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Rooftop Rainwater Harvesting for Mombasa: Scenario Development with Image Classification and Water Resources Simulation

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Abstract: Mombasa faces severe water scarcity problems. The existing supply is unable to satisfy the demand. This article demonstrates the combination of satellite image analysis and modelling as tools for the development of an urban rainwater harvesting policy. For developing a sustainable remedy policy, rooftop rainwater harvesting (RRWH) strategies were implemented into the water supply and demand model WEAP (Water Evaluation and Planning System). Roof areas were detected using supervised image classification. Future population growth, improved living standards, and climate change predictions until 2035 were combined with four management strategies. Image classification techniques were able to detect roof areas with acceptable accuracy. The simulated annual yield of RRWH ranged from 2.3 to 23 million cubic meters (MCM) depending on the extent of the roof area. Apart from potential RRWH, additional sources of water are required for full demand coverage.

Keywords: Mombasa; roof rainwater harvesting; water supply; water demand; integrated water resources management; WEAP

1. Introduction

Rainwater harvesting is a technique used to collect and store rainwater e.g., from buildings, rock catchments, and land or road surfaces. The authors of [1–3] describe rainwater harvesting to be a dominant contributor for sufficing urban water demand. Rooftop rainwater harvesting (RRWH) refers to the collection and storage of water from rooftops [4]. The level of expertise required is low and ownership can be at a household level, making it easily acceptable to many people [1,5,6]. RRWH can support the water supply in almost any place either as a sole source or by reducing stress on other sources through water savings. The authors of [7] observed that the most important feature of RRWH at a domestic level is its ability to deliver water to households “without walking”. This is particularly important in developing countries where women and children have to walk over long distances to fetch water. RRWH can be one aspect of the adaptation of water supply systems to climate change [8]. In Sub-Saharan Africa, the reliability of RRWH systems for domestic water supply can be improved by the consideration of rainfall characteristics, e.g., the number of events above a certain threshold, wet spells, etc., and improved technical design [9].

The quantity and quality of the harvested rainwater greatly depend on the type of roofing material used. Hard surfaces like iron, concrete, and tiles produce the highest amount of collected water because they have high runoff coefficients. A study by [10] showed that galvanized steel yielded the best quality rainwater that met the WHO (World Health Organization) drinking water guidelines for chemical, physical, and biological parameters. Furthermore, the slope of the roof has considerable influence on the roof runoff [11]. The "first flush" is a criteria often used for the design of RRWH systems. It describes the amount of initial rainfall, which is needed after a dry period to remove contaminants such as particles, dirt, bird droppings, and insect bodies from the roof and the gutter. First flush diverters need to be incorporated into the system in order to protect the water quality in the collection tank from contamination [1,12]. Due to first flush diversion, the quantitative yield of RRWH systems is reduced.

The amount of water harvested can be calculated using the rational method commonly used for very small urban catchments if the roof area, amount of rainfall, and the roof runoff coefficient are known. The runoff coefficient represents losses due to evaporation and leakages [1,13]. A study in Jordan showed that the potential of rainwater harvesting is about 15.5 MCM per year, which allowed potable water savings ranging from 0.3% to 19.7% in 12 administrative units [1]. In the UK, an average water saving efficiency (ET) of 87% over a period of 8 months was reported for the total toilet flushing demand of an office building using RRWH. ET is the percentage ratio of rainwater supplied to the total estimated demand [14]. For Iran, [15] reported supply rates of 75% but for different durations of 40–75% of the time, depending on climatic conditions.

The use of collected rainwater for domestic purposes (tertiary uses like gardening) is a major component of water supply in the rural areas of South Africa, with 96% of 34,000 RWH tanks being located in rural regions [8]. When harvested water is used as potable water, the quality becomes paramount. The authors of [6] showed that most people in Zambia expressed interest in RRWH, but were concerned about its quality. Several other studies have shown that rainwater usually meets the WHO standards for physical and chemical parameters but may fail regarding the biological parameters, i.e., fecal and total coliform counts [10,16–18].

The key parameters for estimating RRWH water yield are roof area and rainfall. Another major factor is the estimation of roof areas, which is difficult especially for unplanned city areas. The authors of [10] list several methods:

- Sampling: representative samples of rooftops are obtained and extrapolated to the total area. This method is suitable for estimating roof areas for large areas;
- Multivariate sampling: correlations are drawn between additional variables (e.g., population) and roof area;
- Complete census: gives the most accurate results but involves the computation of the entire area of the rooftops in the area of interest by using statistical information like floor area, number of floors, and number of housing units;
- Digitization or image classification tools can be used from remotely sensed high-resolution images to compute the roof areas with a Geographical Information System (GIS).

The authors of [1] used a complete census to estimate roof areas in Jordan. Available information on the dwelling units such as different types of units, number of units per type, and average area per type were used to estimate the roof area in each of the governorates. The same approach was applied in another study in Seoul, South Korea to determine the city's rooftop photovoltaic (PV) potential [19]. The results were validated by using automated vector detection software. In a study of the informal settlement of Diepsloot near Johannesburg, South Africa, an automatic feature extraction (image classification) method was applied using aerial satellite imagery to extract roof areas with

80% accuracy [20]. Similarly, in the Kibera slums, Nairobi, feature extraction was successfully used to estimate rooftop areas, which was then used to derive the population in the slum [21].

The rooftop area is a crucial input for the incorporation of RRWH systems into water resource system models, which can be applied for the quantitative planning of water resources and the development of water policies. WEAP (Water Evaluation and Planning System), developed by the Stockholm Environment Institute (SEI, Stockholm, Sweden), is a planning tool extensively used in integrated water resources management. It is both a model for simulating water systems in an integrated manner (natural and manmade components/infrastructures) and a policy oriented decision-support system (DSS) [22]. Demand and supply sites are considered concurrently. WEAP follows the principle of the "scenario-based gaming approach" that has been developed to reduce water demand-supply conflicts within the area of interest [23]. The model uses scenarios to promote stakeholder involvement in the entire water resources planning and decision making process. The water resources system in WEAP is represented by demand sites, supply sites, catchments, withdrawal points, transmission links, wastewater treatment, environmental needs, and the generation of pollution. Depending on the need and data availability, WEAP simulates several aspects such as sectoral water demands, water allocation rights and priorities, ground and surface water flows, reservoir operations, and the assessment of vulnerability and cost-benefit analysis, amongst others.

The authors of [24] tested WEAP's demand management scenario evaluation in the water-stressed Olifants river basin, South Africa, and [25] applied WEAP in the study of the Upper Ewaso Ng'iro North Basin, Kenya to balance the water requirements of competing users against the available water resources in the basin. The study found that the use of WEAP improved the complex system of demand-supply of the basin. Applications of WEAP in the development of RRWH strategies have not been documented so far.

In this study, WEAP is applied to develop a variety of future scenarios of RRWH for the city of Mombasa by using projections of population growth and climate change. This research contributes to closing the gaps in the current methods of investigating RRWH by combining remote sensing with water resources modelling. The main objectives of the study are as follows:

- Determination and discrimination of rooftop areas and different roof types from high resolution satellite images;
- Setup and parameterization of an extended WEAP model with an implemented simple RRWH scheme for large scale planning;
- Implementation of future scenarios in WEAP and evaluation of their implications and potential for long-term management of the urban water supply.

2. Materials and Methods

2.1. Study Area and Data

Mombasa City is the second largest city in Kenya with an estimated 1.1 million inhabitants and a land area of 229.7 km^2. The city is located in the southern part of Kenya and is divided into four main areas: Island, South Mainland, West Mainland, and North Mainland (Figure 1).

The city experiences a tropical climate, which is hot and humid throughout the year with a mean daily minimum and maximum temperature of 22 °C and 30 °C, respectively. Annual precipitation is 1024 mm (data from 1984 to 2013 by the Kenya Meteorological Department). There are two rainy seasons. For the long rainy season between April and July, the average monthly rainfall is 134 mm. Between October and December, there are short rains with 100 mm average monthly rainfall. During the dry season, the average monthly rainfall is 37 mm with several months without rain. These variations in climatic conditions are attributable to the S-E and N-E monsoon winds and oceanic factors. The average monthly areal precipitation over the catchment was computed as the arithmetic mean of 10 rain gauge stations within the catchment. Annual potential evaporation exceeds the rainfall by magnitudes, which results in freshwater deficits during the dry periods. Reference evapotranspiration (ET0) data were obtained from the FAO (Food and Agriculture Organization of the United Nations) CLIMWAT 2.0 database using Moi International Airport, Mombasa station located at 4.03° S and 39.61° E. According to the Kenya Integrated Water Resources Management and Water Efficiency Plan, the country's annual average water availability in 2002 was 647 m^3 per capita. This ranks Kenya as a water scarce country according to [26], where below 1700 m^3/capita/year means water stress, below 1000 m^3/capita/year means water scarcity, and below 500 m^3/capita/year means absolute water scarcity. The situation in Kenya is predicted to worsen to 235 m^3 per capita by the year 2020 [27].

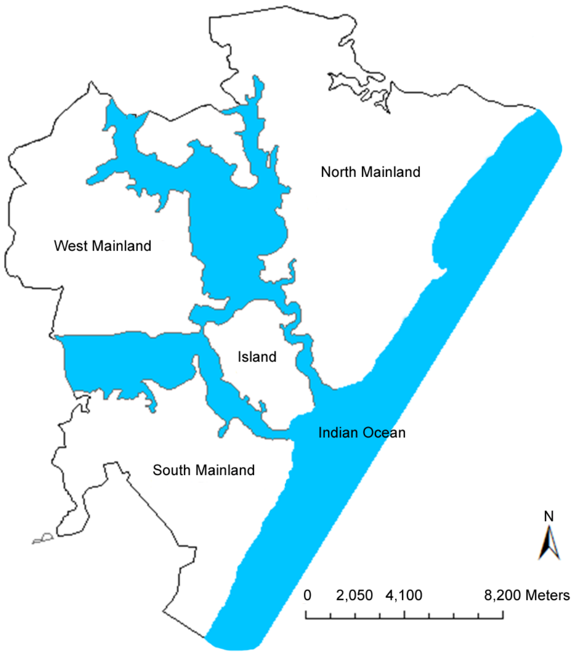

Figure 1. Map of Mombasa City showing the four main zones in the study area.

For future climate projections, downscaled precipitation and temperature data from the CIMP5 Global Climate Models (GCM) were used for the RCP 4.5 and RCP 8.5 pathways. The Intergovernmental Panel on Climate Change (IPCC) in its Climate Change 2014 Synthesis Report uses Representative Concentration Pathways (RCPs) to describe four different pathways of greenhouse gas concentration in the atmosphere, named after the change in radiative forcing in W/m^2 compared to pre-industrial times. In the case of RCP 4.5, the global mean surface temperature is likely to increase from 1.1 K to 2.6 K for 2081–2100 relative to 1986–2005.

The CIP datasets provide time series data (observed and downscaled projections) for different climatic variables for weather stations across Africa. The projections are compiled of downscaled products of 11 GCMs, summarized in Table 1. From the long-term historical (1971–2000) monthly ET0 data, future values can be estimated based on temperature changes. The authors of [28] suggested that for each degree rise in temperature, there is a corresponding 5% increase in ET0. The historical ET0 values were then corrected for both RCP 4.5 and RCP 8.5 to obtain future estimations.

In order to address model uncertainty, multi-model ensemble averages can be used; however, spatiotemporal information, especially of extreme events, can be lost [29,30]. The evaluation of bias (Table 1) and root mean square error (RMSE, not shown) between the downscaled RCP 4.5 and RCP 8.5 data (monthly series) and the observed historical data for the period from 1984 to 2013 showed that the bias for the GFDL-ESM2G model is lower than the ensemble bias, but the RMSE is lowest for the ensemble. Furthermore, it is not clear if the bias is non-stationary. Thus, using the model ensemble is preferable over using one single model. Multi-model means were used to generate future monthly rainfall series in this study.

Table 1. Details of the GCM models used and their bias (%) in the height of precipitation for the historical period from 1984–2013.

Model Name	RCP 4.5	RCP 8.5	Climate Modelling Institution/Centre
MIROC-ESM	−12.70	−15.70	National Institute for Environmental Studies, Japan
CNRM-CM5	−8.00	−8.10	Centre National de Recherches Meteorologiques, France
CAN-ESM2	−3.80	−2.30	Canadian Centre for Climate Modelling and Analysis
FGOALS-S2	−13.80	−19.70	Institute of Atmospheric Physics, Chinese Academy of Sciences
BNU-ESM	−16.00	−15.00	Beijing Normal University
MIROC5	9.20	8.90	National Institute for Environmental Studies, Japan
GFDL-ESM2G	0.40	2.70	Geophysical Fluid Dynamics Laboratory, USA
MIROC-ESM-CHEM	−15.50	−15.40	National Institute for Environmental Studies, Japan
GFDL-ESM2M	−1.20	−1.70	Geophysical Fluid Dynamics Laboratory, USA
MRI-CGCM3	26.90	22.20	Japan Meteorological Agency
BCC-CSM1-1	−10.90	−10.70	Beijing Climate Centre
Ensemble Average	−4.10	−5.00	-

Only domestic water demand was considered in this study. In order to estimate the per capita water consumption (water use rate), the recommended amounts for different categories according to the practice manual for water supply services [31] together with poverty level data for Mombasa City [32] were used (Table 2). The estimated water use rate is around 116 L per capita per day (LCPD).

Table 2. Domestic water use rates for Mombasa City.

Category	Persons	Water Use Rate	Remarks
	Percent	LCPD	
High Class Houses (HCH)	5.00%	250	Poverty level was 37.6% in 2013, remaining 62.4% assumed as 5% for HCH and 57.4% for MCH
Medium Class Houses (MCH)	57.40%	150	
Low Class Houses with individual connections (LCH_IC)	18.80%	75	
Low Class Houses without individual connections (LCH_WIC)	18.80%	20	
Weighted		116	-

Assuming the population will continue to grow at the average rate of 3.2% experienced between 1999 and 2009 [33], the population is expected to rise to 2.2 million people by 2035, leading to an increased water demand from 150,000 m^3/day to 320,000 m^3/day (Figure 2). The existing water supply to the city is 102,000 m^3/day from Mzima springs, Tiwi boreholes, Marere Springs, and the Baricho Wellfield managed by the Coast Water Services Board (CWSB). Considering system losses of around 47%, the current demand coverage is low [34,35].

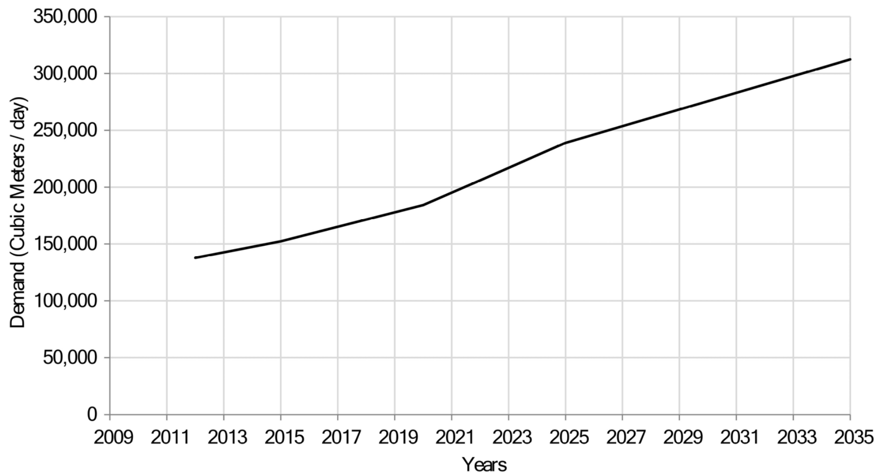

Figure 2. Water demand projections for Mombasa City [34].

The water supply master plan [34] identified several projects to help bridge the gap, mostly by the expansion of the Baricho Wellfield and Mzima Springs to full capacity, the construction of the 228,000 m^3/day Mwache Dam, and the acquisition of the Mkurumudzi dam. The plan considered RRWH, desalination, and wastewater reuse as alternative sources of water even though no estimates of quantities are available at this point. The biggest challenge is the large amount of investment capital required. It is further doubtful if the projects will fully cover the rising demand upon completion or if continued unsustainable extraction may lead to depletion. As a stopgap measure, the Mombasa Water and Sanitation Company (MOWASCO, Kenya) adopted water rationing of 6 h of supply per day [35]. Consequently, around 13,000 households use individual boreholes and hand-dug wells to supplement the conventional piped water supply [32]. Seawater intrusion due to over extraction may soon be a problem.

2.2. Overview of the Methodology

This study involved the following key steps: (i) data collection; (ii) image classification to estimate roof areas within Mombasa City; (iii) using estimated areas to calculate the rainwater harvesting potential and (iv) future scenario analysis with WEAP. In the scenario analysis, impacts of climate change on rainwater harvesting were also incorporated by using an ensemble of projections as shown in Table 1. The overall procedure and workflow is shown in Figure 3.

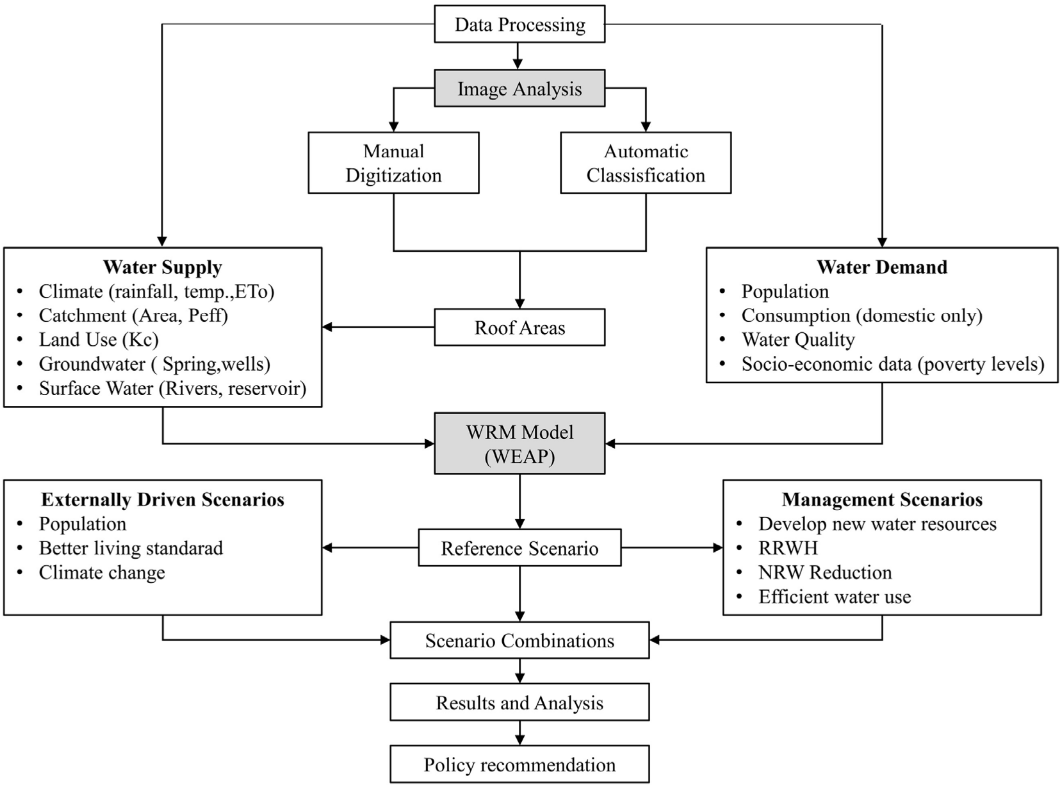

Figure 3. Methodological framework and workflow.

2.3. Roof Area Estimation

Roof areas were estimated manually by digitization and via automatic image classification using the ArcGIS® software by ESRI (Environmental Systems Research Institute, Redlands, CA, USA). The commonly used roofing materials in the city (tile, iron, and concrete making up 90% of the roof area) were considered. The following criteria were used to select the satellite images for this study from the Digital Globe foundation data for 2010 to 2014: (i) spatial resolution (high); (ii) cloud cover (low); and (iii) spatial coverage (extent of the study area covered). The best images in terms of spatial resolution were available from the satellite WorldView2 (WV2). Two WV2 images, which covered the whole study area, were selected for further processing and analysis (Table 3).

For manual digitization, only planned areas within the study area were targeted (referred to subsequently as the "control area") due to the ease of roof type identification for digitization. The other reason was that unplanned congested areas might not be suitable for RRWH since they lack the required space. Furthermore, the inhabitants may not be able to afford the system. Figure 4 shows the difference between planned and unplanned areas within the city.

Table 3. Selected images for processing (digitization and classification). The spatial resolution is after pan-sharpening.

Sensor Name	Acquisition Date	Cloud Cover (%)	Multispectral Bands	Off-Nadir (°)	Spatial Resolution (m)
WV-2	29/11/2013	0.6	8	23.10	0.5
WV-2	15/08/2013	8.9	8	6.60	0.5

(**a**) (**b**)

Figure 4. Planned areas (**a**) and unplanned areas (**b**) (informal settlements).

Automatic image classification was used to estimate roof areas for the whole city. The performance of the automatic classification was assessed using the results from the manual digitization for the common areas covered by both techniques. In this study, supervised classification using the Gaussian maximum likelihood (ML) method was adopted [36]. Six classes were used: tiled roofs, iron roofs, concrete roofs, vegetation, roads, and ground. In ML classification, the user has to provide training areas for each class. In the training phase, the parameters of a Gaussian mean and covariance matrix are estimated from the image feature vectors of each class. The feature vector of an image pixel collects all the spectral values observed at that pixel. In the classification phase, for each pixel to be classified, the feature vector of that pixel is used to compute the Gaussian probability density for each class using the parameters estimated in the training phase. This value is referred to as the likelihood for the feature vector to belong to the respective class. The pixel is assigned to the class of maximum likelihood.

2.4. The WEAP Model for Mombasa City

2.4.1. Conceptual Model Scheme

The main water infrastructure of the city of Mombasa was implemented into WEAP as a conceptual model (Figure 5). Subsequently, a description of the demand and supply elements was incorporated into the model:

(a) Demand site: Even though six different demand sites have been shown in the model (Mombasa City, Malindi Town, Kilifi Town, Kwale Town, Mariakani Town, and Voi Town), the study is focused only on Mombasa City and the rest are used to provide a complete picture of the sharing of water resources in the Coastal region.

(b) Water sources:

   (i) Current situation:

      ○ The city receives water from Mzima Springs, Baricho boreholes, Marere Springs, Tiwi-Likoni boreholes, and individual dug-out wells.
      ○ The rivers of Marere, Mwache, Sabaki, and Rare are some of the rivers that flow around Mombasa City. However, currently there is no abstraction from these rivers.

   (ii) Future (presented in the model):

      ○ The head flow generated from the Mwache catchment feeds the Mwache River. The Mwache Reservoir is expected to supply water from 2020.
      ○ The rooftop areas are implemented as five catchment nodes, corresponding to the roof areas for each of the four zones in Mombasa, namely North Mainland (NML), South Mainland (SML), West Mainland (WML), Island, and new buildings to be constructed in the future. The water, which is collected from the rooftops of these five catchments, is directed into one reservoir "RRWH", which is modelled as a local reservoir.
      ○ Operation of Mkurumudzi Dam in supplying water to Mombasa is expected to start from 2030 [34].
      ○ Return flows are not considered in the WEAP model because the city mainly depends on onsite wastewater disposal methods such as pit latrines, cesspits, and septic tanks that do not allow any return flows to the rivers, and the sewer system of the city drains to the Indian Ocean. The two wastewater treatment plants, Kizingo and West Mainland, serve a very small population and also discharge directly to the Indian Ocean.

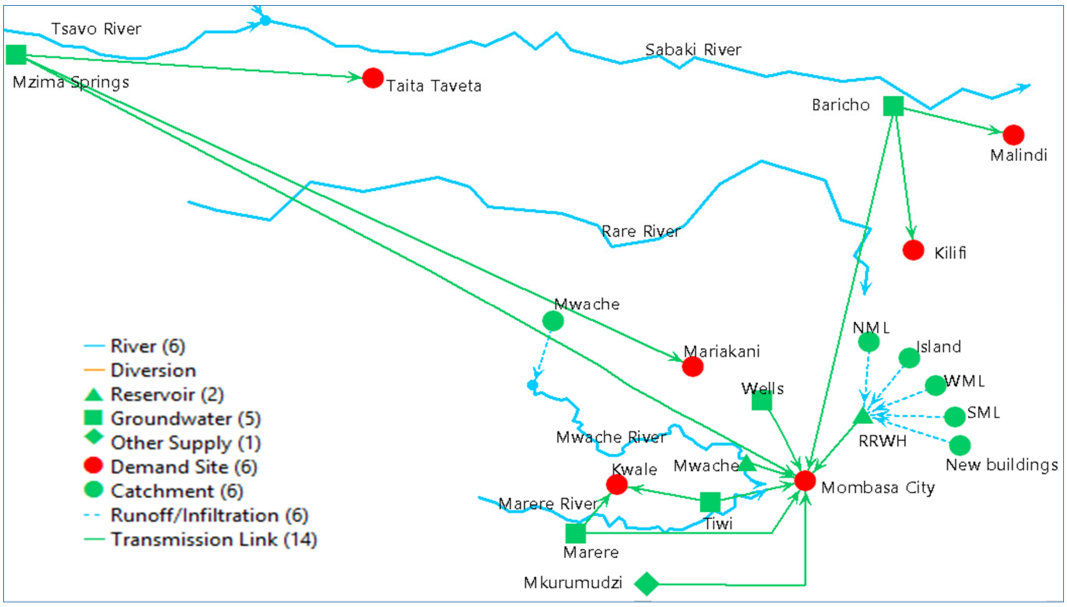

Figure 5. Conceptual model for Mombasa city (not drawn to scale).

2.4.2. Catchment and RRWH Implementation

The FAO rainfall runoff (simplified coefficient) method as implemented in WEAP was used in this study to simulate both natural and RRWH runoff generation from the catchments. This simple method calculates runoff by subtracting evapotranspiration from precipitation. The effective precipitation parameter ranges between 0% and 100% with 0% indicating that all precipitation produces runoff while 100% means that all precipitation is available for evapotranspiration.

The Mwache catchment covers approximately 2250 km^2 and the main vegetation in the catchment are deciduous forest and dry grasslands covering 38% and 62% of the area, respectively [37]. The FAO simplified method uses a crop coefficient K_c, which is relative to the reference crop for a particular land class type. The FAO Paper 56 for Irrigation and Drainage recommends K_c values for deciduous trees on grass between 0.8 and 0.9 and for deciduous trees with bare ground between 0.3 and 0.4. Assuming that dry grasslands are similar to bare ground, the K_c value was set to 0.5, while the effective precipitation was set to 65%. For the Mwache Reservoir, a storage capacity of 118.7 MCM was used, while the volume elevation curve and estimated monthly average reservoir evaporation were obtained from [37].

The five rooftop catchments represent the total rooftop area of each of the four zones of Mombasa with existing buildings (summarized as one catchment each) and one zone with new buildings. The size of the RRWH catchment area was determined from the roof identification by image classification depending on the scenario of roof usage considered. The precipitation of the RRWH catchments was corrected for the first flush loss occurring at the beginning of rainfall. According to the Texas Manual on Rainwater Harvesting [38], the first flush loss amounts to 1 Gallon (1 Gallon = 3.785 Liters) for every 100 Square feet (1 Square foot = 0.092 Square meters) of roof area, which is equivalent to 0.4 mm of rainfall. The average monthly number of rainy days from the observed data from 1984 to 2013 was used to estimate the average monthly first flush loss, which was then subtracted from the precipitation input. The runoff coefficients for the different roof materials were taken from [7], using 0.9 for iron and 0.8 for tile and concrete. Mombasa roofs have different slopes, hence there is no characteristic pitch. The roof pitches could not be obtained from the satellite images used in this study. Stereo images were not available, and an exhaustive ground observation was not possible. Similar to [1] and other studies, the roof angle could not be considered and average runoff coefficients were used based on the material alone.

The water collected from the rooftops of all five catchments is diverted into one reservoir in the WEAP model as a conceptual representation of the RRWH storage systems. This simplification was introduced because the potential of RRWH for additional water supply is investigated on a larger scale here. In reality, there can be centralized and/or decentralized solutions for the storage of the harvested water. The efficiency of different storage techniques, however, is not a subject of this study. The RRWH system storage was modelled using a single reservoir, which receives runoff from the five RRWH catchments (NML, SML, WML, Island, and new buildings) through runoff links. Since the target is to collect all of the rainwater, the storage capacity is set as unlimited. There is no evaporation from the RRWH reservoir, because it is simply a conceptual representation of closed storage tanks in WEAP. Thus, a fictitious volume elevation curve is used (1 m rise in level for each additional 1 m^3). Operation-wise, the top of the conservation zone is set to the storage capacity and no dead storage is provided since all of the water in the tank is assumed to be available for use depending on the demand requirements.

Flow from the supply sources to the demand sites was implemented using transmission links with the consideration of losses due to leakages. Losses were taken as 47% based on the latest Impact Report No. 7 [35] and 20% was assumed for the RRWH structures, representing the losses occurring mainly in the gutters, downpipes, and storage tanks.

2.4.3. Baseline Scenario

Due to the availability of suitable satellite images for roof area estimation and observed precipitation data, the year 2013 was chosen as the base year (Current Accounts Year in WEAP). For the last year of the scenarios, the year 2035 was selected in order to coincide with the last year of the Coast Water Services Board planning horizon and to be after the end of the Government of Kenya's Vision 2030 development blueprint. The temporal resolution of the model was set to yearly with monthly time steps. Parameters that might be subject to changes under different scenarios such as population growth rates, water use rates, non-revenue water (NRW) levels, or crop coefficients (K_c) were further implemented as "Key Assumptions". The data used in the current accounts is compiled in Table 4.

Table 4. Input data for current accounts.

Source	Parameters	Value	Reference
Roof	Crop coefficient, K_c	0.1	Lower than bare soil (0.3 from FAO Paper 56)
	Effective rainfall, Peff	Iron-10% Tile and concrete-20%	Reasonable assumptions
Groundwater sources: Baricho, Mzima, Tiwi, Marere, Ind. Wells	Storage Capacity Initial Storage (MCM) Max Withdrawal (MCM) Recharge	Unlimited 80, 82, 7.3, 7.3, 16 Same as initial storage 83, 405, 21, 15, 23	Reasonable assumptions Mumma and Lane, 2010; [34]; JBG Gauff Ingenieure, 1995; Samez Consultants, 2008; Sincat/Atkins Consultants, 1994; Fichtner/Wanjohi Consultants, 2014
Mwache Dam	Storage capacity (MCM) Evaporation Rate Effective rainfall, Peff Crop coefficient, K_c	118.7 Monthly rates 65% 0.5	[37]
Transmission	Loss in transmission links Loss in RRWH transmission	47% 20%	[35] Reasonable assumptions

2.4.4. Future Scenarios for Mombasa

The Reference Scenario inherits all of the information and data set up under the Current Accounts year (2013) and extends it over the entire timeframe (2014–2035) with no interventions to improve demand coverage. Here, the water supply remains at 102,000 m^3/day from the main sources and 29,143 m^3/day from the individual wells, with losses (NRW) of 47%. The per capita water consumption rate and population growth rate remain at 116 LCPD and 3.2% throughout the period, respectively.

Future scenarios for Mombasa are created to investigate the combined influence of (i) possible future changes of external factors, which are out of direct control of the water managers and which are uncertain, such as population growth, socio-economic dynamics, and climate change; and (ii) management decisions such as construction and expansion of more water sources, reduction of NRW, and implementation of RRWH. The growth assumptions for future scenarios are summarized in Table 5.

Table 5. Growth assumptions for Future Scenarios (External Factors).

Parameters	Value	Reference
High Population Growth (HPG) rate	4.2%	Kenya National Bureau of Statistics (2009), BCEOM/Mangat (2011) and Mombasa County (2014)
Low Population Growth (LPG) rate	1.9%	
Increased water consumption due to better standard of living	116 LPCD to 155 LPCD	

The scenarios driven by management decisions were: (i) Development of New Water Sources (NWS); (ii) Reduction of Non-Revenue Water Strategy (NRWS) where the NRW levels decrease from

47% to 20% to meet the Water Services Regulatory Board (WASREB) sector target; (iii) Efficient Water Use (EWU) where per capita consumption decreases from 116 LPCD to 93 LPCD; and (iv) RRWH scenarios where rainwater harvesting is practiced. The estimated allocated future flows to different parts of the city are shown in Table 6. The following five RRWH scenarios are investigated: (i) All existing roofs are used (RRWH_1); (ii) only new roofs are used (RRWH_2); (iii) selected existing buildings are used (RRWH_3); (iv) selected existing roofs and all new roofs are used (RRWH_4); and (v) all existing roofs and all new roofs to be used (RRWH_5). The different combinations of scenarios used in the model are shown in Table 7.

Table 6. Planned future flows to Mombasa City in m^3/day [34].

Source	Capacity	Current	Phase I		Phase II	Phase III	
		2014	2017	2020	2025	2030	2035
Baricho	175,000	60,000	82,000	55,805	106,594	80,395	80,395
Mzima	105,000	24,000	24,000	15,292	13,370	59,050	59,050
Marere	12,000	8000	8000	7135	6051	3173	3173
Tiwi	13,000	10,000	10,000	10,000	10,000	8662	8662
Mwache	228,000	0	0	95,595	102,859	145,838	145,838
Mkurumudzi	20,000	0	0	0	0	15,191	15,191

Table 7. Scenario combinations under the normal population growth rate.

Scenario Combination	Description
NWS/RRWH_4	Existing system with new water sources developed (NWS) and RRWH_4 (using all new roofs) implemented
NWS/NRWS	Existing system with NWS and non-revenue water (NRWS) reduction strategy implemented
RRWH_4/NRWS	Existing system with both RRWH_4 and NRWS strategy implemented
NWS/EWU	Existing system with new water sources developed and water use efficiency (EWU) improved
RRWH_4/NRWS/EWU	Existing system without new water sources developed but RRWH_4, NRWS, and EWU implemented
NWS/NRWS/EWU	Existing system with new water sources developed and NWRS and EWU implemented, but no RRWH_4
NWS/RRWH_4/NRWS/EWU	All strategies implemented (new water sources, RRWH, non-revenue water reduction, and efficient water use)

3. Results and Discussion

3.1. Determination of Rooftop Area

Figure 6 shows a visual comparison of a part of the classified image with the ground truth obtained by digitization (only roof classes shown). The visual assessment reveals that the classifier performed well in separating the different classes of roof material. The extent or degree of accuracy however cannot objectively be assessed by visual interpretation alone.

The results of manual digitization suggest that the selected control area has around 3 km^2 of suitable roofs for RRWH (based on non-congested planned areas). Table 8 summarizes the results of the manual digitization for the selected areas. Apart from representing one of the scenarios, the manual digitization was further used to assess the performance of the automatic classification technique. The total roof area within the city was found to be approximately 28 km^2 based on automatic image classification with 18.1 km^2 of iron, 5.6 km^2 tile, and 4.3 km^2 concrete (Table 9).

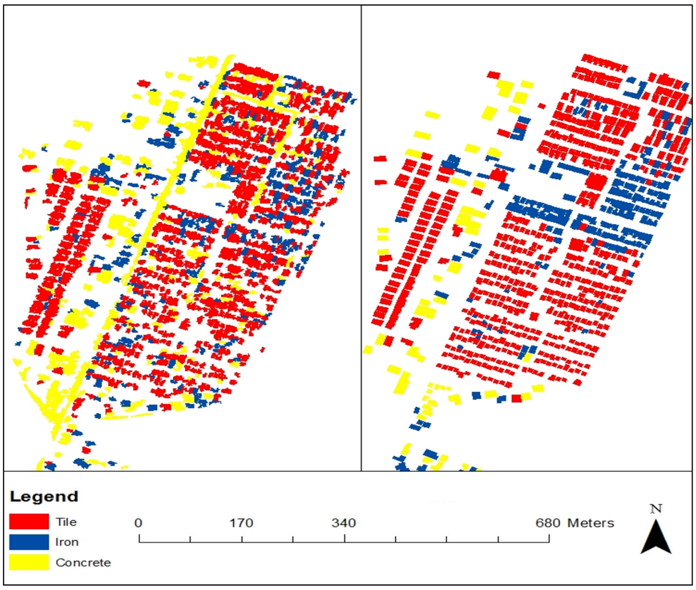

Figure 6. Comparison between manually digitized and automatic classification for a portion of the classified area (only roofing materials shown).

Table 8. Area of different roof materials (in m^2) resulting from the manual digitization for the selected control areas.

Zone	Tile	Iron	Concrete	Total
Island	610,339	114,854	298,186	1,023,379
North Mainland	1,139,521	313,385	418,285	1,871,192
South Mainland	42,367	34,158	2011	78,536
West Mainland	76,738	80,726	8439	165,902
Total	1,868,966	543,123	726,921	3,139,009

Table 9. Area of different roof materials (in m^2) resulting from automatic image classification for the whole investigation area.

Area	Tile	Iron	Concrete	Total
Island	1,686,856	2,874,256	1,300,597	5,861,709
North Mainland	2,115,315	6,550,999	1,934,685	10,600,999
South Mainland	66,500	3,644,231	116,438	3,827,169
West Mainland	1,759,221	5,044,778	944,178	7,748,177
Total	5,627,892	18,114,264	4,295,898	28,038,054

One common way to assess the accuracy of classification is to construct a confusion matrix [39]. The matrix indicates how the classifier confuses between the different classes. Three types of accuracies can be derived from the confusion matrix: overall accuracy (OA), user's accuracy (correctness, UA) and producer's accuracy (completeness, PA). OA is the percentage of pixels assigned to the correct class. For each class, UA gives the percentage of pixels assigned to that class that also belong to that class in the reference, whereas PA gives the percentage of pixels of that class in the reference that were also assigned to that class by the classification procedure.

Table 10 shows the confusion matrix generated from the image classification process. As suspected, the classifier has a significant problem in differentiating concrete from the background, for example, 3.6% of the background pixels are incorrectly labelled as concrete. Error analysis showed that the OA of the image classification was 88.6%. However, this high level of OA could be misleading because the background class constituted a larger percentage of the total area compared to the other three classes.

It was therefore necessary to check the producer's accuracy and user's accuracy for each class. The PA were 92.9%, 58.5%, 37.4%, and 54.3% for the background, tile, iron, and concrete, respectively. The UA on the other hand were 95.7%, 59.1%, 51.3%, and 22.2% for the background, tile, iron, and concrete, respectively. The high OA was due to the high values of PA and OA obtained for the background. When computing the confusion matrix for the differentiation of the background and roof (all materials), the PA is 93.0% for the background and 63.8% for the roof, and the UA is 95.6% for the background and 51.5% for the roof. Moreover, this reveals that the classifier had difficulties in differentiating some classes, especially tiles or concrete, from the background. This is largely because concrete roofs and roads have similar spectral properties. An idea to overcome this problem could be to use a Digital Surface Model, which can be derived from stereo images [40] by techniques such as semi-global matching [41]. Despite some further potential to improve the image classification, the OA of 88.6% indicates that the automatic classification was acceptable. Therefore, the results were used as input for the WEAP model.

Table 10. Confusion matrix based on selected pixels in the classified image.

		Class in Results (Automatic Classification) (All Values in %)					
		Background	**Tile**	**Iron**	**Concrete**	**Sum**	**Completeness**
Class in Reference (Digitized)	Background	83.3	1.7	1.0	3.6	89.6	92.9
	Tile	1.8	2.8	0.1	0.2	4.8	58.5
	Iron	1.0	0.2	1.2	0.8	3.2	37.4
	Concrete	1.0	0.1	0.0	1.3	2.4	54.3
	Sum	87.0	4.8	2.3	5.9	-	-
	Correctness	95.7	59.1	51.3	22.2	-	88.6

3.2. WEAP Scenarios

The projected water demand up to the year 2035 for Mombasa City under the different scenarios, namely the reference scenario, better living standards (BLS), high population growth (HPG), low population growth (LPG), and efficient water use (EWU), are shown in Figure 7.

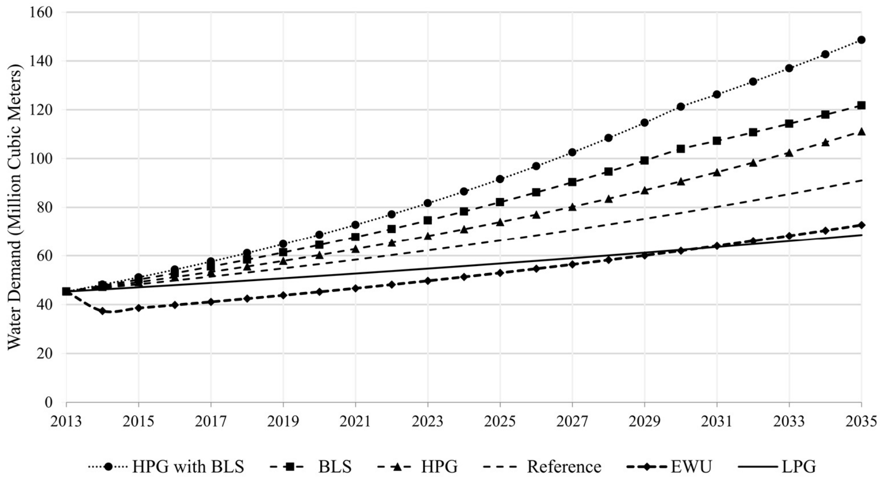

Figure 7. Annual Water demand projections in Million Cubic Metres (MCM) for different scenarios. Abbreviations: better living standards (BLS), high population growth (HPG), low population growth (LPG), efficient water use (EWU).

The simulated demand coverage in 2035 for Mombasa City with no interventions decreases from 54% in 2014 to 28% for the reference scenario. The demand coverage is lower under the HPG with BLS scenario (17%), BLS (21%), and HPG (23%) scenarios, but slightly improves in the EWU (35%) and LPG (37%) scenarios. As water demand coverage for Mombasa City continues to dwindle, it was necessary to investigate the impact of RRWH if practiced under different implementation scenarios. Figure 8 illustrates the amount of rainwater that can potentially be harvested under the various rainwater harvesting scenarios.

The results show that the potential of RRWH varies greatly between the different management scenarios. The inter-annual variability within all the scenarios is due to variations in precipitation over the years. The highest amount of rainwater can be provided under the scenario RRWH_5 (supply of over 28 MCM by 2035). The other scenarios RRWH_1 to RRWH_4 yield between 2.3 MCM and 20 MCM by 2035. These results suggest that the potential of RRWH in the city greatly depends on the strategy adopted by the city water management.

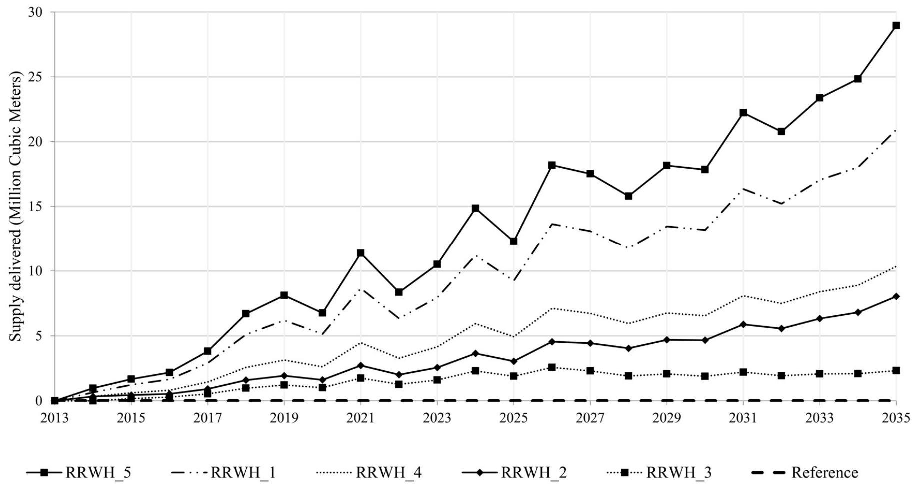

Figure 8. Additional water supply delivered under different RRWH scenarios for Mombasa City.

The average monthly demand coverage using the existing supply and RRWH as the only additional strategy is shown in Figure 9. For the reference scenario where no intervention was made to the existing system, the average monthly demand coverage for the whole 2014–2035 period is around 40%. The results clearly show that implementing RRWH improves the water supply situation. Based on the bimodal rainfall pattern in Mombasa City, higher demand coverage is achieved within the rainy months every year. In the month of May, which records the highest rainfall, the average monthly demand coverage increases to 46%, 53%, 58%, 75%, and 84% for RRWH_3, RRWH_2, RRWH_4, RRWH_1, and RRWH_5, respectively.

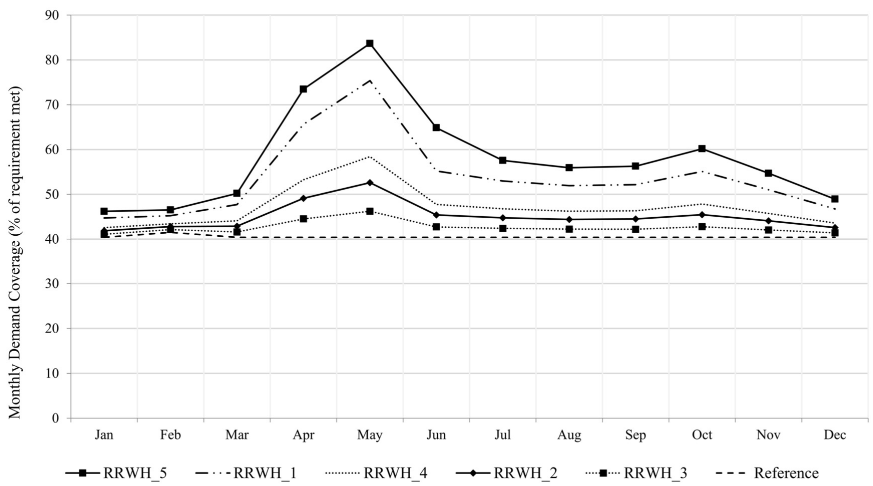

Figure 9. Average monthly demand coverage of RRWH combined with the existing system (2014–2035).

Apart from the RRWH strategies, the other possible management scenarios considered were the development and expansion of new water sources (NWS), efficient water use (EWU), and reduction of non-revenue water (NRWS). In terms of the water supply delivered for the whole period from 2013 to 2035, the responses of the system are presented in Table 11. The NWS scenario, which involves the expansion of existing water sources and the development of new ones, provides the best strategy, which increases the supply by 470 MCM throughout the whole study timeframe. The other strategies result in increases of the supply ranging between 34 MCM to 295 MCM over the same period. The UWE scenario does not increase the supply but reduces the demand, hence its effect can only be seen under demand coverage or unmet demand. Figure 10 indicates that no single strategy will completely solve the water scarcity in the city. Thus, a combination of different strategies is recommended.

Table 11. Total supply delivered under different management scenarios (2013–2035).

Supply/Demand Strategy	Total Supplied (MCM)	Supply Increase (MCM)
New water sources (NWS)	1055	470
All existing and new buildings (RRWH_5)	880	295
Non-Revenue Water Reduction (NRWS)	837	252
All existing buildings (RRWH_1)	804	219
Selected existing and all new buildings (RRWH_4)	696	111
Only new buildings (RRWH_2)	661	76
Selected existing buildings (RRWH_3)	619	34
Efficient Water Use (EWU)	585	0
Reference	585	0

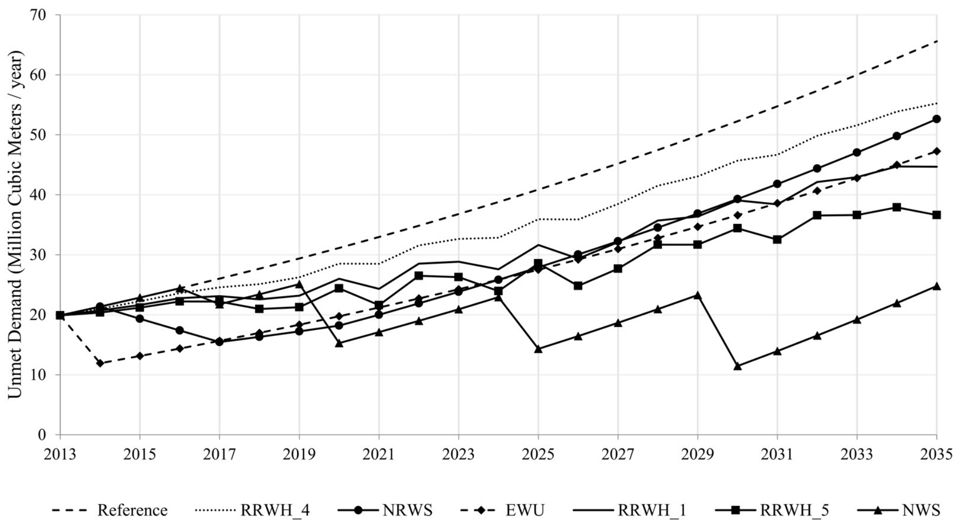

Figure 10. Unmet demand for Mombasa City for different management strategies (see Table 11 for acronym definitions).

For the combined scenarios, only the most feasible RRWH_4 is used, where only selected existing buildings and all new buildings implement RRWH. The results (Figure 11) show that before the year 2017, none of the combined strategies will meet the demand. Subsequently, only two scenario combinations, namely NWS/NRWS/EWU and NWS/RRWH_4/NRWS/EWU cover the demand fully from 2017 to the end of the simulation period. Consequently, meeting the demand before 2017 is not achievable by any of the investigated management strategies.

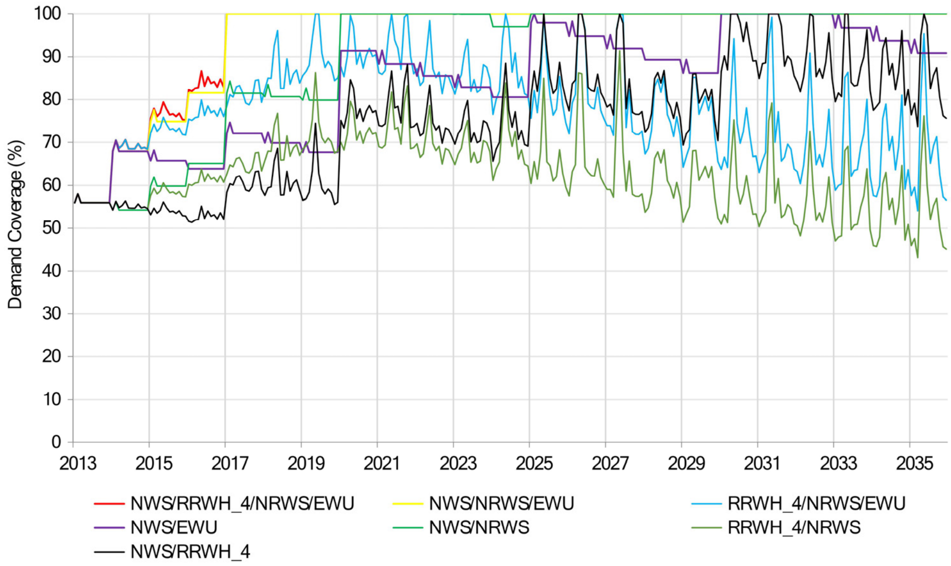

Figure 11. Demand coverage under different scenario combinations for Mombasa City.

The availability of water resources greatly depends on climatic conditions and the success of RRWH depends largely on the available precipitation. In this study, the reference scenario and other scenarios were based on the RCP 4.5 stabilization scenario with RCP 8.5 being used to understand how the system responds to a different climate change forcing scenario. The results show that the effect of predicted climate change considering RRWH_4 and RRWH_5 is not very appreciable (Figure 12). Considering RRWH_4, the average annual amount of rainwater harvested between 2014 and 2035 for RCP 4.5 and RCP 8.5 are 4.8 MCM and 4.7 MCM, respectively. The reduction of 2.5% is small compared to the uncertainty of the different GCM predictions. The two-sample *t*-test gives a *p*-value of 0.93, indicating no significant difference in the means at the 5% significance level. For RRWH_5, the average annual amount of rainwater delivered is 12.7 MCM for RCP 4.5 and 12.4 MCM for RCP 8.5, with a *p*-value of 0.94. Based on the results it can be concluded that the predicted effect of climate change on RRWH is negligible for Mombasa City.

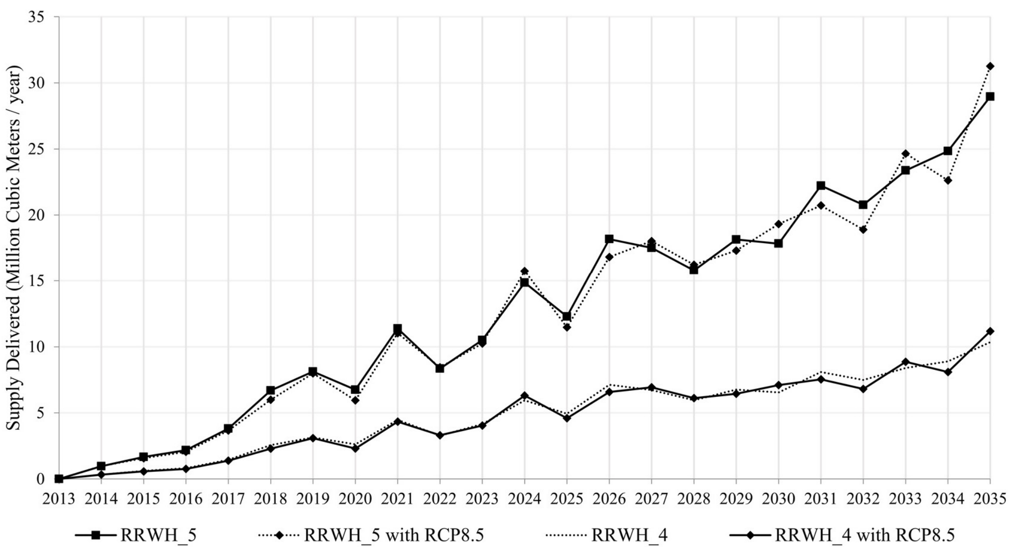

Figure 12. Effect of climate change on the RRWH_4 and RRWH_5 scenarios.

4. Conclusions

Overall, the results from this study show that the water demand for Mombasa City is expected to rise within 2014–2035 mainly due to socio-economic factors. Five possible RRWH implementation scenarios were established and investigated using a WEAP model. Using RCP 4.5 future climate data, the results showed that the average demand coverage improves significantly, mostly during the rainy season.

Comparing all of the management strategies, the development of new water sources (NWS) would lead to the highest demand coverage over the planning period up to 2035. None of the proposed strategies implemented in isolation will lead to full demand coverage. This means that NWS identified under the water supply master plan (2013) can only meet the demand if implemented alongside other strategies.

By combining the various strategies (only RRWH_4 used in the combinations) under a normal population growth rate, it was found that no combination of methods can cover the full demand for the entire 2014–2035 period. Under the highest water demand scenario, i.e., high population growth with better living standards, the city's water demand can never be met even under the most favorable climatic conditions. Any RRWH strategy is able to remedy but not completely solve the problem. The challenge to water managers is to make use of a combination of water supply sources, and to develop other strategies beyond those considered here e.g., river abstractions, desalination, or water reuse.

The results show that climate change will most likely not have an impact on the quantity of water delivered by RRWH systems in Mombasa. This means that RRWH can serve as a robust strategy against climate change effects.

The combination of image classification and water resource modelling proved to be a suitable tool for the development of roof rainwater harvesting strategies under changing water availability and demand. The efficiency of automatic image classification can be further improved by including height information obtained from stereo images.

This study mostly addressed the first part of RRWH supply systems at a larger scale and from a more technical perspective. Conveyance and storage systems have not been investigated in detail, and for the practical implementation of RRWH, socio-economic aspects and water quality issues should be considered as well. Additional studies are recommended on building conditions, roof rainwater quality, tank optimization/design, costs and fundraising, awareness creation, and sensitization of the city residents regarding RRWH. Another interesting area that could be investigated in the future is hydrological aspects, such as the benefit of RRWH for flood risk reduction and the effect of RRWH on groundwater recharge.

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