Paddy Water Environ (2016) 14:231–246
DOI 10.1007/s10333-015-0493-z

ARTICLE

Rainwater harvesting for the management of agricultural droughts in arid and semi-arid regions

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Received: 6 December 2014 / Revised: 5 March 2015 / Accepted: 6 April 2015 / Published online: 12 April 2015

Abstract Human activities, which affect ecosystem dynamics, pose a continuous challenge to individuals and communities trying to survive in arid and semi-arid regions. The development of a method to employ rainwater harvesting (RWH) in the management of agricultural drought in arid and semi-arid regions comprised two phases: (i) detection of agricultural drought in Egypt's El-Beheira governorate using a normalized difference vegetation index differencing technique and (ii) the delineation of RWH locations potentially suitable for the management of agricultural drought in the region using a GIS decision support system (DSS). Temporal vegetation cover analysis showed significant spatio-temporal changes that have occurred in the last 40 years: a general decrease in vegetation cover reflecting a trend towards ecosystem degradation, contrasted by a greening trend in some pockets within the region. Potentially suitable rainwater harvesting areas for agricultural drought management and attendant vegetation recovery were delineated in the region using DSS. The model generated a RWH map with five categories of suitability: excellent, good, moderate, poor and unsuitable. On average, 10.9 % (1104.17 km^2) and 12 % (1215 km^2) of the study area was classified as excellent and good for RWH, respectively, while 11.7 % (1185.21 km^2), 15.4 % (1560 km^2) and 50 % (5065 km^2) of the area were classified as moderate, unsuitable and poor, respectively. Most of the areas with excellent to good suitability predominantly lie in areas which faced severe drought between 2010 and 2014. To successfully implement the drought management plan, a number of RWH sites within the excellent areas must be developed.

Keywords Drought management · Normalized difference vegetation index (NDVI) · Rainwater harvesting · Geographic information system (GIS) · Analytical hierarchy process (AHP) · Multi-criteria evaluation (MCE) · Decision support system (DSS)

Introduction

Stakeholders and managers involved in water resources management in different parts of the world are facing diverse and complex challenges, including climate change (e.g. Adamowski et al. 2010; Nalley et al. 2012), deteriorating water quality and ecosystems (e.g. Haidary et al. 2013), challenges with urban water supply systems (e.g. Campisi et al. 2012; Tiwari and Adamowski, 2014), and challenges in managing watersheds in an integrated, adaptive, and collaborative manner (e.g. Adamowski et al. 2012). Human activities which affect ecosystem dynamics, particularly the extent of natural vegetation cover, pose a continuous challenge to individuals and communities trying to survive in arid and semi-arid regions (Saadat et al. 2011). For instance, the modification of vegetation cover, particularly the clearing of natural vegetation may have a long-term impact on sustainable food production, as well as on freshwater and forest resources (Foley et al. 2007). Many developing countries fail to either detect the onset of

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drought—especially agricultural drought—assess its severity, or provide individuals with any early warning of its occurrence. The challenge is to develop a drought management plan that can help decision-makers in these countries to respond appropriately and in a timely manner to impending drought. Remote sensing (RS) can provide data from which updated land cover information can be efficiently extracted in order to generate inventories and monitor drought and ecosystem changes (Houghton 1991; Roy et al. 1991; Mas 1999; Rao et al. 1999; Munyati 2000; Yelwa 2005; Potter et al. 2007; Owrangi et al. 2011; Belayneh and Adamowski 2012; Daneshmand et al. 2014; Belayneh et al. 2014; and Mahmoud 2014a). The value of satellite imagery for the investigation of vegetation cover has been expounded in different studies (Goward et al. 1985; Tucker et al. 1985).

The normalized difference vegetation index (NDVI) has been used worldwide to predict agricultural production (i.e. crop yield), as well as detect and monitor drought and desert encroachment (Benedetti and Rossini 1993; Moulin et al. 1998). The NDVI is calculated as

$$\mathrm{NDVI} = \frac{\rho_{\mathrm{NIR}} - \rho_{\mathrm{red}}}{\rho_{\mathrm{NIR}} + \rho_{\mathrm{red}}}, \quad (1)$$

where ρ_{NIR} and ρ_{red} are the spectral reflectance in the near infrared band and red band (Justice et al. 1985). Different studies have shown that multi-temporal NDVI measurements are useful for monitoring vegetation dynamics on a regional and continental scale (Goward et al. 1985; Justice et al. 1985; Tucker et al. 1985; Tucker and Choudhury 1987; Eidenshink and Hass 1992). Green leaves have a reflectance of 20 % or less in the 0.5–0.7 μm range (green to red) and about 60 % in the 0.7–1.3 μm range (near infrared). These spectral reflectances are themselves ratios of the reflected over the incoming radiation in each individual spectral band; hence, they take on values between 0.0 and 1.0. While it can take on values of -1.0 to $+1.0$, NDVI generally ranges between -0.1 (area with little if any greenery) and $+0.5$ to $+0.6$ (a very densely green area). Strongly negative values of NDVI (NDVI ≈ -1.0) correspond to deep water, those close to zero ($-0.1 < \mathrm{NDVI} < +0.1$) to barren areas of rock, sand or snow and those between $+0.2$ and $+0.4$ to shrub and grassland, while high values indicate temperate and tropical rainforests.

Rainwater harvesting (RWH) provides an independent water supply during regional water restrictions and in developed countries is often used to supplement the main supply. It provides water when there is a drought, can help mitigate flooding of low-lying areas, and reduces demand on wells, which may enable ground water levels to be maintained. Egypt is characterised as a "water scarce" country. It has limited fresh water supplies, and is expected to be under water stress by the year 2030 (Mahmoud 2014a). Water resources distribution, misuse of water resources and inefficient surface irrigation techniques are the major issues having contributed to the country's critical water security issues. The Nile River, the source of life in Egypt for millennia, services the country's industrial and agricultural demand. With over 20,756 km^2 of irrigated land, Egypt has a historically vibrant agricultural sector (Mahmoud 2014a). However, almost all of this agricultural relies on the Nile for its irrigation water. Given its limited water resources, if Egypt is to avoid agricultural drought, which has already begun to take place in the country, it must develop an alternative, supplementary water source for potable and agricultural uses. It is important to collect rainwater, as its harvest is very important in terms of ensuring an adequate supply of water. Egypt's water resource officials and legislators are facing a significant challenge due to the construction of the Grand Ethiopian Renaissance Dam. Indeed, Egyptian Irrigation Minister Mohamed Bahaa El-Din asserted on June 4, 2013 that, "the Ethiopian dam—especially during periods of water scarcity—would lead to a 'disaster' for Egypt" (Anonymous 2013). As the main problem pressing Egypt towards a significant agricultural drought is surface water scarcity, in the absence of alternative surface water sources, promoting RWH as a drought management solution could help alleviate the suffering associated with severe drought conditions, a problem compounded by a rising population. RWH is therefore gaining importance in Egypt's water resources and agricultural development schemes.

In the past, different forms of RWH have been implemented in Middle Eastern agricultural regions, usually through diversions of spate flow from normally dry watercourses (wadi). Similar methods have been implemented in the Negev desert (Evenari et al. 1971), the desert areas of Arizona and Northwest Mexico (Zaunderer and Hutchinson 1988) and in southern Tunisia (Pacey and Cullis 1986). Critchley and Reij (1989) recognized the importance of traditional, small-scale RWH systems in sub-Sahara Africa, and, more recently, those associated with buildings located in urban areas (Gould and Nissen-Petersen 1999). A vast array of RWH systems and structures are currently in use to address a wide variety of applications (Fewkes 1999; Gould and Nissen-Petersen 1999; Weiner 2003; Mahmoud 2014b; Mahmoud et al. 2014a; Mahmoud and Alazba 2014). The numerous advantages and benefits already ascribed to RWH (Jackson 2001; Krishna 2003; Mahmoud et al. 2014a) are sufficient to render RWH an important tool in achieving water resource management solutions in the face of a changing climate. Studies of ecological and hydrological interactions may determine resource use and influence vegetation composition and diversity (Ludwig et al. 2005; Yu et al. 2008). Identification of potential sites for RWH is an important step towards maximizing water availability and land productivity in semi-arid areas (Mahmoud 2014b; Mahmoud et al. 2014a; Mahmoud and Alazba 2014).

More recently, studies integrating runoff modelling, RS and geographic information systems (GIS) have gained ascendance in targeting suitable sites for water recharging/harvesting structures (Mahmoud 2014b; Mahmoud et al. 2014a, b, c; Mahmoud and Alazba 2014). While there exists a great deal of literature on the research and development of RWH structures, few studies delineate a methodology for the selection of suitable sites for RWH structures in arid regions based on data drawn from information technologies such as RS and GIS. A study conducted in the Al-Baha region of Saudi Arabia (Mahmoud et al. 2014a) employed Remote Sensing and Geographical Information Systems (RS-GIS) to collate and analyse land use, soil, slope and hydrological digital elevation maps (DEM), along with satellite imagery (Landsat 5/7 TM/ETM) for the region. Similarly, Mahmoud et al. (2014b) presented a decision support system (DSS) for the identification of suitable sites for water harvesting/groundwater recharge structures for the Jizzan region of Saudi Arabia. Another case study was developed for the Kali sub-watershed, in Gujarat, India, as a part of the Mahi River Watershed (Ramakrishnan et al. 2008). The parameters generally employed in identifying suitable sites for RWH are runoff potential, slope fracture pattern and micro-watershed area. With the goal of improving an agriculture potential limited by low and erratic precipitation, Jabr and El-Awar (2005) presented a methodology for the localization of water harvesting reservoirs in a 300 km^2 area of Lebanon. Gupta et al. (1997) used a GIS system to digitize information on the topography and soils and created a GIS database. Land cover information was derived from RS satellite data (IRS-1A) in the form of the NDVI. Six basins were delineated using a DEM and an estimation was made of the total acreage in different slope classes. These maps were then used as input to derive a modified Soil Conservation Service (SCS) runoff curve number. Their results demonstrate the capability of GIS in its application to water harvesting planning over larger semi-arid areas.

The selection of potential water harvesting areas depends on several factors including biophysical and socioeconomic conditions (Mahmoud et al. 2014a). Different studies have used different parameters in coming to such decisions: in FAO (2003), as cited by Kahinda et al. (2008), the key factors to be considered when identifying RWH sites were climate, hydrology, topography, agronomy, soils and socioeconomic criteria. Pacey and Cullis (1986) placed greater emphasis on the importance of social, economic and environmental conditions when planning and implementing RWH projects. Using RS and GIS techniques, Ramakrishnan et al. (2008) used slope, soil porosity and permeability, runoff potential, stream order and catchment area as criteria to select suitable sites for various RWH/recharging structures in the Kali watershed, Dahod district, Gujarat, India. Similarly, Rao et al. (2003) identified land use, soil, slope, runoff potential, proximity, geology and drainage as criteria to identify suitable sites for RWH in the wetlands of the Sunderban delta of West Bengal, India. Kahinda et al. (2008) used physical, ecological and socioeconomic factors (land use, rainfall, and soil texture and soil depth), along with an ecological importance and sensitivity criterion.

Multi-criterion decision-making (MCDM) plays a critical role in many real-life problems (Mahmoud et al. 2014a). Almost any local or federal government, industry or business activity involves, in one way or the other, the evaluation of a set of alternatives in terms of a set of decision criteria. Very often, these criteria are conflicting, and, even more often, the pertinent data are very expensive to collect (Triantaphyllou and Mann 1995). The analytical hierarchy process (AHP) is a multi-criteria decision-making approach introduced by Saaty (1977, 1994). A type of GIS-based MCDM that combines and transforms spatial data (input) into result decisions (output), the AHP uses geographical data, the decision-maker's preferences and manipulation of the data and preferences according to specified decision rules referred to as factors and constraints, respectively. Malczewski (2004) cited the considerations of critical importance in decision-making to be (i) the GIS capabilities of data acquisition, storage, retrieval, manipulation and analysis and (ii) the MCDM capabilities for combining the geographical data analysis and the decision-maker's preferences into uni-dimensional values of alternative decisions.

This study presents a methodology to manage agricultural drought in arid and semi-arid regions through RWH: first agricultural drought in El-Beheira governorate, Egypt, was detected using an NDVI differencing technique, then a delineation of potential-suitable RWH areas to manage agricultural drought in the region was generated using RS and GIS.

Materials and methods

Study area

The Beheira Governorate, Egypt's second largest, is located in the northern, coastal portion of Egypt's Nile Delta (30.61°N 30.43°E), and spans a total area of about 10,130 km^2 (Fig. 1). Among governorates, Beheira has by far the largest expanse of agricultural lands (9820 km^2), an estimate which also includes the lands of Nubaria. El-Beheira is famous for its diversified agricultural production, particularly onions, barley, beets, wheat, potatoes and fava beans. The governorate comes first in Egypt in terms of fruit and vegetable production, and with respect to the

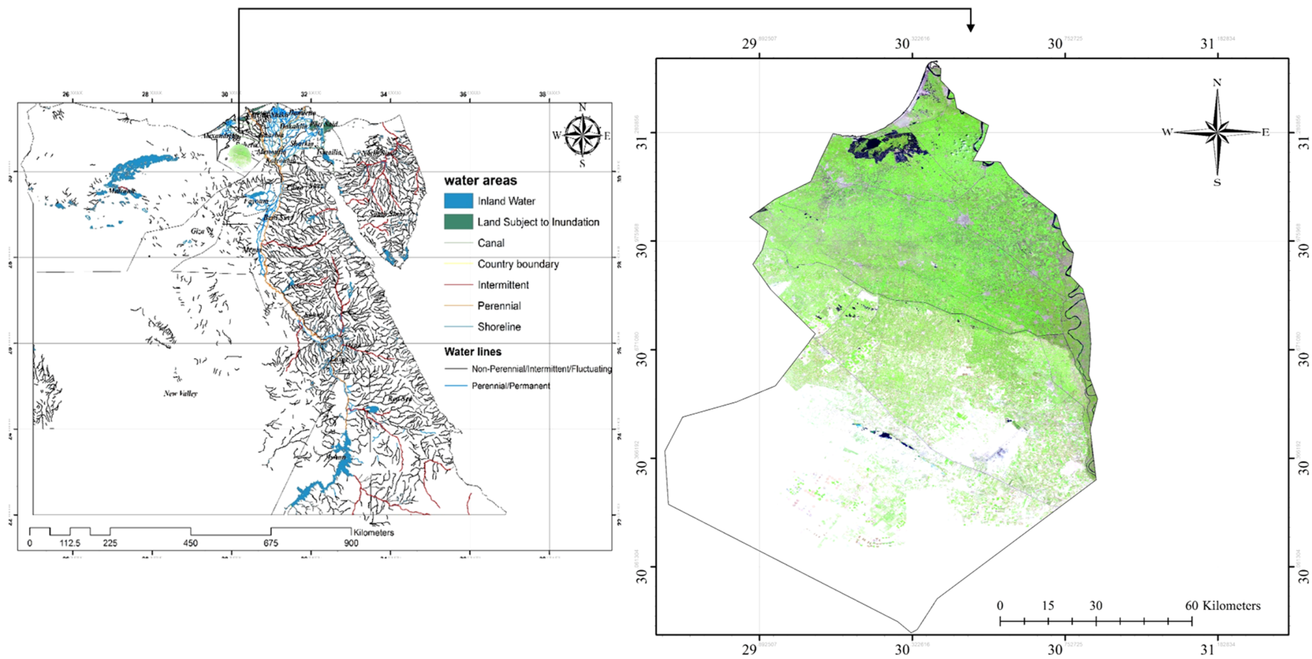

Fig. 1 Location of the study area

export of citrus fruit, potatoes, tomatoes, artichokes, watermelon, string beans and peppers. The Beheira Governorate is bordered to the East by the Rosetta branch of the Nile River, Alexandria and Marsa Matrouh in the West, the Mediterranean Sea in the North, and Elmonofya and Giza governorates in the South. Beheira has many investment opportunities, the most important being the reclamation of government-owned arable lands and opportunities for processing of diverse agricultural products. In addition, given the presence of monuments from different dynasties, religious sites, sea shores and lakes, combined with mild weather, there is an opportunity for tourism investment. The land surface rises on both sides of the governorate reaching about 200 m above sea level in the south and about 2 m above sea level in the north. El-Beheira's climate is characterised by hot dry summers and mild winters. Rainfall is irregular and unpredictable. Annual rainfall ranges between a maximum of about 190 mm in the north to a minimum of nearly 29 mm in the south, with an overall annual average of 110 mm. With a maximum air temperature of 32 °C, the El-Beheira region is, on average, much cooler than the rest of Egypt.

Vegetation cover change and drought detection

Data

Five cloud-free Landsat TM scenes (Table 1), acquired in 1975, 1990, 2000, 2010 and 2014 were obtained for this study, to allow for the detection of changes over time. The images were corrected to remove atmospheric effects and then geo-rectified using ground control points collected by GPS. The NDVI data layer was generated from NIR and Red bands of the Landsat TM image (Eq. 1). The positive NDVI values represent different types of vegetation classes, whereas near zero and negative values indicate non-vegetation classes, such as water, snow and built-up areas. Vegetation indices have long been used in RS for monitoring temporal changes associated in vegetation.

Data preprocessing

The Landsat images were geometrically corrected and projected to the World Geodetic System (WGS-1984). The three Landsat images (1975, 1990 and 2000) were all resampled to 15 m × 15 m pixels using the nearest neighbour re-sampling and registered to the base image for drought detection. A time series of NDVI values was generated using the five images. A simple threshold classification technique was then applied to the NDVI images of 1975, 1990, 2000, 2010 and 2014 using Idrisi Selva software. The thresholds used for classification were based on ground data, which were collected during a field survey. Vegetation change was determined using the ArcGIS spatial analyst toolbox. Based on the classified vegetation cover maps of 1975, 1990, 2000, 2010 and 2014, vegetation cover types were identified and their rate of change was quantified.

NDVI—differencing

Image differencing is based on calculating the difference in pixel-level image information for the study area obtained at

Table 1 Remotely sensed data used for drought detection

Images used for the study	Resolution (m)	Date of acquisition	Format	Product type (cloud cover %)
Landsat 5 TM	30	31/08/1975	GEOTIFF	L1T (0 %)
Landsat 5 TM	30	20/09/1990	GEOTIFF	L1T (0 %)
Landsat 7 ETM+	30	21/10/2000	GEOTIFF	L1T (0 %)
Landsat 7 ETM+	15	7/10/2010	GEOTIFF	L1T (0 %)
Landsat 8 ETM+	15	24/08/2014	GEOTIFF	L1T (0 %)

two different times, and then creating a difference image. In this case, a difference image was created between NDVI images, with the resultant image being threshold based according to the standard deviation of the percentage change in the image.

Identification of suitable RWH locations for drought management

The identification of suitable areas for RWH is a multi-objective and multi-criteria problem. In order to identify potential-suitable areas for RWH, five criteria were selected: (i) soil type, (ii) land cover and land use (derived from available RS data), (iii) slope (topography), (iv) runoff coefficient and (v) surplus precipitation. The criteria used to determine the potential RWH sites for the study area using RS and GIS, presented in a Work Flow Chart (Fig. 2), are measured on different scales; however, Spatial Multi-criteria evaluation (SMCE) requires that the values contained in the criterion map be converted to comparable units. Therefore, the criteria maps were re-classed into 5 comparable units of suitability classes: 5 (“excellent”), 4 (“good”), 3(“moderate”), 2 (“unsuitable”) and 1 (“poor”). The suitability classes were then used as a basis for criteria maps.

Data input and processing

Soil maps Soil samples were collected in accordance with sampling protocols outlined in Ryan and Wilson (2008). Recommended sampling depths were 0–50, 50–150, 150–300, 300–600 and 600–1000 mm. A 50-mm-diameter push tube was used for collecting these samples. A qualified soil scientist identified the soil type of all samples with the project name, unique profile number and depth range from where the sample was taken. The location of the sampling sites was representative of the soil type being assessed and showed attributes that are typical for that soil. The soil type name from any existing soil survey or soil map was used, providing the observed soil could be correlated with the published soil type. Verification sites were examined in sufficient detail to allocate the site to a soil type and soil map unit. In ground truthing, sites are commonly used to accurately position the boundaries of soil map units, to describe the variability within a soil map unit and to validate soil predictions. The verification sites were used to investigate the accuracy and relevance of the existing mapping to the assessment area. The check sites confirmed the existing mapping; therefore, the existing soil map units were sufficient to support a RWH assessment.

Land cover and land use A Landsat TM/ETM image for the year 2013 [2013, with 30-m resolution] was incorporated with collected data and ultimately served in categorizing land use and land cover (LULC). The Iso Cluster unsupervised classification and Maximum likelihood classification function in ArcGIS Spatial Analyst were used for the unsupervised classification. Training samples were collected during field surveys to create spectral signatures (i.e. reflectance values) for the supervised classification to identify what the clusters represented (e.g. water, bare earth, dry soil, etc.). The LULC map is classified into 15 main classes (Fig. 3b). The majority of El-Beheira governorate is agricultural land, most of which is located close to the banks of the Nile River, its main branches and canals, or in the Nile Delta. The total cultivated area (arable land plus permanent crops) is 1615 km^2 (2013) or about 12.5 % of the nation’s total agricultural area. Urban and Built-Up Land accounts for about 293.77 km^2 or 2.9 % of the total governorate area. Irrigated Cropland and Pasture accounts for about 1300 km^2 or about 12 % of the total cultivated area, while Barren or Sparsely Vegetated land occupies 7300 km^2. The areas covered by each land cover and land use are presented in Table 2.

Assessing the accuracy of a land cover map requires ground truthing. Georeferenced ground truthing points were collected using a GPS unit and used to validate the land cover and land use maps developed (Fig. 4). Validation analysis was performed using Kappa Agreement Index (KIA) where a value exceeding 0.8 indicates a high classification performance. The overall kappa statistic was 0.87, indicating that the classification of the land use and land cover map was accurate.

Slope (topography) A DEM with a 30-m resolution was used to generate a slope map for El-Beheira. The DEM was

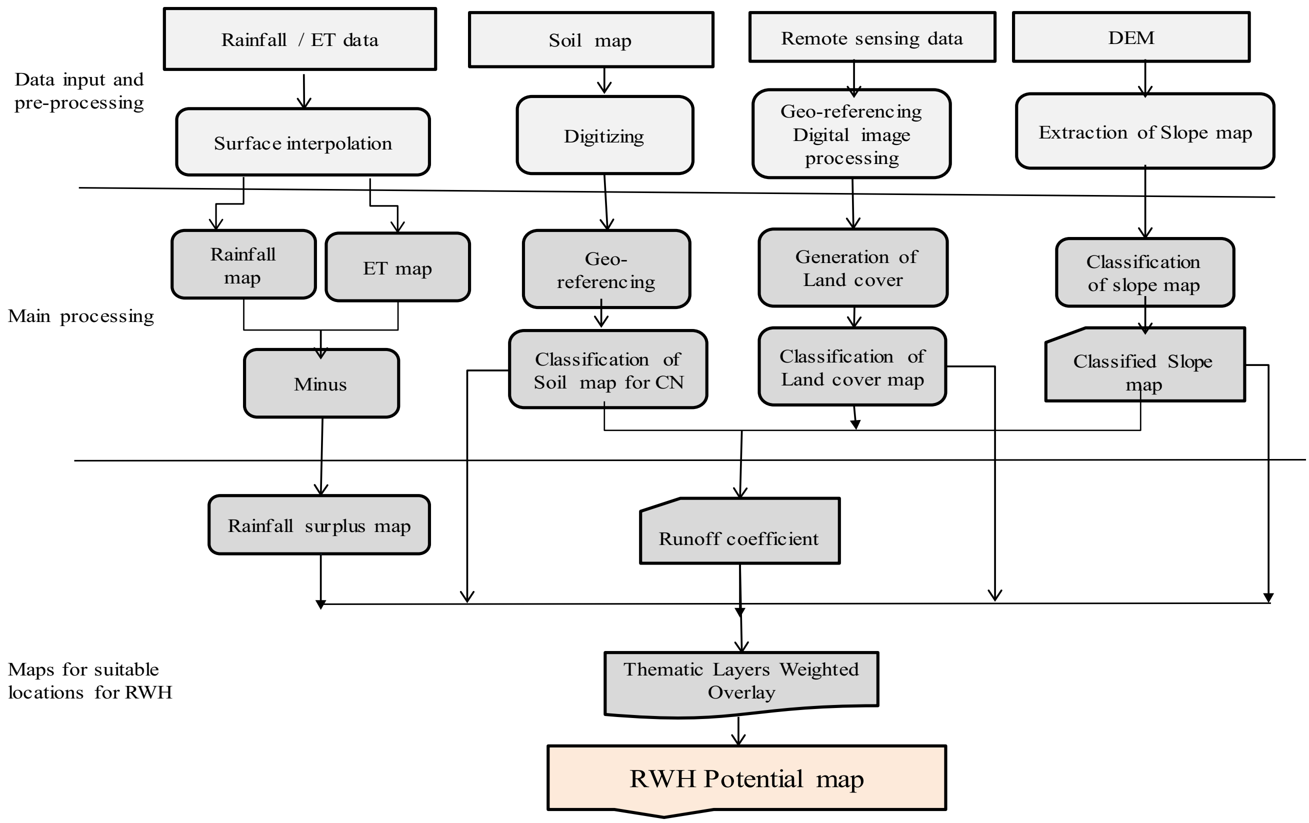

Fig. 2 Conceptual framework of rainwater harvesting (RWH) potential mapping. (*CN* curve number, *DEM* digital elevation model, *ET* evapotranspiration)

developed using GIS, through which sinks and flat areas were removed so as to maintain continuity of flow to the catchment outlets. Once this process was completed, a slope map (Fig. 3c) for the study area was generated for the El-Beheira governorate.

Curve number The curve number (CN) is a hydrologic parameter used to describe the storm-water runoff potential for a given drainage area. It is a function of land use, soil type, and soil moisture. The modelled CN for this study was extracted from Egypt's curve number map developed by Mahmoud (2014a) (Fig. 3d); the CN map shows a variation in the values of runoff from as low as 0.03 to a maximum of 1.0. These values indicate the potential amount of annual rainfall that can be harvested and used for agriculture, potable and groundwater recharge. Therefore, this harvested water can represent an additional water source in Eel-Beheira. Moreover, areas with higher runoff potential are suitable locations to install RWH systems to retain the water.

The potential runoff coefficient approaches 0.0 when slope is negligible and 1.0 when the slope is infinite, the changing magnitude of the potential runoff coefficient decreases along with an increase in surface slope. This confirms that the runoff volume for a certain amount of rainfall is less or even not affected by slope beyond a critical slope (Sharma 1986; Mahmoud et al. 2014a, c; Mahmoud 2014a, b).

Rainfall surplus The amount of rainfall monitored at different locations in El-Beheira governorate over a 31-year period indicates that rainfall is very scarce, ranging from 29 mm year^{-1} in the desert to 190 mm year^{-1} in the northwestern region, with an overall average of 140 mm year^{-1}. The maximum total amount of rain in Egypt does not exceed 1.8 $\times$ 10^{9} m^{3} year^{-1}; however, that which is effectively utilized for agricultural purposes across Egypt is estimated to be 1 $\times$ 10^{9} m^{3} year^{-1} (Mahmoud 2014a). Climatic data were obtained from the Meteorological Department of Ministry of Agriculture, and interpolated using the following sources:

1. Satellite images for monthly global precipitation from 1979 to 2009, obtained from the World Data Center for Meteorology.
2. NASA Tropical Rainfall Measuring Mission (TRMM) Monthly Global Precipitation Data from 1998 to 2010, obtained from NASA GES Distributed Active Archive Center.

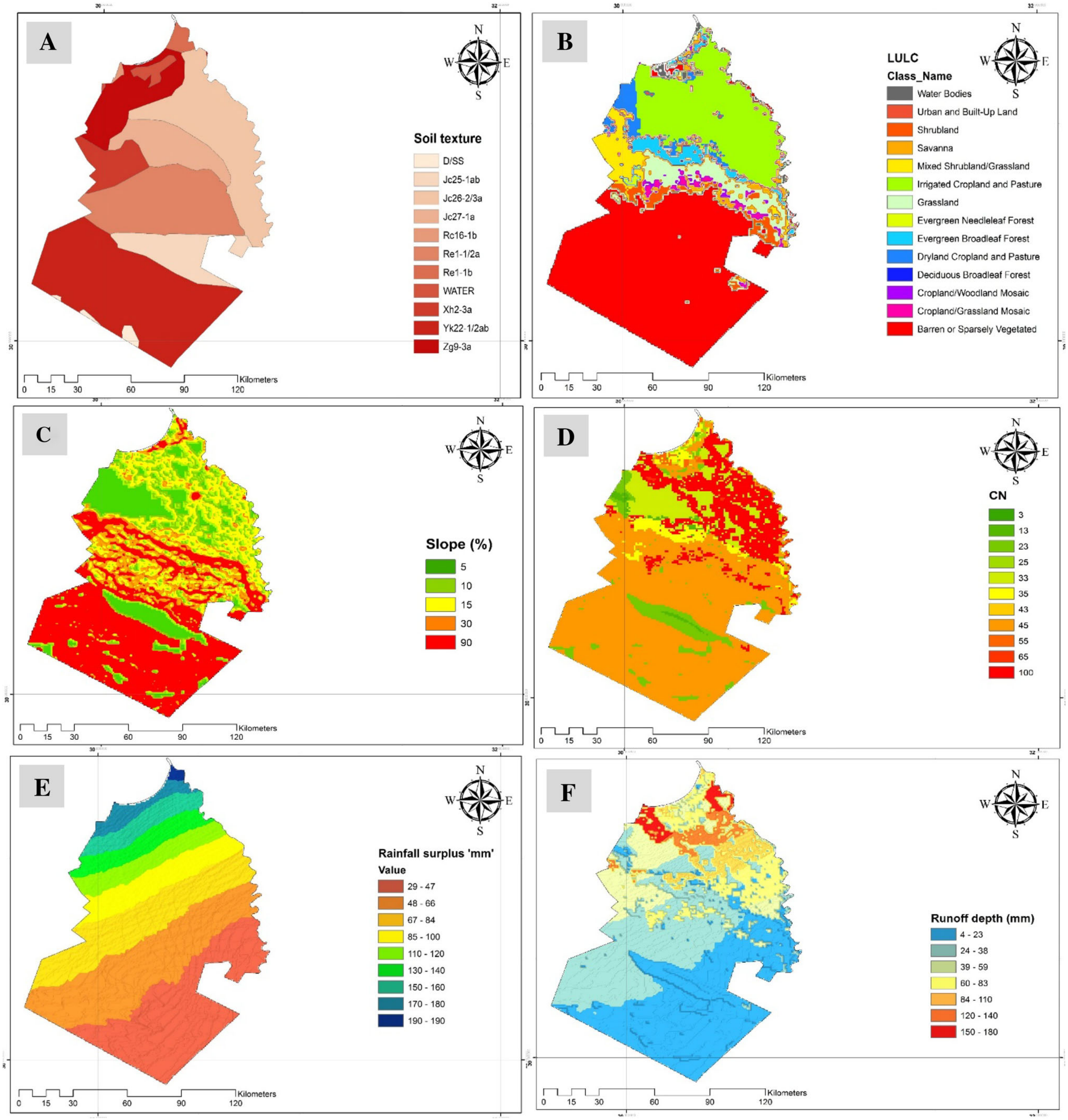

Fig. 3 Typical input maps, used for the development, testing and validation of DSS to identify suitable locations for drought management through rainwater harvesting within the study area: **a** soil texture map, **b** LULC map, **c** slope map for identifying potential RWH sites, **d** PRC distribution map based on curve numbers (Mahmoud 2014a), **e** rainfall surplus map, **f** annual runoff depth

The rainfall surplus (P-ET) map was calculated for all meteorological stations covering the period from 1950 to 2012, by subtracting long-term average monthly evapotranspiration values from the monthly precipitation. The annual rainfall surplus calculated at each meteorological station was obtained by summing only the positive values of the P-ET difference. The map of spatial distribution of rainfall surplus (Fig. 3e) was generated by interpolating previous data values using ArcGIS.

As noticed from Fig. 3e, towards the South of the governorate, rainfall tapers off very rapidly to less than 20 mm year^{-1}, as well as fluctuating widely from year to year (Fig. 3e). One of the main issues is to increase the efficiency of runoff water use for human and animal

Table 2 Class cover distribution from 1975 to 2014

Class cover	1975		1990		2000		2010		2014	
	Area (km^2)	(%)	Area (km^2)	(%)	Area (km^2)	(%)	Area (km^2)	(%)	Area (km^2)	(%)
Water bodies	205.2	2.020	250.2	2.5	233.0	2.3	202.6	2	192.47	1.9
Bare soil	7080.0	68.9	7134.1	70.1	6422.4	63.4	5591.76	55.2	6787	67
Mixed shrub land and grassland	1666.5	16.7	660.3	6.5	455.9	4.5	962.35	9.5	1286.5	12.7
Cropland and pasture	353.4	4.2	745.4	7.3	893.5	8.8	830.66	8.2	709.1	7
Irrigated cropland	824.6	8.1	1385.2	13.6	2127.3	21.0	2542.63	25.1	1154.8	11.4

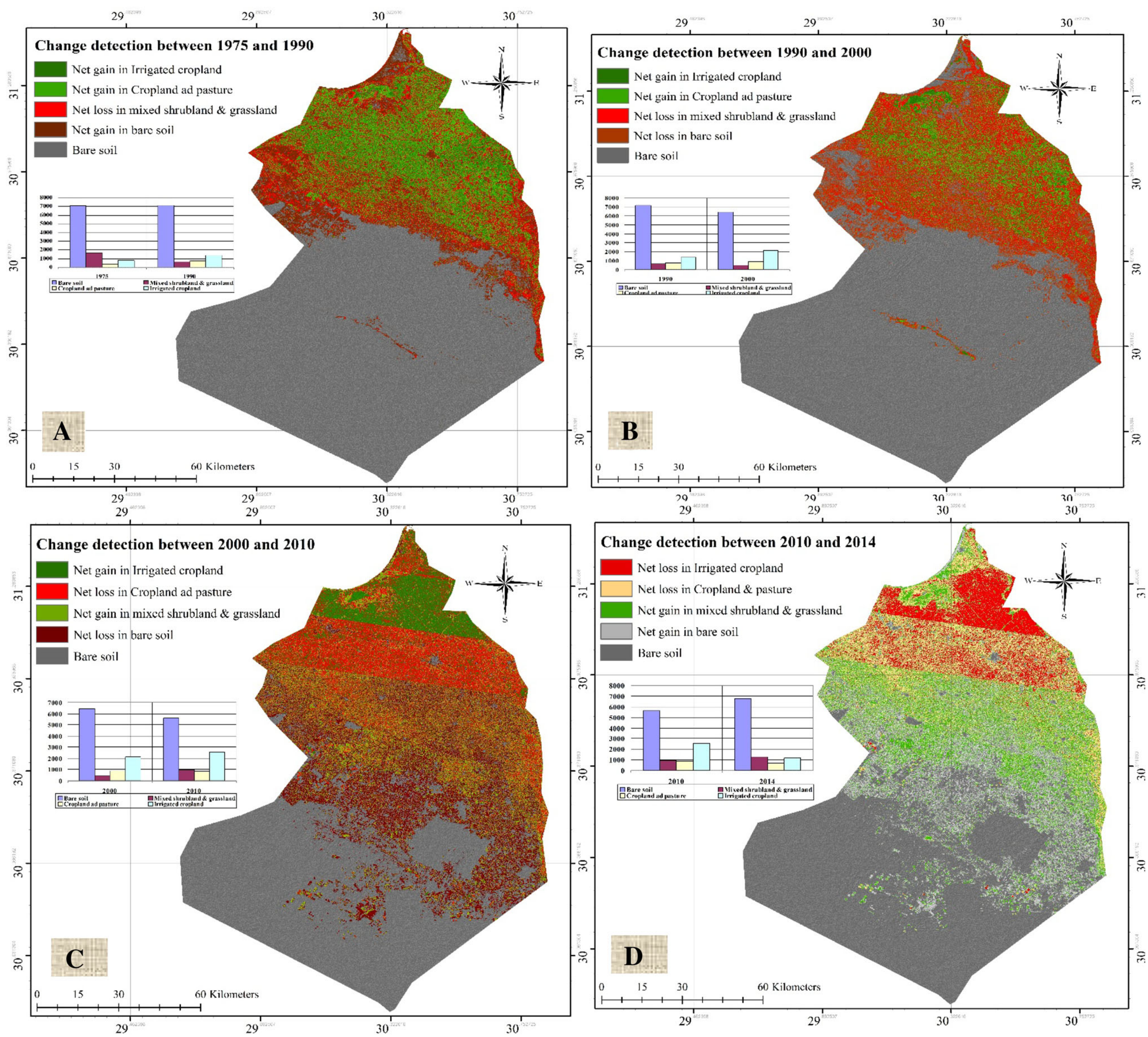

Fig. 4 Vegetation change detection from 1975 to 2014; **a** net change in vegetation cover between 1975 and 1990; **b** net change in vegetation cover between 1990 and 2000; **c** net change in vegetation cover between 2000 and 2010; **d** net change in vegetation cover between 2010 and 2014

consumption and cultivation, and to minimize soil erosion. This is possible because the area's geography and hydrology are ideal for effectively implementing water harvesting systems.

Results and discussion

Drought monitoring

Time series normalized difference vegetation index

Five NDVI images generated from Landsat images for the years 1975, 1990, 2000, 2010 and 2014 were each classified into five classes: water body and four other vegetation classes arranged in an increasing order of vegetation cover (mixed shrub land and grassland, cropland and pasture, irrigated cropland and bare soil). Table 2 shows the distribution of vegetation cover classes across the different images. The vegetation classification maps (Fig. 5a–e) clearly illustrate the spatial patterns of vegetation cover distribution within the region. The classified image of 1975 shows that vegetation cover is dominated by bare soil (68.9 %), followed by mixed shrub land and grassland (16.7 %). Cropland and irrigated cropland represent about 4.2 and 8.1 % of the total area, respectively. Water bodies account for less than 2.5 %. This classification depicts the entire vegetation cover in the subsequent years.

For the vegetation cover in 1990, the pattern remains relatively similar for water bodies with a slight increase in bare soil, which rose to 70.1 % of the study area. Classified NDVI in 1990 shows a significant increase in irrigated cropland associated with the growing food demands of an increasing population. Population growth rate in Egypt was estimated to reach 1.84 % in 2014. Comparatively, the extent of cropland and pasture dropped dramatically from 16.7 % in 1975 to 6.5 % in the 1990. This drop may be due to the development and increase in the agriculture sector during this period, which was driven by the significant increase in population.

The spatial pattern is entirely different in the 2000 classified NDVI image than the 1990 image, and shows a continued drop in bare soil and mixed shrub land and grassland, which reached 63.4 % and 4.5 %, respectively. Irrigated cropland showed a substantial increase from 13.6 % in 1990 to 21 % in 2000. However, over the same period, drought areas increase in concert with a 31 % decline in vegetation cover in mixed shrub land and grassland.

In 2010, a continued rise in irrigated cropland was noticed compared to 2000. A declining expanse of cropland and pasture was apparent in 2010 and coupled with a decline in available water bodies in the region. Similarly, in 2014, mixed cropland and pasture dropped to 7 % of the total area with a concomitant increase in bare soil. The pattern observed from 2010 to 2014 represents the worst degradation scenarios across the period studied: irrigated cropland witnessed a dramatic drop to 11.4 % of the study area, while built-up areas, particularly those located on agricultural lands increased significantly, largely due to the absence of governmental controls or security during Egypt's revolution. People took advantage of the situation to build new homes and destroy agricultural lands, leading to a rapid transition from agricultural land to villages and built-up areas.

Vegetation cover change detection

Change detection, a technique widely used in the agricultural, hydrological, forestry, environmental and ecological fields, allows for the assessment of shifting resources by comparing multi-date images and determines the type and amount of change that has occurred. The very rapid growth of the El-Beheira region and its agricultural production areas have had an unfavourable effect on the environment. Thereof, multi-temporal Landsat TM imagery for the assessment of land cover change has proven to be an ideal tool for this study.

Spatial patterns of vegetation cover changes between 1975 and 1990 (Fig. 4a) show the most significantly altered areas to be irrigated cropland and cropland and pasture, with net gains of 68 % (560 km^2) and 110.9 % (392 km^2), respectively (Table 3). Over the same period, a large area of mixed shrub land and grassland has progressively been degraded to bare soil. In addition, between 1990 and 2000, water bodies have shown a decrease from 2.5 % in 1990 to 2.3 % of the region's area. Over the same period, water bodies, bare soil, mixed shrub land and grassland have shown a net loss of 6.9, 10 and 31 %, respectively (Fig. 4b). The net gain in irrigated cropland and cropland and pasture was significant over the same period, increasing throughout, thereby indicating signs of vegetation restoration and improvement. Although the interval between 1990 and 2000 was relatively short, the rate of vegetation recovery was very high, compared to the 15-year period of 1975 to 1990 which might have witnessed an improvement in the vegetation cover.

For instance, the net gain in irrigated cropland was about 53.6 % between 1990 and 2000 (Fig. 4c), but by 2010, this figure was only 19.5 % (Fig. 4d). However, the structure of the vegetation had greatly changed by 2014. Evidence of severe degradation is quite apparent when looking at the net loss (54.6 %; Table 3), further indicating that this period (2010–2014) presented the worst vegetation conditions of all the periods studied. Drought conditions between 2010 and 2014 contributed to the loss in the irrigated

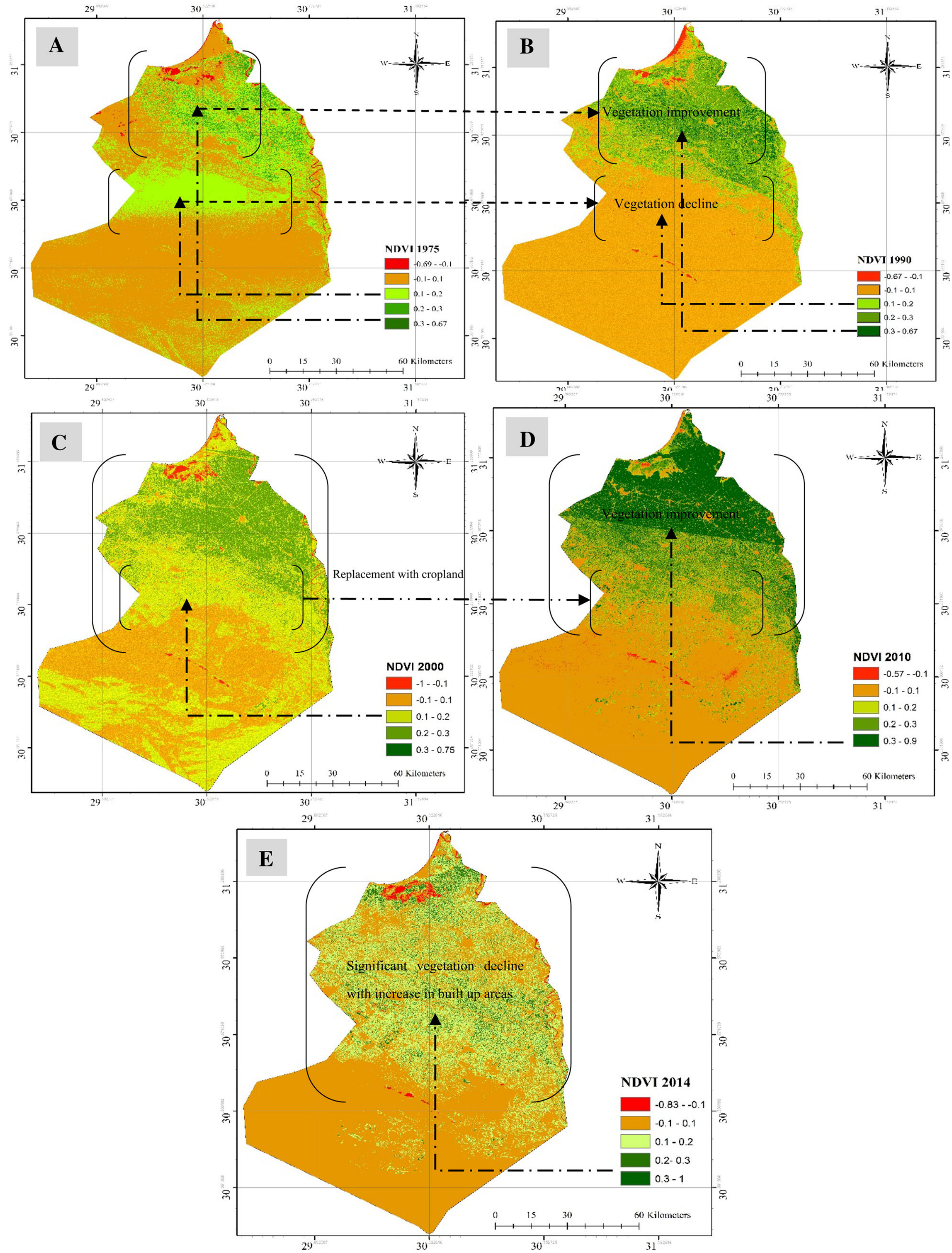

Fig. 5 Time series normalized difference vegetation index (NDVI) in different years: **a** 1975, **b** 1990, **c** 2000, **d** 2010, **e** 2014

Table 3 Net vegetation cover change from 1975 to 2014

Class cover	1975–1990		1990–2000		2000–2010		2010–2014	
	Area (km^2)	(%) loss or gain	Area (km^2)	(%) loss or gain	Area (km^2)	(%) loss or gain	Area (km^2)	(%) loss or gain
Water bodies	−45.0	21.9	17.2	−6.9	30.4	−13.0	10.1	−5.0
Bare soil	−54.1	0.8	711.7	−10.0	830.7	−12.9	−1195.2	21.4
Mixed shrub land and grassland	1006.2	−60.4	204.5	−31.0	−506.5	111.1	−324.2	33.7
Cropland and pasture	−392.0	110.9	−148.1	19.9	62.8	−7.0	121.6	−14.6
Irrigated cropland	−560.6	68.0	−742.1	53.6	−415.3	19.5	1387.8	−54.6

cropland and vegetation cover, and were largely attributable to political factors, climate change and the rising population.

It is quite clear that the north and southeastern parts of the study area show a significant increase in vegetation cover with the exception of the period from 2010 to 2014, which accordingly reflects the worst change scenario in terms of degradation. The El-Beheira region suffered a significant drought during this period especially around its central and northern portions, which led to a dramatic increase in bare soil, which returned to levels only seen in 1975. This trend towards degradation may spread and increase (Table 4).

Delineation of potential RWH for drought management

Assessment of the suitability level of criteria for RWH

Based on a literature review and expert-system-based decisions with respect to drought scenarios in El-Beheira, suitability criteria for RWH will consider soil texture suitability, as well as assign a higher suitability rank for regions with a large rainfall surplus, thereby ensuring the availability of significant harvestable runoff. The installation of RWH structures is generally more appropriate in areas having a flatter slope; however, a slight slope is needed to enhance the harvesting of runoff. Areas with slope ranging from 2 to 8 % are given the highest suitability rank. Runoff index where the CN exceeds 0.5 indicates potentially more suitable areas (Mahmoud 2014b). The criteria used for the different factors employed in identifying potential RWH sites are summarized in Table 5.

Assignments of weights to these criteria

The weights were assigned to the criteria by applying pairwise ranking and rank sum methods. The final weight calculation requires the computation of the principal eigenvector of the pairwise comparison matrix to produce a best-fit set of weights. The Weight module of Idrisi software was used for this calculation. In Idrisi, the weighing procedure is based on an AHP, a multi-factor decision-

Table 4 Areas covered by the different land cover and land use in 2013

Class	Class name	Area (km^2)	% of total area
1	Barren or Sparsely Vegetated	6584.5	65.0
2	Cropland/Grassland Mosaic	152.0	1.5
3	Cropland/Woodland Mosaic	243.1	2.4
4	Deciduous Broadleaf Forest	172.2	1.7
5	Dryland Cropland and Pasture	101.3	1.0
6	Evergreen Broadleaf Forest	202.6	2.0
7	Evergreen Needleleaf Forest	141.8	1.4
8	Grassland	405.2	4.0
9	Irrigated Cropland and Pasture	1215.6	12.0
10	Mixed Shrubland/Grassland	202.6	2.0
11	Mixed Tundra	38.5	0.4
12	Savanna	12.2	0.1
13	Shrubland	162.1	1.6
14	Urban and Built-Up Land	303.9	2.90
15	Water Bodies	192.5	1.95

Table 5 Suitability levels for different factors to identify potential sites for RWH

Suitability values	5	4	3	2	1
Soil texture	Fine	Fine and medium	Medium	Medium and coarse	Coarse
Rainfall surplus	Large surplus	Small surplus	Medium deficit	Large deficit	Very large deficit
Slope (%)	2–8	8–15	0–2	15–30	>30
Land cover	Intensively cultivated	Moderately cultivated	Forest, exposed surface	Mountain	Water body, urban areas
CN	70–100	50–70	40–50	30–40	0–30

making (MFDM) method that helps the decision-maker, facing a complex problem with multiple conflicting and subjective factors (e.g. location or investment selection, project ranking and so forth) come to a decision. The pairwise comparison approach is used in IDRISI as a method for assessing weights to evaluation criteria (factor maps) in GIS-based decision-making. This method has been tested theoretically and empirically for a variety of decision situations, including spatial decision-making. Papers in several widely different fields have documented the success of AHP in such applications (Zahedi 1986; Vargas 1990; Forman and Gass 2001; Kumar and Vaidya 2006; Hossain et al. 2007; Wang et al. 2009; Young et al. 2010; Garfi et al. 2011; Anane et al. 2012; Mahmoud 2014b).

The first step was to make a judgement as to the relative importance of pairwise combinations of the factors involved. In making these judgments, a 9-point rating scale was followed:

1/9	1/7	1/5	1/3	1	3	5	7	9
Extremely	Very strongly	Strongly	Moderately	Equally	Moderately	Strongly	Very strongly	Extremely
Less important					More important			

For n criteria, the expected value method calculates the weights, W_k for criterion k (Eq. 2; Janssen and Van Herwijnen 1994). This method takes uncertainty into account by considering the probability of each possible outcome and using this information to calculate an expected value.

$$W_k^{\mathrm{ev}} = \sum_{i=1}^{n+1-k} \frac{1}{n(n+1-i)}. \tag{2}$$

The rank sum method calculates the weight, W_k, for criterion k according to the following equation.

$$W_k^{\mathrm{rs}} = \frac{n+1-k}{\sum_{i=1}^{n}(n+1-i)}. \tag{3}$$

The accuracy of pairwise comparison was assessed through the computation of a consistency index (CI). This determines the inconsistencies in the pairwise judgments, thus allowing for the re-evaluation of comparisons. The CI, which is a measure of departure from consistency based on the comparison matrices, is expressed as

$$\mathrm{CI} = \frac{\lambda - n}{n-1}, \tag{4}$$

where λ is the mean value of the consistency vector and n is the number of columns in the matrix (Garfi et al. 2009; Saaty 1990; Vahidnia et al. 2008). The consistency ratio (CR) is then calculated as

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}}, \tag{5}$$

where RI, the random index is an index that depends on the number of elements that are being compared (Garfi et al. 2009). Detailed random indices of matrices of order 1–15 are provided by Saaty (1980).

The pairwise rating procedure has several advantages. First, the ratings are independent of any specific measurement scale. Second, the procedure, by its very nature, encourages discussion, leading to a consensus on the weights to be used. In addition, criteria that were omitted from initial deliberations are quickly uncovered through the discussions that accompany this procedure. Experience has shown, however, that while it is not difficult to come up with a set of ratings by this means, the ratings are not always consistent. Thus, the technique of developing weights from these ratings also needs to be sensitive to these problems of inconsistency and error. To provide a systematic procedure for comparison, a pairwise comparison matrix is created by setting out one row and one column for each factor in the problem (Table 6). The rating is then done for each cell in the matrix. Since the matrix is symmetrical, ratings are provided for one-half of the matrix and then inferred for the other half.

The CRs of the matrix show the degree of consistency that has been achieved when comparing the criteria or the

Table 6 Pairwise comparison matrix for RWH areas

Factors	Texture	Land cover	Slope	Rainfall surplus	Runoff
Texture	1	6	5	3	1
Land cover	1/6	1	1/2	1/4	1/7
Slope	1/5	2	1	1/3	1/4
Rainfall surplus	1/3	4	3	1	1/2
Runoff	1	7	4	3	1

Table 7 Weight (% of influence)

No.	Criteria	Weight	Wt%
1	Soil texture	0.361	36.063
2	Land cover/use	0.047	4.683
3	Slope	0.077	7.676
4	Rainfall surplus	0.160	15.996
5	Potential RC	0.356	35.582
	Sum	1	100

probability that the matrix rating randomly generated was 0.02, which was less than 0.10 (Saaty 1977), so the ratings have acceptable consistency.

Development of a GIS-based suitability model

All the processing in developing a RWH suitability map was implemented in a model developed in the model builder of ArcGIS 10.1. The suitability model generates suitability maps for RWH by integrating different input criteria maps using a Weighted Overlay Process (WOP), by utilizing both vector and raster databases. With a weighted linear combination, the criteria were combined by applying a weight to each followed by a summation of the results to a yield a suitability map using the 'weight' module in the Idrisi software. The final weights are presented in Table 7.

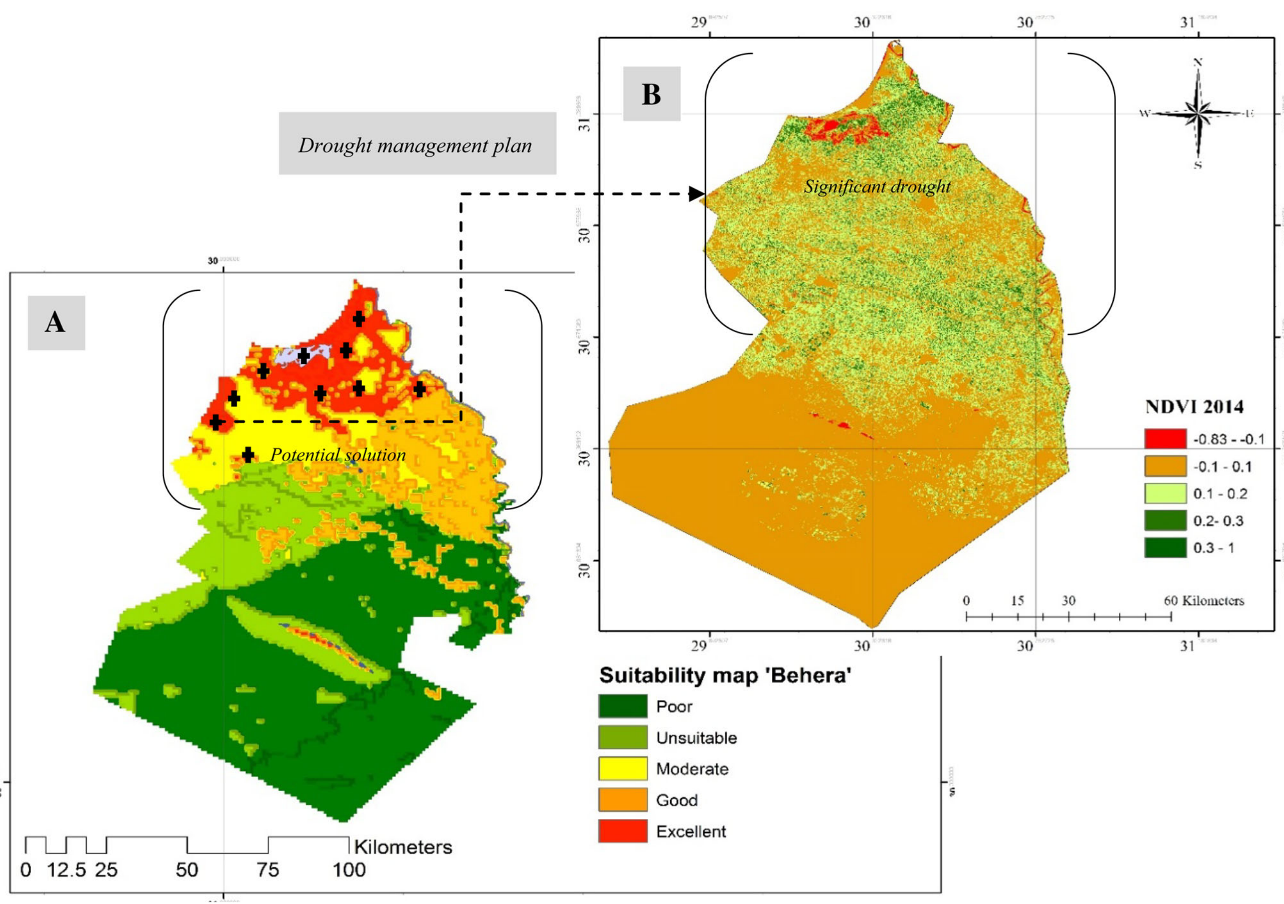

Fig. 6 Rainwater harvesting suitability map for drought management

RWH suitability maps for drought management

Identifying suitable RWH sites was implemented in the ArcGIS model environment using the model builder of ArcGIS 10.1. Based on AHP analysis taking into account the five layers, the spatial extents of RWH suitability areas were identified using MCE. Different spatial analysis tools were used in the model to solve spatial problems in the process of identifying suitable areas. The identification process in this study was considered as a multi-objective and multi-criteria problem.

The suitability model generated a suitability map for RWH with five suitability classes, i.e. Excellent, Good, Moderate, Poor and Unsuitable (Fig. 6). The spatial distribution of these categories showed that 10.9 % (1104.17 km^2) and 12 % (1215 km^2) of the study area were classified as excellent and good for RWH, respectively, while 11.7 % (1185.21 km^2), 15.4 % (1560 km^2) and 50 % (5065 km^2) of the area were classified as moderate, unsuitable and poor (Table 8). Most of the areas with excellent to good suitability had slopes of between 2 and 8 % and were located in intensively cultivated areas, and predominantly where severe drought occurred during the period of 2010–2014. The major soil type in the excellent suitable area is loam and rainfall ranges between 100 and 190 mm year^{-1}.

The most suitable locations for RWH in the study area lie mainly in the north and northwestern regions. Validation of the technique employed requires a comparison of existing RWH structure locations with the generated suitability map using the proximity analysis tool of ArcGIS 10.1. The result of this analysis showed that most of the existing RWH structures were successfully categorized. The fact that most of the existing RWH structures were successfully categorized indicates that most of them were located in excellent suitability areas. That these areas were already facing drought gives an indication of a potential water resource solution in the region.

The outcome of this work could be applied to developing an effective storm-water management system for a drought management programme in the study area by setting up RWH sites at the most suitable locations and thereby ensuring the sustainable use of scarce water resources and enhancing disaster preparedness planning in the governorate and nation.

Table 8 Areas under different suitability classes

Suitability	Area (km^2)	% of total area
Poor	5065	50
Unsuitable	1560	15.4
Moderate	1185.21	11.7
Good	1215.6	12
Excellent	1104.17	10.9

Conclusions and recommendations

Having a permanent and sustainable water supply in an arid region like El-Beheira is desirable both for agriculture activities and in maintaining the region's environment and climate; however, the undesirable side of such a situation may be tied to a number of other factors:

- In the El-Beheira governorate, runoff coefficients vary inversely with the size of the basin; therefore, the quantities of water which can be collected by intercepting the runoff are usually small.
- Evaporation is high and may exceed the maximum depth of most of the ponds even after deepening.
- If significant permanent water supplies can be established, they will probably be used for agriculture, which is a much more profitable activity than other uses.
- Permanent surface reservoirs in a hot climate like El-Beheira may present health hazards (e.g. breeding ground for mosquitoes).

A heavy 94-mm rainfall event in September 2013 is an example of an undesirable climate change impact in El-Beheira. The unexpectedly heavy rainfall destroyed about 121 km^2 of agricultural land and affected drainage system stations in El-Beheira governorate, while farmers were faced with drought in other Egyptian provinces.

In this study, suitable areas for RWH in Beheira governorate have been identified by using a GIS-based DSS and RS. The spatial distribution of the suitability map showed that the excellent suitable areas for RWH were concentrated in the northern part of the governorate, namely the same region which recently faced a severe drought.

This research is valuable because it can enhance water availability and land productivity in the severely arid regions. Nevertheless, there is a need to improve the performance of agricultural systems through ongoing efforts to develop and apply new technologies and adapt them to achieve self-sufficiency, taking into account an assessment of the suitability of these techniques to the environment of the country.

Acknowledgments This project was financially supported by King Saud University, Deanship of Scientific Research, College of Food and Agricultural Sciences, Research Center. The results can help decision-makers and water resources planners in El-Beheira governorate and similar governorates in Egypt to use the newly developed RWH maps for the management of agricultural drought. This study has the potential to help planners manage rainwater in arid and semi-arid regions. Furthermore, a feasibility study can be conducted for

various techniques used in harvesting rainwater to identify site-specific mechanisms that augment groundwater recharge from catchment areas, such as the construction of small dams, bounds, soil pits, recharge wells, tanks, etc. which can be used during drought events. Therefore, capturing rainwater runoff may increase water availability and reduce water demand.

References

Adamowski J, Adamowski K, Bougadis J (2010) Influence of trend on short duration design storms. Water Resour Manag 24:401–413

Adamowski J, Chan H, Prasher S, Sharda VN (2012) Comparison of multivariate adaptive regression splines with coupled wavelet transform artificial neural networks for runoff forecasting in Himalayan micro-watersheds with limited data. J Hydroinform 3:731–744

Anane M, Bouziri L, Limam A, Jellali S (2012) Ranking suitable sites for irrigation with reclaimed water in the Nabeul-Hammamet region (Tunisia) using GIS and AHP-multicriteria decision analysis. Resour Conserv Recycl 65:36–46

Anonymous (2013) Ethiopia dam could lead to 'disaster' for Egypt—DireTube, Latest Ethiopian News (2013, June 5). *DireTube*. http://www.diretube.com/articles/read-ethiopia-dam-could-lead-to-disaster-for-egypt_2981.html. Retrieved 26 Sept 2014

Belayneh A, Adamowski J (2012) Standard precipitation index drought forecasting using neural networks, wavelet neural networks and support vector regression. J Appl Comput Intell Soft Comput 794061:1–13

Belayneh A, Adamowski J, Khalil B, Ozga-Zielinski B (2014) Long-term SPI drought forecasting in the Awash River Basin in Ethiopia using wavelet-support vector regression models. J Hydrol 508:418–429

Benedetti R, Rossini P (1993) On the use of NDVI profiles as a tool for agricultural statistics: the case study of wheat yield estimate and forecast in Emilia Romagna. Remote Sens Environ 45:311–326

Campisi S, Adamowski J, Oron G (2012) Forecasting urban water demand via wavelet-denoising and neural network models. Case study: City of Syracuse, Italy. Water Resour Manag 26:3539–3558

Critchley WRS, Reij C (1989) Water harvesting for plant production: Part 2. Case studies and conclusions from Sub Sahara Africa

Daneshmand F, Karimi A, Nikoo M, Bazargan-Lari M, Adamowski J (2014) Mitigating socio-economic–environmental impacts during drought periods by optimizing the conjunctive management of water resources. Water Resour Manag 28(6):1517–1529

Eidenshink JC, Hass RH (1992) Analyzing vegetation dynamics of land systems with satellite data. GeoCarto Int 1:53–61

Evenari ML, Shanan L, Tadmor NH (1971) The Negev: the challenge of a desert. Harvard University Press, Cambridge

FAO (2003) Land and Water Digital Media Series, 26. Training Course on RWH (CDROM). Planning of Water Harvesting Schemes, Unit 22. Food and Agriculture Organization of the United Nations (FAO), Rome

Fewkes A (1999) The use of rainwater for WC flushing: the field-testing of a collection system. Build Environ 34:765–772

Foley JA, Ramankutty N, Leff B, Gibbs HK (2007) "Global land use changes. In: King MD, Parkinson CL, Partington KC, Williams RG (eds) Our changing planet: the view from space. Cambridge University Press, New York, pp 262–265

Forman E, Gass S (2001) The analytic hierarchy process—an exposition. Oper Res 49(4):469–486

Garfì M, Tondelli S, Bonoli A (2009) Multi-criteria decision analysis for waste management in Saharawi refugee camps. Waste Manag 29(10):2729–2739

Garfì M, Ferrer-Martí L, Bonoli A, Tondelli S (2011) Multi-criteria analysis for improving strategic environmental assessment of water programmes. A case study in semi-arid region of Brazil. J Environ Manag 92(3):665–675

Gould J, Nissen-Petersen E (1999) Rainwater catchment systems for domestic supply: design, construction, and implementation. Intermediate Technology Publications, London

Goward SA, Tucker CJ, Dye D (1985) North American vegetation patterns observed with the NOAA-7 advanced very high-resolution radiometer. Vegetatio 64:3–14

Gupta KK, Deelstra J, Sharma KD (1997) Estimation of water harvesting potential for a semiarid area using GIS and remote sensing. IAHS Publications—Series of Proceedings and Reports-Intern Assoc Hydrological Sciences, vol 242, p 63

Haidary A, Amiri B, Adamowski J, Fohrer N, Nakane K (2013) Assessing the impacts of four land use types on the water quality of wetlands in Japan. J Water Resour Manag 27(7):2217–2229

Hossain MS, Chowdhury SR, Das NG, Rahaman MM (2007) Multi-criteria evaluation approach to GIS-based land-suitability classification for tilapia farming in Bangladesh. Aquac Int 15(6):425–443

Houghton RA (1991) Releases of carbon to the atmosphere from degradation of forests in tropical Asia. Can J For Res 21:132–142

Jabr WM, El-Awar FA (2005) GIS & analytic hierarchy process for siting water harvesting reservoirs, Beirut, Lebanon. J Environ Eng 122(6):515–523

Jackson RB (2001) Water in changing world. J Ecol Appl 11:1027–1045

Janssen R, Van Herwijnen M (1994) Multi-object decision support for environmental management. Kluwer, Dordrecht

Justice CO, Townshend JRG, Holben BN, Tucker CJ (1985) Analysis of the phenology of global vegetation using meteorological satellite data. Int J Remote Sens 6:1271–1318

Kahinda JM, Lillie ESB, Taigbenu AE, Taute M, Boroto RJ (2008) Developing suitability maps for rainwater harvesting in South Africa. Phys Chem Earth 33:788–799

Krishna H (2003) An overview of rainwater harvesting systems and guidelines in the United States

Kumar S, Vaidya O (2006) Analytic hierarchy process: an overview of applications. Eur J Oper Res 169(1):1–29

Ludwig JA, Wilcox BP, Breshears DD, Tongway DJ, Imeson AC (2005) Vegetation patches and runoff-erosion as interacting eco hydrological processes in semiarid landscapes. Ecology 86:288–297

Mahmoud SH (2014a) Investigation of rainfall–runoff modeling for Egypt by using remote sensing and GIS integration. CATENA 120:111–121

Mahmoud SH (2014b) Delineation of potential sites for groundwater recharge using a GIS-based decision support system. DOI, Environ Earth Sci. doi:10.1007/s12665-014-3249-y

Mahmoud SH, Alazba AA (2014) The potential of in situ rainwater harvesting in arid regions: developing a methodology to identify suitable areas using GIS-based decision support system. Arab J Geosci. doi:10.1007/s12517-014-1535-3

Mahmoud SH, Alazba AA, Amin MT (2014a) Identification of potential sites for groundwater recharge using a GIS-based decision support system in Jazan region-Saudi Arabia. Water Resour Manag 28(10):3319–3340

Mahmoud SH, Mohammad FS, Alazba AA (2014b) Delineation of potential sites for water harvesting structures using GIS-based decision support system. Hydrol Res. doi:10.2166/nh.2014.054

Mahmoud SH, Mohammad FS, Alazba AA (2014c) Determination of potential runoff coefficient for Al-Baha Region, Saudi Arabia. Arab J Geosci 7(5):2041–2057

Malczewski J (2004) GIS-based land-use suitability analysis: a critical overview. Prog Plan 62(1):3–65

Mas JF (1999) Monitoring land-cover changes: a comparison of change detection techniques. Int J Remote Sens 20(1):139–152

Moulin SA, Bondeau A, Delecolle R (1998) Combining agricultural crop models and satellite observations: from field to regional scales. Int J Remote Sens 19:1021–1036

Munyati C (2000) Wetland change detection on the Kafue Flats, Zambia, by classification of a multitemporal remote sensing image dataset. Int J Remote Sens 21(9):1787–1806

Nalley D, Adamowski J, Khalil B (2012) Using discrete wavelet transforms to analyze trends in streamflow and precipitation in Quebec and Ontario (1954 – 2008). J Hydrol 475:204–228

Owrangi A, Adamowski J, Rahnemaei M, Mohammadzadeh A, Sharifan RA (2011) Drought monitoring methodology based on AVHRR images and SPOT vegetation maps. J Water Resour Prot 3:325–334

Pacey A, Cullis A (1986) Rainwater harvesting: the collection of rainfall and run-off in rural areas. Intermediate Technology Publications, London

Potter C, Genovese V, Gross P, Boriah S, Steinbach M, Kumar V (2007) Revealing land cover change in california with satellite data. EOS 88(26):269–274

Ramakrishnan D, Bandyopadhyay A, Kusuma KN (2008) SCS-CN and GIS based approach for identifying potential water harvesting sites in the Kali Watershed, Mahi River Basin, India. J Earth Syst Sci 118(4):355–368

Rao KHVD, Bhaumik MK (2003) Spatial expert support system in selecting suitable sites for water harvesting structures—a case study of Song Watershed, Uttaranchal, India. Geocarto Int 18:43–50

Rao BRM, Dwivedi RS, Kushwaha SPS, Bhattacharya SN, Anand JB, Dasgupta S (1999) Monitoring the spatial extent of coastal wetlands ERS-1-SAR data. Int J Remote Sens 20(13):2509–2517

Roy RS, Ranganath BK, Diwakar PG, Vohra TPS, Bhan SK, Singh JJ, Pandian VC (1991) Tropical forest mapping and monitoring using remote sensing. Int J Remote Sens 11:2205–2225

Ryan PJ, Wilson PR (2008) Field operations. In: McKenzie NJ, Grundy MJ, Webster R, Ringrose-Voase AJ (eds) Guidelines for surveying soil and land resources, 2nd edn. CSIRO Publishing, Melbourne, pp 241–262

Saadat H, Adamowski J, Bonnell R, Sharifi F, Namdar M, Ale-Ebrahim S (2011) Land use and land cover classification over a large area in Iran based on single date analysis of satellite imagery. J Photogramm Remote Sens 66:608–619

Saaty TL (1977) A scaling method for priorities in hierarchical structures. J Math Psychol 15:57–68

Saaty TL (1980) The analytic hierarchy process. McGraw-Hill, New York

Saaty TL (1990) How to make a decision: the analytic hierarchy process. Eur J Oper Res 48:9–26

Saaty TL (1994) Fundamentals of decision making and priority theory with the AHP. RWS Publications, Pittsburgh

Sharma KD (1986) Runoff behaviour of water harvesting microcatchments. Agric Water Manag 11(2):137–144

Tiwari M, Adamowski J (2014) Urban water demand forecasting and uncertainty assessment using ensemble wavelet-bootstrap-neural network models. Water Resour Res 49(10):6486–6507

Triantaphyllou E, Mann SH (1995) Using the analytic hierarchy process for decision making in engineering applications: some challenges. Int J Ind Eng: Appl Pract 2(1):35–44

Tucker CJ, Choudhury BJ (1987) Satellite remote sensing of drought conditions. Remote Sens Environ 23:243–251

Tucker CJ, Townshend JRG, Goff TE (1985) African land-cover classification using satellite data. Science 227:369–375

Vahidnia MH, Alesheikh A, Alimohammadi A, Bassiri A (2008) Fuzzy analytical hierarchy process in GIS application. Int Arch Photogram Remote Sens Spatial Inf Sci 37(B2):593–596

Vargas L (1990) An overview of the analytic hierarchy process and its applications. Eur J Oper Res 48(1):2–8

Wang WD, Xie CM, Du XG (2009) Landslides susceptibility mapping based on geographical information system, Guizhou, south-west China. Environ Geol 58(1):33–43

Weiner J (2003) Incorporating rainwater harvesting in the suburban landscape. In: Proceedings of 11th international conference on rainwater catchment systems, Texcoco

Yelwa SA (2005) Land cover changes across Nigeria as detected from high temporal resolution meteorological data. Maiduguri J Arts Soc Sci 3(2):73–79

Young KD, Younos T, Dymond RL, Kibler DF, Lee DH (2010) Application of the analytic hierarchy process for selecting and modeling stormwater best management practices. J Contemp Water Res Educ 146(1):50–63

Yu M, Gao Q, Epstein HE, Zhang X (2008) An ecohydrological analysis for optimal use of redistributed water among vegetation patches. Ecol Appl 18:1679–1688

Zahedi F (1986) The analytic hierarchy process: a survey of the method and its applications. Interface 16(4):96–108

Zaunderer J, Hutchinson CF (1988) A review of water harvesting techniques of the Arid Southwestern US and North Mexico. Working Paper for the World Bank's Sub-Sahara Water Harvesting Study