and distance from relevant areas, such as agricultural area and distance from roads. However, the selection of socio-economic criteria was limited due to the unavailability of spatially mapped data on may socio-economic criteria. Built up area was omitted from site suitability selection because road water harvesting implementations cannot be placed on existing buildings. The road bodies were omitted because the harvesting implementations should not interfere with the main transport function of roads.

Results of the suitability mapping in figure 6 shows that one location can be suitable for multiple techniques. Combination of multiple techniques along a road body is possible (van Steenbergen et al., 2021). For example, mitre drains can be used to directly irrigate the landscape next to a road or guide water to farm ponds for storage (Shadegi et al., 2021; Woldearegay et al., 2017). Mitre drains show ‘very good’ suitability for 5,32% of the study area, followed by farm ponds with 4,4% of the study area (table 8). The high suitability for mitre drains is reflected in the high implementation of this technique since the introduction of the road water harvesting concept in 2016 within Makueni county (Maluki et al., 2023). The high percentage suitable area of mitre drains can be attributed to the high criteria weight scoring for the ‘distance to road’ criteria and a corresponding high feature weight score for a large number of feature classes (table 7). This is because, unlike farm ponds, mitre drain inlets should be placed in direct connection to the road bodies and can guide water some distance away from the road body. This reflects the sensitivity of the analytical hierarchy process to assigned criteria weights in determining area of suitability. This is in line with results from a previous study by Doulabian et al. (2021) that found overall higher sensitivity on suitability mapping results for criteria that were assigned a high initial criteria weight. The same goes for road bodies used as sand dams, where placement is only suitable where road bodies intersect natural drainage areas. This explains the low ‘very high’ suitability area of 0,91% for sand dams. Thus, each technique should be evaluated individually, and no comparisons between different techniques in terms of total suitable area percentages should be made.

In an approach to validate the results of the suitability mapping, implemented mitre drain locations along the Nduluku ctti-Mukuku-Kikuswi-Kwa Ndungi road were compared to locations which showed a ‘very good’ suitability score for mitre drains. This 10 km road stretch includes water harvesting features such as mitre drains, culverts and Gabions with nature based solutions. Of the 11 locations along the road that showed visible mitre drain channels on satellite images, 6 locations were correctly identified by the suitability map as locations with ‘very good’ suitability. Of the other locations 2 were interpreted by the map as ‘good’ suitability. The lower score was due to the placement of the mitre drains on a flat area. All other locations were interpreted as ‘moderate’ suitability, in two cases because of misinterpretation of agricultural area for grassland. In the other case, the interpretation was correct but mitre drains were located on shrubland, which was deemed less suitable when assigning weights. This comparative analysis shows the high sensitivity of the framework to the accuracy and resolution of input data, such as the land cover interpretation, and the assignment of weights to criteria parameters deemed suitable.

In a similar study, Krois et al. (2014) focused on a small 42 km2 area but utilized more site-specific data, highlighting the importance of detailed, high-resolution datasets in smaller-scale studies. However, due to the limited availability of data within rural areas, the reliance on global datasets is the main limiting factor in determining suitability for small scale water harvesting implementations (Bulcock et al., 2013). For example, a study by Senay et al. (2004) utilized data with a 10 x 10 km resolution for suitability mapping and found that this coarse resolution was insufficient for designing individual farm ponds, only providing a generalized overview of suitable areas. In an attempt to mitigate this issue for this study, all map data was resampled based on the highest resolution data available, which was the land cover data with a 10 x 10m resolution. However, this did not increase the accuracy of the available datasets. Another downside of resampling coarse data is that it could increase homogeneity of the data when used for a small study area, which could cause overestimation of the assigned criteria weight when compared with real life influence, as noted by Doulabian et al. (2021). Thus, results from this study should only be used as an initial overall assessment of potential areas but in-field evaluation of the proposed sites will still be required. Also, the use of regional datasets could help improve the data quality and give a more accurate representation of potential areas.

Runoff models have been used before in the context of site suitability mapping in combination with multi criteria analysis (Ammar et al., 2016; Doulabian et al, 2021; Abdelkader et al, 2023). However, hydrological models were mainly implemented to assess runoff within the study area, which is then used as a biophysical criteria within the analytical hierarchy process. This research determined runoff potential based on biophysical criteria, selected using the analytical hierarchy process. This approach was chosen due to the lack of high resolution data within the study area, which made determining runoff using hydrological models unfitting. However, the SWMM dynamic runoff model was used in an attempt to quantify the amount of rainwater that could be harvested after implementing a technique. SWMM was chosen because it allows the inclusion of man-made drainage features such as roads and trenches, which makes this applied model suitable for the simulation of different road water harvesting implementations.

Only mitre drains were included in the model, since SWMM is not suitable for implementing sand dams in their model and farm ponds serve as retention areas for water diverted by mitre drains from roads. Total inflow over a time period in a drain would still correspond to the quantity of water captured by a farm pond if it was implemented, not taking into account infiltration and evaporation losses. Due to the inability of the model to implement sand dams, quantifying potential capture of water using natural drainage paths crossing road bodies was omitted for the selected road body. Analysis of captured water thus only includes runoff generated by water falling directly on the road body. This means that model results will likely be an underestimation the total capacity to capture water, due to the missing potential of using a combination of road water harvesting techniques. However, because the road areas only crosses a stream on one location and the location of the road is on the border of two sub-catchments, it is assumed that the road itself receives minimal input from natural drainage patterns in the landscape. Thus, it was assumed that only modelling mitre drains would be sufficient for estimating capture of runoff during a storm event.

However, since SWMM is designed for urban stormwater systems, several concessions had to be made in order to adjust for lacking natural drainage features found in rural areas. Mitre drains were designed as horizontal curb openings with a height bigger than the road curb to allow for open channel inflow. Road runoff was calibrated based on runoff values for unpaved roads, resulting in a modelled value of 0,64 for all road sections (van Steenbergen et al., 2019). A comparative analysis was conducted for two runoff scenarios to compensate for lack of calibration and validation data of runoff. Implementation of mitre drains showed a reduction of 62% in runoff losses in water captured by a road body based on a 6 hour 70 mm storm event. Model results show that five mitre drains with a 100 meter interval were able to capture 171 m3 of water. However, since quantitative data on harvested water could not be validated with field measurements, the results are limited in interpreting the amount of harvested water as a relative reduction in runoff, not in absolute quantities. Since comparative assessment does not necessitate calibration and validation processes (Doulabian et al., 2021). Other limitations include the absence of simulations of erosion and sediment transport, two factors that are also important in designing an effective and sustainable water harvesting system (Garcia-Landarte Puertas et al., 2014; Temmink, 2015).

Overall this study has shown that the analytical hierarchy process is suitable for assessing optimal road water harvesting locations. And this framework can be used as a tool that can aid in preliminary planning of harvesting implementations, by giving an initial overall assessment of potential sites. This preliminary planning will in turn reduce the fieldwork time needed for selecting implementation locations, something that is currently a manual and time-consuming procedure. Thus, this tool could effectively lead to a more efficient design and management process.

5. Conclusion

With water scarcity becoming an increasing issue for arid and semi-arid regions under future climate projections, utilizing existing roads in a multi-functional way to capture rainfall and surface runoff can positively impact water resilience, crop production and reduce rain-related damages in the surrounding area. The aim of this study was to improve the implementation of road water harvesting techniques in Makueni County, Kenya, to enhance the effectiveness of water management practices.

Selection and ranking of relevant criteria for road water harvesting site suitability was applied within an analytical hierarchy process framework. For this several biophysical and socio-economic criteria were selected, assigned a weight and combined into several suitability maps. Suitabile areas along road bodies within Mbooni sub-county, Kenya, were derived for three common road water harvesting techniques. Techniques include mitre drains, farm ponds and sand dams. Results show very high suitability for 5,32%, 4,4% and 0,91% of the total study area for mitre drains, farm ponds and sand dams respectively. Results for mitre drains were validated using comparison with existing mitre drain locations along a 10km road stretch. 8 out of the 11 compared locations were correctly interpreted as good or very good suitability. Demonstrating that this framework shows potential in being an effective tool for preliminary site evaluation. To calculate how much water could be captured by implementing the water harvesting techniques on locations derived from the results, a stormwater runoff model was used. Implementation of mitre drains showed a reduction of 62% in runoff losses in water captured by a road body based on a 6 hour 70 mm storm event. However, lack of calibration and validation data did not allow for definite conclusions in absolute volumes of water captured. Further calibration and validation of selected criteria parameters with in-field observations and measurements is recommended to improve the effectiveness of the framework and the runoff model. More spatial data on socio economic factors influencing water harvesting technology adaptation could improve the site selection criteria further. Using more inclusive strategies such as the analytic network process, that use relationships networks instead of hierarchical processes could further finetune the relations between relevant criteria. In general, this framework provides a tool that is able to give theoretical backing for the effectiveness of implementations. Which could aid in convincing stakeholders and governments to implement road water harvesting techniques.

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Declaration of use of AI

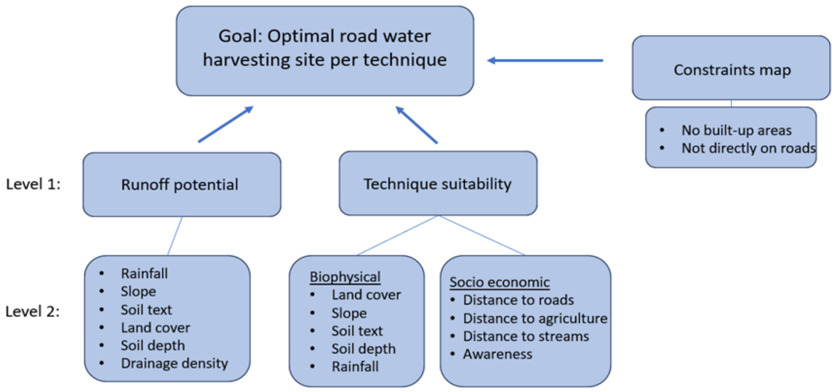
I hereby declare that I have used ChatGPT only to help in condensing and improving clarity in python code used in this project (Appendix 1). However all steps and procedures required were of my own making. Due to the long term adjustments of code over the three months using multiple iterations and use of my personal google account, I cannot provide a clear conversation history from ChatGPT. I hope that through this declaration I have met the conditions for the permissible use of AI.

7. Appendix

1. Python code for the site suitability mapping process

Results of the AHP process (example for the current study)

Fist we have to determine what criteria we want to give a weight and combine. A decision hierarchy was set up to select criteria affecting the main goal of finding optimal sites per road water harvesting technique (figure below). On the first level it was determined that two main factors influence the goal. These include: the potential for runoff generation within an area and the suitability of the environment to place different road water harvesting techniques. The selection of level 1 factors was based on assumption that the amount of runoff affects the water that can be captured on the surface and different road water harvesting techniques have different optimal sites based on technical specifications. An added constraints map with general areas that are generally omitted from site suitability selection was used to filter predetermined unsuitable areas. It was assumed that technique suitability is two times as important as the runoff potential with respect to the goal. This assumption causes all level 2 criteria groupings to have the same importance with respect to the goal. For level two factors the Runoff was subdivided into biophysical criteria for which weights were derived using pairwise comparison. The technique suitability is both affected by biophysical criteria and socio-economic criteria that were assumed to have the same amount of influence in determining the technique suitability. For both runoff potential and technique suitability the all the criteria were subdivided into features classes based on the range of data observed in the study area. These feature classes were assigned a weight as well. For the constraints map a Boolean method for the two criteria was applied to omit them in the site selection.



The resulting weights for the level 2 criteria after the analytical heirarchy process are put in an excel table that looks like the table below. The criteria are shown on the left side. The column headers ending on '_cw' contain the criteria weights per criteria based on the overall level 1 goal (as shown above). Column headers ending on '_fw'contain the normalized feature weights per level 2 criteria. This table will be read in by the script as a dictionary and data exctracted for calculations.

criteria	runoff_cw	techsuit_	ranges	runoff_value	runoff_fw	pond_value	pond_fw	mitre_value	mitre_fw	sanddam_value	sanddam_fw
slope	0,24	0,20048	0-0.57	4	0,090909091	9	0,409090909	0	0	3	0,157894737
			0.57-1.72	5	0,113636364	8	0,363636364	0	0	7	0,368421053
			1.72-2.86	6	0,136363636	5	0,227272727	7	0,304348	9	0,473684211
			2.86-5.71	7	0,159090909	0	0	9	0,391304	0	0
			5.71-8.53	8	0,181818182	0	0	7	0,304348	0	0
			8.53-16.7	9	0,204545455	0	0	0	0	0	0
			16.7>	5	0,113636364	0	0	0	0	0	0
soiltype	0,18	0,12336	1	9	0,257142857	9	0,257142857	0	0	0	0
			2	8	0,228571429	9	0,257142857	1	0,037037	1	0,037037037
			3	7	0,2	9	0,257142857	3	0,111111	3	0,111111111
			4	5	0,142857143	5	0,142857143	5	0,185185	5	0,185185185
			6	4	0,114285714	2	0,057142857	9	0,333333	9	0,333333333
			9	2	0,057142857	1	0,028571429	9	0,333333	9	0,333333333
			9>	0	0	0	0	0	0	0	0
landcove	0,1	0,21715	10	5	0,113636364	3	0,107142857	0	0	0	0
			20	7	0,159090909	8	0,285714286	0	0	8	0,258064516
			30	6	0,136363636	8	0,285714286	0	0	6	0,193548387
			40	6	0,136363636	0	0	9	1	8	0,258064516
			50	9	0,204545455	0	0	0	0	0	0
			60	8	0,181818182	9	0,321428571	0	0	9	0,290322581
			80	1	0,022727273	0	0	0	0	0	0
			90	2	0,045454545	0	0	0	0	0	0
			90>	0	0	0	0	0	0	0	0
rainfall	0,31	0,37743	<400	5	0,135135135	5	0,135135135	5	0,135135	5	0,135135135
			400-600	7	0,189189189	7	0,189189189	7	0,189189	7	0,189189189
			600-800	8	0,216216216	8	0,216216216	8	0,216216	8	0,216216216
			800-1000	8	0,216216216	8	0,216216216	8	0,216216	8	0,216216216
			1000>	9	0,243243243	9	0,243243243	9	0,243243	9	0,243243243
soildepth	0,11	0,08158	<72	9	0,272727273	0	0	0	0	9	0,3
			72-98	8	0,242424242	1	0,033333333	1	0,033333	8	0,266666667
			98-124	7	0,212121212	5	0,166666667	5	0,166667	7	0,233333333
			124-149	5	0,151515152	7	0,233333333	7	0,233333	5	0,166666667
			149-175	3	0,090909091	8	0,266666667	8	0,266667	1	0,033333333
			175>	1	0,03030303	9	0,3	9	0,3	0	0
drainage	0,06		0-0.0015	1	0,033333333						
			0.0015-0.0025	5	0,166666667						
			0.0025-0.003	7	0,233333333						
			0.003-0.0035	8	0,266666667						
			0.0035>	9	0,3						
road_dis		0,46155	<3			0	0	9	0,333333	9	0,391304348
			3-10			0	0	9	0,333333	9	0,391304348
			10-50			9	0,346153846	9	0,333333	5	0,217391304
			50-100			8	0,307692308	0	0	0	0
			100-250			5	0,192307692	0	0	0	0
			250-500			3	0,115384615	0	0	0	0
			500>			1	0,038461538	0	0	0	0
agri_dist		0,28077	<100			9	0,36	5	0,172414	9	0,428571429
			100-200			7	0,28	9	0,310345	6	0,285714286
			200-500			5	0,2	7	0,241379	4	0,19047619
			500-1000			3	0,12	4	0,137931	1	0,047619048
			1000-2000			1	0,04	3	0,103448	1	0,047619048
			2000>			0	0	1	0,034483	0	0
stream_dist		0,15063	<10			0	0	0	0	9	0,5625
			10-50			5	0,172413793	1	0,045455	7	0,4375
			50-100			9	0,310344828	5	0,227273	0	0
			100-200			8	0,275862069	7	0,318182	0	0
			200>			7	0,24137931	9	0,409091	0	0
awareness		0,10705	7			9	0,375	9	0,375	9	0,375
			4			7	0,291666667	7	0,291667	7	0,291666667
			3			5	0,208333333	5	0,208333	5	0,208333333
			2			3	0,125	3	0,125	3	0,125

Install and load the necessary libraries

Lets first install the necessary libraries

```
!pip install rasterio
!pip install rioxarray
!pip install rasterstats
!pip install geopandas
!pip install matplotlib
!pip install scipy
```

Import the necessary libraries for use in the coding

```
import math
import rasterio
import numpy as np
import rioxarray
import geopandas as gpd
import pandas as pd
from rasterio.features import rasterize
from scipy.ndimage import distance_transform_edt
```

Preparing the datasets

Now it's time to load in the datasets that will be used for calculations. All selected criteria in the AHP need to contain a spatial dataset for the weighted linear combination. Datasets are derived via open source downloads or via private institutions. Most of the data consist of .tif rasterdata, some of which have been prepared in the QGIS programm before implementation in the coding.

Create paths to the datasets depending on where the data is stored on the computer.

```
DEM_path = "C:/Users/joram/Thesis GECP/GeoData/demClip.tif"
LC_path = "C:/Users/joram/Thesis GECP/GeoData/LC_Mbooni.tif"
Slope_path = "C:/Users/joram/Thesis GECP/GeoData/slopeClip.tif"
Makueni_path = "C:/Users/joram/Thesis GECP/GeoData/Makueni_County_shapefile.shp"
```

```
RF_path = "C:/Users/joram/Thesis GECP/GeoData/Clip_interpolated_RF.tif"
DD_path = "C:/Users/joram/Thesis GECP/GeoData/DrainageDens_Mbooni_raster.tif"
Soil_type_path = "C:/Users/joram/Thesis GECP/GeoData/Soil_type_Makueni.tif"
soil_depth_path = "C:/Users/joram/Thesis GECP/GeoData/Soil_depth2.tif"
roads_path = "C:/Users/joram/Thesis GECP/GeoData/Roads_Mbooni_corrected_all.shp"
streams_path = "C:/Users/joram/Thesis GECP/GeoData/Strahlersteams_vector_clipped.shp"
awareness_path = "C:/Users/joram/Thesis GECP/GeoData/Awareness_subcounties.tif"
```

Open the datasets using rasterio for the .tif files and geopandas for the .shp shapefiles.

```
DEM = rioxarray.open_rasterio(DEM_path, masked = True)
LC = rioxarray.open_rasterio(LC_path, masked = True)
Slope = rioxarray.open_rasterio(Slope_path, masked = True)
RF = rioxarray.open_rasterio(RF_path, masked = True)
Makueni = gpd.read_file(Makueni_path)
Soil_type = rioxarray.open_rasterio(Soil_type_path, masked = True)
DD = rioxarray.open_rasterio(DD_path, masked = True)
Soil_depth = rioxarray.open_rasterio(soil_depth_path, masked = True)

Roads = gpd.read_file(roads_path)
Streams = gpd.read_file(streams_path)
Awareness = rioxarray.open_rasterio(awareness_path, masked = True)
```

Creating the socio-economic criteria maps

The socio-economic criteria maps consist of two maps including the distance from a road body and the distance from stream channels. The available data for these maps consist of a road and a stream line shapefile. Our first step will be converting the shapefiles into raster files so they can be used for later calculations. This is done with the function below, that creates a buffer around the line polygons and covertinging that buffer into a raster file using the extent and resolution of the most detailed map you have (target_dataarray). which in this case is the land cover dataset.

```
# Convert LineString geometries to Polygon geometries by buffering with a small distance
def rasterize_to_np(criteria, target_dataarray):
    buffered_criteria = criteria.geometry.buffer(0.00009009)  # Adjust the buffer distance as needed, a
ssuming one pixel width is 10 meters which is in this case also assumed to be the average road width.

    # Open the raster dataset to get the desired shape and transform
    with rasterio.open(target_dataarray) as src:
        transform = src.transform
        shape = src.shape

    # Rasterize the road geometries into a NumPy array
    criteria_mask = rasterize(
        shapes=zip(buffered_criteria, [0]*len(buffered_criteria)), # Assume all roads have the same val
ue (0)
        out_shape=shape,
        transform=transform,
        fill=1,  # Value to fill for pixels outside the polygons
        dtype=np.uint8
    )

    return (criteria_mask)

#convert the roads and streams shapefiles into numpy rasters
road_mask = rasterize_to_np(Roads, LC_path) # this is also a constraint map for the road body itself
stream_mask = rasterize_to_np(Streams, LC_path)
```

Now we have to create a distance map from the created numpy raster files above. For this we will using the 'distance_transform_edt'. Since our crs of the datasets is in degrees, the function also converts the degrees into meters, since this is the input in the excel file. The distance function is used for the roads, streams and agricultural area. The agricultural area locations are extracted from the landcover dataset.

```
def distance(data_mask):
    distance_pixel = distance_transform_edt(data_mask)
```

```
    #calculate the distance from amount of pixels to meters
    latitude_makueni = -1.5  # In degrees south

    # Calculate the conversion factor from degrees to meters at the latitude of Makueni County
    equator_distance = 111320  # Distance at the equator in meters
    conversion_factor_makueni = equator_distance * math.cos(math.radians(latitude_makueni))

    # Distance in degrees
    distance_in_degrees = 8.333333333333326279e-05

    # Convert the distance from degrees to meters
    distance_in_meters_makueni = distance_in_degrees * conversion_factor_makueni

    distance = distance_pixel * distance_in_meters_makueni
    return (distance)

agri_area = (LC == 40) # Extract the agriculture area from the Land cover data
agri_area_array = np.where(agri_area, 0, 1) # save the agriculture data array as a boolean array

distance_agri = distance(agri_area_array)
distance_roads = distance(road_mask)
distance_streams = distance(stream_mask)
```

Save all the created socio economic maps

We will save the socio-economic numpy arrays maps as Geotif files to later match with all other datasets so the calculations are performed with datasets of equal size. This is done with the following function. The target data array is the land cover dataarray again.

```
def saveas_tif(data_array,file_name, target_dataarray):
    with rasterio.open(target_dataarray) as src:
        transform = src.transform

    # Define the profile for the output GeoTIFF file
    profile = {
        'driver': 'GTiff',
        'height': data_array.shape[0],  # Number of rows
        'width': data_array.shape[1],   # Number of columns
        'count': 1,                      # Number of bands
        'dtype': data_array.dtype,      # Data type of the array
        'crs': 'EPSG:4326',              # CRS information
        'transform': transform,  # Transformation information
        'nodata': None                   # Specify nodata value if applicable
    }


    # Write the NumPy array to the GeoTIFF file
    with rasterio.open(file_name, "w", **profile) as dst:
        dst.write(data_array, 1)

saveas_tif(distance_roads,"distance_roads2_m_Mbooni_imp2.tif", LC_path)
saveas_tif(distance_streams,"distance_streams_m_Mbooni_imp2.tif", LC_path)
saveas_tif(distance_agri[0],"distance_agri_m_Mbooni2.tif", LC_path)

# Open the created .tif files for road, agri and stream distance for immedeate use :
Distance_roads = rioxarray.open_rasterio("distance_roads2_m_Mbooni_imp2.tif", masked = True)
Distance_agri = rioxarray.open_rasterio("distance_agri_m_Mbooni2.tif", masked = True)
Distance_streams = rioxarray.open_rasterio("distance_streams_m_Mbooni_imp2.tif", masked = True)
```

Create the constraints map

The constraints map, i.e. the locations that are not used for calculation suitabiltiy since it is not possible to build there, are derived by creating boolean maps for urban areas and the road body itself. The boolean map for the road body ('road_mask') is already derived when creating the socio-economic criteria maps. The urban areas are extracted from the land cover data, just as the agricultural area was.

```
urban_area = (LC == 50)
urban_area_array = np.where(urban_area, 0, 1) # Create a new array where values equal to 50 (urban area
) become 0 and others become 1 using the mask
```

Standardizing the datasets before calculations

The following function sets the crs, resolution and extent of the map data equal to the lowest resolution data (the LC map in this case, with a resolution of 10 by 10 meters)

```
def match_extent(source_dataarray, target_dataarray):
    # Reproject/match the source DataArray to the extent, resolution, and CRS of the target DataArray
    matched_dataarray = source_dataarray.rio.reproject_match(target_dataarray)

    return matched_dataarray
```

Save the matched datasets as a separate variable for later use. In this case only the rainfall, slope, soil type, drainage density and soil depth still need to be matched as well as the socio economic criteria.

```
Soildepth2 = match_extent(Soil_depth, LC)
DD2 = match_extent(DD,LC)
RF2 = match_extent(RF,LC)
Slope2 = match_extent(Slope, LC)
Soiltype2 = match_extent(Soil_type, LC)
Awareness2 = match_extent(Awareness, LC)
Distance_roads2 = match_extent(Distance_roads, LC)
Distance_agri2 = match_extent(Distance_agri, LC)
Distance_streams2 = match_extent(Distance_streams, LC)
```

The matched datasets can also be saved through the .rio.to_raster() command. If that is the case the new datasets can be used immediately and the previous steps will not have to be repeated for every run. An example is shown below:

```
#RF2.rio.to_raster('RF_Mbooni.tif') # for saving the raster file
#RF2 = rioxarray.open_rasterio("RF2_Mbooni.tif", masked = True) # to open a saved raster file
```

Transfering Excel data to a dictionary

The following code creates a dictionary from the excel file, containing all the assigned weights derived from the AHP calculations. For each criteria on a row (slope, rainfall etc.). The values per column are extracted and saved. The names of the columns are derived from the column headers in the excel file. Thus, adding a column with a new name will automatically be read in by the dictionary when re-running the code.

```
def create_reclass_dict(excel_file):
    # Read Excel file into a pandas DataFrame
    df = pd.read_excel(excel_file)

    # Initialize an empty dictionary to store the criteria and their corresponding data
    reclass_dict = {}

    # Get all column names dynamically
    columns = df.columns

    # Identify the criteria column and other columns
    criteria_col = 'criteria'
    other_cols = [col for col in columns if col != criteria_col]

    # Initialize variables to store the current criteria and its corresponding data
    current_criteria = None
    current_data = {col: [] for col in other_cols}

    # Iterate over the rows in the DataFrame
    for index, row in df.iterrows():
        # Extract the criteria from the current row
        criteria = row[criteria_col]
```

```
        # Check if the criteria value is not empty
        if pd.notna(criteria):
            # If it's not empty, update the current criteria and store the previous criteria values
            if current_criteria is not None:
                # Clean up current_data before adding to reclass_dict
                cleaned_data = {}
                for col, values in current_data.items():
                    non_nan_values = [v for v in values if pd.notna(v)]
                    if len(non_nan_values) == 1:
                        cleaned_data[col] = non_nan_values[0]
                    elif len(non_nan_values) > 1:
                        cleaned_data[col] = non_nan_values
                reclass_dict[current_criteria] = cleaned_data

            # Update current criteria and initialize current_data for the new criteria
            current_criteria = criteria
            current_data = {col: [] for col in other_cols}

        # Append the data to the current lists
        for col in other_cols:
            current_data[col].append(row[col])

    # Add the last criteria and its corresponding data to the reclass_dict
    if current_criteria is not None:
        # Clean up current_data before adding to reclass_dict
        cleaned_data = {}
        for col, values in current_data.items():
            non_nan_values = [v for v in values if pd.notna(v)]
            if len(non_nan_values) == 1:
                cleaned_data[col] = non_nan_values[0]
            elif len(non_nan_values) > 1:
                cleaned_data[col] = non_nan_values
        reclass_dict[current_criteria] = cleaned_data

    return reclass_dict


excel_file = 'C:/Users/joram/Thesis GECP/Adjusted_dictionary.xlsx'
reclass_dict = create_reclass_dict(excel_file)
```

Reclassifying the excel data

All the data that we have collected so far has to be assigned a weight corresponding to a value in the data. The following function tells the model how the weights and ranges used for reclassification are read in from the dictionary. This function will be used in another function that does the reclassification and weighted linear combinaton of the available datasets.

```
def reclassify_data(map_data, criteria, reclass_dict, feature_weight_column):
    # Convert DataArray to NumPy array
    map_array = map_data.values

    # Create a copy of the map array to perform reclassification
    rec = map_array.copy()

    # Extract the reclassification information for the map
    print(f"Criteria: {criteria},{feature_weight_column}")
    map_reclass_info = reclass_dict.get(criteria, None)
    if map_reclass_info is None:
        print(f"Reclassification information for '{criteria}' not found in the dictionary.")
        return None  # Return None if reclassification info not found

    ranges = map_reclass_info['ranges']
    reclass_values = map_reclass_info[feature_weight_column]  # Use specified column for reclass values

    # Iterate over each range and reclassified value
    for i in range(len(ranges)):
        range_str = ranges[i]
        reclass_value = reclass_values[i]

        # Handle different range notations
        if range_str.startswith('<'):  # Handle '<' notation
            range_max = float(range_str[1:])
```

```
            rec[map_array < range_max] = reclass_value
        elif '-' in range_str:  # Handle '-' notation
            range_min, range_max = map(float, range_str.split('-'))
            rec[(map_array >= range_min) & (map_array < range_max)] = reclass_value
        elif range_str.endswith('>'):  # Handle '>' notation
            range_min = float(range_str[:-1])
            rec[map_array >= range_min] = reclass_value
        else:  # Handle simple numbers
            range_value = float(range_str)
            rec[map_array == range_value] = reclass_value

    return rec
```

Reclassify the maps

The following function reclassifies the data and combines the created maps for each level 1 criteria with eachother. The level 1 criteria maps include runoff potential and technique suitability for three different techniques. This means a total of 4 maps will be created. The steps are explained in the code below:

```
def reclassify_maps(map_list, reclass_dict, reclassify_data, feature_weight_column, criteria_weight_col
umn):
    WLCresults_dict = {}
    for map_data, criteria in map_list: # the function iterates over each dataset and corresponding cri
teria in the created list
        reclassified_map = reclassify_data(map_data, criteria, reclass_dict, feature_weight_column) # t
he datasets are reclassified using the assigned feature weights
        WLC_map = reclassified_map * reclass_dict[criteria][criteria_weight_column] # the resulting fea
ture weight maps are multiplied with the criteria weight assigned for eatch level 2 criteria i.e. slope
, rainfall etc.
        WLCresults_dict[f"Rec_{criteria}"] = WLC_map # the resulting maps with the combined feature and
criteria weights are saved in a dictionary
    WLC = sum(WLCresults_dict.values()) # All the level 2 maps are combined, resulting in the level 1 c
riteria map.
    return WLC
```

Before the maps can be created the datasets need to be linked to their corresponding criteria. For example the dataset on rainfall should be linked to the weights and values of the 'rainfall' criteria in our excel file. This is done for the level 1 runoff potential and technique suitability separately since they have different weights. It is important to note that when adding or removing criteria (such as slope, rainfall etc.) in the excel file, this list has to be manually altered as well. When running the 'reclassify_maps' function input on the criteria weights and feature weigths columns has to be set to the column header corresponding to the corresponding weights for each level 1 criteria.

```
# Create a list of datasets with their corresponding criteria names
map_list_runoff = [
    (Slope2, "slope"),
    (DD2, "drainage"),
    (RF2, "rainfall"),
    (LC, "landcover"),
    (Soiltype2, "soiltype"),
    (Soildepth2, "soildepth")
]

# Reclassify the maps for runoff potential and create the weighted linear combination map for runoff th
is already combines the biophysical and socio-economic criteria for the technique suitability
runoff_WLC = reclassify_maps(map_list_runoff, reclass_dict, reclassify_data, "runoff_fw", "runoff_cw")

map_list_techsuit = [
    (Slope2, "slope"),
    (RF2, "rainfall"),
    (LC, "landcover"),
    (Soiltype2, "soiltype"),
    (Soildepth2, "soildepth"),
    (Distance_roads2, "road_dist"),
    (Distance_agri2, "agri_dist"),
    (Distance_streams2, "stream_dist"),
    (Awareness2, "awareness")
```

```
]

# Reclassify the maps for technique suitability and create the weighted linear combination maps
pond_WLC = reclassify_maps(map_list_techsuit, reclass_dict, reclassify_data, "pond_fw", "techsuit_cw")
mitre_WLC = reclassify_maps(map_list_techsuit, reclass_dict, reclassify_data, "mitre_fw", "techsuit_cw"
)
sanddam_WLC = reclassify_maps(map_list_techsuit, reclass_dict, reclassify_data, "sanddam_fw", "techsuit
_cw")
```

You can plot the reclassified data maps to visually check for correctness:

```
# Plot the reclassified data (assuming the reclass variable is a 2D array)
plt.imshow(pond_WLC[0], cmap='viridis')  # Adjust the colormap as needed
plt.colorbar(label='Class')  # Add a colorbar for reference
plt.title('reclassified_slope_test 4 Map')
plt.xlabel('Column')
plt.ylabel('Row')
plt.show()
```

Weighted Linear Combination

This final step combines the reclassified maps and generates a final map showing the water harvesting potential suitability based on the selected criteria and their assigned weighting. This step combines the runoff potential, technique suitability (for each of the three techniques) and Boolean constraints maps defined earlier. Values of zero are turned to not a number values to improve the relative scaling of the colors when visualizing the maps.

```
def WLC(technique_suitability_map):
    Site_Potential = (runoff_WLC + technique_suitability_map)*road_mask*urban_area_array
    mask_zeros = (Site_Potential == 0)
    Site_Potential[mask_zeros] = np.nan
    return Site_Potential

WC_sanddam_suitability = WLC(sanddam_WLC)
WC_mitre_suitability = WLC(mitre_WLC)
WC_pond_suitability = WLC(pond_WLC)
```

To visualize a map before saving:

```
plt.imshow(WC_sanddam_suitability_runoff[0], cmap='viridis')  # Adjust the vaiable as as needed to what
map you want to see
plt.colorbar(label='Class')  # Add a colorbar
plt.title('Weighted combination runoff potential ')
plt.xlabel('Column')
plt.ylabel('Row')
plt.show()
```

Save the final map on your computer

If the plot looks good, the water harvesting potential maps can be saved and stored as a Geotiff file so it can be opened in QGIS. The weighted combination is a numpy array that doesnt contain a crs or extent for the data. Thus the crs, extent and resolution from an existing Geotiff file with the smallest resolution is extracted. In this case that is the Land Cover dataset with a 10x10 m resolution. The other suitability maps can be saved the same way by changing the variable 'site_potential_map' used as input in the function.

```
def site_pot_saveas_tif(site_potential_map, file_name, target_dataarray):
    with rasterio.open(target_dataarray) as src:
        transform = src.transform

    # Create the profile for the output GeoTIFF file
    profile = {
        'driver': 'GTiff',
        'height': site_potential_map.shape[1],
        'width': site_potential_map.shape[2],
        'count': site_potential_map.shape[0],
```

```
        'dtype': site_potential_map.dtype,
        'crs': 'EPSG:4326',
        'transform': transform,
        'nodata': None
    }
    # Write the NumPy array to the GeoTIFF file
    with rasterio.open(file_name, "w", **profile) as dst:
        for band_idx in range(site_potential_map.shape[0]):
            dst.write(site_potential_map[band_idx], band_idx + 1)  # Write each band to the correspondi
ng band in the GeoTIFF file

site_pot_saveas_tif(WC_pond_suitability, "WC_pond_newcode", LC_path)
site_pot_saveas_tif(WC_mitre_suitability, "WC_mitre_newcode", LC_path)
site_pot_saveas_tif(WC_sanddam_suitability, "WC_sanddam_newcode", LC_path)
```

2. EPA STORM WATER MANAGEMENT MODEL - VERSION 5.2 (Build 5.2.4) REPORT:

****

Element Count

****

Number of rain gages 1

Number of subcatchments ... 12

Number of nodes 29

Number of links 22

Number of pollutants 0

Number of land uses 0

****

Raingage Summary

****

Name	Data Source	Data Type	Recording Interval
Gage2	TS1	INTENSITY	60 min.

****

Subcatchment Summary

****

Name	Area	Width	%Imperv	%Slope	Rain Gage	Outlet
Road2	0.31	6.40	0.00	2.0000	Gage2	J13
S23	0.06	6.40	0.00	7.0000	Gage2	J31
S24	0.06	6.40	0.00	7.0000	Gage2	J34
S25	0.06	6.40	0.00	0.5000	Gage2	J37
S26	0.06	6.40	0.00	0.5000	Gage2	J38
S27	0.06	6.40	0.00	0.5000	Gage2	J39
S28	0.31	6.40	0.00	2.0000	Gage2	J42
S29	0.06	6.40	0.00	7.0000	Gage2	J44
S30	0.06	6.40	0.00	7.0000	Gage2	J46
S31	0.06	6.40	0.00	7.0000	Gage2	J48
S32	0.06	6.40	0.00	7.0000	Gage2	J50
S33	0.06	6.40	0.00	7.0000	Gage2	J52

****

Node Summary

****

		Invert	Max.	Ponded	External
Name	Type	Elev.	Depth	Area	Inflow
J10	JUNCTION	1114.00	0.20	0.0	
J13	JUNCTION	1123.00	0.20	0.0	
D1	JUNCTION	1114.00	0.00	0.0	
J29	JUNCTION	1106.03	0.20	0.0	
D2	JUNCTION	1106.03	0.00	0.0	
J31	JUNCTION	1113.03	0.20	0.0	
J32	JUNCTION	1098.96	0.20	0.0	
D3	JUNCTION	1098.96	0.00	0.0	
J34	JUNCTION	1105.96	0.20	0.0	
J35	JUNCTION	1091.89	0.20	0.0	
J36	JUNCTION	1084.82	0.20	0.0	
J37	JUNCTION	1098.89	0.20	0.0	
J38	JUNCTION	1091.82	0.20	0.0	
J39	JUNCTION	1084.75	0.20	0.0	
D5	JUNCTION	0.00	0.00	0.0	
D4	JUNCTION	0.00	0.00	0.0	

J42	JUNCTION	1123.00	0.20	0.0
J43	JUNCTION	1114.00	0.20	0.0
J44	JUNCTION	1113.03	0.20	0.0
J45	JUNCTION	1106.03	0.20	0.0
J46	JUNCTION	1105.96	0.20	0.0
J47	JUNCTION	1098.96	0.20	0.0
J48	JUNCTION	1098.89	0.20	0.0
J49	JUNCTION	1091.98	0.20	0.0
J50	JUNCTION	1091.82	0.20	0.0
J51	JUNCTION	1084.82	0.20	0.0
J52	JUNCTION	1084.75	0.20	0.0
Out4	OUTFALL	1077.00	0.20	0.0
Out8	OUTFALL	1077.00	0.20	0.0

****

Link Summary

****

Name	From Node	To Node	Type	Length	%Slope	Roughness
C1	J13	J10	CONDUIT	491.0	1.8333	0.0200
C2	J31	J29	CONDUIT	100.0	7.0172	0.0200
C10	J10	J31	CONDUIT	1.0	399.0047	0.0200
C11	J29	J34	CONDUIT	1.0	7.0172	0.0200
C12	J34	J32	CONDUIT	100.0	7.0172	0.0200
C13	J32	J37	CONDUIT	1.0	7.0172	0.0200
C14	J37	J35	CONDUIT	100.0	7.0172	0.0200
C15	J35	J38	CONDUIT	1.0	7.0172	0.0200
C16	J38	J36	CONDUIT	100.0	7.0172	0.0200
C17	J36	J39	CONDUIT	1.0	7.0172	0.0200
C18	J39	Out4	CONDUIT	100.0	7.7734	0.0200
C19	J42	J43	CONDUIT	491.0	1.8333	0.0200
C20	J43	J44	CONDUIT	1.0	399.0047	0.0200
C21	J44	J45	CONDUIT	100.0	7.0172	0.0200
C22	J45	J46	CONDUIT	1.0	7.0172	0.0200
C23	J46	J47	CONDUIT	100.0	7.0172	0.0200
C24	J47	J48	CONDUIT	1.0	7.0172	0.0200
C25	J48	J49	CONDUIT	100.0	6.9266	0.0200
C26	J49	J50	CONDUIT	1.0	16.2088	0.0200
C27	J50	J51	CONDUIT	100.0	7.0172	0.0200

C28	J51	J52	CONDUIT	1.0	7.0172	0.0200
C29	J52	Out8	CONDUIT	100.0	7.7734	0.0200

****

Cross Section Summary

****

Conduit	Shape	Full Depth	Full Area	Hyd. Rad.	Max. Width	No. of Barrels	Full Flow
C1	kavingo	0.20	0.87	0.13	6.40	1	1.49
C2	kavingo	0.20	0.87	0.13	6.40	1	2.92
C10	kavingo	0.20	0.87	0.13	6.40	1	22.01
C11	kavingo	0.20	0.87	0.13	6.40	1	2.92
C12	kavingo	0.20	0.87	0.13	6.40	1	2.92
C13	kavingo	0.20	0.87	0.13	6.40	1	2.92
C14	kavingo	0.20	0.87	0.13	6.40	1	2.92
C15	kavingo	0.20	0.87	0.13	6.40	1	2.92
C16	kavingo	0.20	0.87	0.13	6.40	1	2.92
C17	kavingo	0.20	0.87	0.13	6.40	1	2.92
C18	kavingo	0.20	0.87	0.13	6.40	1	3.07
C19	kavingo	0.20	0.87	0.13	6.40	1	1.49
C20	kavingo	0.20	0.87	0.13	6.40	1	22.01
C21	kavingo	0.20	0.87	0.13	6.40	1	2.92
C22	kavingo	0.20	0.87	0.13	6.40	1	2.92
C23	kavingo	0.20	0.87	0.13	6.40	1	2.92
C24	kavingo	0.20	0.87	0.13	6.40	1	2.92
C25	kavingo	0.20	0.87	0.13	6.40	1	2.90
C26	kavingo	0.20	0.87	0.13	6.40	1	4.44
C27	kavingo	0.20	0.87	0.13	6.40	1	2.92
C28	kavingo	0.20	0.87	0.13	6.40	1	2.92
C29	kavingo	0.20	0.87	0.13	6.40	1	3.07

****

Street Summary

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Street kavingo

Area:

0.0005	0.0018	0.0041	0.0074	0.0115
0.0165	0.0225	0.0294	0.0372	0.0460
0.0556	0.0662	0.0777	0.0901	0.1034

0.1176	0.1328	0.1489	0.1659	0.1838
0.2027	0.2224	0.2431	0.2647	0.2872
0.3107	0.3350	0.3603	0.3865	0.4136
0.4416	0.4706	0.5000	0.5294	0.5588
0.5882	0.6176	0.6471	0.6765	0.7059
0.7353	0.7647	0.7941	0.8235	0.8529
0.8824	0.9118	0.9412	0.9706	1.0000

Hrad:

0.0150	0.0300	0.0451	0.0601	0.0751
0.0901	0.1052	0.1202	0.1352	0.1502
0.1653	0.1803	0.1953	0.2103	0.2254
0.2404	0.2554	0.2704	0.2855	0.3005
0.3155	0.3305	0.3455	0.3606	0.3756
0.3906	0.4056	0.4207	0.4357	0.4507
0.4657	0.4808	0.5102	0.5396	0.5689
0.5981	0.6272	0.6563	0.6853	0.7143
0.7432	0.7720	0.8007	0.8294	0.8580
0.8865	0.9150	0.9434	0.9717	1.0000

Width:

0.0312	0.0625	0.0938	0.1250	0.1562
0.1875	0.2188	0.2500	0.2812	0.3125
0.3437	0.3750	0.4063	0.4375	0.4688
0.5000	0.5313	0.5625	0.5938	0.6250
0.6563	0.6875	0.7188	0.7500	0.7813
0.8125	0.8438	0.8750	0.9063	0.9375
0.9688	1.0000	1.0000	1.0000	1.0000
1.0000	1.0000	1.0000	1.0000	1.0000
1.0000	1.0000	1.0000	1.0000	1.0000
1.0000	1.0000	1.0000	1.0000	1.0000

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Analysis Options

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Flow Units .... CMS

Process Models:

Rainfall/Runoff .... YES

RDII .... NO

Snowmelt .... NO

Groundwater .... NO

Flow Routing .... YES

Ponding Allowed .... NO

Water Quality .... NO

Infiltration Method ...... CURVE_NUMBER

Flow Routing Method ...... KINWAVE

Starting Date 02/01/2013 00:00:00

Ending Date 02/01/2013 12:00:00

Antecedent Dry Days 0.0

Report Time Step 00:15:00

Wet Time Step 00:05:00

Dry Time Step 01:00:00

Routing Time Step .... 20.00 sec

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Control Actions Taken

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************************** Volume Depth

Runoff Quantity Continuity hectare-m mm

************************** --------- -------

Total Precipitation 0.086 70.000

Evaporation Loss 0.000 0.000

Infiltration Loss 0.031 24.950

Surface Runoff 0.055 44.886

Final Storage 0.000 0.183

Continuity Error (%) ..... -0.02

************************** Volume Volume

Flow Routing Continuity hectare-m 10^6 ltr

************************** --------- ---------

Dry Weather Inflow 0.000 0.000

Wet Weather Inflow 0.055 0.551

Groundwater Inflow 0.000 0.000

RDII Inflow 0.000 0.000

External Inflow 0.000 0.000

External Outflow 0.055 0.551

Flooding Loss 0.000 0.000

Evaporation Loss 0.000 0.000

Exfiltration Loss 0.000 0.000

Initial Stored Volume 0.000 0.000

Final Stored Volume 0.000 0.001

Continuity Error (%) ..... -0.076

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Highest Flow Instability Indexes

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All links are stable.

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Routing Time Step Summary

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Minimum Time Step : 20.00 sec

Average Time Step : 20.00 sec

Maximum Time Step : 20.00 sec

% of Time in Steady State : 0.00

Average Iterations per Step : 1.00

% of Steps Not Converging : 0.00

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Analysis begun on: Wed Jun 26 17:53:04 2024

Analysis ended on: Wed Jun 26 17:53:04 2024

Total elapsed time: < 1 sec