

Article

Mapping Prospective Areas of Water Resources and Monitoring Land Use/Land Cover Changes in an Arid Region Using Remote Sensing and GIS Techniques

Tong Sun ¹, Wuqun Cheng ¹, Mohamed Abdelkareem ^{2,3,*}  and Nasir Al-Arifi ^{4,*}

¹ Institute of Urban and Rural Construction, Hebei Agricultural University, Baoding 071000, China

² Geology Department, South Valley University, Qena 83523, Egypt

³ Remote Sensing Lab., South Valley University, Qena 83523, Egypt

⁴ Chair of Natural Hazards and Mineral Resources, Geology and Geophysics Department, King Saud University, Riyadh 68953, Saudi Arabia

* Correspondence: mohamed.abdelkareem@sci.svu.edu.eg (M.A.); nalarifi@ksu.edu.sa (N.A.-A.)

Abstract: Groundwater is a vital water resource for economic, agricultural, and domestic purposes in arid regions. To reduce water scarcity in arid regions, recently, remote sensing and GIS techniques have been successfully applied to predict areas with prospective water resources. Thus, this study attempted to spatially reveal groundwater potential zones (GWPZs) and to conduct change detection on the desert fringes of Wadi Asyuti, a defunct tributary of Egypt's Nile basin in eastern Sahara. Eleven influential groundwater factors generated from remote sensing imagery, and geological, hydrological, and climatic conditions were combined after giving a weight to each factor through a GIS-based Analytical Hierarchy Process (AHP) coupled with the weighted overlay technique (WOT). The results revealed six distinctive zones with scores ranging from very low (10.59%) to excellent (3.03%). Thirty-three productive groundwater wells, Interferometry Synthetic Aperture Radar (InSAR) coherence change detection (CCD), a land use map derived from Sentinel-2, and the delineated flooding zone derived from Landsat-8 data were used to validate the delineated zones. The GWPZs indicated that 48% of the collected wells can be classified as consistent to excellent. The Normalized Difference Vegetation Index (NDVI) and image classification were applied to the multi-temporal Landsat series and Sentinel-2 along with the InSAR CCD data derived from Sentinel-1 images to reveal dramatic changes in land use/land cover (LU/LC) in terms of agricultural and other anthropogenic activities in the structurally downstream area, which is the most promising area for future developments. Overall, the integration of radar and multispectral data through the GIS technique has the ability to provide valuable information about water resources in arid regions. Thus, the tested model is a promising technique, and such information is extremely significant for the guidance of planners and decision makers in the area of sustainable development.

Keywords: groundwater; remote sensing; GIS; modeling; arid region; change detection



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1. Introduction

Increasing demand for freshwater resources, which represent only 2.5% of all the water on our planet [1], is being driven by the increasing population and many environmental, climatic, social, and economic conditions. In arid regions with limited rainfall and surface freshwater, these conditions threaten the sustainable development goals [2]; thus, it is necessary to preserve groundwater resources for agricultural, urbanization, industrial, and human activities. Rainwater that infiltrates into shallow aquifers through soil pores is an essential source of groundwater [3]. This hidden water resource beneath the strata represents the second largest of all freshwater resources, representing approximately 20% of all freshwater resources on the Earth. Lakes and rivers account for no more than 1% of all freshwater, and glaciers account for 79% [4]. The demand for groundwater for

different activities has increased worldwide [5], as it is fresher and more reliable than surface water, less susceptible to pollution, exists at a constant temperature, has a wide range of availability, is of excellent natural quality, is clean and accessible, and has low development costs [6–8]. It can be exploited when needed, and it is an alternative to surface water, of which the quantity available is insufficient [9]. Accordingly, ~80% of the world's rural population depends on groundwater as a safe water supply. Groundwater represents approximately 50% of currently known freshwater resources and is used to fulfill 40% of industrial water requirements and 20% of agriculture irrigation requirements [10,11].

Considerable volumes of groundwater might be retained in numerous regions, including the Sahara region of North Africa and the Arabian Peninsula. These areas are currently experiencing water shortages due to insufficient rainfall, but they have previously had pluvial conditions [12,13]. Therefore, several approaches have been carried out to explore groundwater availability as a way to address the problem of water resource depletion and scarcity [13–18]. Remote sensing (RS) and GIS techniques are fast and cost-effective tools for the exploration, prediction, and regional estimation of groundwater occurrences [19–25] that can be used by applying different predictive models [13–15,26,27]. The widely applied models for mapping groundwater potentiality are knowledge and data-driven techniques [28]. Knowledge-driven techniques include the overlay analysis [16], analytical hierarchy process (AHP) [29–31], Boolean logic [32], index overlays, and fuzzy methods [5,33], and the data-driven techniques are the frequency ratio [34,35], machine learning models [36], logistic regression [37,38], weight-of-evidence method [39], Evidential Belief Function [40], and artificial neural network model [41].

The knowledge-driven AHP technique [42,43], which is based on the GIS-weighted overlay analysis, has been successfully applied to explore GWPZs maps in different environmental conditions [44–46]. The GIS technique can handle large volumes of spatial data for processing and can combine data types to predict and find additional water resources [47]. In this approach, a hierarchical tree with multiple levels is used, and the criteria are separated into several sub-criteria. This multi-criteria decision-making technique has been used in a number of prediction studies [48–51] to develop a solution to a complex choice analysis based on hierarchical ordering criteria [52–54] in areas with limited and undistributed well data [16]. The input data used in this model include information about the basin topography, hydrology, geology, and climate, e.g., the elevation, slope, curvature, Terrain Roughness Index (TRI), Topographic wetness index (TWI), distance to river (DR), drainage networks and drainage density (Dd), rainfall, and lineaments [19]. Most of these criteria are generated from the SRTM DEM, which allows for geomorphic and morphometric analyses, ensuring the production of consistent results in a timely and cost-effective manner [19,55]. In addition to these criteria, land use/land cover (LU/LC) maps have the potential to be used to characterize the existence of water resources that enhance agricultural and other anthropogenic activities. Research into LU/LC fluctuations is essential for appropriate natural resource planning, consumption, and management for complex environmental research [16]. Using the LU/LC allows researchers to examine and monitor the dynamics of natural resources through the application of remote sensing and GIS technologies. This is extremely crucial for environmental management [56,57]. Additionally, LU/LC provides significant evidence about water resource availability.

Egypt has a water shortage, and as a result of its growing population and scarce water supplies, which primarily come from the Nile River, there will certainly be an increased need for freshwater resources. Thus, effort should be made to search for additional water resources to ensure sustainable development. Therefore, the main aim of the present study was to find potential areas of water resources through an elaborate series of actions, as follows: (1) characterization of the geological, hydrological, and climatic characteristics of the studied catchments; (2) testing of the application of the GIS-based hydride AHP-weighted overlay technique to reveal promising areas for water resources; and (3) the development of change detection maps through an analysis of multi-temporal optical and

radar remote sensing data to monitor the dynamics and development in reclamations of desert fringes.

2. Study Area

The study area is situated east of the Nile River in the Asyuit Governorate, Egypt (Figure 1). This area includes the Ma'aza plateau in the northeastern Desert of Egypt. It is situated at longitudes $31^{\circ}15'$ to $32^{\circ}30'$ E and latitudes 27° to $27^{\circ}40'$ N, covering about 6000 km^2 . It is a defunct tributary that drains into the Nile basin during rainstorms. It is aligned from east to west and cuts through the Ma'aza plateau, which is capped by limestone. There are many known tributaries in the area, such as W. Habib, W. Arishi, W. Hubara, and W. Maraheil, and also numerous elevated areas, such as G. Himu and G. Um Hubuwa, which characterize the area (Figure 2). Cretaceous/Tertiary rocks and Pliocene/Pleistocene deposits make up the basin area [58]. The NW and EW trends dominate others and control the aquifers [59]. These trends dominate the downstream area, which is shaped as a graben and displays low elevations (Figure 2). The study area is classified as arid/hyperarid based on its yearly precipitation of less than 10 mm/day on average (January 1998 to November 2013) [19]. Its arid climate conditions make it a suitable location for remote sensing research. Overcrowding throughout the narrow Nile Valley, particularly in Asyuit city, has created the need for residential, agricultural, and industrial regions. This has promoted government leaders, planners, and decision makers to seek for new cities to allow sustainable growth. Accordingly, the New city of Asyuit was built east of the Nile, downstream of W. Asyuti. This territory serves as a crucial link between Egypt's north and south parts. In fact, different development projects have been set up at the study site, and a significant amount of land has been reclaimed from the desert surroundings.

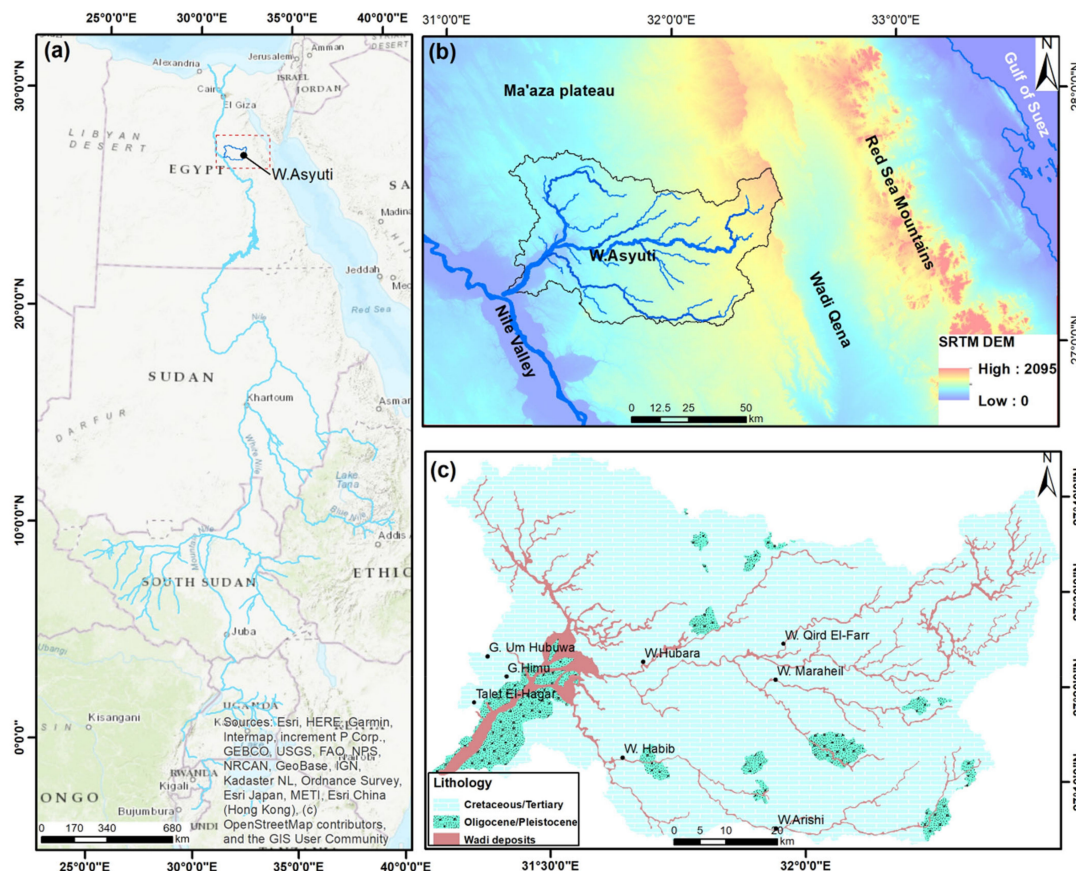


Figure 1. (a) Location of Wadi Asyuti in the northern part of the Nile basin; (b) SRTM DEM overlaid by Wadi Asyuti; (c) Geological map of the W. Asyuti basin (Conoco, 1987) [58].

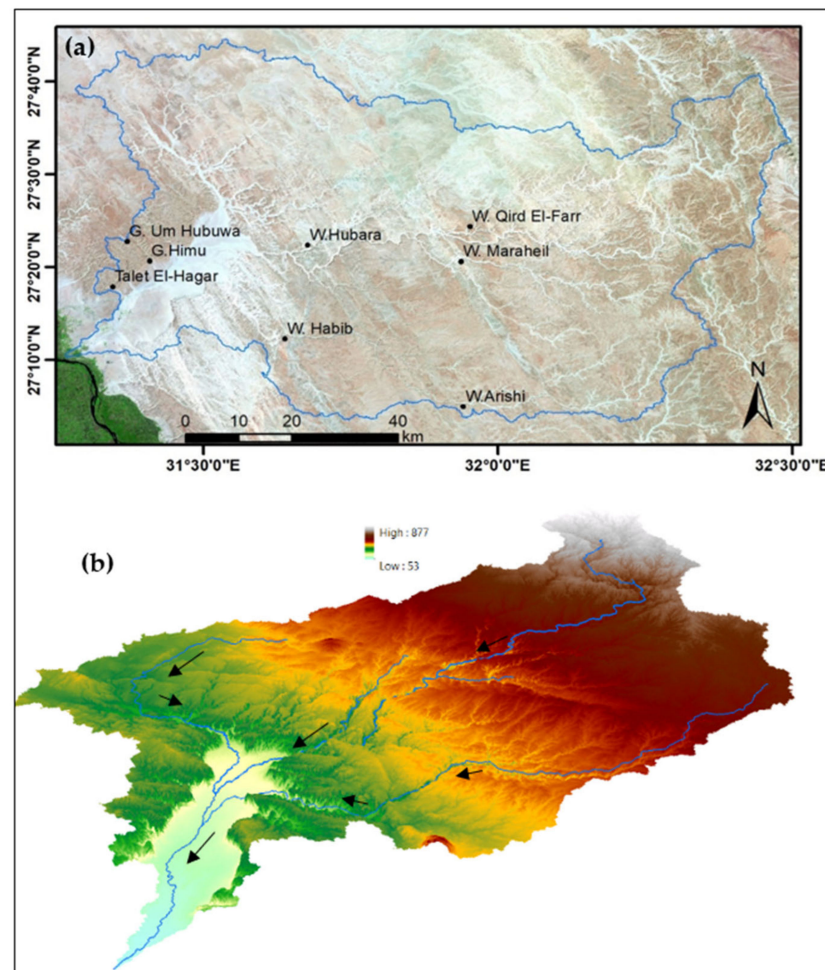


Figure 2. (a) Landsat mosaic overlaid with the W. Asyuti watershed; (b) 3D oblique view of Wadi Asyuti; (b) Rainfall storm on 8 to 9 March 2014 overlaid by the floodway extracted from Landsat data collected on 15 March 2014.

3. Data and Methods

Remote sensing imagery from various sensors, as well as geological, hydrological, and other existing information were used in this study to identify potential water resource locations. Eleven influential thematic maps obtained through remote sensing, e.g., elevation, drainage networks, slope, distance to river, lineaments, radar intensity, roughness, curvature, TWI, and rainfall, as well as ancillary data (geology), were integrated using GIS-based AHP and WOT (Figure 3). The Environment for Visualizing Images (ENVI; Harris Geospatial Solutions, Broomfield, CO, USA) v5.3, ArcGIS (ESRI Company, Redlands, CA, USA, software packages vs. 10.5), and SNAP software programs were utilized to process remote sensing data/images.

Digital Elevation Models (DEMs) were taken from Shuttle Radar Topography Mission (SRTM) data (30 m cell size). To assess the topographic characteristics, SRTM DEM data (1 arc second) were acquired from NASA. The drainage network was created automatically using the Deterministic eight-neighbor (8D) technique [60]. This was then turned into a drainage density map using a geospatial tool. Furthermore, in order to describe areas of water accumulation, the depressions were approximated using the ‘fill-difference’ approach [16].

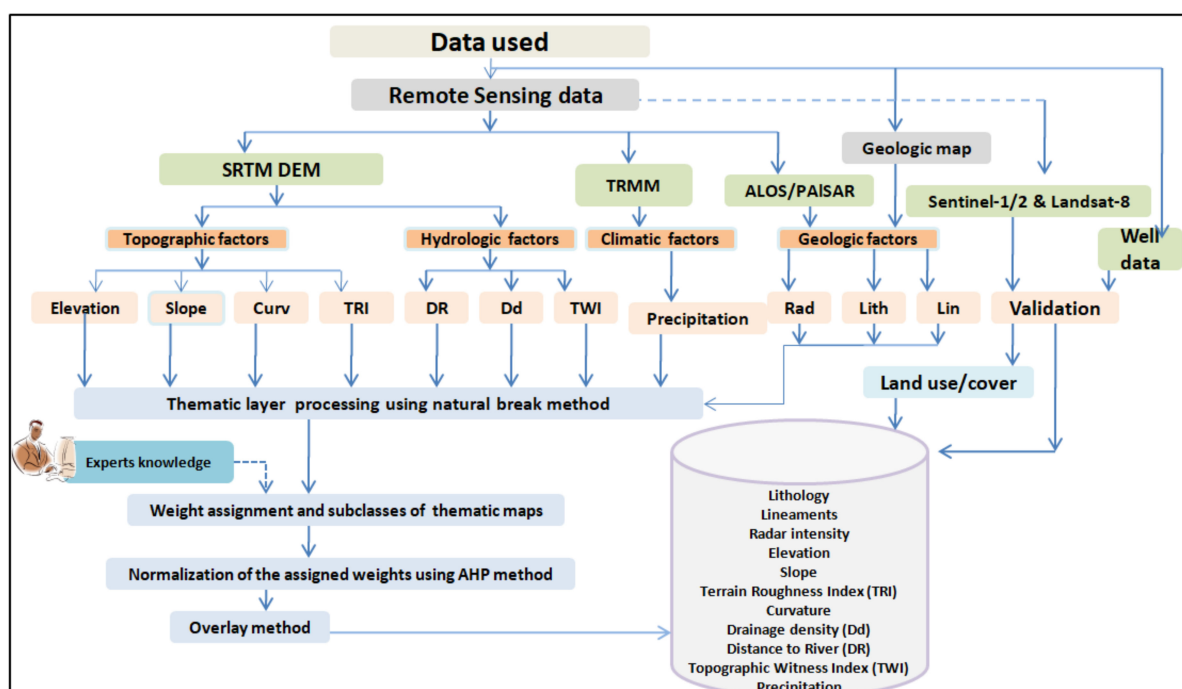


Figure 3. Data used and methods performed in the present study.

The Landsat data series (Table 1) was obtained from the United States Geological Survey (USGS) website. The Landsat-8 Operational Land Imager (OLI) and Landsat-5 Thematic Mapper (TM) were processed and analyzed to reveal the changes in LU/LC. The OLI and thermal infrared sensor (TIRS) sensors were carried by Landsat-8, which was deployed on 11 February 2013. Landsat-8 data for the downstream area acquired on 15 March 2014 were processed to determine the land-cover and floodway after a rainstorm on 9 March 2014. This was performed after applying the Normalized Difference Vegetation Index (NDVI), which was used to divide the image into vegetated and non-vegetated sections. The GIS technique was used to identify planted regions, water bodies, and the most recent flood zones based on their reflectance signatures. To map LU/LC, visible-near-infrared and shortwave-infrared wavelength areas were used. The acquired scenes, which included OLI bands 2, 3, 4, 5, 6, and 7, were mosaicked and used to perform image transformation and enhancement processes. Likewise, bands 1, 2, 3, 4, 5, and 7 from the Landsat-5 data were used. The NDVI was utilized to map the vegetated areas [15], which were delineated by applying the visible infrared bands ($NDVI = \frac{NIR - R}{NIR + R}$), where NIR (band 5) and R (band 4). The ArcGIS v.10.8 change detection “Difference” method was utilized to output the difference map to show the change between 1987 and 2021.

Sentinel-2 data come from the ESA spacecraft, an optical satellite platform. This mission consists of a pair of land-monitoring satellites that cover a larger area of the Earth’s surface and generate large optical images with more consistency. Sentinel-2 satellites have temporal resolutions of 10 and 5 days, making them extremely valuable to future investigations. The ENVI and SNAP software packages were used to process two scenes imaged on 20 March 2016 and 14 March 2022 (Table 1) to display the changes in LU/LC.

The Tropical Rainfall Measuring Mission (TRMM) satellite recordings provided the average rainfall data. The obtained average rainfall data were for the period from January 1998 to November 2015. This included numerous discontinuous storms that occurred in December 2010, January 2010, and March 2014 and 2015. The information can be found at Giovanni/NASA.

Table 1. Data used in the present study.

No	Type of Data	Source	Date	Resolution
1	Landsat-8 OLI	USGS	15 March 2014 26 September 2021	bands 2, 3, 4, 5, 6, and 7 (30 m)
2	Landsat-5 TM	USGS	29 September 1987	bands 1, 2, 3, 4, 5, and 7 (30 m resolution)
3	Sentinel-1	ESA/Copernicus	19 February 2017 18 February 2015	C-band SLC (12.5 m)
4	Sentinel-2	ESA/Copernicus	14 March 2022 20 March 2016	bands 2, 3, 4, 8 ("10" m), 11, and 12 ("20" m)
5	PALSAR-2 Jaxa	Jaxa	2017	25 m
6	SRTM DEM	USGS	11–22 February 2000	C-band (30 m)
7	TRMM data	NASA	1 January 1998–1 November 2015	0.25 degrees in latitude and longitudes

The advanced land observing satellite (ALOS)/phased-array-type L-band synthetic aperture radar (PALSAR-2) satellite provided radar data at different polarization levels using a synthetic aperture radar (SAR) L-band frequency (1257.5 MHz; λ 14 22.9 cm) with an incidence angle of 8 to 70 degrees (e.g., HH and HV). This is a high-tech Japanese land observation satellite with remote-sensing capabilities. It is widely used for studying and monitoring the ground surface under severe weather conditions. HH polarization at 25 m and a 70 km swath width of the Jaxa Palsar mosaic 'PALSAR-2 Global Forest/Non-forest 2017 Map' were used in this investigation to highlight the variance in radar intensity to represent soil characteristics.

The coherence change detection (CCD) approach of interferometric SAR (InSAR) has also been used to assess changes in the land surface over time [26]. The radar intensity and phase variations between two temporally distinct SAR images are used in the CCD approach to detect land surface changes [61,62]. On 18 February 2015 and 19 February 2017, two Sentinel-1 scenes were recorded, and VV polarization was used to obtain a CCD image by using phase and intensity information from the single look complex (SLC) SAR output. This revealed changes in the LUC. The interferometric coherence (γ) of two SAR scenes can be estimated using the equation shown below:

$$\gamma = \frac{\left| \sum_{k=1}^N f_k g_k^* \right|}{\sqrt{\sum_{k=1}^N |f_k|^2 \sum_{k=1}^N |g_k|^2}}, \quad 0 \leq \gamma \leq 1 \quad (1)$$

where (γ) is the value of the coherence at a specific pixel, f_k and g_k are the SAR scenes, and g_k^* is the linear complex of the other scene. N is the assessed window size. The γ value is between 0 and 1.

Using the AHP technique, each layer was given a weight [42]. The predictive layers were then compared with a pair-wise comparison matrix (Table 2). Sub-classes of each layer were given a weight based on their relevance in calculating mineral resources. In this model, the consistency ratio (CR) was obtained (Table 3) by comparing the Principal Eigen value (λ), which was calculated using the eigenvector technique, and the Consistency Index (CI), which was calculated using the following equation:

$$CI = \frac{(\lambda_{\max} - n)}{(n - 1)} \quad (2)$$

where $\lambda_{\max}$ represents the principal eigenvalue, and n is the number of factors.

$$\lambda_{\max} = \frac{121}{11} = 11 \quad (3)$$

$$CI = \frac{(11 - 11)}{(11 - 1)} = 0 \quad (4)$$

$$CR = \frac{0}{1.51} = 0 \quad (5)$$

Table 2. Pair-wise matrix of the eleven indices.

	Lith	Lin	Rad	Elev	Slope	TRI	Curv	Dd	D.R	TWI	Rainfall
Lith	1.00	1.33	1.14	1.60	1.33	1.60	2.00	1.33	1.00	1.14	1.60
Lin	0.75	1.00	0.86	1.20	1.00	1.20	1.50	1.00	0.75	0.86	1.20
Rad	0.88	1.17	1.00	1.40	1.17	1.40	1.75	1.17	0.88	1.00	1.40
Elev	0.63	0.83	0.71	1.00	0.83	1.00	1.25	0.83	0.63	0.71	1.00
Slope	0.75	1.00	0.86	1.20	1.00	1.20	1.50	1.00	0.75	0.86	1.20
TRI	0.63	0.83	0.71	1.00	0.83	1.00	1.25	0.83	0.63	0.71	1.00
Curv	0.50	0.67	0.57	0.80	0.67	0.80	1.00	0.67	0.50	0.57	0.80
Dd	0.75	1.00	0.86	1.20	1.00	1.20	1.50	1.00	0.75	0.86	1.20
D R	1.00	1.33	1.14	1.60	1.33	1.60	2.00	1.33	1.00	1.14	1.60
TWI	0.88	1.17	1.00	1.40	1.17	1.40	1.75	1.17	0.88	1.00	1.40
Rainfall	0.63	0.83	0.71	1.00	0.83	1.00	1.25	0.83	0.63	0.71	1.00

Table 3. Computing consistency ratio.

	Lith	Lin	Rad	Elev	Slope	TRI	Curv	Dd	D.R	TWI	Rainfall	Sum	$\lambda_{\max}$
Lith	0.119	0.119	0.119	0.119	0.119	0.119	0.119	0.119	0.119	0.119	0.119	1.313	11
Lin	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.985	11
Rad	0.104	0.104	0.104	0.104	0.104	0.104	0.104	0.104	0.104	0.104	0.104	1.149	11
Elev	0.075	0.075	0.075	0.075	0.075	0.075	0.075	0.075	0.075	0.075	0.075	0.821	11
Slope	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.985	11
TRI	0.075	0.075	0.075	0.075	0.075	0.075	0.075	0.075	0.075	0.075	0.075	0.821	11
Curv	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.657	11
Dd	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.985	11
DR	0.119	0.119	0.119	0.119	0.119	0.119	0.119	0.119	0.119	0.119	0.119	1.313	11
TWI	0.104	0.104	0.104	0.104	0.104	0.104	0.104	0.104	0.104	0.104	0.104	1.149	11
Rainfall	0.075	0.075	0.075	0.075	0.075	0.075	0.075	0.075	0.075	0.075	0.075	0.821	11

The CR (Table 3) of the calculated parameters is 0 ($CR = 0/1.1.51$) based on this formula, and the parameters are recognized as consistent if the CR is below 0.1; otherwise, the AHP is meaningless [42].

4. Results

4.1. Geological Conditioning Factors

4.1.1. Geology/Geomorphology

Because the porosity and permeability of the surface strata control the penetration of precipitated water into the groundwater aquifer, lithological features are prominent [13].

Both the porosity and permeability of the aquifer constituents are influenced by the lithology [63]. The main factor influencing the management and development of groundwater resources is the geology. Sand and gravel sediments increase the porosity, which is an important factor in groundwater recharge [64]. The movement of groundwater in impermeable rocks is difficult due to their compactness and low fracture rate, as is expected for areas with weak groundwater potential [16]. As a result, the amount and flow of groundwater in a given area is governed by the lithology [65]. Geomorphology has received significant attention, since it is crucial to the movement and storage of groundwater in any region.

Based on the digitized geological map [58], W. Asyuti is classified as having Cretaceous/Tertiary, Oligocene/Pleistocene, and Wadi deposits. The lithological characteristics of the Wadi Asyuti basin area (Figure 1c) consist of a plateau of limestone belonging to the Eocene period with Cretaceous/Tertiary sedimentary succession. The plateau overlaid by sand and gravel deposits is mostly from the Oligocene/Pleistocene period. The incision wad is filled with sand, silt, and gravel deposits from the surrounding rocks that were carried to streams and down streams during heavy storms. The lithologic map can be categorized into three groups, including Cretaceous/Tertiary, Oligocene/Pleistocene, and Wadi deposits. These areas were assigned weights of 1 (low), 4 (moderate), and 8 (high), respectively (Table 4). They cover 86.81, 6.05, and 7.14% of the entire basin, respectively, (Table 4).

Table 4. Map of weighted prospective groundwater factors.

Factor	Factor/Weight	Subclasses	Rank	Normalized Sub-Class	Area %
Geologic factors	Lithology (0.119)	Cretaceous/Tertiary	1	0.077	86.81
		Oligocene/Plei stocene	4	0.308	6.05
		Wadi deposits	8	0.615	7.14
	Lineaments (0.090)	0 to 14.24	1	0.063	23.79
		14.24 to 33.23	3	0.188	33.24
		33.23 to 54.38	5	0.313	29.71
		54.38 to 110.487	7	0.438	13.26
	Palsar (0.104)	0 to 68	7	0.438	22.68
		68 to 110	5	0.313	39.46
		110 to 190	3	0.188	29.73
		190 to 250	1	0.063	8.13

Table 4. Cont.

Factor	Factor/Weight	Subclasses	Rank	Normalized Sub-Class	Area %
Topographic factors	Elev (0.075)	627 to 877	1	0.056	10.07
		491 to 627	2	0.111	21.62
		369 to 491	3	0.167	31.29
		230 to 369	5	0.278	30.35
		53 to 230	7	0.389	6.67
	Slope (0.090)	15.01 to 37.16	1	0.067	1.35
		8.74 to 15.01	2	0.133	4.42
		4.80 to 8.74	3	0.200	12.19
		2.18 to 4.80	4	0.267	30.33
		0 to 2.18	5	0.333	51.72
	TRI (0.075)	0.1110 to 0.3124	8	0.364	10.40
		0.3124 to 0.4222	7	0.318	22.86
		0.4222 to 0.5198	4	0.182	30.22
		0.5198 to 0.6235	2	0.091	11.90
		0.6235 to 0.8889	1	0.045	24.62
	Curvature (0.060)	−2.57 to 0.01	1	0.167	13.48
		0.01 to 0	2	0.333	40.71
		0 to 2.72	3	0.500	45.81
Hydrologic factors	Dd (0.090)	0 to 0.3967	1	0.10	18.48
		0.3967 to 0.6121	2	0.20	34.13
		0.6121 to 0.8275	3	0.30	33.01
		0.8275 to 1.4511	4	0.40	14.39
	DR (0.119)	0–200	8	0.348	27.35
		200–400	7	0.304	23.50
		400–600	5	0.217	19.94
		600–800	2	0.087	16.61
		800–1000	1	0.043	12.59
	TWI (0.104)	4.697 to 8.038	1	0.100	41.08
		8.038 to 10.344	2	0.200	40.04
		10.344 to 13.923	3	0.300	14.59
		13.923 to 25.058	4	0.400	4.29
Climatic factors	TRMM (0.075)	0.0095 to 0.016	1	0.077	62.65
		0.016 to 0.0248	2	0.154	27.04
		0.0248 to 0.029	4	0.308	4.73
		0.029 to 0.0758	6	0.462	5.58

4.1.2. Lineaments

Lineaments are linear or curved geological features on the land surface that indicate sub-surface fractures [66,67]. A fault, fracture, or master joint; a lengthy and linear geological formation; a topographic linearity; or the straight paths of streams are all examples of lineaments [68]. They have the ability to generate secondary porosity and can be seen as textural changes in satellite images when contrasted with other topographical features.

They play an important role in the occurrence and transport of groundwater in crystalline rocks. They have an impact on surface runoff infiltration into the subsurface and are crucial for groundwater storage and flow [69]. The infiltration of surface runoff and recharging of the hard-rock aquifer are caused by lineaments that form as a result of tectonic stress/strain. Many researchers have utilized the link between groundwater occurrence and lineaments to argue that a high lineament density contributes to a high groundwater potential [65,70,71].

The lineaments that control Wadi Asyuti (Figure 4a) were identified from a geological map of Conoco [58], drainage networks, radar, and Landsat data. The lineaments that are controlling the basin are directed mainly in the NW–SE and NE–SW directions, and the downstream area is shaped as a graben. The lineament density (Figure 4b) was calculated based on the lengths of segments in a certain section compared with the area. Most of the areas of high density are located in north W. Hubara, W. Qird El-Farr, and W. Habib.

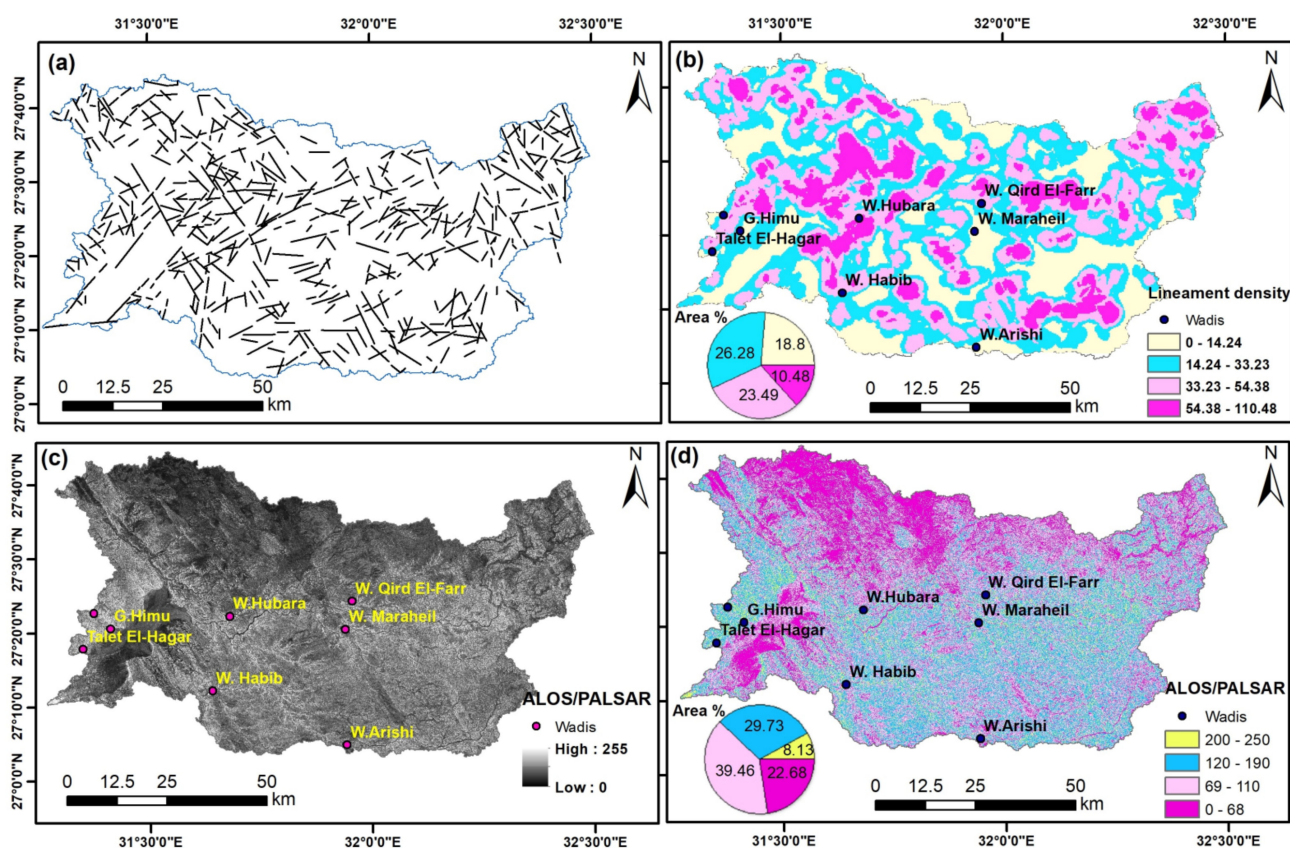


Figure 4. (a) Lineaments controlling the studied basin; (b) Lineament density map; (c) ALOS/PALSAR map; (d) ALOS/PALSAR classified map.

The lineament density map of Wadi Asyuti (Figure 5b) was categorized into four zones: 0–14.24, 14.24–33.23, 33.23–54.38, and 54.38–110.48, representing low (1), moderate (3), high (5), and very high (7) zones. These zones cover 23.79, 33.24, 29.71, and 13.26% of the total basin area, respectively (Table 4). Dense zones of lineaments, which were deemed to be potential groundwater recharge zones with high well production, were given a higher-ranking “numeric value”.

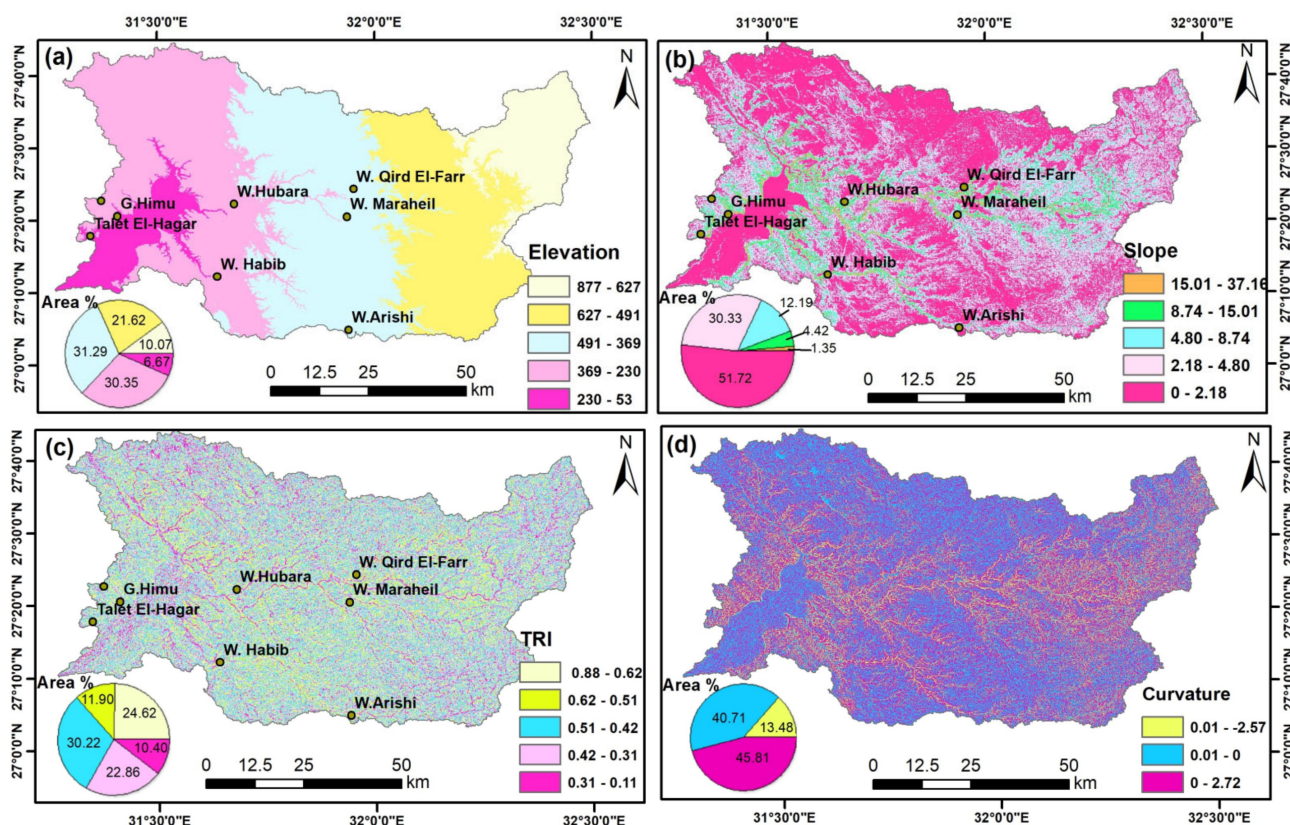


Figure 5. Topographical factors of the W. Asyuti basin (a) elevation classes; (b) slope degree classes; (c) Terrain Roughness Index (TRI); (d) Curvature classes.

4.1.3. Radar Intensity

Throughout the day or night, satellite-based SAR can penetrate clouds, aerosol, gaseous, water molecules, and even sand cover. It identifies and recognizes clastic sedimentary vicinities in contrast to bed rocks. Other than during seasonal changes, rainfall is low in locations with high aridity. This encourages erosion and sand accumulation while also facilitating recharge. Due to scattering, the ALOS/PALSAR (L-band; ≈ 24 cm) has the ability to portray soil features and disclose fine sediments in dark tones in contrast to bedrock, which is displayed in bright tones [72]. Fine-textured areas, such as areas of sand and gravel, are suitable replenishing regions [13]. The Arc GIS software packages (Figure 2b) classify data backscattering into five categories. Radar intensity maps (Figure 4) are classified into four classes: 0–68 (very high), 68–110 (high), 110–190 (moderate), and 190–250 (low).

The L-band intensity of backscattering data from ALOS/PALSAR revealed important information regarding the presence of alluvial deposits, as indicated by the dark tone. Sand accumulation areas can be called preferred water accumulation zones, since they are characterized by loose sediments that accumulate precipitated water during rainy storms in arid locations. The Arc GIS software packages classified the present study area into four zones: low (1), moderate (3), high (5), and very high (7). It is worth noting that the classes from low to high potentiality covered 8.13, 29.73, 39.46, and 22.68% of the entire basin area, respectively (Figure 4c; Table 4).

4.2. Topographical Conditioning Factors

4.2.1. Elevation

Surface indicators used for determining the groundwater potential include the altitude, slope angle, terrain roughness, and curvature [73,74]. The potential for groundwater in flood plain zones is usually considerable due to the strong penetration of river water, but it

is lower in elevated areas. Because runoff reduces the groundwater potential in the study area's rocky sections, the recharge capacity is similarly reduced [75]. The topographical layer is an essential element that determines the direction of water flow over land as well as the occurrence of groundwater and the capacity for recharge [5].

The elevation of the W. Asyuti basin ranges from 53 m in the downstream area to 877 m in the upstream area east of the watershed that divides W. Asyuti and northern W. Qena. The elevation of the studied basin can be divided into five zones based on the level of infiltrating water: 877–627, 627–491, 491–369, 369–230, and 230–53. These areas were given grades of 1, 2, 3, 5, and 7 and cover 1.07, 21.62, 31.29, 30.35, and 6.67% of the total basin area, respectively (Figure 5a; Table 4).

4.2.2. Slope

The slope influences the major precipitation direction and physiographical trends [69]. Groundwater prospects are very high, high, moderate, low, and very low on flat, gentle, medium, steep, and very steep terrains, respectively [13]. The importance of slope analysis in groundwater potential zone mapping and watershed management cannot be neglected. The slope percent can be used as a surface indicator to determine the groundwater condition [73]. In other words, these thematic layers can be seen as a proxy for the surface runoff velocity and vertical percolation (infiltration is inversely proportional to the slope), influencing the recharge rates [18]. Because water moves quickly, rain does not have enough time to permeate the surfaces of a steep hill and replenish the saturated zone; thus, steeper slopes allow less recharge [76,77]. Flat lands and moderate slope regions are deemed “extremely good” for groundwater recharge among the classes [65]. The slope of a region has a considerable role in harvesting precipitation and runoff control. While the slope is directly related to the amount of runoff, it is inversely proportional to the surface water infiltration for groundwater storage [27,69].

The slope angle of W. Asyuti ranges from 0 to 37.16 degrees and is classified into five classes: 0–2.18, 2.18–4.80, 4.80–8.74, 8.74–15.01, and 15.01–37.16 (Figure 5b). These zones cover 51.72, 30.33, 12.19, 4.42, and 1.35% of the area, respectively (Table 4). Areas with a low slope angle are considered potential groundwater areas and are given a high grade of “5”, but areas with high slope angles are given a low grade of “1”.

4.2.3. Roughness

One of the linked morphological characteristics is the terrain roughness index (TRI). It was created to assess landscape heterogeneity and can also be employed to search for groundwater [78,79]. The following equation can be used to determine this parameter:

$$TRI = \sqrt{(\max^2 - \min^2)} \quad (6)$$

where max and min are the largest and smallest values of the cells.

The TRI map results were categorized into five zones based on the accumulation and infiltration of groundwater: 0.6235 to 0.8889 (very low), 0.5198 to 0.6235 (low), 0.4222 to 0.5198 (moderate), 0.3124 to 0.4222 (high), and very high (0.1110 to 0.3124). These areas cover 24.62, 11.90, 30.22, 22.86, and 10.40% of the entire basin (Figure 5c; Table 4).

4.2.4. Curvature

The geometry of the land surface is represented by the land surface curvature, which is a key element in slope accumulation, infiltration, and runoff [36,80]. The DEM is used to generate the land surface curvature layer, which is divided into three categories: concave, convex, and flat (Figure 5d). Areas that will capture water resources from rainfall can be identified using the land surface curvature. Areas with curvature and flat areas collect water more easily and provide a better infiltration capacity than convex surfaces. Because water tends to collect on concave and flat land surfaces, locations with high curvature values (or vice versa) are given high weight values [75]. The curvature map results were classified

into three groups: low (-2.57 to 0.01), moderate (0.01 to zero), and high (0 to 2.72). These areas cover 13.48, 40.71, and 45.81 of the entire basin, respectively (Figure 5d; Table 4).

4.3. Hydrological Factors

4.3.1. Drainage Density (Dd)

The total length of all streams/rivers in a drainage basin divided by the drainage basin's total area is known as the drainage density [81]. The drainage system of a given location is influenced by the nature and structure of the bedrock, the kind of vegetation present, the rainwater absorption capacity of soils, the level of infiltration, and the slope gradient [9]. Low-drainage-density locations have more infiltration and less surface runoff. This suggests that areas with a low drainage density are conducive to groundwater productivity [82,83]. Because drainage density is a measure of surface runoff, it indirectly implies the occurrence of groundwater recharge [24]: the higher the drainage density, the lower the infiltration and the faster the surface flow movement [84]. Because high drainage density values favor runoff, they suggest a low groundwater potential zone [77,85]. Drainage networks that catch large amounts of precipitation, on the other hand, would have improved infiltration and recharge potential, since more water means greater recharge and infiltration. As a result, high Dd zones are ideal for recharging groundwater, especially highly dissected land surfaces with mostly low terrain roughness [13,86–88]. The stream order of the studied basin was of the seventh order (Figure 6a). Therefore, W. Asyuti basin was classified into four classes: $0-0.39$, $0.39-0.61$, $0.61-0.82$, and $0.82-1.45$. These areas were given weights of 1, 2, 3, and 4 and were found to cover 18.48, 34.13, 33.01, and 14.39% of the basin (Figure 6a,b; Table 4).

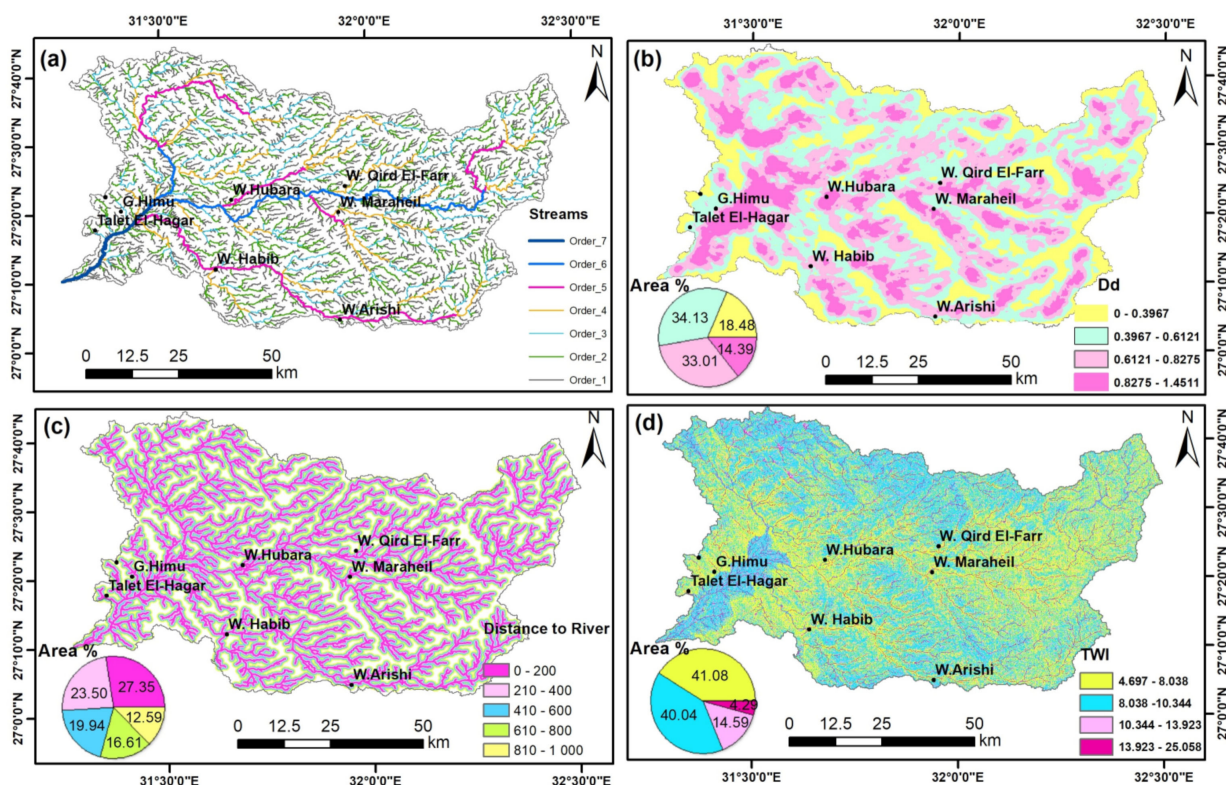


Figure 6. Hydrological factors: (a) stream-network order; (b) drainage density; (c) distance to river; (d) TWI classes.

4.3.2. Distance to River (DR)

The proximity to the river is positively related to the presence of groundwater; thus, as the distance from a river increases, the probability of groundwater occurrence decreases [89,90]. The distance from rivers was determined by applying the “Euclidean

distance function” in ArcGIS to the drainage networks. Areas close to rivers have a greater impact on the groundwater availability [91]. The distance of the W. Asyuti basin to a river was grouped into five classes: 0–200, 200–400, 400–600, 600–800, and 800–1000. These areas were given weights of 8, 7, 5, 2, and 1 and were found to cover 27.35, 23.50, 19.94, 16.61, and 12.59% of the basin (Figure 6c; Table 4).

4.3.3. TWI

The TWI index is used to measure topographical factors in order to better understand the hydrological conditions. Moore et al. (1991) developed the TWI [92]. The TWI describes the size of the stream accumulation at a selected spot in the drainage basin and the propensity of the surface runoff downhill slope under gravitational forces, both of which accelerate water flow accumulation and can also describe the wetness conditions of a region [75,92]. The TWI has been used in several studies to map possible freshwater regions [75]. The TWI can be estimated by the below equation:

$$TWI = \ln\left(\frac{Ac}{\tan s}\right) \quad (7)$$

where Ac is the specific catchment area (m^2/m), and S is the slope gradient (in degrees).

Figure 6d shows the TWI values for the W. Asyuti basin ranged from 4.78 to 17.69. Very high (13.92–25.05), high (10.34–13.92), moderate (8.03–10.34), and low (4.69–8.03) are the four classifications of the TWI. The TWI is beneficial for recharging prospects and GWPZs, since areas with greater TWI scores are given greater weights and vice versa [30,75].

4.3.4. Rainfall Data

Rainfall is an essential hydrological factor that has long been regarded as a primary source of recharge [83,93]. Precipitation has a considerable impact on infiltration [13,18]. Areas exposed to rainfall storms replenish groundwater recharge in the context of rainfall. Rainfall data from the TRMM satellite allow investigators to track, observe, and measure rainstorm rates in the examined watershed. Rainfall storms result in losses in the provision of water resources as well as damage from heavy precipitation, which result in floods that wreak havoc on infrastructure. This information could be useful for identifying regions that are prone to water accumulation. This is due to the fact that precipitation is the most important component in groundwater recharge [15,16].

Because the upper stream of Wadi Asuyti reaches 877 m (a.s.l.) at the uplifted Ma’aza plateau in conjunction with the watershed divide with northern Wadi Qena (Figure 1b), the studied basin frequently receives heavy seasonal rainfall, e.g., on 29 December 2010, 8–9 March 2014, and March 2015 (Figure 7a–d). Figure 7 shows how the spatial distribution of rainfall intensity differs from one storm to the next. On 29 December 2010, the rate of precipitation reached up to 22.85 mm/day, particularly in the downstream area, but on 8–9 March 2014, it reached up to 14.81 mm/day in the upstream area. Moreover, in March 2015, slight showers occurred in both the upstream and downstream area. These storms inundated streams and replenished groundwater resources by recharge the shallow aquifers.

The precipitation intensity in Wadi Asuyti was interpolated using the Kriging tool in ArcGIS using average daily precipitation data obtained from the TRMM satellite from 1 January 1998 to 30 November 2015 (Figure 7d). The average rainfall map (Figure 7d), which ranges from 0.0095 to 0.0758 mm/day, was divided into four groups: very high, high, moderate, and low (Figure 7d). These zones cover 5.58, 4.73, 27.04, and 62.65% of the entire area, respectively (Table 4). Areas of high precipitation are given high weights and are promising areas of groundwater availability due to their high recharge potential. Based on the spatial distribution, the average precipitation intensity is higher in the downstream area close to the Nile (Figure 7d).

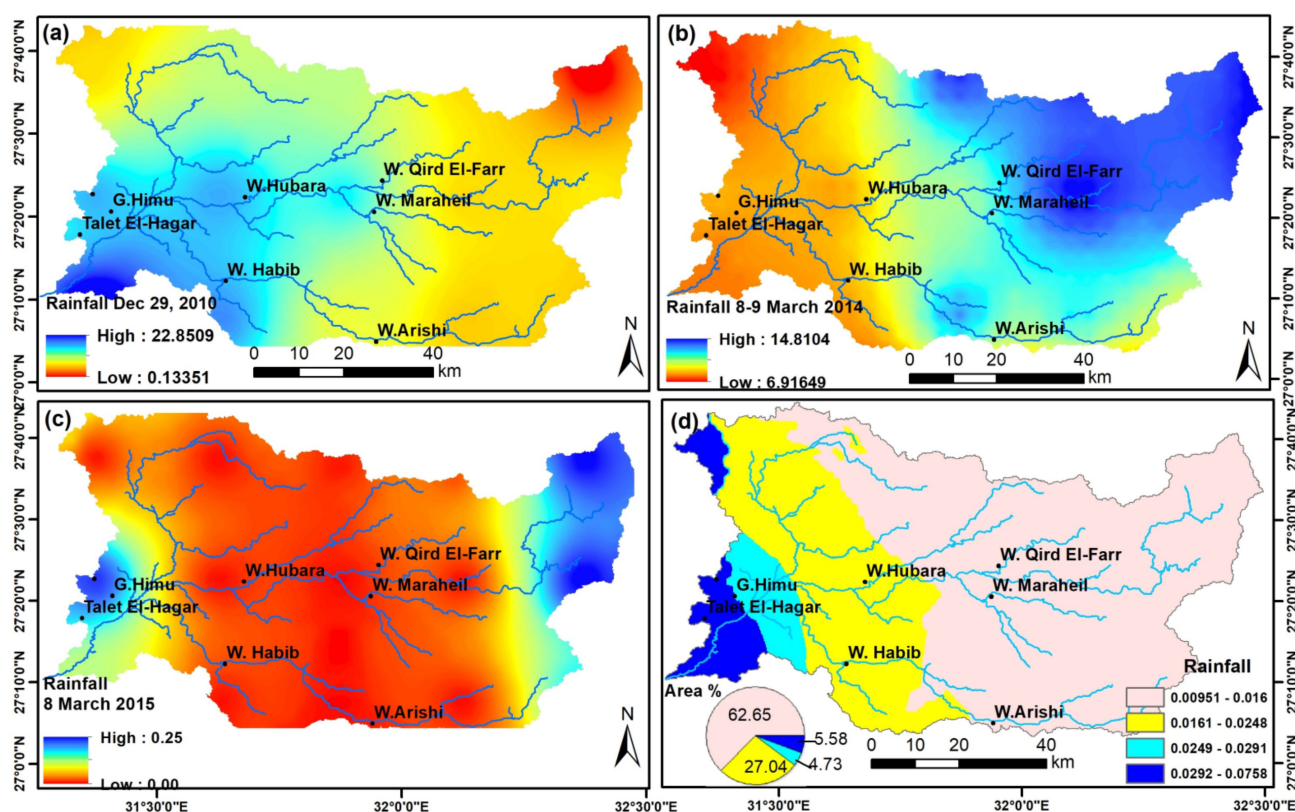


Figure 7. Precipitation data (mm/day) covering Wadi Asyuti: (a) Kriging distribution of precipitation following the storm on 29 December 2010, (b) distribution of precipitation on 8 to 9 March 2014; (c) precipitation on 8 to 9 March 2015, (d) average precipitation (years 1998–2015) in Wadi Asyuti.

5. Prospective Groundwater Zones

The geological (lithology, lineaments, and radar back-scattered), topographical (elevation, slope, curvature, and TRI), hydrological (drainage density, distance to river, and TWI), and climatic (rainfall) data derived from satellite images were combined to identify promising areas (GWPZs). The area was then divided into six zones based on the likelihood of groundwater occurrence. Very low (10.59%), low (23.06 percent), moderate (27.47%), high (22.22%), very high (13.62%), and excellent (3.03%) were the categories considered (Figures 8 and 9). The area with excellent to very high potential represents 33% of the basin. It is noteworthy that the downstream area represents the most promising area for prospective groundwater. The presence of sand and gravel, low elevation, and a high lineament density flat/gentle slope in areas of alluvial deposit support the presence of GW recharge zones in this location (Figure 8b,h–k). To support the projected model, the 33 identified wells were used to verify the GWPZs. Furthermore, excellent to very good groundwater prospective zones are associated with areas of vegetation and agricultural activity, as well as a floodway path (Figure 8d–f). Dams (Figure 10a,b) in this range would enable water harvesting and the protection of infrastructure [94]. There are dams at W. Habib and Hubara. Water was clearly detected behind the W. Habib dam, as indicated in Landsat–OLI band composites 7, 5, and 3 and the InSAR CCD data from February 2015 and February 2017 (Figure 8c,e,g). Using the InSAR CCD image (Figure 8h,j), the wadi bed showed change and a low coherence value (~ 0.042), reflecting the occurrence of runoff activity during heavy storms.

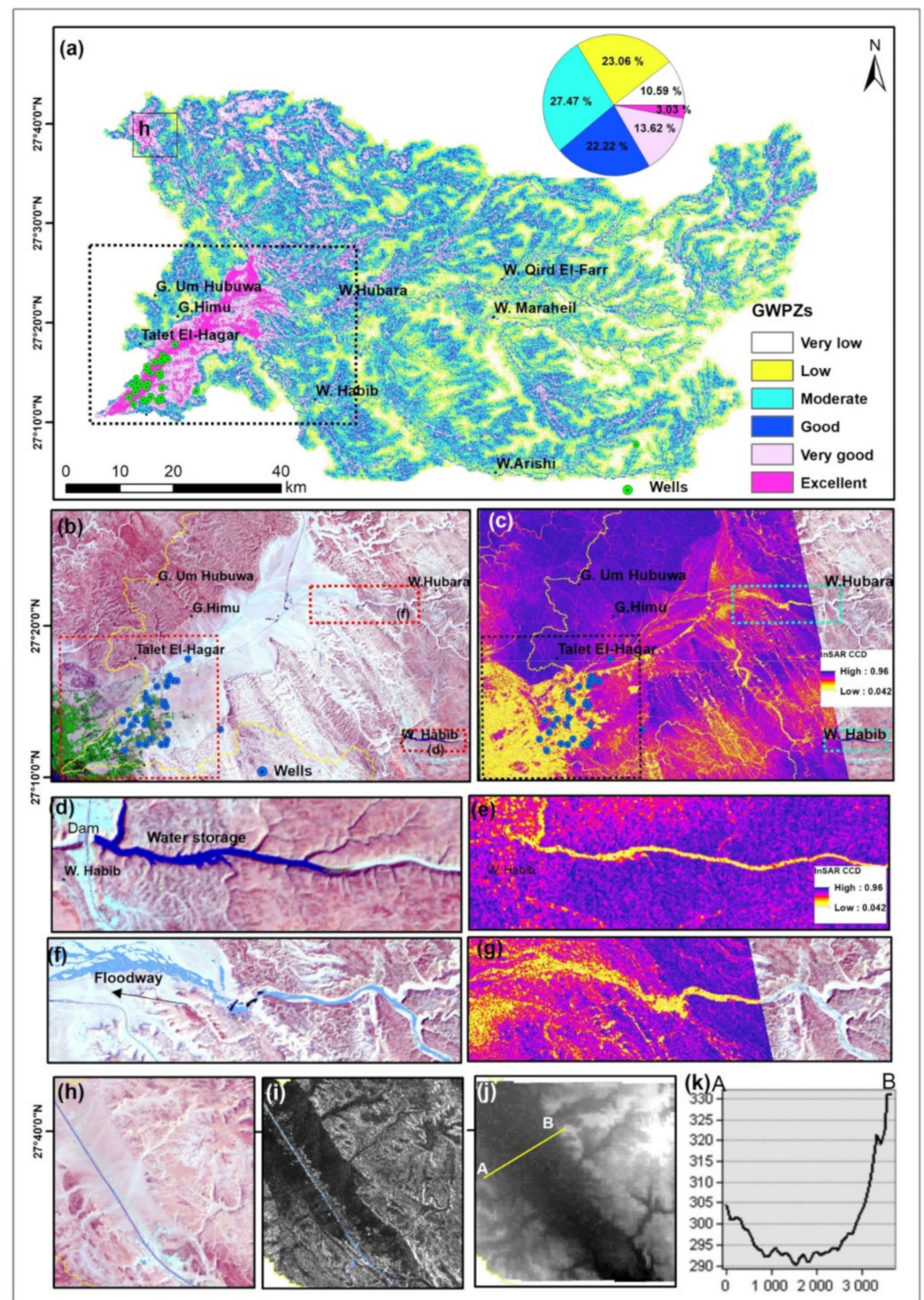


Figure 8. GWPZs (a) GWPZs overlaid by well data in the downstream area; (b) Landsat data in the downstream area overlaid by wells that are presented in blue points; (c) InSAR CCD data for the downstream area; (d) Landsat image display water accumulation in blue color behind a dam; (e) InSAR CCD same as area in (d). (f) extracted floodway marked in light blue derived from the NDVI of the OLI image from 2014; (g) InSAR CCD data for February 2015 to February 2017; (h) subset of Landsat image as indicated subfigure (a); (i) ALOS/PALSAR display alluvial deposits in dark tone; (j) DEM, and elevation profile A–B; (k) elevation profile reveal the topographic characteristics of the wadi.

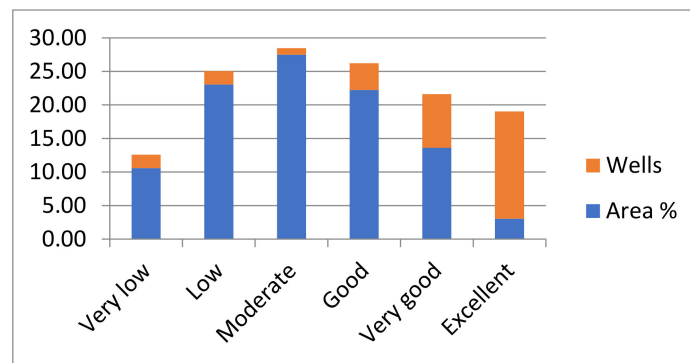


Figure 9. A column chart showing the GWPZ grades related to covered areas and the number of wells.

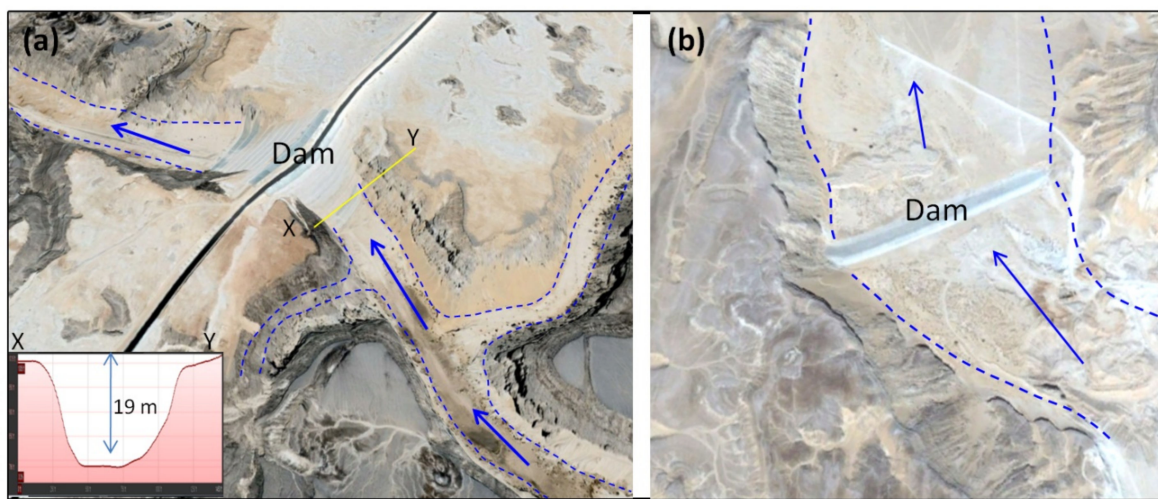


Figure 10. Dams along Wadi Asyuti: (a) W. Habib dam, (b) Wadi Hubara dam.

The groundwater prospective model indicates that highly ranked probabilities coincide with the locations of wells in the downstream area. Hence, 16 well locations (48%) from the inventory map were fitted to excellent GWPS zones, 8 wells (24%) were in consistent to very good areas, and only 6% were in very low zones (Table 5; Figures 8 and 9). Additionally, several dams (Figure 10) were erected to collect rainwater during heavy storms.

Table 5. GWPZs and well locations in the study area.

S.No	Zone	GWPZ %	Wells
1	Very low	10.59	2
2	Low	23.06	2
3	Moderate	27.47	1
4	Good	22.22	4
5	Very good	13.62	8
6	Excellent	3.03	16

6. Implications for the Detection of Changes in Land Use/Cover

Several studies have quantified changes in LU/LC. The results revealed that vegetation developed based on time series of Sentinel-2 data taken from 14 March 2022 and 20 March 2016 (Figure 11a,b). When using the “Difference” function in ArcGIS, differences between Sentinel-2 images from 2016 and 2022 are shown in light pink to pink, depending on the

extent of change (Figure 11c), with most changes in the infrastructures being shown in light color. The application of the NDVI technique showed that, in 2016, vegetation covered an area of around 56,481,244 m², while in 2022, it covered approximately 57,048,855 m², a difference of approximately 567,611 m². The vegetated area (Figure 11d,e) that developed in 2022 is shown in pink, but that present in 2016 is shown in green (Figure 11f). There is a reasonable agreement for those extracted with the NDVI method and the difference between the two images (Figure 11c). Variations in soil moisture, growing seasons, crop planting, harvesting, irrigation, non-vegetated areas, and mixed pixels provide some issues for classification methods used in agricultural settings.

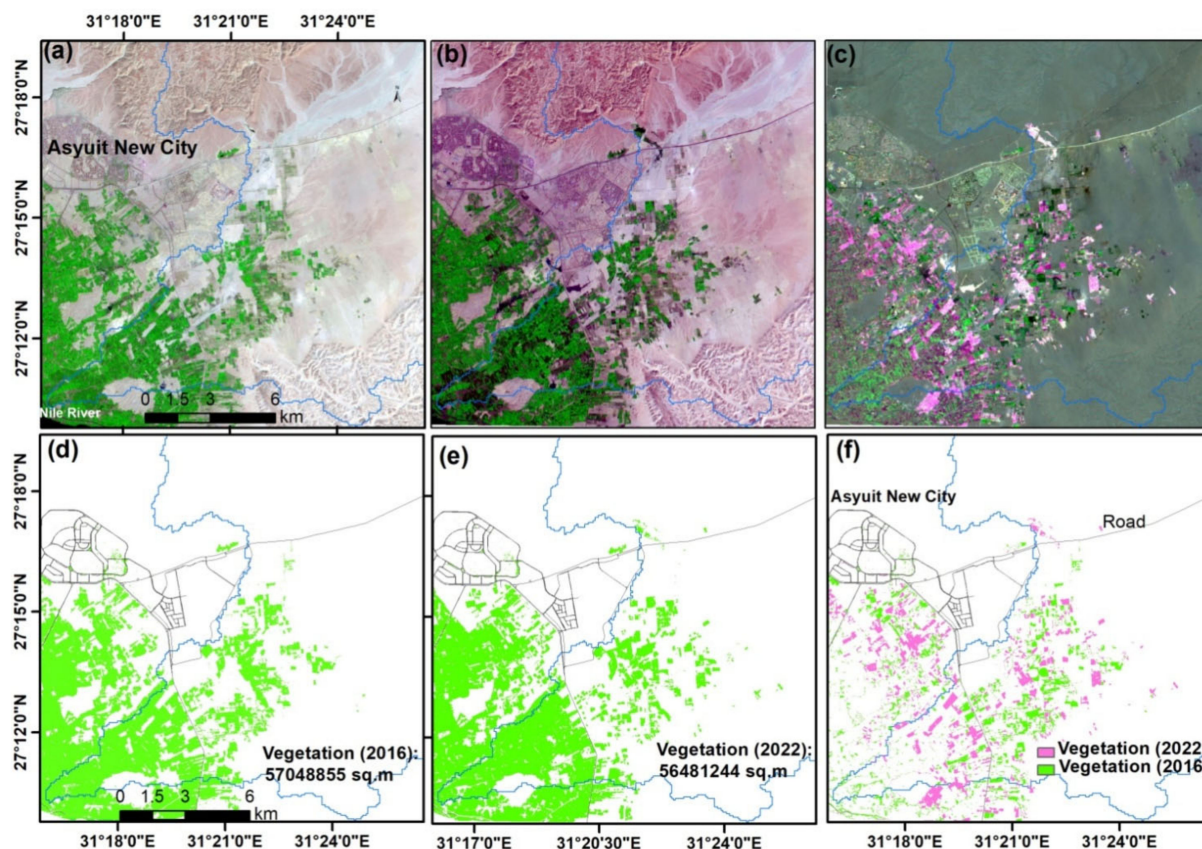


Figure 11. (a,b) Sentinel-2 data from the downstream area; (c) difference map between two scenes of Sentinel-2 14 March 2022 and 20 March 2016; (d) vegetated area in 2016; (e) vegetated area in 2022; (f) differences in vegetation between 2016 and 2022.

The Landsat-5 band composites 7, 4, and 2 in R, G, and B (29 September 1987) reveal that the downstream area displays no evidence of agricultural, economic, and residential activities, but few farms are located in the most downstream area (Figure 12a). A multi-temporal analysis using Landsat series between 29 September 1987 and 26 September 2021 (Figure 12a, b) detected major changes in LU/LC in terms of agricultural and other anthropogenic activities (Figure 12c).

The multi-temporal analysis using InSAR coherence change detection (InSAR CCD) analysis revealed major changes in LU/LC recorded between the two scenes acquired in February 2015 and February 2017 (Figure 12d). Natural and/or human-caused changes could explain the low SAR coherence values. The LU/LC changes in the downstream parts of the current research area are mostly linked to changes in vegetation cover along wadi streams, runoff during rainy storms, sand erosion, and residential and industrial activities, as revealed by the subset of GeoEye-1 images and Landsat images (Figure 12e,f). The InSAR CCD data clearly display the changes in either natural or anthropogenic activities, rather than changes detected using the Landsat series (Figure 12c).

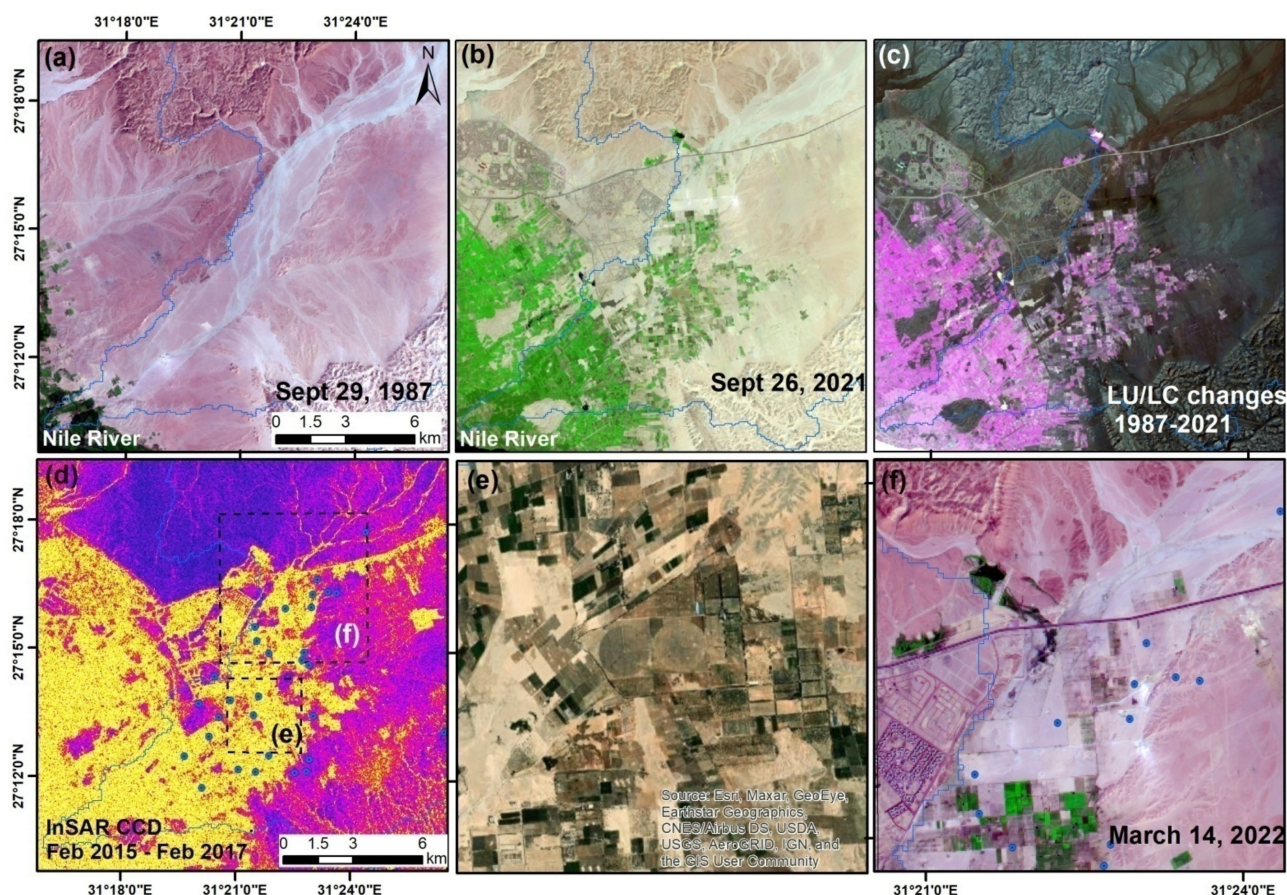


Figure 12. (a) Landsat-5 band composite data from bands 7, 4, and 2 from 29 September 1987; (b) Landsat-OLI band composite 7, 5, and 3 band composite data from 26 September 2021; (c) Difference image between 1987 and 2021; (d) InSAR CCD data from February 2015–February 2017; (e) subset of GeoEye-1 as marked by the dashed black polygon in figure (c); (f) a subset of Landsat overlay by wells in blue points.

7. Discussion

The studied area, Wadi Asyuti, is mostly desert with the exception of a few areas of urbanization and a few small agricultural areas in the downstream area (Figures 11 and 12). Therefore, it was necessary to search for new groundwater resources, which are required for sustainable agricultural expansion. Accordingly, geological, topographical, hydrological, and climatic factors were normalized using AHP techniques with the capability to predict promising areas [48] in the present study. Such data successfully revealed the GWPZs, with six zones shown. The most promising zones were mostly found in the downstream area and covered about 3% of the total area. This area is occupied by alluvial deposits, as depicted by the dark tone on ALOS/PALSAR, low elevation, and flat to gentle slopes and occurs along a structural zone [13,15,16], (Figure 9b–e).

Because Wadi Asyuti is a tributary of the Nile that has dried up, the presence of paleohydrologic relics and rich clastic deposits [95] indicate that these dead Nile tributaries received water under wetter Tertiary conditions, likely linked to the Pleistocene epoch or previous environmental conditions [96]. The thick clastic deposits with high porosity variation constitute a collection of groundwater capabilities, particularly in the downstream area, as indicated by the ALOS/PALSAR image (Figure 13a). A comparison of Landsat, InSAR, and PC1 data revealed probable areas of water accumulation, as revealed by low coherence values behind a dam (Figure 13h–j). Notably, the basin has clearly been subjected to structural events that shaped the downstream area into a graben (Figure 13a–g), as revealed by ALOS/PALSAR and DEM data, making the area of special interest. This basin was

shaped in a contemporaneous manner with the uplift, which originated from sub-surface convection processes [97]. The areas subjected to two sets of lineaments in the NW–SE (pink arrows) and NE–SW directions facilitated the subsidence of the downstream area, which allowed sediment accumulation, thus providing the possibility for groundwater occurrence. The down-throw faults reached about 130 m, as revealed by elevation profiles A–B to G–H, and the lineaments (NW–SE) are also structurally controlled (Figure 13). These zones are promising areas for groundwater occurrence (Figures 8a and 12a,b), as they represent weakness zones and conduit zones of water [29]. The occurrence of Quaternary sand layers that are very porous yield the recharging capability; consequently, these locations were designated as having a ‘excellent’ to ‘very high’ potential for groundwater recharge, especially those in the downstream area, as they have a flat to gentle slope and low elevation [88].

DEM and ALOS/PASAR data and a topographical profile were used to illustrate the cracks and faults (Figure 13c–f) controlling the downstream area. More than 30% of the basin has an excellent to very high likelihood of groundwater occurrence, which aided in cultivating the downstream area. Moreover, precipitation during rainstorms covering both the upstream and downstream areas allowed water infiltration into the layers below [98]. In addition, the high TWI values in these areas lead to wet and moist soil, suggestive of groundwater accumulation [99].

Dams are built to control flood water and preserve rushing water in order to capture precipitated water and cultivate downstream land. These dams aid in the capture of rainwater, flood management, and the reduction of torrential hazards, as well as the improvement of renewable water sources and groundwater recharge. They also assist people with achieving water and food security. If they have critical knowledge and believe that flooding ruins infrastructure, government leaders and decision makers should seek to prevent flash flood hazards [100]. In recent decades (1994, 2010, 2014), multiple flash floods have surged through the Wadi Asyuti area, destroying many buildings and impacting many people. Notably, agricultural activity has undergone major changes in the downstream area from 1984 to the present day, as depicted in Figure 11.

Land reclamation for various agricultural operations, as well as for the construction of new communities (e.g., New Asyut city) in the downstream area, has led to significant changes east of the Nile River, as seen by the Landsat series (Figures 11 and 12) and InSAR CCD method. The coherence is close to 1 when the target has not changed over time (Figures 12d and 13i) and close to 0 when the target has changed [101]. Based on InSAR data, the regions of probable groundwater sources and agricultural and anthropogenic activities in the downstream sector appear to have low coherence. Low coherence areas indicate that water has recharged into the rocks beneath the sand [102]. In comparison to bare plains, agricultural areas changed substantially from 1987 to 2021.

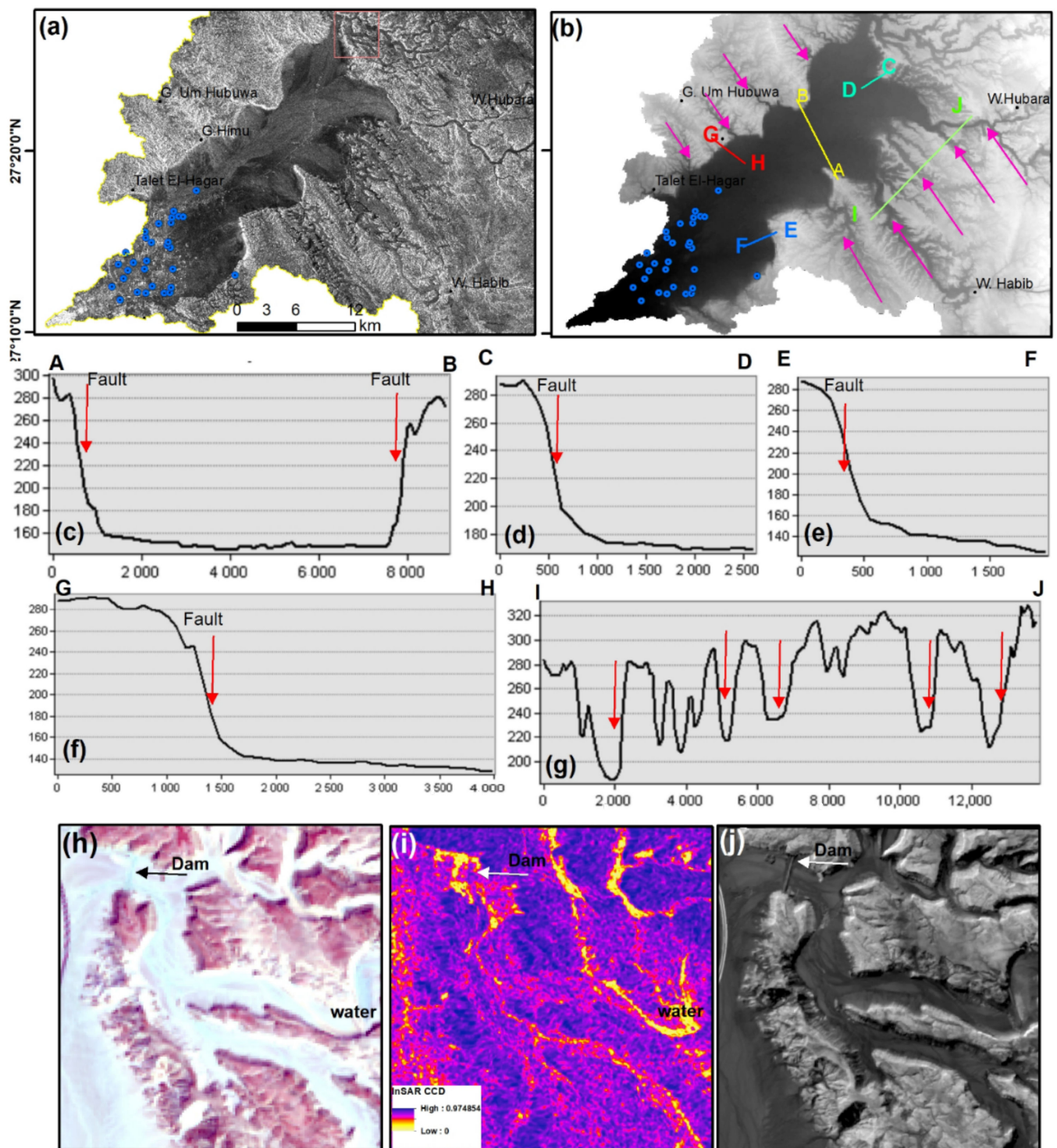


Figure 13. Downstream area of Wadi Asyuti: (a) ALOS/PALSAR covering the downstream area; the dark tone reveals the structurally controlled area that is overlaid by productive groundwater wells in blue; (b) DEM data are overlaid by topographic profiles; the pink arrows refer to the downstream direction of the wadis from NW to SE; (c–g) Topographical profiles A–B to I,J; (h) subset of OLI data showing the dam site and the signature of the water in cyan; (i) the InSAR CCD data for February 2015–February 2017 reveal the changes in yellow, representing the flood zone; (j) PC1 of the 2022 Sentinel-2 data displays the dam site and wadis.

8. Conclusions

The present study provides a comprehensive understanding of the geological, hydrological, topographical, and climatic characteristics of the Wadi Asyuti area, Egypt. Integrated multi-criteria derived from remote sensing imagery and geological data through GIS-based hydride AHP-weighted overlay techniques allowed the mapping of plausible areas of groundwater resources. The groundwater potential zones map revealed that about 15% of the area may contain groundwater resources. The results are quite positive, and the integrated method, which includes satellite imagery and geological data, was demonstrated to be useful for exploring groundwater in arid regions. Additionally, the study developed change detection maps through a multi-temporal analysis of Sentinel-2, Landsat series, and InSAR CCD data, which provided further information about the major changes in land reclamation over the last few decades. Overall, the downstream area is the most promising area for groundwater resources. This area has witnessed rapid development over the past three decades. Moreover, the modeling of GWPZs is beneficial, as it may indicate the presence of further groundwater resources to decision makers in the research area who are concerned with long-term sustainability.

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Abbreviations

SRTM	Shuttle Radar Topography Mission	DEM	Digital Elevation Model
TRMM	Tropical Rainfall Measuring Mission	OLI	Operational Land Imager
ALOS	Advanced Land Observing Satellite	RS	Remote Sensing
PALSAR	Phased-Array-Type L-band Synthetic Aperture Radar	AHP	Analytical Hierarchy Process
GIS	Geographic Information System	LU/LC	land use/land cover
TWI	Topographic Wetness Index	NIR	Near Infrared
GWPZs	Groundwater Prospective Zones	TIRS	Thermal Infrared Sensor
InSAR	Interferometry Synthetic Aperture Radar	CCD	Coherence Change Detection
NDVI	Normalized Difference Vegetation Index	MHz	Megahertz
8D	Deterministic eight-neighbors	CR	Consistency ratio
USGS	United States Geological Survey	CI	Consistency Index
TRI	Terrain Roughness Index	SLC	single look complex
ENVI	Environment for Visualizing Images	R	Red band
WGS 84	World Geodetic System 1984	DR	Distance to river
Dd	Drainage density	Lin	Lineaments
Lith	Lithology	Rad	Radar intensity
Curv	Curvature	GW	Groundwater

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