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JOURNAL OF NATURAL RESOURCES AND DEVELOPMENT

JOURNAL OF NATURAL RESOURCES AND DEVELOPMENT

Research article

Using Open-Access Data to Determine Potential Rainwater Harvesting Sites in the Blue Nile Basin, Sudan and Ethiopia

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Article history

Received 09.07.2021
Accepted 16.02.2022
Published 15.06.2022

Keywords

Rainwater Harvesting
Multi-criteria analysis
Remote Sensing
Geographical Information System
Water scarcity
Blue Nile Basin.

Abstract

Rainwater Harvesting (RWH), the systematic collection and storage of rainwater, can contribute to satisfy current and future water demand in water-scarce regions. The main challenge to successfully implement RWH systems, is to identify the most suitable RWH sites and correctly assessing which methods to apply. To achieve this, we need reliable data that are often not available. The increasing number of open-access data products, such as remote sensing (RS) datasets, have the potential to substitute in-situ observations. In this context, this study aims to identify potential RWH zones in the Blue Nile Basin (BNB) using open-access data, multi-criteria analysis (MCA), RS and geographical information systems (GIS). To achieve this aim, seven biophysical and socio-economic RWH criteria were selected. The results showed that high and moderate-suitability zones are dominant in the BNB, with an area of 51% and 45%, respectively. The high-suitability zone was found predominantly in Sudan while the moderate-suitability zone in Ethiopia. We conclude that our approach is useful to identify adequate RWH zones in data scarce regions and that it can be applied to similar environments.

1. Introduction

Water scarcity is the result of rainfall deficits and an increase in water demand resulting from rapid population growth, urbanization and economic development (Bastiaanssen et al., 2014; Elagib et al., 2019). Water-scarce arid and semi-arid regions (ASARs) cover nearly a quarter of the world's land surface (approximate area of 50 million km2) (Ziadat et al., 2012) and include about 50% of the world's population (Naba et al., 2016). In most ASARs, farmers suffer from fluctuating rainfall patterns and their spatial distribution, especially during the dry period, when they depend on rain-fed agricultural systems (Ammar et al., 2016). Rainwater harvesting (RWH) is a recognized and efficient adaptation measure to increase water productivity and to meet water demand. In many ASARs and areas of water shortage, RWH is efficient and can minimize the cost of supplementary irrigation and increase yield productivity to guarantee sustainable agriculture (Buraihi & Shariff, 2015). Consequently, many countries, especially arid and water-scarce areas, depend on RWH as an alternative to freshwater (Prinz, et al., 1998). In this paper, we used Jha et al. (2014) definition of RWH, which is "the concentrating, storing and collecting runoff from rainwater for domestic and agricultural uses". To successfully practice RWH, requires selecting the convenient sites and using convenient techniques (Al-Adamat et al., 2012), and thus an essential prerequisite is applying an appropriate approach to select RWH sites.

Previous research identified which criteria should be used to identify potential RWH sites. These criteria fall into two categories, biophysical and socio-economic, and include such considerations as to whether the site generates surface runoff during the rainy period (Mati et al., 2006; Ammar et al., 2016), which can have a significant impact on the suitability of RWH sites (Ammar et al., 2016). The Food and Agriculture Organization of the United Nations (FAO, 2003) has identified "climate, hydrology, topography, agronomy, soils, and socio-economics" as the main criteria in identifying RWH sites (Kahinda et al., 2008; Jha et al., 2014; Ammar et al., 2016). Most studies on RWH published after 2000 favor including both biophysical and socio-economic criteria in RWH assessments, to identify suitable RWH sites (Kahinda et al., 2008; Naba et al., 2016; Al-shabeeb, 2016), and these criteria are based on the availability of data required to identify site suitability (Jha et al., 2014) and on indicating which criteria are most influential in helping to create desirable surface runoff for harvesting.

Developing countries lack adequate data and data management systems, for economic and structural reasons (Prinz, et al., 1998), yet several promising solutions currently exist. Open-access datasets are promising sources to fill missing ground-data gaps and can provide information on spatial coverage, which is useful for conducting the spatial analysis that is required to identify potential RWH sites. Another tool is integrating remote sensing (RS) data with Geographic Information Systems (GIS), which makes it possible to produce the thematic layers required for identifying suitable RWH sites (Ammar et al., 2016), to identify the proper sites for RWH on a large scale (Oweis et al., 2013), and to support decision-makers (Ammar et al., 2016). The methods for selecting suitable RWH sites depend on the scale of analysis. For small-scale areas, for example, a field survey can be conducted (Prinz, et al., 1998) while for large-scale areas, RS and GIS can provide a solution (Prinz, et al., 1998; Makhamreh, 2011). Other common methods and tools to identify suitable RWH sites in ASARs is the multi-criteria analysis (MCA), which considered the most common and efficient method, and the analytical hierarchy process (AHP), which is a multi-criteria decision tool based on the pairwise comparison matrices (PCMs) (Ammar et al., 2016). The AHP method helps to determine criteria weighting values, while the MCA can be easily carried out by using the weighted linear combination (WLC) method in GIS environmental tools (Malczewski, 2000; Ammar et al., 2016; Al-shabeeb, 2016) and has been efficiently used in many different regions (Al-shabeeb, 2016; Naba et al., 2016; Al-Rukaibi et al., 2017; Diouf et al., 2017; Memarbashi et al., 2017; Singh et al., 2017).

We selected the Blue Nile Basin (BNB), which is a shared basin between Ethiopia and Sudan, not only because of its importance for water, food, and energy for millions of people in this region but also because of the severe impacts of climate variability and drought on some areas in the basin which may aggravate water scarcity in the region. This makes the BNB a representative area where RWH can play a crucial role in securing water and food for millions of people, and a potential area for our research objectives. Prior research (Binyam & Desale, 2015; Dile et al., 2016) have focused on upstream or downstream BNB but has not considered the BNB as a whole. A major challenge to RWH assessment in developing countries such as Ethiopia and Sudan is a lack of ground data (Prinz, et al., 1998). Even when ground data is available, it usually represents only scattered points (e.g., meteorological stations) and has limited spatial coverage (Weerasinghe et al., 2020). The aims of this analysis are to overcome some of these challenges by (i) Checking whether using open-access data and MCA methods can identify the most suitable sites for RWH in the BNB using the most relevant criteria, and (ii) documenting the change in the number and size of potential RWH sites between 2000 and 2015. We believe that the results of this study will bridge a knowledge gap in research in this area by providing decision-makers with initial information and knowledge about the best locations for RWH applications and the potential open-access data and methods for RWH assessments. Filling this knowledge gap can facilitate better implementation of RWH projects and offer a predictable approach that can be transferred to other similar regions.

2. Data and methods

2.1. Study area

The Nile River (NR) is the longest river in the world, with a total length of 6,650 km (Melesse et al., 2013), and represents the main water source for nearly 257 million people living in the Nile basin region (https://atlas.nilebasin.org/). Shared by 11 countries, the Nile Basin is a transboundary basin (Burchett, 2012) whose water is a major source of tension among the respective riparian countries (Melesse et al., 2013) and the BNB is part of this region and includes Ethiopia and Sudan (Figure 1). Located between the coordinates 16° 2' N and 7° 40' N, latitude 32° 30' E and longitude 39° 49' E (Yilma & Awulachew, 2009), the BNB has a total drainage catchment area of 307,176.8 km^2. The basin starts from Lake Tana (that has an area of 3,156 km^2) in the Ethiopian highlands, at an elevation of 1,786 m above sea level (Melesse et al., 2013), and flows north towards Sudan where it meets the White Nile at Khartoum City and forms the main NR. The NR crosses the Sudanese-Egyptian borders and moves through the Egyptian territory to drain into the Mediterranean Sea (Gebrekristos, 2015). The basin has 18 sub-basins (Yilma & Awulachew, 2009) and the upstream portion of the BNB located in Ethiopia covers around 17% of the country's area, with an area of 176,000 km^2 (Conway, 2000; Melesse et al., 2013). Figure (1) shows the geographical setting of both the Nile River Basin (NRB) and BNB.

The BNB is an essential water source for the NR and the Ethiopian portion of the BNB contributes between 60 % and 70 % of the total annual NR water during the rainy season (Gebrekristos, 2015; Roth et al., 2018). The annual rainfall in the BNB varies by region; in the southwest, rainfall reaches more than 2,000 mm/year, and in the northeast, up to 800 mm/year (Conway, 2000; Melesse et al., 2013). The Sudanese part of the basin receives less rainfall than the Ethiopian part, where the average annual rainfall is nearly 120 mm/year in Khartoum (Roth et al., 2018), and assumed the lowest rainfall in the basin (Yilma & Awulachew, 2009). The scarcity of water and its contested nature thus make this site suitable for our study and its aims.

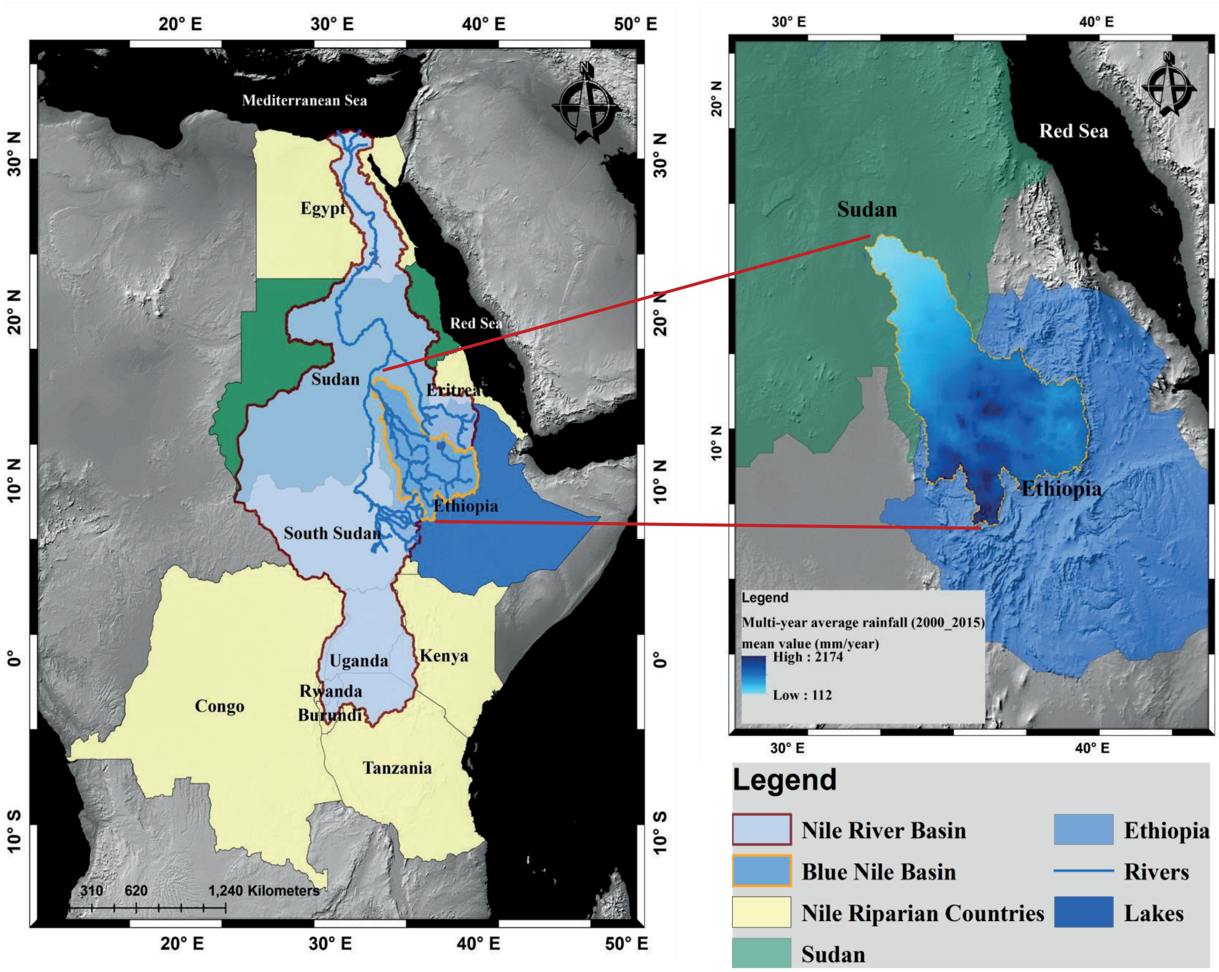

Figure 1: Location map of the Nile River Basin, Blue Nile Basin (BNB), Nile riparian countries, general features of the study area (BNB), and the mean annual rainfall in the BNB.

2.2. Data

We conducted a literature review and consulted FAO guidelines to select RWH site suitability criteria in ASARs (FAO, 2003; Jha et al., 2014; Ammar et al., 2016). For our purpose, we selected and verified data sources with the best resolution that provided the most suitable temporal and spatial coverage. To ensure compatibility and comparability, there was a need to modify the source data prior to our final modeling phase (e.g., extracting, re-projecting, resampling, and reclassifying the raster maps), since the original data were downloaded from different data sources (Table 1). We chose 2000 to 2015 as our study period since all of our data sources (open-access data) are all provided data during this period, which is considered one of the conditions for selecting criteria required to identify suitable RWH sites (Jha et al., 2014).

We used several sources for our analysis. We selected the Climate Hazards Group InfraRed Precipitation with Station data – version 2 (CHIRPS v2.0) as the source for the precipitation data in this study. CHIRPS v2.0 provides global rainfall data estimates between latitudes 50°S and 50°N from 1981 to the present at a spatial resolution of 0.05° (Funk et al., 2015; Basheer & Elagib, 2019). This database was developed by the United States Geological Survey (USGS) and the Climate Hazards Group at the University of California, Santa Barbara (UCSB) to produce high-quality precipitation data to use in early warning missions and drought monitoring (Funk et al., 2015). It has

Table 1: List of all the applied criteria to identify RWH sites in the BNB and related information.

Thematic layer	Data Source	Products Name	Resolu-tion	Temporal coverage	Spatial coverage	Reference
Rainfall	(http://chg.ucsb.edu/data/)	CHIRPS v2.0	0.05^0	1981-near present	Global	(Funk et al., 2018)
Slope%	Own work-GIS-SRTM30m	SRTM	30 m	-	-	-
Elevation (DEM)	(https://earthexplorer.usgs.gov/)	SRTM	30 m	2000	Global	(Farr, T. G., et al., 2007)
Soil	(http://webarchive.iiasa.ac.at/Research/LUC/External-World-soil-database/HTML/)	HWSD	900 m	2012	Global	(FAO/IIASA/ISRIC/ISS-CAS/JRC, 2012)
Land cover	http://due.esrin.esa.int/page_globcover.php	GlobCover 2009	300 m	2010	Global	(Bontemps et al., 2011)
Drainage Density	Own work-GIS-SRTM30m	(DEM-SRTM)	30 m	-	-	-
Population	(http://www.fao.org/geonetwork/srv/en/metadata.show?id=37139)	Geonetwork	9 km	2010	Global	(Geonetwork, 2013)

been used with other precipitation products to check their performance over the BNB (Khalifa, 2020), to validate six different precipitation products in South Sudan (Basheer & Elagib, 2019), and to determine the impact of climate variability on vegetation productivity and water use efficiency (Khalifa et al., 2018), to evaluate different rainfall products for monitoring drought in the Upper BNB in Ethiopia and was recommended as a basis for developing drought-monitoring tools to give decision-makers in Ethiopia early warning (Bayissa et al., 2017). Funk et al., (2015) assessed the efficiency of CHIRPS v2.0 for making hydrological predictions in southeastern Ethiopia. We used the Shuttle Radar Topography Mission (SRTM) 30m resolution in this study to produce the elevation and slope data. SRTM is an elevation project managed by the National Aeronautics and Space Administration (NASA), and its data can be downloaded free from the USGS distribution website (Nikolakopoulos et al., 2006). The product was selected because the first author's previous analysis and outcomes with this product showed that it provides detailed information. We also chose SRTM because it offers data in GeoTIFF format which can be directly applied in a GIS program and used in other types of research (Gorokhovich & Voustianiouk, 2006). Besides, the SRTM-30m resolution was used in different studies, for example in the Upper BNB to derive slope data (Worqlul et al., 2017). Finally, we used DEM-SRTM-30m resolution for our drainage density map.

Soil data was obtained from the Harmonized World Soil Database (HWSD), which provides global coverage, and includes high-quality data for the study area (Mahmood, 2013). To produce Landcover information, we selected the GlobCover (version 2009). GlobCover 2009, is a product released in 2010 that provides a landcover map for 2009, with global coverage at 300m resolution. In addition, it distinguishes between rainfed and irrigated landcover (Bontemps et al., 2011). The land cover criteria have a relevant impact on the surface runoff, which is important in defining the suitable RWH sites. For population data, we used the FAO GeoNetwork-Esri Grid, which offers online data in the form of satellite images, maps, and databases, including global population density data. The data is a compilation of census data and provides population density per (9 km x 9 km) as a spatial resolution. We collected all thematic layers representing the selected criteria and applied them in the WLC method to produce a potentiality for the RWH map for the BNB, see (Figure 2).

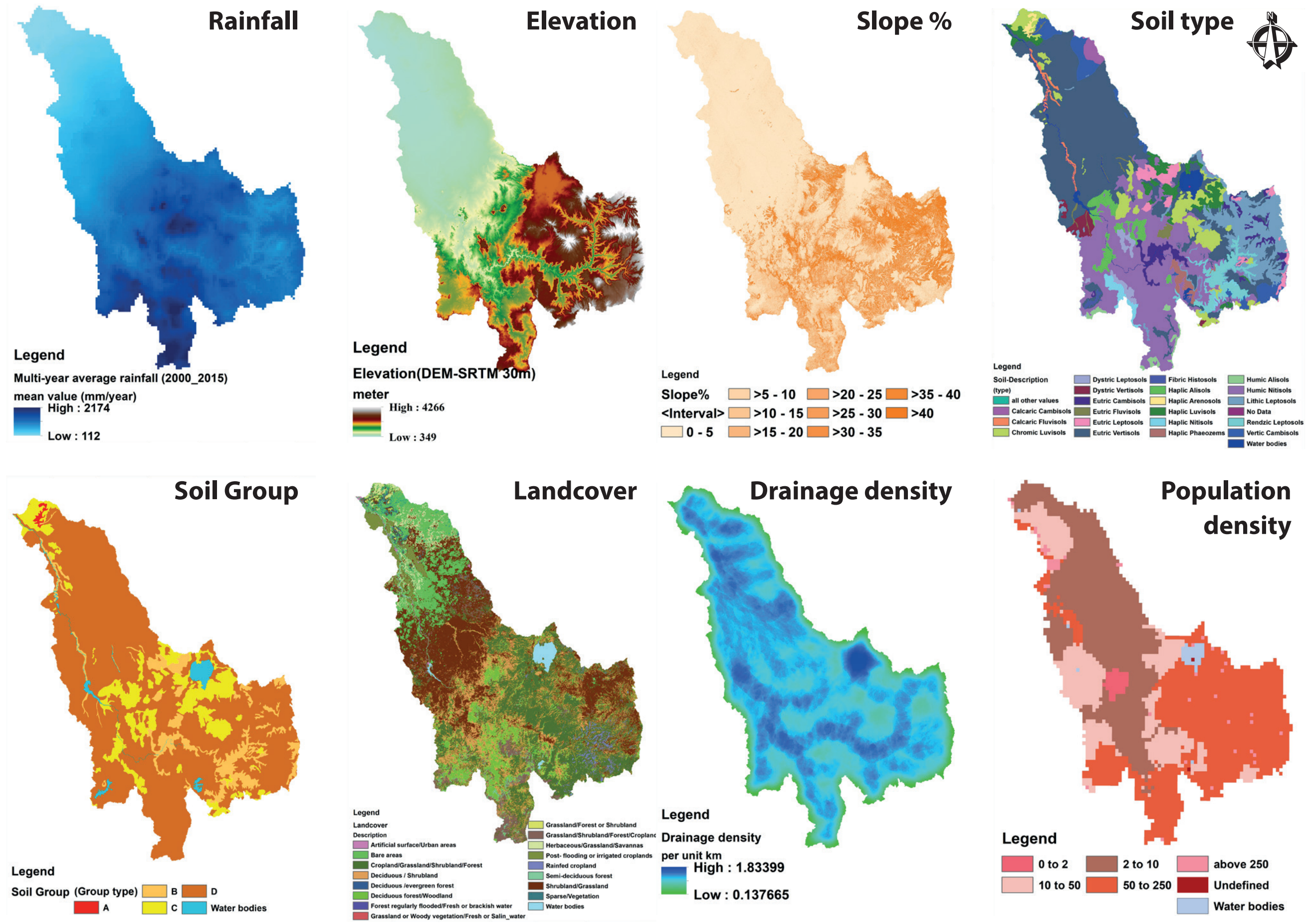

Figure 2: Thematic layers of the applied criteria in identifying suitable RWH sites for the BNB that mentioned in (Table 1).

We processed our data in GIS to produce the required thematic layers, which aggregated the daily rainfall data from CHIRPSv2.0 to monthly and annual levels. We also downloaded rasters from SRTM-30m and combined them to create a newly merged raster that covers the study area using the Mosaic-to-New-Raster tool in GIS. An essential step was using the extract-by-mask tool in GIS to extract the study area from the global and continental dataset, which was based on a prepared BNB boundary shapefile. Finally, we reprojected all data into a unified coordinate system.

2.3. Methods

2.3.1. Multi-Criteria Analysis Method (MCA)

The multi-criteria analysis (MCA), GIS, and RS approaches were selected to identify potential RWH sites. The MCA method is flexible and is, therefore useful for identifying the best sites (Al-Adamat et al., 2010). Additionally, MCA can be easily integrated into GIS to combine a set of thematic layers that spatially represent the criteria. Using appropriate MCA characteristics ensures that this method can successfully identify suitable RWH sites (Jha et al., 2014), and it includes the Analytical Hierarchy Process (AHP) and the Pairwise Comparison Matrices (PCMs) tools, which estimate the weighted value of each selected criterion instead of giving all criteria the same weight (Jha et al., 2014; Al-shabeeb, 2016; Ammar et al., 2016; Diouf et al., 2017; Saha et al., 2018; Kazakis, 2018). The MCA is a widely used method in water resource management (Al-shabeeb, 2016), RWH planning (Jha et al., 2014), and specifically, is used to identify RWH sites and structures (Kahinda et al., 2008; Maina and Raude, 2016; Al-Rukaibi et al., 2017).

The AHP is a MCA method (Al-shabeeb, 2016; Saha et al., 2018) developed in 1970 by Saaty (Ammar et al., 2016) that constructs organized mathematical operations of PCMs, and uses them to compare the selected criteria to one another based on a defined objective (Jha et al., 2014; Al-shabeeb, 2016; Ammar et al., 2016). Saaty (1980) scaled the PCMs criteria in order of importance, from 1 to 9, where 1 represents a criterion equally important in a pair and 9 represents an extremely important (Table 2) (Jha et al., 2014; Buraihi & Shariff, 2015; Al-shabeeb, 2016; Ammar et al., 2016; Satheeshkumar et al., 2017; Saha et al., 2018; Kazakis, 2018; Alkhatib et al., 2019). The values, therefore, indicate which sites are suitable for RWH based on priority and importance, the higher the value, the greater the influence and priority of the criteria on the objective (Kazakis, 2018). The diagonal cells in the PCMs were assigned a value of 1.

We examined the scale's consistency using computation of consistency ratio (CR) to detect the appropriate weighting (Jha et al., 2014), define the judgment error and redefine the scaled criteria value (Al-shabeeb, 2016). Calculating the CR requires determining the consistency index (CI), which we did use Equation (1) and Equation (2), below (Jha et al., 2014; Al-shabeeb, 2016; Kazakis, 2018).

$$CI = (\lambda_{max} – n) / (n – 1) \quad \text{……………. Equation (1)}$$

Where:

λ_{max}, Principle Eigenvalue, and n= the number of selected criteria.

$$CR = CI / RI \quad \text{……………….. Equation (2)}$$

Where:

CI, Consistency index from Equation (1), and RI= Random consistency ratio, derived based on the number of selected criteria in the study.

The CR value should be equal to or less than 0.10 (Al-Rukaibi et al., 2017; Al-shabeeb, 2016; Saha et al., 2018), any CR values greater than 0.10, should be re-assessed and corrected (Mu & Pereyra-Rojas, 2017). This decision probability scaling explains why the criteria are not all equally weighted in importance (Ammar et al., 2016). Our next step was using the selected alternative to define the criteria weightings applied in the WLC method.

Table 2: Description of the scale of importance and numbers using the (PCMs) method adapted from Al-shabeeb, (2016) based on Saaty (1980).

Intensity of Importance	Value Definition	Description
1	Equal Importance in a pair	Two criteria contribute equally to the objective
3	Moderate Importance	Judgment and experience slightly favor one criterion over another
5	Strong Importance	Judgment and experience strongly favor one criterion over another
7	Very Strong Importance	Judgment and experience very strongly favor one criterion over another
9	Extreme Importance	The evidence favoring one criterion over another is of highest possible validity
2,4,6,8	Intermediate Values	When compromise is needed
Reciprocals	Values for Inverse Comparison	If criterion I had one of the above numbers assigned to it when compared with criterion J; Then J has the reciprocal value when compared with I.

2.3.2. Weighted Linear Combination Method (WLC)

The WLC method has been used in many studies to assess various site suitability in several regions, (Al-Adamat et al., 2010; Buraihi and Shariff, 2015; Dile et al., 2016; Al-shabeeb, 2016; Diouf et al., 2017; Saha et al., 2018). This method involves harmonizing and standardizing suitability maps, where each map is assigned a weighted value generated by a previously applied AHP method. All data in vector format were transformed into raster layers so they could be processed using the WLC method in the GIS program. A condition of the WLC method is that the pixel size of all raster files needs to be unified, which we did by resampling all raster to 1 km resolutions using the resample function in ArcGIS (Diouf et al., 2017). This approach makes it possible to combine different spatial layers in the form of maps, where each map displays one specific criterion (Al-shabeeb, 2016). We later reclassified each thematic layer to different classes and assigned a score value from 1 to 4 based on certain conditions, as shown in (Table 3). To ensure a reasonable and accepted reclassification, we conducted literature reviews and relied on the experience of different RWH experts. This reclassification reflects the impact of each class within each thematic layer regarding RWH potential sites (Singh et al., 2017). The weighted sum overlay analysis tool in the GIS environment aggregates all the inserted rasters and multiplies them by their corresponding weighted value as shown in Equation (3) below, and yields the final RWH site suitability (Al-Rukaibi et al., 2017; Diouf et al., 2017; Memarbashi et al., 2017).

$$SS = \sum_{i=1}^{n} wi\ si \qquad \text{............ Equation (3)}$$

Where:

SS= the sum of all multiple criteria with their weightings and scores (i.e., final suitability map and value = RWH suitable sites), wi: = the given weightings of suitability for each criterion (i), si = the score of criteria i, and n = number of criteria.

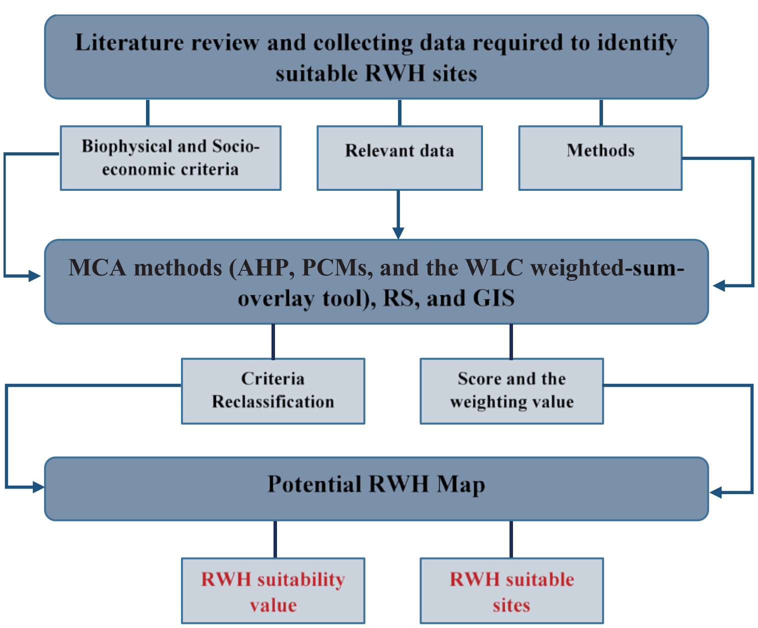

Figure 3: The applied conceptual framework in the present study.

2.3.3. Rainwater Harvesting Potentiality Map

We created a potential RWH site map by applying the WLC method using the weighted sum overlay analy-sis tool in GIS. The suitability results using this tool were illustrated in the form of a GIS map, and the suitability map was classified into different zones in area percentage to indicate their spatial coverage in the BNB. We used Equation (4) in the field calculator-GIS tool to calculate the area percentage for each suitability zone (Maina and Raude, 2016).

$$\frac{\text{Suitability class (Zone) area}}{\text{Total area}} \times 100 \quad \text{…….. Equation (4)}$$

We clarified the temporal and spatial variations of the potential RWH sites over the BNB for the period 2000 to 2015.

3. Results

3.1. Multi-Criteria Analysis Method (MCA)

We selected seven criteria (rainfall, elevation, slope percentage, soil, land cover, drainage density, and population density), and identified suitable RWH sites based on the results of AHP and PCMs-MCA tools, which showed a variation in the weighted value of each criterion (Table 3). The resulting weighted values were, from highest to lowest, rainfall (0.26), slope (0.20), elevation (0.19), drainage density (0.14), soil (0.09), land cover (0.08), and population density (0.04). The computed CR was less than 0.10, indicating that the random-matrix rating applied in the AHP using PCMs was accurate.

3.2. Weighted Linear Combination (WLC)

Using the WLC method with the weighted sum overlay helped us identify suitable RWH sites in the BNB by giving us a relevant suitability value. Reclassifying the selected criteria clarified the impact of each criterion for different classes. For instance, rainfall, with a high-suitability class was assigned a score of 4 and had a coverage area of approximately 33 %. By contrast, the poor-suitability class for rainfall had a coverage area of nearly 38 % and that was assigned a score of 1, representing areas where the rainfall class is less than 200 mm and more than 1200 mm. Areas where slope percentage is between 0 and 5 % are highly and moderately suitable and received a score of 4, representing a coverage area of 70.4 % (highly suitable) and 14.3 % (moderately suitable). Poor suitability areas are those with a slope of more than 15%, representing around 7.9% of the study area. For soil, four groups were classified using the hydrological soil groups (HSG) description from the National Resource Conservation Service (Mahmoud, 2013; Maina & Raude, 2016). Soil group D is the dominant soil, covering 75.6 % of the area, and is considered highly suitable for RWH applications. Bare areas, are also highly suitable, and cover 9.6 % of the area, while urban areas and water bodies cover 1.5 % of the area and poor suitability as sites for RWH applications. Drainage density ranged from 0.14 to 1.83 per unit km. The areas with a high suitability population density cover 42.8 % of the area. Table (3) shows all the criteria applied, the suitability classes of each, the score, the percentage of area for each class of suitability, and the weights generated from the AHP method.

Table 3: Applied criteria with suitability classes and score, the area (%) for each class of suitability, and the generated weightings value.

Class (mm/y)	Rainfall			
≤ 200 and > 1200	38.67	Poor-suitability	1	0.26
200-400	7.83	Low suitability	2	
400-800	19.92	Moderate suitability	3	
800-1200	33.58	High suitability	4	
Total	100			
Class (m)	Elevation			
> 600	66.15	Poor-suitability	1	0.19
> 500 to <= 600	9.86	Low suitability	2	
> 450 to <= 500	11.87	Moderate suitability	3	
< = 450	12.12	High suitability	4	
Total Area	100			
Class (%)	Slope%			
> 15%	7.97	Poor-suitability	1	0.2
10-15%	7.26	Low suitability	2	
5-10%	14.33	Moderate suitability	3	
0 - 5%	70.44	High suitability	4	
Total	100			
Class (Soil Group)	Soil			
A	0.29	Poor-suitability	1	0.09
B	8.97	Low suitability	2	
C	13.33	Moderate suitability	3	
D	75.57	High suitability	4	
Water Bodies &Marsh	1.83	Poor-suitability	1	
No data	0.01	Poor-suitability	1	
Total	100			
Class (%)	Landcover			
Water Bodies, Urban areas	1.45	Poor-suitability	1	0.08
Dense forest, vegetation, woodland, grassland, shrublands	52.23	Low suitability	2	
Agricultural, Croplands, irrigated land	36.68	Moderate suitability	3	
Bare areas	9.64	High suitability	4	
Total	100			
Class (per unit km)	Drainage Density			
>1.6	0.51	Poor-suitability	1	0.14
> 0.9 to <= 1.6	84.39	Low suitability	2	
> 0.5 to <= 0.9	13.33	Moderate suitability	3	
< = 0.5	1.77	High suitability	4	
Total	100			
Class (per km2)	Population Density			
Undefined / Water Bodies	0.88	Poor-suitability	1	0.04
0_10	36.56	Low suitability	2	
10_50	19.74	Moderate suitability	3	
50_ >250	42.81	High suitability	4	
Total	100			

3.2.1. Rainwater Harvesting Potential Map

A potential RWH map should indicate the minimum and maximum range of suitability values for the area examined (Dile et al., 2016). In our study, the suitability value varied from 1.26 to 3.6 and was distributed over four zones of suitability (High, Moderate, Low, and Poor suitability for RWH sites). The score values are shown in (Table 4) and indicate that most BNB areas are highly (45 % of the area) and moderately (51.6 % of the area) suitable for RWH.

Poor suitability areas cover a negligibly small percentage of the area (0.002 %), in small distributed spots in Ethiopia, and low-suitability areas covered around 3.3 % of the BNB area. The suitability result using the weighted sum overlay in GIS is illustrated in (Figure 4).

Table 4: The rainwater harvesting suitability index adopted in the present research for the Blue Nile Basin using the MCA methods.

Class	Area%	RWH suitability zone	Score
≤1.3	0.002	Poor-suitability	1
> 1.3 to ≤1.7	3.3	Low suitability	2
> 1.7 to ≤2.7	45.1	Moderate suitability	3
> 2.7	51.6	High suitability	4
Total	100		

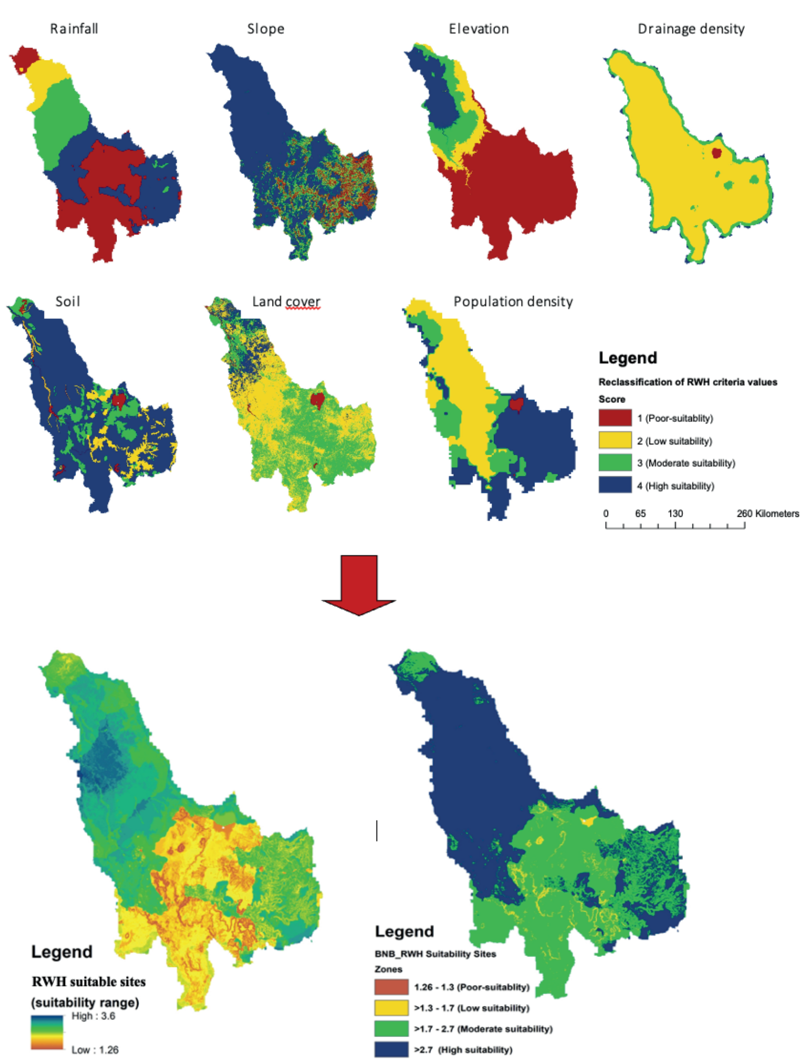

Figure 4: Weighted sum overlay results for RWH suitability in the Blue Nile Basin.

3.2.2. Temporal and Spatial Variation of Rainwater Harvesting Potentiality in the Blue Nile Basin

RWH site suitability in the BNB region changed between the years 2000 and 2015. Figure (5) shows the percentage change in suitability for each zone during this period. In 2002, for instance, the RWH high suitability zone increased, while in 2008 it decreased and the moderate suitability zone increased. In 2000 and 2006 as well, the moderate suitability zone was larger, and in 2006 and 2011, the low suitability zone increased slightly, while in 2002, it decreased significantly. The poor suitability zone in the basin was consistently low over time.

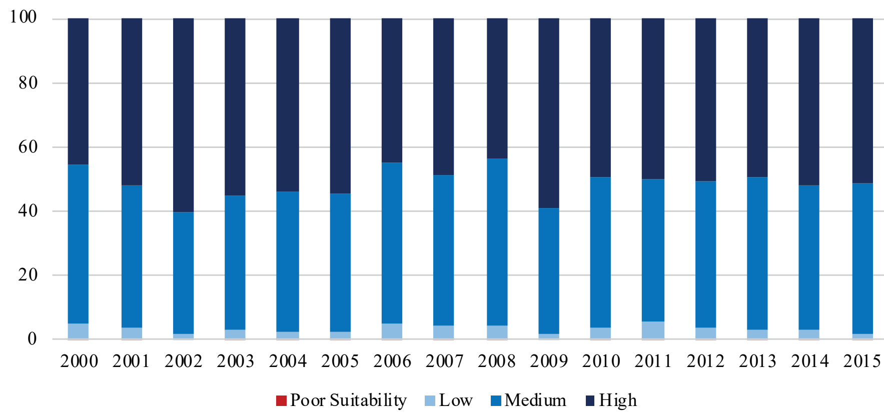

Figure 5: Temporal variation for rainwater harvesting potentiality in the Blue Nile Basin for the period 2000 to 2015.

Maps for each year show the variation in the area of suitability zones. From 2000 to 2015, the Sudanese part of the BNB had predominantly highly suitable zones, and in some years, such as 2009, those highly suitable zones extended into Ethiopia. In Ethiopia and the northern part of Sudan, moderately suitable zones predominated but were not constant. In 2002, 2004, 2009, 2011, and 2013, east and west Sudan and areas close to the Ethiopian border were moderately suitable, while in Ethiopia in 2002, 2003, 2004, 2005, and 2009, RWH potential varied widely, as the moderate zone decreased and the high suitability zones increased.

Most of Ethiopia, especially in the central and western areas, were characterized by moderate suitability, while the east went from a moderate to a highly suitable zone in 2001, 2005, 2012, 2013, 2014, and 2015. Low-suitability zones were mainly confined to Ethiopia, while in 2011, poor suitability zones were spread across the northern and western parts of Ethiopia. The low percentage of low-suitability zones underscores the high potential for RWH application. Figure (6) shows the spatial variation for the RWH potentiality between 2000 and 2015.

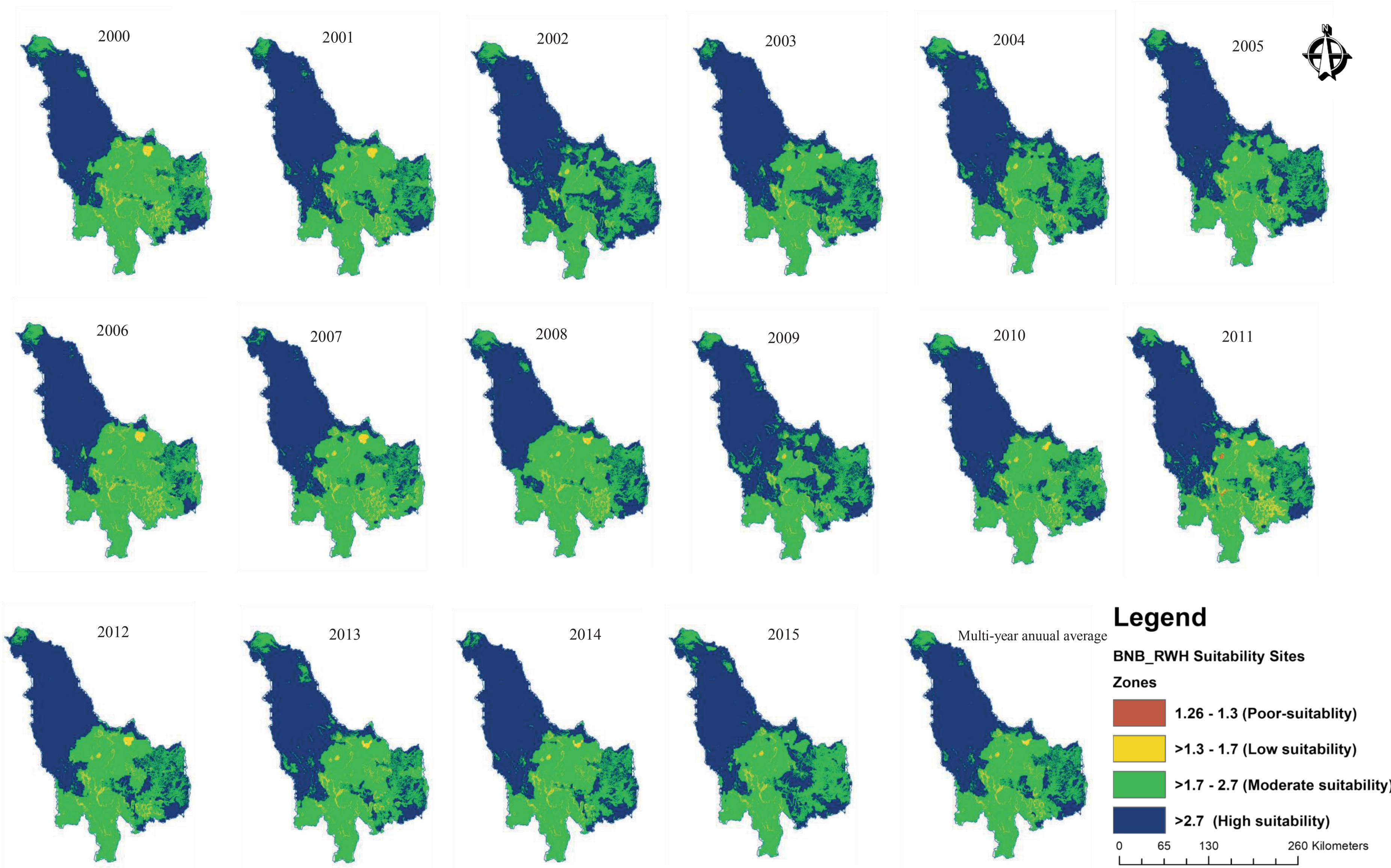

Figure 6: Showing the spatial variation of rainwater harvesting suitability sites in the Blue Nile Basin for the period 2000 to 2015 and the multi-year average.

4. Discussion

Applying the AHP-MCA method allowed us to produce weighted values for the selected criteria. Not all criteria had the same impact in selecting suitable sites, which is consistent with the findings of Diouf et al., (2017). The weighted values of our criteria showed how important each criterion was, and its influence in identifying suitable RWH sites in the basin. For instance, rainfall and slope percentage had the highest weighted values of 0.26 and 0.20, respectively, indicating that both are important for identifying suitable RWH sites. These findings confirm the results of previous studies (Al-Adamat et al., 2010; Al-shabeeb, 2016; Ammar et al., 2016) and clarify that rainfall is the most important parameter for providing surface runoff (Prinz et al., 1998; Adham et al., 2016).

Analyzing the RWH criteria using open-access data gave us an initial overview of the study area. For instance, it revealed that annual rainfall between 2000 and 2015 in the BNB territory ranged from 112 mm in the northern part (Sudan) to 2174 mm in the Ethiopian region. These results are comparable to the estimated average values for the period 2000 to 2013 (less than 250 mm in Sudan and more than 2000 mm for Ethiopia (Khalifa et al., 2018)). Areas that are highly suitable for RWH applications include those with average annual rainfall between 400 mm and 1200 mm (Mati et al., 2006; Dile et al., 2016). In areas that receive rainfall of more than 1200 mm, there is no need to apply RWH (Mati et al., 2006), as many farmers in these areas tend to drain rainfall water to protect their farms and crops instead of harvesting it (Dile et al., 2016). Nor is RWH recommended in areas with less than 200 mm of annual rainfall (dray areas) and that have few inhabitants. In addition to these criteria, the cost is a critical factor that needs to be considered.

We used these guidelines to identify those areas that were with poor suitability for RWH, and which we assigned a score value of 1 (Kahinda et al., 2008; Dile et al., 2016). Elevation and slope percentage were two criteria whose weighted values (0.19 and 0.20, respectively) revealed how important they are in RWH applications since they influence precipitation patterns and runoff distribution (Taye et al., 2015). Areas with nearly level and nearly level to moderate slope received the highest RWH suitability scores (4 and 3, respectively) (Ramakrishnan et al., 2009; Al-Adamat et al., 2010; Kadam et al., 2012; Jha et al., 2014; Dile et al., 2016; Al-shabeeb, 2016) and could explain why the BNB in Sudan is a high and moderate-suitability zone since slope influences surface runoff and distribution (Ramakrishnan et al., 2009; Jha et al., 2014). The slope may also explain why Ethiopia, with extremely rugged topography, had poor and low suitability zones since RWH applications are not desirable in areas with a steeper slope (Ammar et al., 2016).

Our results on soil revealed that group D covers most of the BNB (75.6 % of the area), followed by group C, covering an area of 13 %. These groups increasing RWH suitability since they contain clay, silty clay loam, silty clay, sandy clay, and sandy clay loam. In contrast, soil group B and A are the least suitable or unsuitable soils for RWH applications because they have high infiltration rate and low runoff, and contains sand, loamy sand, sandy, loam silt loam, and loam (Maina & Raude, 2016). A major constraint for RWH application is soil with a sandy texture (Al-Adamat et al., 2010) because it increases infiltration and decreases the rate of generated surface runoff.

Several factors govern RWH suitability, including rainfall, runoff, and types of areas, population density, and cost. We reclassified 17 land cover types for the BNB using various sources (Kadam et al., 2012; Jha et al., 2014; Dile et al., 2016; Maina & Raude, 2016; Diouf et al., 2017) and focused on runoff productivity, since bare areas increase runoff productivity (Maina & Raude, 2016), making them a highly suitable and giving them a score of 4. Urban areas and water bodies, by contrast, are considered as poor suitability RWH sites (Kadam et al., 2012;

Maina & Raude, 2016; Dile et al., 2016). RWH suitability increases as drainage density decreases, and vice versa (Jha et al., 2014; Buraihi & Shariff, 2015), since drainage density, governs concentration time (Jha et al., 2014). Another factor affecting RWH suitability is population density, which varies in the BNB. An essential factor in deciding whether to apply the RWH projects is cost, and such projects should have the widest reach possible. Cost should be a considered in terms of population density—in areas with low population density RWH is not efficient.
Areas with low rainfall (less than 200 mm) receiving low score since these arid areas with low population do not have many activities requiring water productivity (Kahinda et al., 2008; Dile et al., 2016). Therefore, areas with a high population density in the BNB received a higher score.

Finally, the success of RWH applications depends on socio-economic criteria, which, if they are not promising, can doom RWH applications (Ammar et al., 2016). Each of these factors influenced RWH suitability and reinforces the notion that no one individual criterion influences the decision to apply RWH projects.

5. Conclusion

This study aimed to map potential RWH sites in the BNB and to highlight the usefulness of using open-access data, such as integrating RS into GIS and using it as an alternative source of data in areas that lack reliable ground data. Using open-access data overcomes the problem of limited ground data. The methodology we applied, based on open-access data that integrated RS into GIS, and the MCA (AHP, PCMs, and WLC) methods were highly efficacious in achieving the study aims. Our study also underscores the usefulness of the MCA (AHP) method to indicate how sensitive certain criteria are to each other for identifying suitable RWH sites and using AHP to validate the weightings ensured that the final index was consistent. Rainfall, which was assigned the highest value, emphasizes how important it is and how much RWH applications depend on it. After rainfall, slope and elevation criteria were the next most important topographical characteristics in RWH. These two findings are vital, and clarify the relationship between rainfall and slope, underscoring their essential role in identifying suitable RWH sites. Our findings confirm the suitability of choosing these criteria and are consistent with the findings of Ammar et al., (2016).

In addition to identifying RWH criteria, another key finding is the breadth of suitable RWH locations in the BNB, specifically, 96 % of the BNB area exhibited high to moderate suitability. The highly suitable RWH zone covers most of Sudan and some of Ethiopia, while most of the moderate suitability RWH zone is located in Ethiopia.

Our study also shows that the MCA method using the weighted-sum-overlay tool in GIS can be used more widely to identify suitable RWH sites in regions with similar characteristics. This study confirms prior research emphasizing the usefulness of RS and GIS for identifying suitable RWH sites in large areas and how it can save time and cost. Non-GIS users can access our maps in Microsoft Office by converting these images into JPEG format in GIS. We also showed that RWH potential over time and space can be predicted based on the change in rainfall pattern in the basin. Our findings can be used to assist decision-makers, researchers, donors, NGOs, and private initiatives working on flood and drought hazards to better understand the RWH potentiality required for different sectors and development projects. In addition, the results of the current research are useful to investigate the impact of RWH on crop productivity in the BNB.

Involving the local community is crucial for RWH to succeed. One limitation of our study is the lack of ground data, which meant that we could not independently validate the outcomes of the current study. Despite this limitation, we believe our study has valuable and practical implications.

Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

Acknowledgments

This study was carried out under the framework of a Ph.D. program for the first author. The authors would like to thank the editor-in-chief and reviewers for their productive comments and suggestions, which helped us to significantly improve the article. We would also like to thank the providers of CHIRPS, SRTM, HWSD, GlobCover2009, and Geonetwork for making available the datasets used in the present study via their publicly available websites. Many thanks go to my colleague Dr. M. Khalifa for his constructive remarks and feedback on the manuscript, and to everyone who contributed to the success of the current work.

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