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PREDICTING WATER DEMAND AND EFFICIENT USE IN MBAGATHI SUB-CATCHMENT USING WEAP MODEL

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ABSTRACT

Water systems have complex component interactions necessitating development and evaluation of management amidst uncertainties of climate and constrained natural resources. Conceptual models such as Water Evaluation and Planning (WEAP) when used are effective in planning and management as they forecast future effects of resource use efficiently for sustainable development at sub-catchment level by using existing hydrological and climate data. Conceptual models act as corrective measures to poor water resources management. This study aimed at using WEAP model to forecast future demand by analyzing scenarios on efficient water use in Mbagathi sub-catchment. To run WEAP model, a GIS map of the sub-catchment, climate data, hydrological and water demand data were used. High population growth and prolonged drought were predicted to increase water demand. Re-use though not optimally practised, was predicted to reduce unmet water demand by 51-59% compared to reduced conveyance losses of 4-12% throughout the year. The study concluded that wastewater re-use could be a viable solution to challenges experienced in Mbagathi sub-catchment and ultimately, the area's sustainability.

Keywords: WEAP model, Mbagathi sub-catchment, water demand, groundwater, surface water, scenarios, sustainability

INTRODUCTION

Despite its fundamental importance, water is a scarce resource making it impossible to maximise on its net returns for sustainable growth. Poor configuration of irrigation systems, climate variability, subsidy policies and production costs aggravate the situation making water expensive to manage and use (Mounir *et al.,* 2011). Allocation of the resource, policies on water sustainability and environmental quality are issues of priority in water management (Uitto, 2004; Conway *et al*., 2009). Using models such as WEAP, helps simulate available water resources effectively and reliably, as well as analysing the consequences of mutual-conflicting interests of divergent water allocation and management, which results to sustainable development (Alfarra, 2004; Kinoti *et al*., 2010).

The threat of water scarcity due to over-exploitation and a growing population in Mbagathi sub-catchment as reported by Katana *et al*. (2013) necessitates WEAP modelling to better plan and manage the resource sustainably. In addition, the region suffers extended drought, over-abstraction of water, poor water conservation strategies and corruption among water management enforcers (Koskei & Ngigi, 2013). Timing to reverse these challenges necessitated the current study whose objective was to forecast water demand and efficient use in Mbagathi sub-catchment now and unto the future using WEAP model.

MATERIALS AND METHODS

Location of Study Area

The study was conducted in Mbagathi sub-catchment of Athi catchment, which traverses Nairobi, Kajiado and Machakos counties and is situated in North- South grid 240000-269000 and East West grid 9855000-984300. The sub-catchment covers an area of 166km^2 and has Keraraponi, Kisembe, Mokoyeti, Kandisi and Kiserian streams as major tributaries of the main river, Mbagathi River that originates from Ngong hills at an altitude of 1980m above sea level and flows through the industries to Athi River town (Krhoda, 2002; Kihara, 2002). During wet seasons, Mbagathi River flow is estimated at 0.6m^3/s and 0.01m^3/s in dry seasons (Krhoda, 2002). Kiserian dam has been constructed along Mbagathi River to retain excess surface flow. Nairobi Aquifer Suite supplies Mbagathi sub-catchment with groundwater. Rapid population growth and unplanned settlements have resulted to land degradation upstream of the sub-catchment negatively affecting the quantity and quality of its fresh water resources and leading to unsustainable development. Inter-tropical Convergence Zone (ITCZ) controls the climate of the area, as in most parts of Kenya, as the winds and pressure belts shift (FAO, 1998; Karuku *et al*., 2014).

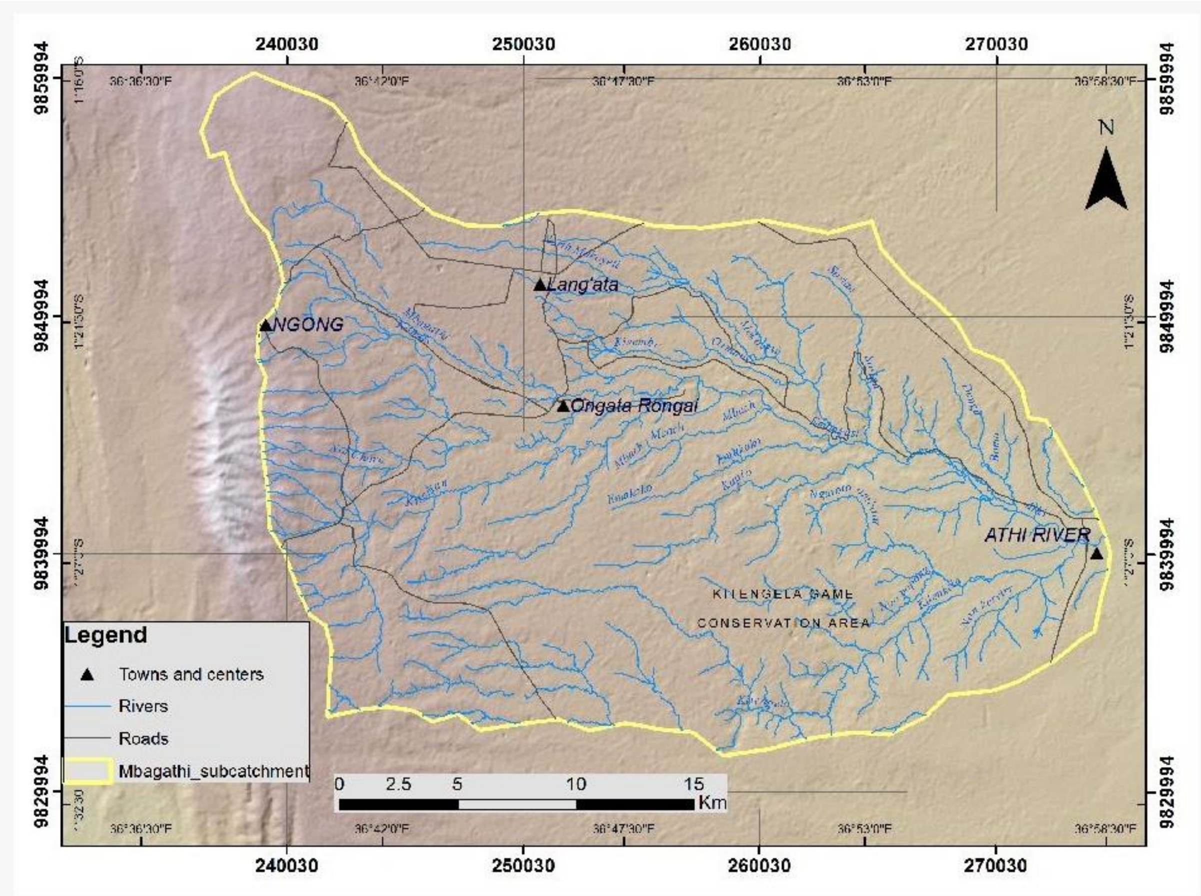


Figure 1: Mbagathi sub-catchment map (Researcher, 2016).

DATA REQUIREMENTS

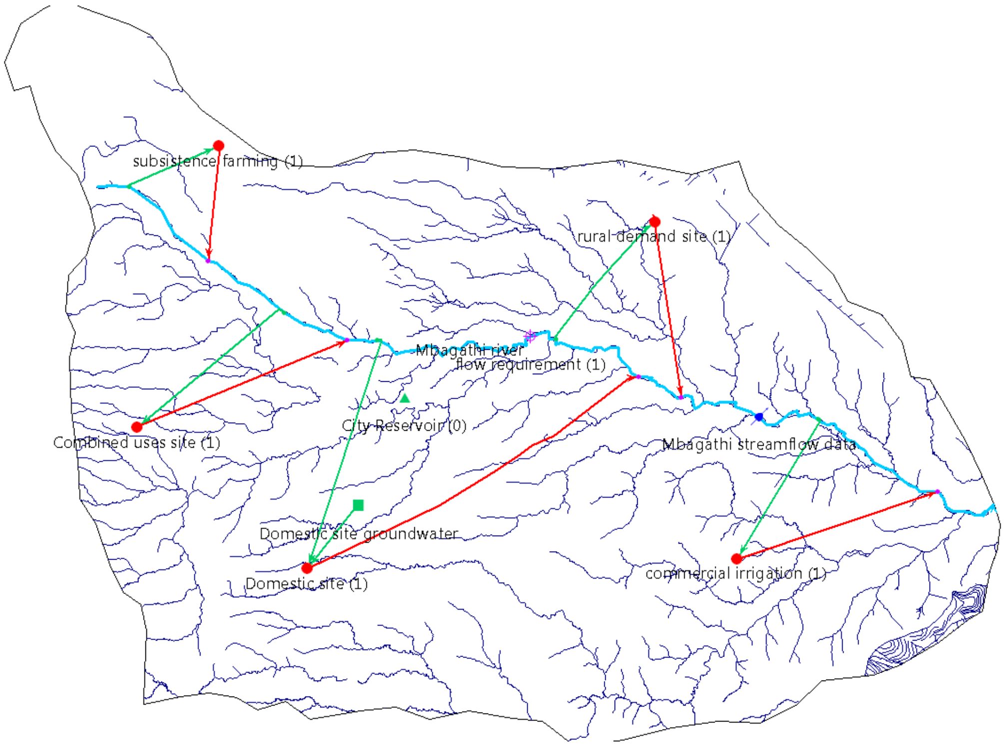
Modelling in WEAP required a raster file, which are pixels of Mbagathi sub-catchment map and its main river, made using Q-GIS. Data on water use for domestic, industrial, commercial and subsistence farming was derived from a survey conducted in 2015, which involved 716 respondents selected through a snowballing approach. Secondary data on demand drivers such as population, irrigation withdrawals per person and per hectare, percentage consumption, return flows, losses and water re-use as well as hydrological data on river gauge flows, flow requirements and groundwater storage were obtained from WRMA databases of 2010 to 2015. Climate data for 2010-2015 was obtained from Kenya Meteorological Department at Dagoretti Corner Station (No. 9136164).

CALIBRATION OF WEAP MODEL

Calibration was a three-step process involving training, testing and analyses of data. In training, effective precipitation, runoff/infiltration ratio and soil hydraulic conductivity were kept unfixed while groundwater characteristics were fixed.

The period of calibration was between 1999 and 2015, when naturalised flow and precipitation time series were available for the three stream-flow gauge stations that formed divisions A, B and C of Mbagathi sub-catchment as in Figure 1. Calibration was manually done by trial and error optimisation of unfixed parameters. Effective precipitation, runoff/infiltration ratio and soil hydraulic conductivity were assigned initial values of 100%, 50/50 and 1, respectively which were altered one at a time using steps of ± 0.5 %, ± 5/5 and ± 0.1 until the routine exhausted the assessment criterion. The model was run to test and compare changes in simulated and observed flow before and after parameter optimization.

Figure 2: Map of the Sub-catchment in WEAP Model



Validation of WEAP model

To validate WEAP model performance, two objective functions estimated the accuracy of the simulation. In this study, two criteria were used; the Nash-Sutcliffe efficiency criterion and the least squares objective function: Equ.1 and 2:

$$EFF = 1 - \frac{\sum_{i=1}^{N} (Qobs_i - Qsim_i)^2}{\sum_{i=1}^{N} (Qobs_i - Qbar_i)^2} \quad \ldots\ldots 1$$

$$LSL = \frac{\sum_{i=1}^{N} (Qobs_i - Qsim_i)^2}{N} \quad \ldots\ldots 2$$

Where, EFF is the one minus the sum of absolute squared differences between observed and simulated values standardized by the variance of historical values during the validation period and LSL is a regression analysis that minimizes total squared errors resulting from differences in observed and simulated values to fit them in a model.

Where, Qobs*i* is the observed stream-flow (m^3/s), Qsim*i* the simulated stream-flow (m^3/s), N the number of observations and Qbar is the observed monthly flow over the whole period.

Least squares objective function prevented bias towards larger flows during optimization while Nash- Sutcliffe Efficiency Criterion is an efficiency criterion where 1 means perfect agreement of observed and simulated flows while negative values show disagreement. The coefficient of determination (R^2) that indicates the capacity of a model to replicate the observed values based on total differences of outcomes was calculated to test the goodness-of-fit of the simulation.

WATER DEMAND SCENARIOS BUILD-UP

Assessment of changes in sustainable development in aspects of population, climate, water re-use and controlled conveyance losses in the sub-catchment from 2015 to 2050 involved three scenario building i.e. current, reference and what if (future) scenarios. The baseline year, 2015 was used to develop the current scenario, while the reference scenario was an evaluation if where no management measures are taken on the current scenario and the what if scenarios were assessments of future socio-economic developments. Five what if scenarios were analysed as follows:-

1. What is the effect on available water demand if population growth increases?
2. What is the effect on unmet water demand if prolonged dry climate sequence occurs?
3. What is the effect on water demand if the storage capacity of sub-catchment reservoir is increased?
4. What is the effect on monthly-unmet water demand if water conveyance losses are reduced?
5. What is the effect on monthly-unmet water demand if water re-use is intensified?

Scenarios generated were compared against their water requirements and impacts in the domestic, industrial, subsistence and commercial farming demand sites. Predictions were made using the reference scenario after which, they were compared with proposed water use efficient practices.

Data estimated on stream-flow and demand was subjected to Analysis of Variance (ANOVA) and mean separated using LSD to compare the means of treatments and their interactions. The statistical significance referred to $\alpha = 0.05$ unless otherwise stated.

RESULTS AND DISCUSSION

WEAP model Calibration and Validation

A comparison of observed and simulated yearly flows for the calibration period is shown in Table 1. The model showed closeness of fit between observed and simulated flows. However, in the year 2001, 2002, 2006, 2008 and 2014 when the area experienced peak flows, the model underestimated simulated values compared to 2000, 2005, 2007, 2010 and 2012 when flows were down and the model overestimated low flows though not significantly ($p \leq 0.05$). Over- and under-estimation of simulated flows could be attributed to inaccurate estimation of non-calibrated water balance elements such as groundwater recharge and evapotranspiration by the model and the use of effective precipitation, runoff/infiltration ratio and soil hydraulic conductivity alone to calibrate. Similar observations were made in Pangani basin, Tanzania where calibration errors were attributed to the use of effective precipitation and soil hydraulic conductivity alone to adjust WEAP model (Ndomba *et al.*, 2008).

Table 1: Simulated and observed yearly flow in Mbagathi sub-catchment in the calibration period (1999-2015)

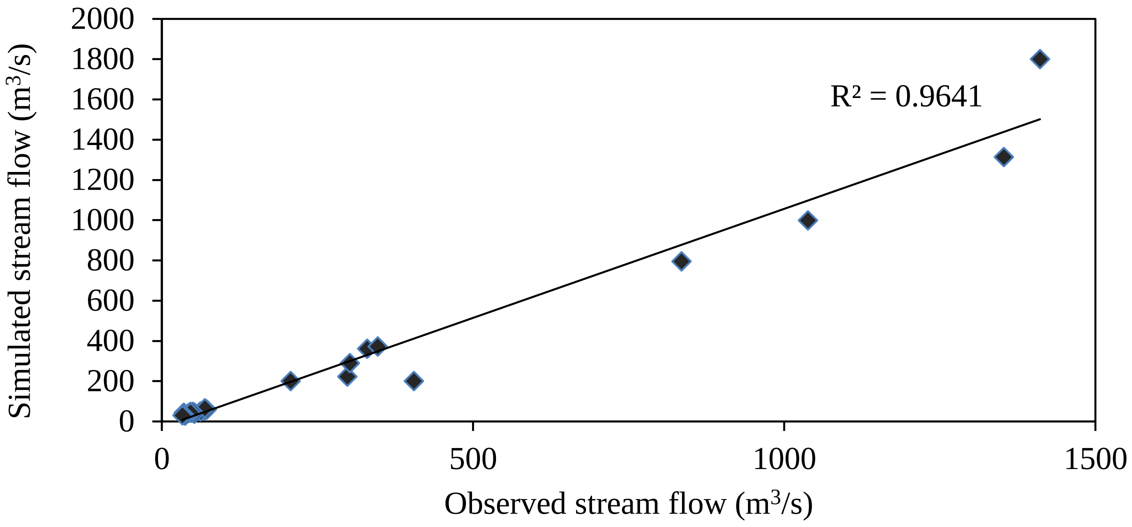
Year	Observed flow (m^3/s)	Simulated flow (m^3/s)	Mean (m^3/s)	Year	Observed flow	Simulated flow	Mean
1999	357[a]	332[a]	344.5[a]	2008	1020[c]	902[c]	961[c]
2000	145[b]	167[b]	156[b]	2009	323[a]	352[a]	337.5[a]
2001	1350[c]	1213[c]	1281.5[c]	2010	195[b]	224[b]	209.5[b]
2002	995[c]	978[c]	986.5[c]	2011	378[a]	313[a]	345.5[a]
2003	302[a]	282[a]	292[a]	2012	175[b]	205[b]	190[b]
2004	298[a]	270[a]	284[a]	2013	766[c]	692[c]	729[c]
2005	102[b]	191[b]	146.5[b]	2014	1378[c]	1296[c]	1337c
2006	817[c]	745[c]	781[c]	2015	290[b]	387$_{b}$	338.5[b]
2007	178[b]	234[b]	206[b]				

Mean figures followed by similar letters on rows are not significantly different at p=0.05

WEAP model priorities that capture base flow during wet seasons and stream-flow during dry seasons probably explain over- and under-estimation of extreme flows in the study area. During wet seasons when water is plenty, WEAP model does not prioritize on estimating peak flows hence their under-estimation unlike drier seasons when base flow estimation is a priority in the model due to its importance to water users downstream hence over-estimation of low flows in the study. Similar observations were made in Quiroz-Chipillico watershed in California where high and low flows were under- and over-estimated in WEAP model calibration due to its priority differences (Notter *et al.*, 2012; Flores-Lopez *et al.*, 2016). The conceptual nature of WEAP model that assumes even distribution of rainfall, runoff and stream-flow throughout the sub-catchment, which under natural conditions is impossible probably explains observed over-and under-estimation of flows. The data concurs with that in Upper Tana catchment where the conceptual nature of WEAP model assuming even distribution of rainfall and runoff resulted to simulation errors ranging between 2.9 and -4.5% during dry and wet years, respectively (Droogers, 2009).

The relationship between observed and simulated flows gave an acceptable performance of WEAP model $R^2 \geq 0.964$ (Figure 2). This fulfilled the requirement by Santhi *et al.* (2001) who recommended R^2 values above 0.60 and showed WEAP's ability to replicate sub-catchment processes accurately by predicting their responses to various outputs. Similar findings were reported in Nyando (Dienya, 2007), Pekerra (Mugatsia, 2010) and Ruiru basins (Thubu, 2012), Kenya where R^2 values were 0.88, 0.79 and 0.85, respectively.

Figure 2: Observed and simulate stream-flow of Mbagathi sub-catchment in the validation period (Researcher, 2017)



Results on the goodness-of-fit in observed flows are represented in Table 2. EFF values in the sub-catchment ranged between 0.59 and 0.87. EFF in station 3BA29 was significantly ($p \leq 0.05$) lower at 0.59 compared to 3AA04 and 3AA06 at 0.87 and 0.85, respectively. This observation could be because EFF compares observed and simulated flows using squared values hence the tendency to over-estimate higher flows in 3AA04 and 3AA06 while ignoring lower ones in 3BA29. Krause *et al*. (2005) made similar observations when validating WEAP model in a study at Wilde Gera catchment, Germany where EFF values in stream-flow gauge stations with high flows were overestimated compared to those with lower ones. LSL values ranged between 0.07 and 1.0, which shows its high variability in the sub-catchment. The observation could be due to the short validation period of 17 years applied in this study due to data unavailability to capture long-term variability of flow in the three gauging stations adequately and accurately. Mango *et al*. (2011) made similar observation in a Soil and Water Assessment Tool (SWAT) calibration, a hydrological model related to WEAP where a shorter calibration period of 5 years resulted to LSL values ranging between 0.15 and 0.87. Stream-flow gauge station 3AA04 had a significantly ($p \leq 0.05$) higher LSL of 1.0 compared to 3AA06 and 3BA29 with 0.22 and 0.07, respectively.

Table 2: Nash-Sutcliffe efficiency criterion and least squares logarithms for three stream gauges in Mbagathi sub-catchment

Stream-flow gauge station	EFF	LSL
3AA04	0.87[a]	1.0[a]
3AA06	0.85[a]	0.22[b]
3BA29	0.59[b]	0.07[b]
Mean	0.77[a]	0.43[b]
LSD ($p \leq 0.05$)	0.24	0.33
CV%	11.3	13.7

Values followed by different letters within columns are significantly different.

The high calculated LSL value could be due to spatio-temporal variations in rainfall and stream-flow since areas around 3AA04 were upstream and had high rainfall and flow volumes. Areas around gauging stations 3AA06 and 3BA29 had lower rainfall and stream-flow was subjected to abstractions leading to low LSL compared to 3AA04. In Olifants catchment, South Africa, variability in calculated LSL values was attributed to differences in rainfall and stream-flow whereby areas that had high rainfall and stream-flow were reported to have high LSL values and vice versa (Le Roy, 2005).

Scenario Analyses

Reference Scenario Analysis

Model prediction on water use changes in the sub-catchment during the reference scenario, which is a situation where management measures are not applied is presented in Table 3. The model predicted an increase in groundwater use from 12.4 to 24.5 million m^3 between 2015 and 2050. Increases in groundwater consumption in the years 2040, 2045 and 2050 were significantly ($p \leq 0.05$) higher at 20.2, 22.3 and 24.5 million m^3 compared to 18.3, 16.6, 15, 13.6 and 12.4 million m^3 in 2035, 2030, 2025, 2020 and 2015, respectively. Predicted increase in groundwater use could be due to a rising population leading to its demand for irrigation to produce food and for domestic uses. This trend concurs with reports by Amarasinghe *et al*. (2006) and Bharati *et al*. (2009) in Godavari and Krishna river basins, India that predicted 67 and 49% rise in groundwater use and its unsustainable development, respectively by 2025 due to increased demand for agriculture and domestic uses.

Table 3: Ground- and surface-water use predictions in the reference scenario

Year	Groundwater use (Million m^3)	Surface water use (Million m^3)
2015	12.4^a	7.0^c
2020	13.6^a	7.3^c
2025	15.0^a	7.5^c
2030	16.6^a	8.1^c
2035	18.3^a	9.2^a
2040	20.2^b	10.1^a
2045	22.3^b	11.6^a
2050	24.5^b	12.3^a
Mean	17.9^a	9.0^a

Mean figures followed by similar letters on columns are not significantly different at p=0.05

The model predicted an increase in surface water use from 7.0 to 12.3 million m^3 between 2015 and 2050. Increase in surface water use in 2035 to 2050 were significantly ($p \leq 0.05$) higher and ranged between 9.2 and 12.3 million m^3 compared to use of the resource in 2015 to 2030 that were between 7 and 8.1 million m^3. Unsustainable surface water increases are attributed to expected economic development pressures focusing on commercial agriculture that is more water consuming. Nyikal (2003) confirmed of an expected shift from subsistence to commercial farming in Kenya due to its economic gains but noted that increased water use would be the resultant opportunity cost as it is not sustainable. Poor water harnessing during high flows resulting to its loss into the ocean as runoff and inefficient water use leading to wastage and conveyance losses could lead to increased ground- and surface-water use in future as predicted. In Diadessa sub-basin, Ethiopia (Tena *et al.*, 2016) and Olifants catchment, South Africa (Arranz, (2006), similar predictions showing a future rise in ground- and surface-water use due to poor water harvesting and inefficient agricultural practices causing resource wastage and its unsustainable development were made using WEAP model.

Model predictions on reductions in groundwater storage of sub-catchment in the reference scenario are shown in Table 4. According to the model, water storage is predicted to reduce in the next 35 years by 278 million m^3 from 385.6 in 2015 to 107.6 million m^3 in 2050 indicating its unsustainable development. Predicted groundwater storage reductions between the years 2040 and 2050 were significantly ($p \leq 0.05$) lower ranging between 173.9 and 107.6 compared to 2035 and 2030 at 298.5, 309.1million m^3, respectively. Groundwater depletion between the years 2030 and 2035 was significantly ($p \leq 0.05$)

lower ranging between 309.1 and 298.3 compared to 2025, 2020 and 2015 predictions at 351.4, 364.9 and 385.6 million m^3, respectively.

Table 4: Projected Groundwater storage between 2015 and 2050 in Mbagathi sub-catchment

Year	Groundwater storage (million m^3)
2015	385.6[a]
2020	364.9[a]
2025	351.4[a]
2030	309.1[b]
2035	298.5[b]
2040	173.9[c]
2045	143.2[c]
2050	107.6[c]
Mean	266.8[b]

Mean figures followed by similar letters on columns are not significantly different at p=0.05

These reductions could be due to excessive abstractions without adequate recharge of Nairobi aquifer especially in drier seasons. Mulwa, (2001) and Gichuki & Kiteme, (2000), predicted groundwater depletion in Ngong sub-catchment and Upper Ewaso Ngiro North basin, respectively due to excessive drilling of boreholes, unsustainable developments with the drawn water and over-reliance on the resource for agricultural and domestic uses. Predicted reductions in groundwater storage could be attributed to pollution of surface water in the sub-catchment and under-exploitation of alternative water resources such as polished wastewater, which leads to over-pumping. Similar projections have been made in Bangladesh, Middle East, China and India (Ali *et al*., 2009; Wada *et al*., 2010) where pollution of rivers by agrochemicals and industrial effluent, limited wastewater re-use and recycling were predicted to limit groundwater's sustainable use.

Effects of high population growth on water demand

Predictions on water demand changes with the high population growth scenario for the domestic, industrial, commercial and subsistence irrigation sectors of the study area compared to reference scenario are represented in Table 5. Commercial farming water demand was predicted to increase from 85.3 to 113 between 2015 and 2050 in the reference scenario compared to 85.3 to 141.6 million m^3 for the high population growth scenario in the same period, respectively. Predicted increments with a high population growth scenario between the years 2045 and 2050 were significantly ($p \leq 0.05$) higher compared to other years and the reference scenario.

Table 5: Water demand changes in the high population growth scenario

Sector	Scenario	2015	2020	2025	2030	2035	2040	2045	2050	Mean
		Water demand in million m^3								
Commercial farming	Reference	85.3[a]	88.8[a]	92.5[a]	96.3[a]	100.1[a]	104.3[a]	108.6[a]	113.0[a]	98.6[a]
	High Population	85.3[a]	91.1[a]	96.5[a]	103.1[a]	110.0[a]	116.4[a]	124.2[b]	141.6[b]	108.5[a]
Domestic use	Reference	53.2[c]	55.4[c]	57.6[c]	60.0[c]	62.5[c]	65.0[c]	67.7[c]	70.5[c]	61.5[c]
	High population	53.2[c]	56.8[c]	60.2[c]	62.3[c]	68.6[c]	72.6[c]	77.1[a]	88.3[a]	67.4[c]
Subsistence	Reference	24.5[d]	25.5[d]	26.8[d]	27.6[d]	28.7[d]	29.9[d]	31.1[d]	32.4[d]	28.3[d]
	High Population	24.5[d]	26.1[d]	27.7[d]	29.5[d]	31.9[d]	33.4[d]	36.0[d]	40.6[d]	31.2[d]
Industrial	Reference	15.3[e]	16.2[e]	16.3[e]	17.5[e]	18.2[e]	18.9[e]	19.4[e]	19.9 [e]	17.7[e]
	High Population	15.3[e]	16.6[e]	17.6[e]	18.8[e]	20.0[e]	21.2[d]	22.6[d]	25.8[d]	19.7[e]

Mean figures followed by similar letters on rows are not significantly different at p=0.05

Subsistence farming water demand was predicted to increase from 24.5 to 32.4 in the reference scenario and 24.5-40.6 million m^3 in the high population growth scenario between 2015 and 2050 and increments did not have significant ($p \leq 0.05$) differences. Increased water demand in commercial and subsistence farming sectors could be due to overstretched and unsustainable water resources, as it is expected that agricultural practices will intensify and expand for food production to cater for the rising population, and for economic sustenance of the sub-catchment in future. In Tana River basin, population rise increased water use for commercial farming due to rising food demand and therefore leading to more water abstractions for irrigation in the area (Grieg-Gran *et al*., 2006).

Domestic water demand was predicted to increase from 53.2 to 70.5 between 2015 and 2050 in the reference scenario compared to 53.3 to 88.3 million m^3 in the high population growth scenario for the same period. Predicted increments in the high population growth scenario for the years 2045 and 2050 were significantly ($p \leq 0.05$) higher at 77.1 and 88.3 compared to a range of 53.2 to 72.6million m^3 between 2015 and 2040. Predicted increments in domestic water demand could be due to population rise and limited exploitation of alternative water sources such as treated wastewater depicting unsustainable water management. Rukuni, (2007) projected a future increase in domestic water demand in Mzingwane catchment in Zimbabwe and attributed the increase to the population of growth and limited wastewater re-use and recycling.

Industrial water demand was predicted to increase from 15.3 to 19.9 between the years 2015 and 2050 in the reference scenario compared to 15.3 to 25.8 million m^3 in the high population growth scenario for the same period. Predicted increases in water demand for the high population growth scenario in 2040, 2045 and 2015 were significantly ($p \leq 0.05$) high at 21.2, 22.6 and 25.8 million m^3, respectively compared to the period between 2015 and 2035 with a demand range of 15.3-20.0 million m^3. Rise in industrial water demand could be attributed to increased waste generation, extensive pollution of available water resources, expansion in processing industries for value addition and also for job creation in the area and limited polishing of wastewater generated from manufacturing processes. In India, Bhardwaj (2005) predicted a 25% rise in industrial water demand by 2025 due to pro-industrialization tendencies that will increase pollution through effluent discharge into the water sources and are antagonistic to sustainable development.

Effects of prolonged drought sequence on unmet water demand

Predicted effects of prolonged drought sequence on water demand in the study area are shown in Table 6. Commercial farming water demand was predicted to increase from 85.3 to 113 between the years 2015 and 2050 in reference scenario compared to 85.3 to 133.8 million m^3 for the extended drought scenario in the same period. Predicted increments in the years 2045 and 2050 for the extended drought scenario were significantly ($p \leq 0.05$) higher at 125.6 and 133.8 million m^3, respectively compared to the reference scenario at 109.6 and 113 million m^3 in the same period. The model predicted increases in subsistence farming water demand from 24.5-32.4 and 24.5-38.4 million m^3 in the reference and extended drought scenarios, respectively in 2015 to 2050 but increments were not significantly different compared to the reference scenario. Predicted increases in water demand for commercial and subsistence farming in the extended drought scenario could be due to the unsustainable and dried up rivers and low groundwater recharge leading to limited availability of the resource for irrigation. These predictions concur with those in Sacramento basin where extended drought led to increased water demand in the agriculture sector as rivers had dried up and yields of aquifers reduced due to poor recharge (Purkey *et al*., 2008).

Predicted domestic water demand rose from 53.2-70.5 and 53.2-83.4 million m^3 in the reference and extended drought scenarios, respectively between the years 2015 and 2050. In the years 2045 and 2050, predicted values at 78.3 and 83.4 million m^3, respectively were significantly ($p \leq 0.05$) higher compared to 2015-2040 values that ranged between 53.2 and 73.5 million m^3. These observations could be attributed to excessive consumptive uses of water with limited re-use and under-exploitation of alternative water sources from roof rainwater harvesting for sustainability of the resource. In Ho Chi Minh city of Vietnam (Dan *et al.*, 2011), domestic water demand in prolonged drought periods was predicted to rise because of limited water harnessing practices when flow was high and limited re-use despite increased demand.

Industrial water demand was predicted to rise from 15.3-20.6 and 15.3-24.4 million m^3 in the reference and prolonged drought scenario, respectively and increments in the years 2040, 2045 and 2050 for the latter scenario were significantly ($p \leq 0.05$) higher at 21.5, 22.9 and 24.4 million m^3, respectively in comparisons with other years. Predicted increments in industrial water demand could be attributed to unsustainable polishing of wastewater and loss as effluent to water sources. Purkey *et al.* (2008), Yates *et al.* (2015) and Azlinda and Mohd (2008) made similar predictions in Sacramento, Langat and Upper Colorado basins, respectively where rising industrial water demand was associated with poor adoption of wastewater re-use and recycling by firms.

Table 6: Changes in Water demand in the prolonged drought sequence scenario

Sector	Scenario	2015	2020	2025	2030	2035	2040	2045	2050	Mean
						Water demand in million m^3				
Commercial farming	Reference	85.3[a]	89.6[a]	93.3[a]	97.1[a]	101.1[a]	105.3[a]	109.6[a]	113.0[a]	98.6[a]
	Extended drought	85.3[a]	91.7[a]	97.6[a]	104[a]	110.8[a]	118.0[a]	125.6[b]	133.8[b]	108.4[a]
Domestic use	Reference	53.2[c]	55.9[c]	58.2[c]	60.6[c]	63.0[c]	65.6[c]	68.3[c]	70.5[c]	61.5[c]
	Extended drought	53.2[c]	57.2[c]	60.9[c]	64.8[c]	69.1[c]	73.5[c]	78.3[a]	83.4[a]	67.6[c]
Subsistence	Reference	24.5[d]	25.7[d]	26.7[d]	27.8[d]	29.0[d]	30.2[d]	31.4[d]	32.4[d]	28.3[d]
	Extended drought	24.5[d]	26.3[d]	28.0[d]	29.8[d]	31.8[d]	33.8[d]	36.0[d]	38.4[d]	31.1[d]
Industrial	Reference	15.3[e]	16.3[e]	17.0[e]	17.7[e]	18.4[e]	19.2[e]	19.2[e]	19.8[e]	17.7[e]
	Extended drought	15.3[e]	16.7[e]	17.8[e]	18.9[e]	20.2[e]	21.5[d]	22.9[d]	24.4[d]	19.7[e]

Mean figures followed by similar letters on rows are not significantly different at p=0.05

Effects of increased reservoir capacity on water demand

Predicted effects of increasing sub-catchment's reservoir capacity for storage on water demand in various land-use sectors are shown in Table 7 and domestic water demand increased from 53.2 to 93.7 million m^3 between the years 2015 and 2050.

Table 7: Effects of increasing reservoir capacity on water demand

Sector	2015	2020	2025	2030	2035	2040	2045	2050	Mean
				Water demand in million m^3					
Commercial Farming	85.3[a]	83.1[a]	79.3[a]	77.5[a]	72.9[a]	70.6[a]	68.1[b]	64.8[b]	75.2[a]
Domestic use	53.2[b]	58.7[b]	63.3[b]	69.2[b]	78.9[a]	81.3[a]	85.6[a]	93.7[a]	73[b]
Subsistence farming	24.5[c]	23.5[c]	21.9[c]	19.4[c]	16.2[c]	13.7[c]	11.7[c]	8.9[d]	17.5[c]
Industrial use	15.3[c]	15.1[c]	15.0[c]	14.8[c]	14.7[c]	14.6[c]	14.4[c]	14.2[c]	14.8[c]

Mean figures followed by similar letters on rows are not significantly different at p=0.05

Predicted water demand in the years 2035, 2040, 2045 and 2050 was significantly ($p \leq 0.05$) higher at 78.9, 81.3, 85.6 and 93.7 compared to 53.2, 58.7, 63.3 and 69.6 million m^3 in 2015, 2020, 2025, and 2030, respectively. This observation could be due to an expected population rise due rural-urban migration and increased availability of the resource encouraging its inefficient and unsustainable use in the sub-catchment. In Nablus City of Palestine (Rahma, 2009) and western Algerian cities (Hamlat *et al*., 2011), WEAP model predictions showed that increasing the storage capacity of reservoirs would lead to inefficient use of the water resource by residents since scarcity would not be a concern.

Commercial farming water demand was predicted to reduce from 85.3 to 64.8 million m^3 between the years 2015 and 2050. In 2045 and 2050, predicted reductions were significantly ($p \leq 0.05$) lower at 68.1 and 64.8 million m^3, respectively compared to the period between 2015 and 2040 where increments ranged from 85.3 to 70.6 million m^3. Expected reductions in commercial farming water demand could be attributed to an altered flow regime of Mbagathi River leading to poor groundwater recharge and surface water unavailability especially downstream of the sub-catchment where commercial farming is concentrated. Limited water availability will encourage commercial farmers to shift to other sustainable economic activities where water is not a priority such as quarrying and stone cutting. Similar results were reported in India after construction of Narmada and Sardar-Sarovar dams where commercial farmers located downstream of the Narmada basin abandoned the farming for quarrying due to water unavailability (Manatunge *et al*., 2010).

Subsistence water demand in the study area was predicted to reduce from 24.5 to 8.9 million m^3 between the years 2015 and 2050 and the latter was predicted to have significantly ($p \leq 0.05$) low water demand at 8.9 million m^3 compared to other years. This projection could be because of land use changes that will favour real estate development and construction of green houses in Ngong and Kikuyu areas where subsistence farming is currently concentrated. Mundia and Aniya (2006) predicted a reduction in subsistence water demand in Nairobi basin by 15% in 2030 following intensified knowledge on construction of greenhouses and urbanization of its rural areas.

Water demand in the industrial sector was predicted to reduce from 15.3 to 14.2 million m^3 between the years 2015 and 2050 though reductions were not significant ($p \leq 0.05$). This projection could be due to the expectation that companies, most of which are located downstream the sub-catchment will adopt cheap wastewater polishing, recycling and re-use techniques in the coming years after experiencing unavailability due to increased abstraction and altered hydrological regime upstream. The prediction concurs with Stanton and Fitzgerald's (2011) report in Sacramento basin, California where industrial water demand is expected to reduce by 12% in 2028 due to increased acceptance of polished wastewater for sustainable water management after the sector suffered of water scarcity from an altered flow regime after construction of Shasta dam.

Effects of reduced water conveyance losses on monthly unmet demand

Predicted effects of reducing water conveyance losses in Mbagathi sub-catchment on monthly-unmet demand compared to reference scenario are presented in Table 8. The model predicted reductions in unmet demand ranging from 4-12% in the reduced water conveyance compared to the reference scenario throughout the year, despite the observed monthly fluctuations in both cases resulting from rainfall variations.

Reducing water conveyance losses increase amounts delivered to target users and enhances efficient and effective accounting of used water, which could account for predicted reductions in unmet demand in the study area. In South Africa (Wilson, 2016), Pakistan, Egypt and India (Sultan *et al*., 2014), lowering water conveyance losses was predicted to reduce unmet demand by 10% as more would be delivered to target users leading to a positive contribution to sustainable development. Similar trends were established in Muzzaffarabad, Azad Jammu and Kashmir districts of Pakistan (Azad & Sarwar, 2014) and in Thessaloniki, Greece (Arampatzis & Evangelides, 2016) where controlling water conveyance losses by repairing broken water pipes and using drip irrigation in agriculture enhanced efficient and sustainable resource use through reduced unmet demand. However, reductions were not significant different probably because in WEAP models only water losses from leaked pipes that contribute minimally to unmet demand compared to irrigation losses during field application and distribution that contribute heavily to total losses. In the Mediterranean area, water losses from leaking pipes contributed to only 10% of all unmet demand while 90% of losses occurred during distribution and field application (Hamdy, 2007).

Table 8: Effects of reducing conveyance losses on unmet demand

Scenario/ Month	Reference Scenario	Reduced conveyance scenario	Mean
	Monthly unmet water demand in hundred thousand m^3		
Jan	44.0[a]	41.6[a]	42.8[a]
Feb	33.5[a]	33.0[a]	33.3[a]
Mar	36.9[a]	35.4[a]	36.2[a]
Apr	35.1[a]	33.5[a]	34.3[a]
May	35.6[a]	34.1[a]	34.9[a]
Jun	36.9[a]	34.1[a]	35[a]
Jul	38.4[a]	34.9[a]	36.7[a]
Aug	43.8[a]	41.3[a]	42.6[a]
Sep	36.9[a]	35.4[a]	36.2[a]
Oct	37.0[a]	35.3[a]	36.2[a]
Nov	35.7[a]	34.1[a]	34.9[a]
Dec	36.9[a]	35.2[a]	36.1[a]

Mean figures followed by similar letters on rows are not significantly different at p=0.05

Effects of water re-use on monthly unmet demand

Predicted effects of water re-use in Mbagathi sub-catchment on monthly-unmet demand are shown in Table 9. The model predicted reductions that were significantly ($p \leq 0.05$) higher in unmet demand and ranged between 51 and 59% in the increased water re-use compared to the reference scenario. This observation is attributed to the ability to redirect wastewater for environmental flow allocation and aquifer recharge after its re-use thus increasing groundwater availability, reducing pollution on freshwater resources and reducing unmet water demand for sustainability of the resource as predicted. Kusanto (2013) reported similar evidence in Colorado basin, USA where unmet water demand reduced by 17% after adopting water re-use due to increased aquifer recovery and groundwater availability. In India (Kaur *et al.*, 2014) and Bahrain (Ansari, 2013), water re-use adoption was reported to enhance recharging of water sources leading to sustainable use of the resource**.**

Re-using water could reduce unmet demand as predicted because it substitutes demands that do not require high quality water and therefore, providing an alternative water source. As such, the limited freshwater would be redirected fully for human consumption and other high priority needs. In Israel (Metcalf & Eddy, 2007; Friedler & Penn, 2011) and Palestine (Jamal, 2013), wastewater re-use as an alternative water source was predicted to ease unmet demand by substituting constrained ground-and surface-water resources that were redirected for high priority needs.

Table 9: Effects of increased water re-use on unmet demand

Scenario/ Month	Reference	Increased water re-use	Mean
Monthly unmet water demand in hundred thousand m^3			
Jan	44.0[a]	15.5[b]	29.6[a]
Feb	33.5[a]	17.9[b]	25.7[a]
Mar	36.9[a]	17.6[b]	27.3[a]
Apr	35.1[a]	16.2[b]	25.7[a]
May	35.6[a]	16.8[b]	26.2[a]
Jun	36.9[a]	17.4[b]	27.2[a]
Jul	38.4[a]	17.4[b]	27.9[a]
Aug	43.8[a]	17.5[b]	30.7[a]
Sep	36.9[a]	16.9[b]	26.9[a]
Oct	37.0[a]	17.5[b]	27.3[a]
Nov	35.7[a]	16.8[b]	26.3[a]
Dec	36.9[a]	17.4[b]	27.2[a]

Mean figures followed by similar letters on rows are not significantly different at p=0.05

CONCLUSIONS

The study established that WEAP is a useful tool in predicting future water demand and effects of adopting water-use efficient methods for sustainability. The model predicted an increase in groundwater use from 12.4 to 24.5 million m^3 between 2015 and 2050. In addition, the model predicted reductions in unmet demand ranging from 4-12% and 51-59% in the reduced water conveyance and increased water re-use scenarios, respectively compared to the reference scenario throughout the year. Reductions in unmet demand for the increased water re-use scenario were significantly ($p \leq 0.05$) higher compared to the reference scenario. The model further predicted that if sustainable water management measures are not taken (reference scenario) in the study area, groundwater resource will be depleted from 385.6 to 107.6 million m^3 between 2015 and 2050, as recharge will decrease with demand increase. Therefore, implementing water management strategies such as re-use and polishing, which are under-exploited water sources in the study area should be a priority towards sustainable development. The information obtained from WEAP model enhanced understanding on water demand drivers and its efficient use, which will help in sustainable management of the resource in Mbagathi sub-catchment. Obtained results can be extrapolated to help in water management of neighbouring counties now and into the future.

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