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Assessing the potential of Rainwater Harvesting (RWH) for sustaining small-scale irrigated coffee farming in the Bigasha watershed, Uganda

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Abstract

A study was carried out during 2022 to assess the potential of rainwater harvesting for sustaining small-scale irrigated coffee farming in the Bigasha watershed of Isingiro District, south-western Uganda. In this study, remote sensing, Geographical Information System (GIS), the Quantum GIS Soil and Water Assessment Tool (QSWAT+) and Crop Water and Irrigation Requirements Program (CROPWAT) models were utilised to assess the potential of rainwater harvesting (RWH) that can be used for irrigation. The criteria used to identify suitable RWH sites were based on four factors namely; topography, soils, land use land cover and rainfall. It was found out that seventy per cent of the watershed is hilly with slopes greater than 10 per cent and half of the area is covered by Leptosols. Three temporal land use land cover (LULC) maps (of 1999, 2010 and 2022), were derived using the K-nearest neighbor (KNN) algorithm. These LULC databases were used to assess the impacts of land use land cover changes on the runoff hence potential for RWH.

The annual average rainfall received in the study area over the 21-year period studied (2000 – 2020) was 954 mm which is adequate for irrigation if harvested. The QSWAT+ model simulated runoff depths from 62, 125 and 114 Hydrologic Response Units (HRUs) of the 1999, 2010 and 2022 LULC maps respectively, were used to estimate potential RWH sites. The 114 HRUs from the 2022 LULC map could generate an annual average surface runoff volume of 1.39 million cubic meters (MCM) which could potentially irrigate 101.8 per cent of the current coffee production areas in the Bigasha watershed. The prediction accuracy of the Kagera river basin model was very good with NSE (R^2) of 0.81(0.82) for calibration and 0.87(0.88) for validation. The Kagera watershed model fitted parameters were further used to calibrate the Bigasha watershed model. This was done because the Bigasha is a sub-basin of Kagera and it does not have its own gauged outlet.

Keywords: Coffee farming; Irrigation; RWH; Bigasha watershed

1. Introduction

Globally, Uganda is ranked as the eighth largest coffee producer, accounting for over 31 per cent of the total coffee exports from Africa [1, 2]. Coffee accounts for over 20 per cent of Uganda's total foreign exchange earnings and 1.5 per cent of the annual gross domestic product [1, 3]. During the coffee year 2021/2022, the country realised an export revenue of over US$ 741.03 million [4]. The Uganda Coffee Development Authority has emphasised that the global markets for both Robusta and Arabica coffee are sustainable and assured and that there is rising demand for good quality coffee.

In 2020/2021, the global demand was 164.9 million bags which is projected to rise to 170.3 million bags by 2021/2022, against a production of 167.2 million bags [5]. According to Nalunga [2], Uganda still has an immense untapped coffee

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production potential that if leveraged alongside good field management practices such as irrigation could bridge the above coffee production gap and earn coffee farmers over Uganda shillings (UGX) 10 million per hectare per year.

During the year 2012, the Nile Basin Initiative irrigation potential assessment project identified suitable soils for coffee farming in the Bigasha watershed, located in South-western Uganda. These soils were categorised as ferralsols with an average land productivity of 0.6 based on the normalised difference vegetation index [6]. However, due to recurrent drought conditions in Bigasha, coffee production is still low in this area [7, 8]. The severity of drought is more felt in the months of December to February (DJF) and June to August (JJA) [9]. For instance in 2017, drought contributed to nearly 60 per cent drop in coffee yield in Luwero district, one of the leading coffee growing districts in Uganda [10].

The Food and Agricultural Organization (FAO) AQUASTAT climatic statistics show that in the recent past (2010 - 2021), the annual average rainfall received in the Bigasha watershed has dropped to 960 mm, yet the coffee plant requires a minimum of 1 200 mm of water annually for its proper growth [1, 11]. Nyasimi et al [9] and McDonnel [10] warned that the current global adverse variations in climatic conditions could reduce potential coffee production areas worldwide by 50 per cent by 2050.

Therefore, adoption of irrigation by the Bigasha watershed's coffee farmers becomes paramount for successful coffee growing in this area. However, the major impediment to irrigation practice in the Bigasha watershed is the absence of a reliable irrigation water source [6] . There are two water sources adjacent to the watershed, namely, Lake Nakivale, which is located several kilometers away and would require substantial investments to convey water for irrigation and the Kagera river, which is a trans-boundary watercourse between Uganda, Tanzania, Burundi and Rwanda and hence requires formal approval from the Kagera Basin Organization (KBO) to abstract water [12].

In situ and/or ex situ rainwater harvesting (RWH), which is the collection and storage of local surface runoff, could perhaps provide irrigation water for the Bigasha watershed's small-scale coffee farmers. A variety of locally known engineered and cost friendly techniques and structures could be used to harvest the rainwater [13, 14]. However, due to the lack of information and knowledge of potential RWH sites as well as maximum runoff yield from these sites, RWH opportunity is yet to be explored by coffee farmers [15]. The objectives of this research work were: (i) characterise RWH sites in the Bigasha watershed, (ii) map potential RWH sites in Bigasha using remote sensing, GIS and the QSWAT+ model, (iii) determine quantities of harvestable rainwater at potential sites, and (iv) estimate the potential area under coffee irrigable using this water.

2. Material and methods

The logical arrangement of the steps undertaken to assess the potential of RWH for sustaining small-scale irrigated coffee farming in the Bigasha watershed are summarised in Figure 1.

2.1. Description of the study area

The Bigasha watershed is found in the Isingiro district, located in the absolute South-western part of Uganda. It lies between the latitude of 0^{o} 48'30" S and 0^{o} 59' 0" S and longitude of 30^{o} 45' 30" E and 30^{o} 59' 30" E as depicted graphically in Figure 2. The watershed occupies a total land area of 348 km^2. Its landscape can generally be described as undulating, with alternating highlands and lowlands spread throughout the watershed. The elevation ranges from 1 208 – 1 788 m above sea level and most slopes in the area are greater than 10 per cent. The Bigasha watershed is drained by seasonal watercourses which flow into the Kagera River.

Croplands is the third largest land use type here after grasslands and shrublands. The leading agricultural activities in this watershed are small-scale banana growing and livestock rearing, with bananas accounting for nearly 70 per cent of the total annual crop production [16]. The predominant soil type in Bigasha are Leptosols, which are very shallow soils with minimal development, dominated by coarse fragments overlying a continuous rock mostly found in areas with medium to high altitude. The climate of the area is characterised as tropical savannah with annual average temperatures ranging from 15 to $27^{o}C$. The annual average precipitation and reference evapotranspiration estimates are 954 and 1 347 mm, respectively [11].

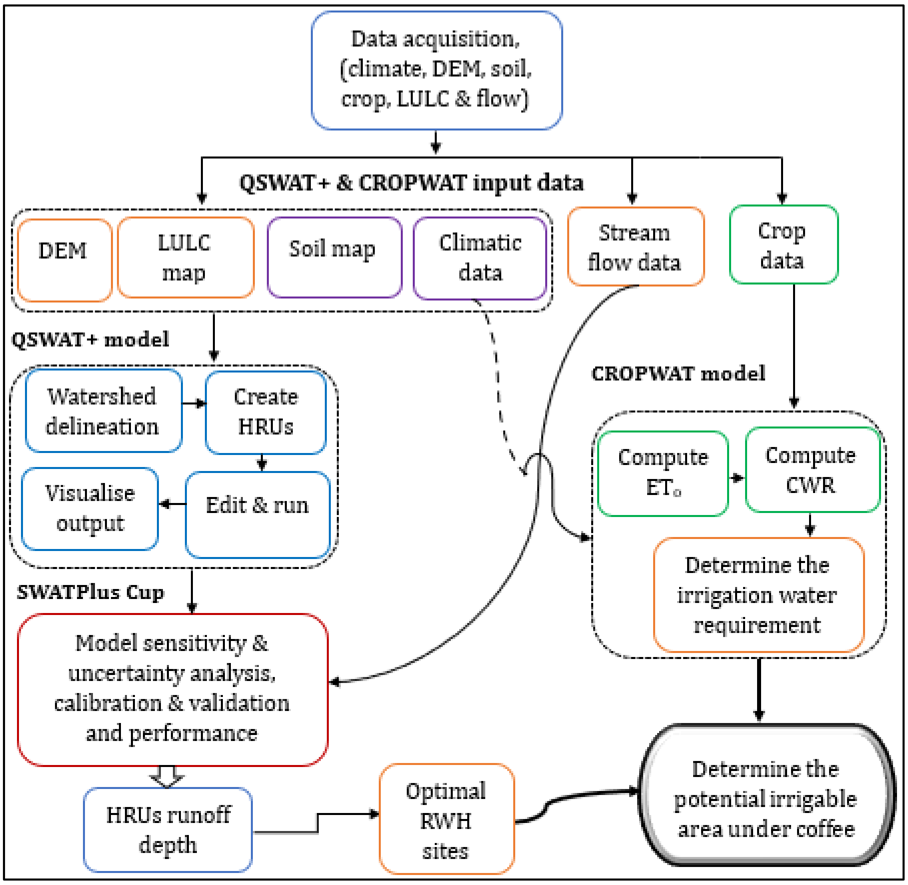

Figure 1 Steps in assessing the potential of RWH in the Bigasha watershed

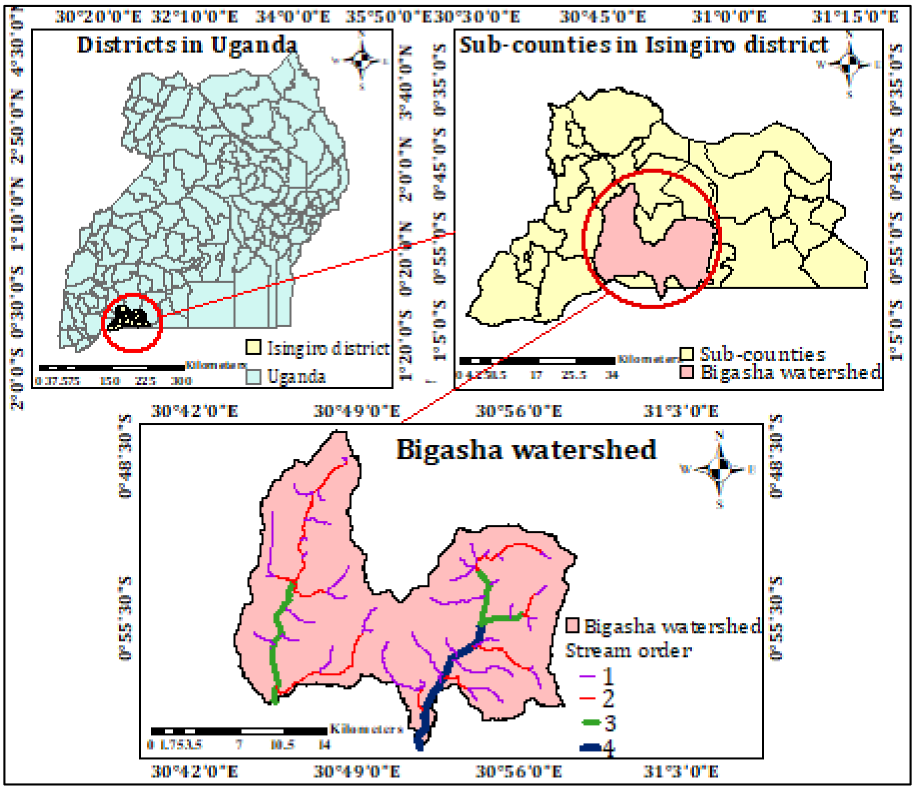

Figure 2 Map of the study area

2.2. Data acquisition, preparation and processing

2.2.1. The QSWAT+ model input data

The four input datasets required to build a QSWAT+ model, that is to say; Digital elevation model (DEM), land use land cover and soil maps and their lookup tables and climate and stream flow data, were acquired, prepared and processed as discussed below.

DEM

A resampled 30-meter spatial resolution Shuttle Radar Topographic Mission (SRTM) DEM, which was required for watershed delineation, was downloaded from the United States Geological Survey (USGS) database (www.earthexplorer.usgs.gov). The downloaded grids of the DEM were loaded on the QGIS working space where they were clipped to extract a raster layer that covers the study area using the "Clip raster by extent" tool. The clipped grids were then merged with the help of the "Merge tool" and later reprojected to the Bigasha watershed's projected coordinate system (WGS 1984 UTM Zone 36S). The resultant DEM was then resampled from 30 m to 10 m, so as to match with the spatial resolution obtained for the 2022 LULC image. To reduce time spent delineating the watershed as well as to improve accuracy, a rectangular mask of the DEM was created ensuring that it covered the Bigasha watershed.

Land Use Land Cover (LULC) map

The LULC map was used for creating the HRUs in the QSWAT+ model. The three LULC maps used in this study were created using the supervised classification method of the Landsat 7 ETM+, Landsat 5TM and Sentinel 2A imageries, which were acquired in 1999, 2010 and 2022, respectively. The Level 1TP ("precision and terrain correction") Landsat images were downloaded from the USGS database (www.earthexplorer.usgs.gov) while the Level 1C Sentinel imagery was obtained from the European Space Agency (ESA) data portal (www.copernicus.eu). The production of each of the three LULC maps was performed in three stages, namely, image preprocessing, image classification and accuracy assessment, using the procedures developed by Congedo [17] described below.

Image preprocessing

The downloaded image bands (Landsat or Sentinel bands, one product at a time) were loaded onto the semi-automatic classification plugin (SCP) interface, which was installed in QGIS. The SCP is a software interface that can be used for supervised classification of remote sensing images, providing tools for downloading the images and image preprocessing and post processing [17]. The image bands were then clipped to the extent of the study area using the "Clip multiple rasters" tool. The "dark object subtraction" atmospheric correction was then performed on the clipped image bands before they were converted to surface reflectance [17].

Image classification

The images were classified using the SCP integrated with the KNN algorithm and Google Maps satellite image layer, all of which were installed in QGIS. The KNN classification algorithm is a non-parametric supervised machine learning algorithm, widely used to perform classification and regression tasks [18]. There are two steps in the classification process of the KNN algorithm, these are: (1) the learning step where the training input data is used to build the classifier (this involves the determination of the factor of K, that is to say, a parameter that determines the number of nearest neighbors to include in the majority voting process) and (2) Evaluation of the prediction accuracy of the classifier, based on the values of the "classification precision" obtained from the confusion matrix of the classification accuracy assessment report. Once the factor of K is known, the KNN algorithm groups the new input unclassified data into subsets and classifies it based on its similarity with previously trained data [18]. The image classification was performed as follows: firstly, the "band set" for the preprocessed image bands was created within the SCP interface and its color composite (red, green, blue) also known as RGB was changed for easy visual interpretation of the land use land cover features. The training input shapefile was then created inside the "SCP dock" window of the SCP. The regions of interest (ROIs) were created hereafter through an iterative process by manually drawing a polygon on the image being classified, covering pixels of the same spectral signature. Each ROI corresponded to a LULC Class ID (C ID). The created C IDs were then grouped into eight macro class IDs (MC IDs) which represent the eight LULC classes in the Bigasha watershed. The identified LULC classes were: forest/trees, shrublands, grasslands, croplands, built-up areas, water bodies, bare land and flooded vegetation. The Google satellite map and the "Display NDVI" option in the SCP dock were used to assign the correct LULC classes to the ROIs created. The KNN algorithm was then run to execute the classification task. KNN classifier was chosen for its simplicity, effectiveness (high prediction accuracy) and low computational time [18], compared to other classifiers.

Accuracy assessment

The accuracy assessment for each of the three LULCs was performed using the error matrix method, which is the most widely used method to assess the accuracy of a LULC classification process [19, 20]. This was conducted as follows: firstly, a point feature shapefile with "Ground truth" and "Reference" fields in its attributes table was created in QGIS. A stratified random sampling technique, that was recommended by Congalton [21] was then used to collect sample points from each of the eight LULC feature classes on the classified image. These sampled points were stored in the above shapefile. After gathering at least 270 sample points from the eight LULC classes, the shapefile was uploaded onto Google Earth Pro and its "Reference" field was filled with the actual land cover IDs. Using the "show historical imagery" option in Google Earth Pro, it was possible to select an imagery with a close acquisition date to that of the LULC image being validated, so as to minimise the differences in the temporal resolution of the classified and reference images. The sample size collected from each LULC category depended on the inherent spatial variability of the LULC category, as recommended by Congalton [21]. The filled point shapefile was then imported to ArcMap to generate the error matrix, which was later copied and pasted on an Excel sheet and the user, producer and overall accuracies and the Kappa coefficients were calculated using the following expressions:

$$\text{User accuracy} = \frac{\text{Number of correctly classified pixels in each category}}{\text{Total number of pixels in that category (row total)}} * 100 \quad \text{......(2.1)}$$

$$\text{Producer accuracy} = \frac{\text{Number of correctly classified pixels in each category}}{\text{Total number of pixels in that category (column total)}} * 100 \quad \text{......(2.2)}$$

$$\text{Overall accuracy} = \frac{\text{Total number of classified pixels (diagonal)}}{\text{Total number of reference pixels}} * 100 \quad \text{......(2.3)}$$

$$\text{Kappa coefficient} = \frac{(\text{TS} * \text{TCS}) - \sum(\text{column total} * \text{row total})}{\text{TS}^2 - \sum(\text{colum total} * \text{row total})} \quad \text{......(2.4)}$$

Where TS represents the total number of sample points and TCS is the total number of correctly classified pixels. In case the computed overall accuracy was less than the minimum acceptable accuracy of 85 per cent as proposed by Anderson et al [22], the image was reclassified. Finally, the 1999 and 2010 LULC classified images from the Landsat were resampled from 30 m to 10 m, so as to match with the spatial resolution obtained for the 2022 classified image.

Soil map

Like the LULC map, the soil map was also used to create HRUs in the QSWAT+ model. A map (jpg format) for the entire Isingiro district (1: 50 000 scale) was obtained from the Uganda National Agricultural Research Laboratories. The shapefile layer of the soil map was not available at the time of this study because the Uganda soils mapping database was being updated. The acquired soil map had four soil types, viz. Orthic Ferralsols, Plinthic Ferralsols, Humic Gleysols and Leptosols/Lithosols. The soil map for the Bigasha watershed was created with the help of ArcMap software as follows: firstly, the acquired soil map was loaded onto ArcMap where it was georeferenced using the administrative boundaries shapefile layer for Isingiro district and then reprojected to WGS 1984 UTM Zone 36S. The resultant map was then converted to a raster and later to a polygon using the "raster to polygon" spatial analyst tool in ArcMap after which it was resampled to 10 m, so as to match with the spatial resolution obtained for the 2022 LULC image. The World Reference Base (WRB) soil names in the attributes table of the soil map were then converted to the FAO soil symbols that is recognised by the QSWAT+ model.

Land use and soil lookup tables

The LULC and soil map look up tables were used for linking the land use and soil maps to the QSWAT+ model and they were both prepared as comma separated (csv) files. The land use lookup table had two columns, the land use identifier (LANDUSE_ID) and the SWAT_CODE. The SWAT_CODEs assigned to the eight LULC classes in the Bigasha watershed were: FRST, RNGB, RNGE, AGRL, URBN, WATR, SWRN and WETL for forests/trees, shrublands, grasslands, croplands, built-up areas, water bodies, bare land and flooded vegetation, respectively. Similarly, the soil lookup table had two columns, the soil identifier (SOIL_ID) and the soil name (SNAM) columns. The SWAT+ soil symbols assigned to the SOIL_IDs of the Bigasha watershed were: Fo43-2b-498, Fp10-2a-560, Gh7-2a-57 and I-U-c-3132 for Orthic Ferralsols, Plinthic Ferralsols, Humic Gleysols and Leptosols/Lithosols, respectively. The "global user soil" file was used to assign soil properties to the soils.

Daily observed weather data (2000 – 2020)

The weather data used for simulating surface runoff in the QSWAT+ model include: daily precipitation, relative humidity, wind speed, minimum temperature, maximum temperature and solar radiation. The observed weather data for the first five variables were obtained for Mbarara from the Uganda National Meteorological Authority (UNMA) database while the solar radiation data was obtained from the Climate Forecast System Reanalysis (CFSR) database. The datasets were prepared in *.txt files. The station information file contained the station Id (ID), station name (NAME), latitude (LAT), longitude (LONG) and the altitude (ELEVATION) while the observed weather files had the starting date of the measurements (01/01/2000) and the measured data. The missing climate data for the days between 1/1/2000 and 31/7/2014 were filled with CFSR data while those after July 2014 were filled with -99 [23].

Observed stream flow data (2001 – 2018)

This dataset was required for calibrating and validating the QSWAT+ model runoff simulations. Since the rivers within the Bigasha watershed are not gauged, the stream flow data (covering a period from 2001 – 2018) for the Kagera river whose catchment, the KRB covers the Bigasha watershed was used for this purpose. The dataset had to be further processed in order to estimate the Bigasha watershed flow. This data was obtained from the Ministry of Water and Environment (MWE) in Uganda. The monthly stream flow records for the 18 years (2001 – 2018) were prepared in an Excel file. This file had two columns, the first one being the "Date" when the data was acquired (year and month) while the second one had the monthly "Flow" data itself.

2.2.2. CROPWAT 8.0 model input data

The input datasets were climatic data (rainfall, relative humidity, minimum temperature, maximum temperature, wind speed and sunshine hours) and crop data [24, 25]. The climate data for the first five climate variables above, used here, were the same as those used for the QSWAT+ model. The measured sunshine hours data was missing and therefore the CROPWAT model sunshine hours estimates were used in this work. The monthly weather data of the variables with available data were compiled using Microsoft Excel. For the months where the climate data was missing, CFSR data was used to fill the gaps for periods between 2000 and July 2014 while CROPWAT model estimates were used to fill those for periods after July 2014.

The coffee crop information required in the CROPWAT model was the length of crop growing stages, crop coefficient, critical depletion factor, rooting depth and yield response factor. These were obtained from the Uganda coffee handbook and FAO Irrigation and Drainage papers 33 and 56 [1, 26, 27].

2.3. Data analysis

2.3.1. Building of the QSWAT+ model for the Bigasha watershed

The model was built within the software interfaces of QGIS (version 3.2.29), QSWAT+ (version 2.2.5) and the SWAT+ Editor (version 2.1.3), using the procedures developed by Yihun Dile [23]. It was discovered that the majority of the HRUs created under the FRST, URBN, WATR, SWRN and WETL land uses had areas less than 0.1 hectares, which may not provide adequate catchments for RWH. In this regard, a threshold of 10, 10 and 2 per cent for land use, soil and slope, respectively was applied to eliminate such HRUs.

The weather generator (which was downloaded together with the QSWAT+ software), weather stations information and daily observed weather data were then imported into the SWAT+ editor interface. The simulation and warmup periods ({2000 – 2020} and 3 years respectively) were set and the outputs to be printed and their temporal scales were selected after which the QSWAT+ model was run to simulate the runoff from the Bigasha watershed. The monthly and yearly runoff from the two outlet channels (55 and 68) and the annual average HRUs runoff depths were then visualised. The latter was later used to identify potential sites for RWH.

2.3.2. Model sensitivity analysis, calibration, validation and performance evaluation

These were performed with the help of SWATPlusCUP, which is the calibration program for the QSWAT+ model. The calibration was performed in line with the protocol prescribed by Abbaspour et al [28]. There was only one outlet specified for the entire watershed which was drawn on the model's main channel located at a point close to the Kagera river gauging station at Masangano (latitude: 0^{o} 56'21'' S and longitude: 31^{o} 45' 48'' E). This was the station whose surface runoff data was used to calibrate the simulated runoff from the KRB for the 15-year period results (1999 – 2013).

The surface runoff data was obtained by subtracting the long term low flow of the Kagera river of 85 m^3/s [29], from the observed monthly stream flow records. After the QSWAT+ model simulations for the 15-year period were complete, a SWATPlusCUP project named "KageraQ" was created in the SWATPlusCUP interface and the SWAT parameter estimator (SPE) was selected as the calibration algorithm. A pre-calibration model run with a dummy parameter, "r_WDPQ.bsn...0...0" was then performed and the results were visualised. Considering the behavior and performance of the initial model, 14 parameters listed in Table 1 were identified from previous studies [28, 30–33] for the calibration process.

Table 1 Selected parameters for model calibration

Parameter change	Description	Initial range	Calibrated value
r__GW_REVAP.gw	Groundwater "revap"/percolation coefficient	-0.5 – 0.5	-0.02173
r__GW_DELAY.gw	Groundwater delay	-0.8 – 0.8	-0.05932
r__SOL_K().sol	Saturated soil hydraulic conductivity.	-0.8 – 0.8	-0.15274
r__SOL_AWC().sol	Available water capacity of the soil layer	-0.5 – 0.5	0.18058
r__CN2.mgt	SCS runoff curve number	-0.3 – 0.2	-0.12056
r__OV_N.hru	Manning's "n" value for overland flow	-0.4 – 0.5	-0.13405
r__HRU_SLP.hru	Average slope steepness	-0.5 – 0.4	-0.35059
r__SLSUBBSN.hru	Average slope length	-0.4 – 0.5	0.19574
r__ALPHA_BF.gw	Baseflow alpha factor	-0.8 – 0.8	0.70174
v__SURLAG.bsn	Surface runoff lag time	0.05 – 24	10.12326
r__REVAPMN.gw	Threshold depth of water in the shallow aquifer for "revap"/percolation to occur	-0.5 – 0.5	-0.48033
v__CANMX.hru	Maximum canopy storage	0 – 100	56.25000
r__SOL_BD().sol	Moist soil bulk density	-0.6 – 0.6	-0.15274
r__GWQMN.gw	Threshold depth of water in the shallow aquifer required for return flow to occur	-0.8 – 0.8	-0.24134

The model was calibrated for nine years (2005 – 2013) and validated for six years (1999 – 2004), with the first two and three years, respectively, set as warm up periods. Since CANMX.hru is a parameter that introduces water to the watershed, it was calibrated first to minimise identifiability problems during calibration. The remaining 13 parameters were then added to the "calibration input files" and the first iteration of 300 simulations was run, as recommended by Abbaspour [34]. A global parameter sensitivity analysis was then performed from which a decision was made to use all the selected parameters in the subsequent calibration processes. When the first iteration run was complete, the outputs were visualised, specifically the 95 per cent prediction uncertainty (95PPU) graph, the goodness of fit indices, p and r-factors and the accuracy criteria, NSE, R^2 and PBIAS. Since the SPE is iterative, three more iterations, each of 300 simulations were performed. The results of the best simulation after the fourth iteration were then used to assess the accuracy of the calibration as well as the goodness of the KRB model. The parameters of the calibrated model were then used for validation. Finally, 10 out of the 14 parameters, viz. GW_REVAP.gw, GW_DELAY.gw, SOL_K().sol, SOL_AWC ().sol, CN2.mgt, ALPHA_BF.gw, REVAPMN.gw, CANMX.hru, SOL_BD().sol and GWQMN.gw, used to calibrate and validate the KRB model were selected and used to calibrate the Bigasha watershed model, using the "NO obsevation" option of SWATPlusCUP. It is at this point that the HRUs runoff depths from the Bigasha watershed were extracted and used to estimate potential sites for RWH.

2.4. Rainwater harvesting site suitability analysis

The suitable sites for RWH in the Bigasha watershed for each of the three LULC maps were obtained from the HRUs that could generate an annual average runoff depth of at least 92 mm. To achieve this, the HRUs runoff depths extracted in the foregoing section were sorted in descending order and those above the 92 mm threshold were selected to constitute potential RWH sites. The RWH suitability maps were then generated using QGIS. This involved deleting the contents of the HRUs whose runoff depths were less than the 92 mm threshold, from the attributes table of the HRUs shapefile. Lastly, the total volume of surface runoff attainable from the potential RWH sites was computed as the sum of the individual runoff volumes harvestable from the selected HRUs.

2.5. Determination of the irrigation water requirement of the coffee crop

This was calculated using the CROPWAT 8.0 software. The calculation was performed as described below: firstly, the monthly reference evapotranspiration (ET_o) for 18 years (2003 –2020), which corresponds to the period when the QSWAT+ model simulations were printed, was computed when the climate data (relative humidity, minimum temperature, maximum temperature, wind speed and sunshine hours) were added to the CROPWAT model interface. The monthly sunshine hours were estimated by the CROPWAT model. In order to incorporate the effects of climate variability and uncertainty on the resultant crop and irrigation water requirements, Weibull distribution analysis was conducted on the calculated ET_o values. This involved transfer of the computed ET_os onto a new Microsoft Excel sheet where they were ranked in descending order and their probabilities of exceedance (POEs) were calculated. The 25 per cent POE threshold, which is close to the 33 per cent POE used for flood frequency analysis in hydrological studies, was then selected and its corresponding ET_o was used to determine the crop water requirements of the coffee crop after the crop data was imported to CROPWAT. Finally, the monthly rainfall data was added and the CROPWAT model automatically calculated the decadal net irrigation water requirements, which were later summed up to obtain the annual net irrigation water requirement. The annual gross irrigation water requirement was then computed as a ratio of the annual net irrigation water requirement to the irrigation efficiency, assuming a drip irrigation system with an irrigation efficiency of 90 per cent was used.

2.6. Determination of the potential irrigable area under coffee

The total area of coffee fields that could be irrigated using the harvestable rainwater at the Bigasha watershed was computed from: the ratio of the annual average volumes of surface runoff attainable from the potential sites derived from the 2022 LULC map to the annual average gross irrigation water requirement of the coffee crop. The runoff volume attainable from the 2022 LULC map was selected because it gives a better representation of the current conditions at the Bigasha watershed as compared to that from the 2010 and 1999 LULC maps.

3. Results and discussion

3.1. Slope analysis

The DEM and the slope map shown in Figure 3a developed for the Bigasha watershed show that the elevation of this area ascends from 1 208 to 1 778 m above sea level. After the watershed was delineated, the slope report revealed that 70 per cent of the watershed's total area had slopes greater than 10 per cent while only 17 per cent had slopes less than 5 per cent. Although such hilly terrain would imply high runoff generation, it could be inferred based on literature that only 17 per cent of the Bigasha watershed's total area is best suited for RWH. This is because areas with slopes less than 5 per cent are less susceptible to soil erosion and hence reduced sediment loading problems on the RWH reservoirs.

3.2. LULC analysis

The three LULC maps (of 1999, 2010 and 2022) created by the supervised classification method using the KNN algorithm show that there were eight major LULC types in the Bigasha watershed. These were forests/trees, shrublands, grasslands, croplands, built-up areas, waterbodies, bare land and flooded vegetation. Grasslands were the most dominant LULC class in all three of the maps, occupying 78, 73 and 59 per cent of the 1999, 2010 and 2022 LULC maps, respectively. This was already an indicator that the majority of the Bigasha watershed's area could be poor runoff generators. The presence of surface vegetation on grasslands interfere with runoff generation by increasing surface roughness to runoff, lengthening the runoff flow path and raising the soil's infiltration capacity through the rooting system of the vegetation [35]. That notwithstanding, high surface runoff was expected in the 2022 LULC map (shown in Figure 3b) than in the 1999 LULC map due to the reduced grassland LULC class in the former. The overall classification accuracies and Kappa coefficients of the LULC maps were 92.5, 96.7 and 94.0 per cent and 0.90, 0.96 and 0.93 respectively. Since these accuracies were above the minimum acceptable accuracy of 85 per cent proposed by Anderson et al [22], these LULC maps were suitable for use in the analyses conducted in this study.

3.3. Soil analysis

The final soil map (shown in Figure 3c), that was clipped using the extent of the Bigasha watershed had three soil types, namely, Orthic Ferralsols (Fo43-2b-498), Humic Gleysols (Gh7-2a-57) and Leptosols (I-U-c-3132). The dominant soils in the Bigasha watershed were Leptosols/Lithosols which occupied 50 per cent of the total land area. According to

Gliński et al [36], Leptosols are very shallow soils with minimal development, formed typically on hard rock or highly calcareous materials. The Leptosols (I-U-c-3132) soil type found in the Bigasha watershed has a sandy clay loam texture and was categorised under hydrologic soil group (HSG) C soils. Maidment et al [37] indicated that the HSG C soils have low infiltration rates when thoroughly wetted and their layers impede downward movement of water. This soil property makes Leptosols high runoff generators and the area it occupies could constitute potential sites for RWH. Orthic Ferralsols which covered 26 per cent of the study area are also HSG C soils and hence high runoff generators while Humic Gleysols are HSG B soils. Group B soils have moderate infiltration rates which make them poor runoff generators as compared to Group C and D soils.

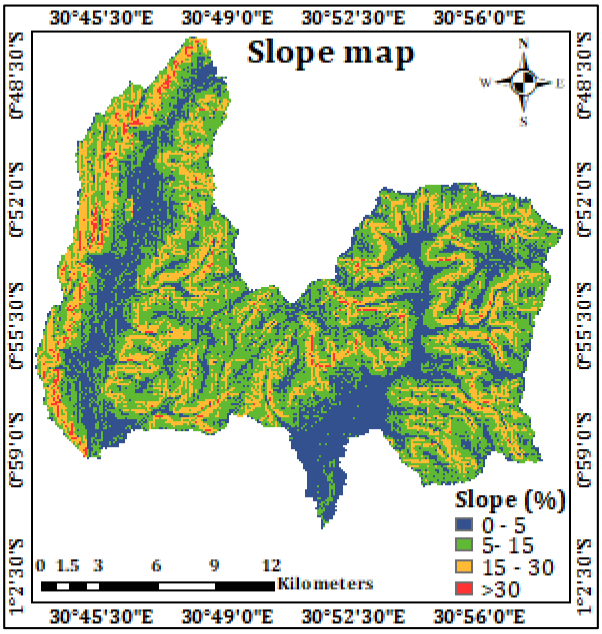

Figure 3a Slope map

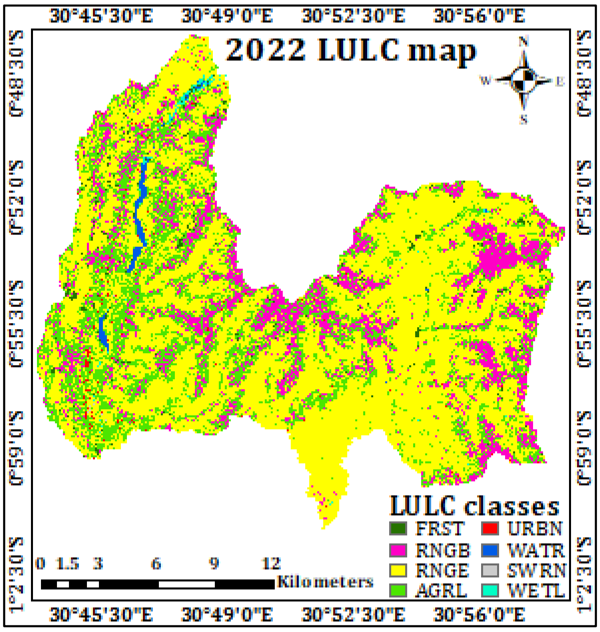

Figure 3b The 2022 LULC map

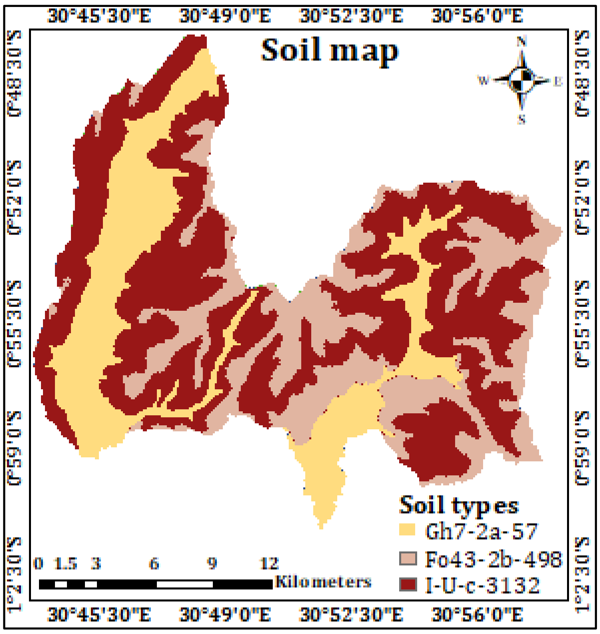

Figure 3c Soil map

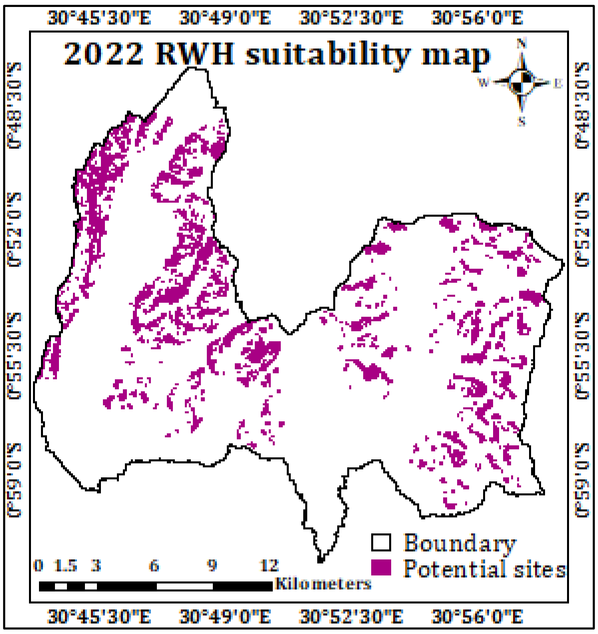

Figure 3d The 2022 RWH site suitability map

3.4. Rainfall analysis

The annual average rainfall received in the Bigasha watershed over the 21-year period studied was 954 mm. The wettest and driest years were 2008 and 2006, with a total annual rainfall of 1 277 and 744 mm respectively. The average seasonal rainfall received in the March to May and September to November rainfall seasons was 328 and 398 mm while those received in June to August and December to February dry seasons was 139 and 189 mm, respectively. However, it is important to note that the onset and recession dates of the seasonal rainfalls were inconsistent across the years. In general, the annual average rainfall received in the Bigasha watershed lies within the 100 – 1 000 mm range recommended by FAO for RWH [38]. Therefore, these rains were adequate for this research project's analyses.

3.5. The Bigasha watershed uncalibrated model outputs

The watershed delineation process divided the Bigasha watershed into 4 subbasins with a total of 68 landscape units. The number of potential (full) HRUs "read" from the three LULC maps, the 1999, 2010 and 2022 were 1 643, 1 652 and 2 083, respectively. However, after the thresholds were applied, the actual number of HRUs reduced to 690, 720 and 995, respectively. As it was expected, a smaller number of HRUs were created from the 1999 LULC map than the other two maps. This is because 78 per cent of the 1999 LULC map was covered by a single LULC class (grasslands). Therefore, the creation of HRUs in areas under this LULC class was based only on soil and slope variations.

The simulated annual average surface runoff from channel 68 (the Bigasha river) for the years 2011 and 2012 was 0.54 m^3/s which agrees with the annual average surface runoff of 0.5 m^3/s recorded by Droogers et al [6] between February 2011 and May 2012, when the Nile Basin Initiative irrigation potential assessment project was conducted within the Bigasha watershed. Therefore, it could be assumed that the simulated surface runoff from this study is reliable.

The annual average runoff depth generated by the 690, 720 and 995 HRUs were 33.5, 41.8 and 35.6 mm, respectively. The runoff depth from the 720 HRUs category was high because the proportion of shrublands (RNGB) LULC class in the 2010 LULC map was higher than those in the other two maps. Under constant soil and slope conditions, areas with shrublands generate higher runoff than those with croplands (AGRL) and grasslands (RNGE). This is attributable to the low interception of precipitation and runoff in areas with shrublands.

3.6. Suitable sites for RWH

The number of HRUs selected to detect potential sites for RWH were: 62, 125 and 114 out of the original 690, 720 and 995 HRUs, respectively. The 125 HRUs category could generate the highest total annual average surface runoff volume of 2.68 MCM from a catchment area of 2 596 ha while the 114 HRUs category had the lowest total annual average surface runoff volume of 1.39 MCM, harvestable from an area of 1 327 ha. The 62 HRUs category could generate more runoff (1.61 MCM) than the 114 HRUs category because they occupied a large area (1 591 ha) than the latter.

The dominant land use, soil and slope from the potential sites were shrublands (RNGB), Leptosols (I-U-c-3132) and >10 per cent slope, respectively. Shrublands are often characterised by sparsely distributed vegetation which offer minimal interception to precipitation and are thus capable of generating high surface runoff. Leptosols are moderately fine to fine textured soils with low infiltration rates and hence high runoff generators while slopes >10 per cent are often characterised by fast flowing surface runoff which reduces the time the water needs to infiltrate into the soil. The RWH site suitability map developed from the 114 HRUs is shown in Figure 3d. All three of the RWH site suitability maps were then overlaid onto Google Earth Pro and it was confirmed that the predicted potential sites fell in areas that are dominated by shrublands and hilly terrain, as indicated earlier.

3.7. Reference evapotranspiration, crop and irrigation water requirements of coffee

The ET_o with the 25 per cent POE that was used for computing the crop and net irrigation water requirements of the coffee crop over the 18-year period studied was 4.76 mm/day. This figure accounted for high ET_os whose resultant irrigation water requirements should be met by the harvestable rainwater at the Bigasha watershed to safeguard coffee farmers from risks of crop losses. The annual average effective rainfall, crop and net irrigation water requirements of the coffee crop computed by the CROPWAT model were 772 mm, 1 632 mm and 860 mm, respectively. The above crop water requirement lies within the range of 1 200 – 1 800 mm of water required annually for coffee grown in Uganda [39].

3.8. Potential irrigable area under coffee

The total area of the coffee fields that could be irrigated annually with the harvestable rainwater at the Bigasha watershed is 145 hectares. This figure was obtained from an annual average surface runoff volume of 1.39 MCM, harvestable from the 114 HRUs derived from the 2022 LULC map and an annual average gross irrigation water requirement of 955 mm, assuming a drip irrigation system with an irrigation efficiency of 90 per cent was used. The 145 hectares is equivalent to 1.8 per cent of the current cropped area in the Bigasha watershed and 0.4 per cent of the entire watershed. Therefore, it could be concluded that RWH for irrigated coffee farming could expand the current cropped area in the Bigasha watershed by up to 1.8 percent.

4. Conclusion

- Based on the overall classification accuracy assessment results of 92.5, 96.7 and 94.0 per cent, obtained from the 1999, 2010 and 2022 LULC maps, respectively, created and used in this study, it could be inferred that the integration of the semi-automatic classification plugin and the K-nearest neighbor algorithm provides an effective tool for LULC classification.
- Although the Bigasha watershed's RWH sites are (i) located in hilly areas with 70 per cent of the slopes being greater than 10 per cent, (ii) moderately pervious with 76 per cent of the soils being hydrologic soil group C soils and (iii) receive an annual average rainfall of about 954 mm, which is adequate for RWH, the potential for RWH in the area could be reduced by grasslands and croplands land use land covers, which occupy 82 per cent of the watershed.
- Since the potential sites for RWH that were identified from all three of the LULC maps are from areas that are dominated by a combination of shrublands, Leptosols and >10 per cent slope, it could be concluded that landscapes with such characteristics are best suited for RWH.
- It turned out that the 125 HRUs that were created from the 2010 LULC map could generate the highest volume of harvestable rainwater (2.68 MCM) while the 114 HRUs that were created from the 2022 LULC map had the lowest runoff generating potential (of 1.39 MCM). This is because the 125 HRUs covered a land area that is almost twice as large as that covered by the 114 HRUs.
- The 145 hectares of coffee fields that could be irrigated using the 1.39 MCM of rainwater, which could currently potentially be harvested in the Bigasha watershed, is equivalent to 1.8 per cent of the current area under crop production in the Bigasha. Therefore, it can be inferred that RWH for irrigated coffee farming could increase the cropped area and the cropped area under coffee in this watershed by up to 1.8 and 101.8 per cent, respectively, since the estimated potential sites for RWH are located in areas that are currently not under crop production.

Recommendations

This study recommends that:

- Field visits to the identified potential RWH sites be conducted to ascertain whether the model results are reliable.
- Silt and sediment traps be installed at the future RWH reservoirs to minimise problems of soil erosion since the majority of the estimated potential RWH sites are located in hilly areas.
- Hydrological data collection in the Bigasha watershed (especially the flow data) be enhanced for future use during validation of models that utilise such data.
- A detailed irrigation suitability study be conducted in the Bigasha watershed to assess whether all the 145 hectares of coffee fields determined from this study could actually be irrigated.

Compliance with ethical standards

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Disclosure of conflict of interest

The authors declare non-existence of any conflict of interest in this publication.

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