A remote sensing solution for estimating runoff and recharge in arid environments

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SUMMARY

Efforts to understand and to quantify precipitation and its partitioning into runoff evapo-transpiration, and recharge are often hampered by the absence or paucity of appropriate monitoring systems. We applied methodologies for rainfall–runoff and groundwater recharge computations that heavily rely on observations extracted from a wide-range of global remote sensing data sets (TRMM, SSM/I, Landsat TM, AVHRR, AMSR-E, and ASTER) using the arid Sinai Peninsula (SP; area: 61,000 km²) and the Eastern Desert (ED; area: 220,000 km²) of Egypt as our test sites. A two-fold exercise was conducted. Spatiotemporal remote sensing data (TRMM, AVHRR and AMSR-E) were extracted from global data sets over the test sites using RESDEM, the Remote Sensing Data Extraction Model, and were then used to identify and to verify precipitation events throughout the past 10 years (1998–2007). This was accomplished by using an automated cloud detection technique to identify clouds and to monitor their propagation prior to and throughout the identified precipitation events, and by examining changes in soil moisture (extracted from AMSR-E data) following the identification of clouds. For the investigated period, 246 of 327 events were verified in the SP, and 179 of 304 in the ED. A catchment-based, continuous, semi-distributed hydrologic model (Soil Water and Assessment Tool model; SWAT) was calibrated against observed runoff values from Wadi Girafi Watershed (area: 3350 km²) and then used to provide a continuous simulation (1998–2007) of the overland flow, channel flow, transmission losses, evaporation on bare soils and evapo-transpiration, and groundwater recharge for the major (area: 2014–22,030 km²) watersheds in the SP (Watir, El-Arish, Dahab, and Awag) and the ED (Qena, Hammamat, Asyuti, Tarfa, El-Quifa, El-Batur, Kharit, Hodein, and Allaqi) covering 48% and 51% of the total areas of the SP and the ED, respectively. For the investigated watersheds in the SP, the average annual precipitation, average annual runoff, and average annual recharge through transmission losses were found to be: 2955 × 10^6 m³, 508 × 10^6 m³ (17.1% total precipitation (TP)), and 463 × 10^6 m³ (15.7% TP), respectively, whereas in the ED these values are: 807 × 10^6 m³, 77.8 × 10^6 m³ (9.6% TP), and 171 × 10^6 m³ (21.2% TP), respectively. Results demonstrate the enhanced opportunities for groundwater development in the SP (compared to the ED) and highlight the potential for similar applications in arid areas elsewhere. The adopted remote sensing-based, regionalization approach is not a substitute for traditional methodologies that rely on extensive field datasets from rain gauge and stream flow networks, yet could provide first-order estimates for rainfall, runoff, and recharge over large sectors of the arid world lacking adequate coverage with spatial and temporal precipitation and field data.

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the Eastern Desert (ED) of Egypt, (Fig. 1) as our test sites. These sites were chosen because Egypt's landscape with its minimal vegetative cover and cloud coverage are ideal for remote sensing-based investigations. The presence of clouds and/or vegetation could modulate or even obscure the light reflected off the targeted ground surface. Moreover, Egypt's climate, landscape, and hydrologic settings resemble those of surrounding areas in North Africa and the Arabian Peninsula hence, results could potentially be applicable to neighboring countries and other similar arid settings (Inset: Fig. 1).

The distribution of rain gauges in the study area is inadequate, (<20 stations; red circles in Fig. 2) and with few exceptions (Eareda in the ED and St. Catherine in the SP), all rain gauges are located in the lowlands along the Nile River valley and Red Sea coastlines. Orographic barriers are known to affect the vertical distribution of precipitation, such that precipitation is more pronounced over the highlands compared to that in the lowlands (Hershy and Fairbridge, 1999). To alleviate problems arising from the paucity of rain gauges and their general distribution in areas of low elevation, we extracted precipitation data from satellite-based sensors and developed procedures to verify identified precipitation events using other remote sensing data sets. Three-hourly 3B42 v6 Tropical Rainfall Measuring Mission (TRMM) that provides global data on rainfall was used as our main source for precipitation data from 1998 to 2007.

Previous estimates of runoff in arid and semi-arid areas, where runoff data is unavailable were obtained using uncalibrated, distributed, rainfall–runoff models (e.g., Lange et al., 1999), and where this data is available, calibrated rainfall–runoff models were successfully applied to obtain realistic simulations of runoff (e.g., Ye et al., 1997). The construction and application of calibrated rainfall–runoff models on regional scales are often hindered by the general paucity of detailed field data on such scales. To minimize uncertainties related to data limitation, we utilized global remote

Fig. 1. Location map for the SP and the ED showing the distribution of soil types (crystalline basement, limestone, sandstone, and alluvium) in the study area and their corresponding SCS curve numbers (SCS, 1972). The soil types were assigned using information extracted from geologic maps (Klitzsch, 1987a–e), Landsat TM images (Tucker et al., 2004), and field observations. Lines A–A' and B–B' denote the locations of schematic cross sections shown in Fig. 3. Inset shows the distribution of similar surrounding terrains to the south (Sudan) and east (Arabian Peninsula) in which the adopted methodologies could potentially be applied. Areas assigned the symbol "X" mark the Arabian–Nubian Shield outcrops.
sensing data sets as previously described, applied methodologies encompassing parameter estimation and multiple calibration techniques over areas where field data is available, and conducted regionalization techniques to extrapolate results to surrounding domains. A physically-based, semi-distributed Soil Water and Assessment Tool (SWAT) model was used taking advantage of spatially distributed remote sensing and GIS datasets and physically-based parameters. These parameters were evaluated by applying sensitivity analysis and calibrated using the Shuffled Complex Evolution techniques (Duan, 1991).

Regionalization techniques have been successfully applied in transferring calibrated catchment-specific parameters to similar ungauged proximal catchments (e.g., Burn and Boorman, 1993; Kokkonen et al., 2003; NERC, 1975; Pandey and Nguyen, 1999; Pilgrim, 1983). These techniques involve identification of a set of physical catchment descriptors (PCDs: e.g., geography, climate, catchment size, topography, geology, vegetation, land use, and density of stream networks) that could be used as indicators to whether catchment-specific parameters extracted from calibrated catchments could be extrapolated to other ungauged proximal catchments. For example, Jirayoot and Trung (2005) demonstrated using a SWAT model, that catchment-specific parameters from calibrated catchments in the Lower Mekong Basin could be transferred to similar ungauged proximal catchments with similar land use, soil types, and climatic conditions. Using a conceptual rainfall–runoff model of low complexity, Kokkonen et al. (2003) showed that the critical PCDs for 13 catchments in the Coweeta Hydrologic Laboratory are elevation, slope, and overland flow

Fig. 2. Average annual precipitation derived from TRMM 3B42.v6 three-hourly data over the study area and surroundings throughout the investigated period (1998–2007). Also shown are the centers of each of the TRMM footprints, each covering 0.25° × 0.25° and the locations of climatic stations from which atmospheric data (e.g., precipitation, relative humidity, temperature, solar radiation, and wind speed) were collected and used as inputs to the SWAT model. With two exceptions (St Catherine and Eareda) all stations are located in the lowlands (e.g., River Nile Valley, Red Sea coastline).
distance. Catchment-specific parameters from the only gauged watershed (Wadi Girafi) in the Red Sea Hills in the SP and the ED were extrapolated to watersheds in the ED and the SP with similar critical PCDs. The selected watersheds were found to occupy approximately 50% of the total area of each of the ED and the SP. In summary, the adopted methodologies enable implementation of first order rainfall–runoff models on regional scales taking advantage of: (1) readily available global remote sensing data sets and (2) parameter estimation and regionalization techniques to transfer catchment-specific information extracted from commonly available geologic data sets over a calibrated watershed to neighboring surrounding catchments.

**Site description**

Most of the SP and the ED are classified as arid to hyper-arid terrains. Rainfall is generally less than 35 mm/year and relative humidity is low (50% in winter, 15% in summer) (EMA, 1996). Most of the precipitation falls near the coastlines; these areas receive up to 250 mm of precipitation per year. Fig. 2 shows the average annual precipitation extracted (using RESDEM) from TRMM over Egypt from 1998 to 2007. Despite the paucity of the rainfall events, many flash flood events were reported from the ED and the SP occurring once every three to four years in the ED and more frequently in the SP (Gheith and Sultan, 2002; Naim, 1995).

Two main groups of rock units crop out in the ED and the SP: (1) the basement complex consisting of volcano-sedimentary rock units that are part of the Neoproterozoic (550–900 Ma) Arabian–Nubian Shield (David, 1984; Engel et al., 1980; Greenwood et al., 1980) (Inset Fig. 1) and (2) the Phanerozoic sedimentary successions that crop out to the west of the Precambrian complex in the ED and to the north of these rocks in the SP (Fig. 1).

The major stratigraphic units along E–W and N–S-trending cross sections in the ED and the SP are shown in Fig. 3 and the locations of these cross sections (AA’ and BB’) are plotted on Fig. 1. The two cross sections show similar stratigraphic relations: a thick sequence of sedimentary rock units unconformably overlying basement rocks and is largely comprised of Cretaceous (ED) and Jurassic (SP) Nubian Sandstone and Tertiary and Cretaceous limestone. Networks of minor valleys dissect the Red Sea Hills and the adjacent Cretaceous and Tertiary rocks in the ED and the SP, and join into main valleys that ultimately drain into adjacent water bodies (Red Sea, and Nile River in the ED; Mediterranean Sea and Gulfs of Suez and Aqaba in the SP). These networks of channels collect rainfall as surface runoff in the main valleys and as ground water flow in the shallow alluvial aquifers (Sultan et al., 2007).

The Wadi deposits are of variable composition and include clasts of Precambrian and overlying Phanerozoic rocks (Klitzsch, 1987a–e) that were eroded from the dissected plateau and the Red Sea Hills and deposited in the valleys. The low infiltration capacity of the basement rocks and limestone creates substantial

![Fig. 3. Schematic E–W trending cross-section in the ED (A–A’, Fig. 1) and N–S-trending cross-section in the SP (B–B’, Fig. 1) showing similar lithologic and hydrogeologic settings, modified from Gheith and Sultan (2002) and JICA (1999).](image-url)
runoff over the Red Sea Hills even from low precipitation events. The dry alluvial deposits with their high infiltration capacities and the large and extensive drainage networks (e.g., El-Arish, Khartoum, Qena, Tarfa, Asyu, Hammamat, and Allaqi valleys) create substantial opportunities for alluvial aquifer recharge through transmission losses. Support for this model comes from chemical and isotopic (H, O, and tritium) groundwater analysis of a suite of groundwater samples from the ED that showed that infiltration into the shallow alluvial aquifers was derived mainly from recent precipitation and flash floods having modern meteoric to evaporated meteoric compositions (δD and δ¹⁸O range from −10‰ to +34‰ and −2‰ to +5.2‰, respectively) (Sultan et al., 2000). The presence of tritium in the examined ED groundwater samples further corroborates the notion that infiltration occurred within the past fifty years. The apparent progressive enrichment in the isotopic composition of Nubian groundwater from the Eastern Desert to Sinai was interpreted to indicate variable degrees of mixing between highly depleted fossil water that precipitated during wet climatic periods and meteoric precipitation that is deposited during the interleaving dry climatic periods (e.g., present) (Sultan et al., 2007). This hypothesis is supported by the patterns of modern precipitation (EMA, 1996). Currently, rainfall over the Nubian sandstone outcrops (recharge areas) in southern Sinai is high compared to their counterparts in the ED (Fig. 2) (EMA, 1996; Legates and Wilmott, 1997; Nicholson, 1997). In this manuscript we provide first-order estimates of modern runoff magnitudes and contributions to the reservoirs of the ED and the SP. No attempts are made to estimate partitioning of meteoric contributions between these various reservoir types.

Methodology

Our attempts to utilize four-hourly precipitation data from the Special Sensor Microwave Imager (SSM/I) for time periods predating the deployment of the TRMM sensors in 1998 were less successful. Correlation of TRMM and SSM/I with in situ precipitation over the SP and the ED confirmed earlier findings (e.g., Bauer et al., 2002) in arid environments that showed good correspondence between satellite-based precipitation and in situ precipitation for the TRMM data and to a lesser extent for the SSM/I-based precipitation data (Milewski et al., 2005). In arid environments, SSM/I can misidentify a variety of Earth surfaces for precipitating clouds giving a false indication for light rainfall (Turk et al., 2003), a phenomenon that is less problematic in TRMM data. Thus, for this study, we restrict our analysis to TRMM data and to the time period during which the sensor was brought into operation and up to the year 2007 with the realization that the SSM/I data could be utilized for time periods as early as 1987, over less arid environments (e.g., humid Okavango River Basin, Southern Africa (Wilk et al., 2006).

The adopted approach has three main steps. Firstly, we collect and pre-process relevant remote sensing data. Secondly, we identify and verify using multiple remote sensing datasets the relatively larger precipitation events that are more likely to produce runoff and recharge. Following the identification of rainfall events, we verify the validity of the identified precipitation events using several remote sensing techniques. Thirdly, we adopt a catchment-based, continuous, hydrologic model to quantify the spatial and temporal distribution of surface runoff and potential groundwater recharge. Three types of remote sensing datasets were collected and processed over the same time period (1998–2007) to enable the extraction of realistic spatial and temporal distribution of rainfall over the ED and the SP. These include: (1) TRMM data that provides global (50°N–50°S) data on rainfall using microwave and visible–infrared sensors every three hours with a 0.25° × 0.25° footprint, (2) Advanced Very High Resolution Radiometer (AVHRR) data with a spatial resolution of 1.1 km was used for verifying precipitation events through cloud detection, and (3) Advanced Microwave Scanning Radiometer (AMSR-E) with a footprint of 0.25° × 0.25°, was used to extract soil moisture content taking advantage of the large differences in dielectric constants of wet and dry soils. A fourth type of remote sensing data set, Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) sensor visible image data was used to extract digital elevation for the SP and the ED to enable runoff and groundwater recharge computations; ASTER images provide high spatial resolution data (15 m) and stereo viewing capability. Thus, an integral part of the developed methodology entails the extraction and processing of relevant remote sensing data sets.

Collection and pre-processing of relevant remote sensing data

The four sets of remote sensing data identified in the previous section were extracted from the following sources: (1) TRMM 3B42.v6 products were downloaded from NASA’s Distributed Active Archive System (DAAC) at http://daac.gsfc.nasa.gov; (2) AVHRR products were obtained from the NOAA CLASS website at http://class.nsstc.noaa.gov; (CLASS, 1978) (3) The AMSR-E was downloaded from NASA’s Distributed Active Archive System (DAAC) at http://daac.gsfc.nasa.gov; (4) L1A ASTER products were downloaded from NASA’s EOS Data Gateway (EDG) at http://redhook.gsfc.nasa.gov/~imswww/pub/imswelcome/ and digital elevations at a spatial resolution of 30 m were extracted using procedures described in Cheng et al. (1999) and Hijazi (2001).

The pre-processing step for the large (>3 TB) temporal remote sensing data sets (TRMM, AVHRR, AMSR-E) was enabled using a recently developed module, the Remote Sensing Data Extraction Model (RESDEM), that was developed using an Interactive Data Language (IDL) code. RESDEM allows: (1) extraction of subsets of remote sensing data sets over user-defined spatial and temporal domains and (2) processing of the images to bring each of the data sets to a common projection and to eliminate spectral variations (within and between scenes) related to differences in sun angle elevations. Applying user defined functions (e.g., area, duration), global remote sensing data sets (TRMM, AVHRR, AMSR-E) were subset to cover the selected area and the time period (1998–2007) of interest (Fig. 4).

An additional parameter (threshold value) was applied to refine the TRMM subset data to include only the events exceeding a selected threshold value. Since the “smaller” precipitation events are unlikely to produce significant runoff and groundwater recharge, we omitted events that fell short of our pre-determined precipitation threshold value of 5 mm, the minimum amount of precipitation that was found to produce runoff in any of the examined watersheds. By adopting such procedures, we minimized the labor involved in the generation and inspection of the verification products cited in this section.

The selected events, the ones exceeding the threshold value were then verified within the RESDEM domain using a module (cloud detection module: CDM) that tests for the presence of clouds and another (soil moisture module: SMM) that tests for changes in soil moisture for precipitation events (Milewski et al., 2006). Next, we describe in detail our reasoning for the selection of our preferred TRMM precipitation dataset (3B42.v6), sources of error in this data and methodologies adopted to correct these errors, and finally procedures for the extraction and verification of precipitation events from a suite of satellite data. RESDEM was used to accomplish the extraction and verification steps (Milewski et al., 2006).
Identification and verification of identified rainfall events

Four types (3B42.v5, 3B43.v5, 3B42.v6, 3B43.v6) of TRMM data are available for users. The 3B4X.v5 products are earlier versions of the three-hourly TRMM products, whereas the 3B43.vX is a monthly product. The three-hourly 3B42.v6 TRMM dataset was selected for our analyses because it has lower false alarm rates (FAR), higher probability of detection (POD) rates during dry periods, and an overall greater critical success index (CSI) compared to the other products (Chokngamwong and Chiu, 2006; Schaefer, 1990).

The overall correspondence between the precipitation derived from the 3B42.v6 TRMM product and rain gauge data was evaluated for the study area. A good correspondence ($R^2 = 0.92$; Fig. 5a) was observed between the average annual precipitation (1998–2000) from the available rain gauge stations (Aswan, Asyuti, Ismailia, El-Suez, Minya, Elat, Sohag, and Ras-Benas) (EMA, 1996) in the ED (Fig. 2) and average annual precipitation extracted from the individual TRMM picture elements (co-located over the investigated stations). Similarly, the precipitation during individual storm events reported from 10 rain gauge stations (Asyuti, Aswan, El-Suez, Cairo, Minya, Elat, Sohag, Ras-Benas, Kosseir, and Ismailia) were found to be in general correspondence ($R^2 = 0.76$; Fig. 5b) with TRMM-derived precipitation over the investigated stations for the same events.

One should not expect a 1:1 correspondence between the TRMM and rain gauge data sets given the fact that the rain gauges provide local measurements, whereas the TRMM integrate observations over much larger domains (covered area: $0.25^\circ \times 0.25^\circ$). Despite the observed general agreement between the gauge and TRMM-derived precipitation, there seems to be discrepancies that cannot be attributed solely to differences in the footprint size between TRMM and gauge data. For example, TRMM identifies events in the ED that are not recorded by gauge data (black circles on Fig. 5b). This is due to the fact that the TRMM sensor can misidentify a variety of Earth surfaces for precipitating clouds (e.g., Bauer et al., 2002) giving a false indication for light rainfall (<0.5 mm/h) (Turk et al., 2003). Because TRMM measurements are acquired every three hours, short events that start and end in between two consecutive TRMM acquisitions can go undetected as well. Thus, there is a tendency for satellite-based rainfall to underestimate event-based precipitation especially in arid areas where precipitation events tend to be short and intense (Morrissey and Janowiak, 1996). For the examined events from the 10 investigated rain gauges, the averaged TRMM-based precipitation is underestimated by ~15% compared to the average precipitation from the rain gauges (Fig. 5b). These results are consistent with earlier findings of Chiu et al. (2006) and Chokngamwong and Chiu (2006) who showed that TRMM in arid environments could underestimate precipitation by 15–30%. Next, we describe the procedures we adopted to address these two potential sources of error.

To correct for the fact that the TRMM is apparently underestimating precipitation in the study area, the TRMM datasets were calibrated by multiplying the TRMM data by a factor (1.18) to bring the TRMM values to match those observed at the rain gauges (Fig. 5b). False positives were addressed as well. We verified the major precipitation events (inferred from TRMM) by conducting the following steps: (1) applying automated methods to detect the presence of clouds in processed temporal AVHRR scenes acquired before (up to 2 days) and throughout the examined precipitation events and (2) visual inspection of soil moisture difference images to detect an increase in soil moisture. The latter was derived from pairs of AMSR-E images, an image acquired before (1–4 days) and another (1–4 days) after the investigated event. We used the VUA-NASA Land Surface Parameter Model which utilizes passive microwave remote sensing approaches to retrieve soil moisture from observed brightness temperatures (Wagner et al., 2007). Microwave observations are sensitive to soil moisture content due to the large differences in dielectric constant values for wet (~80) and dry soils (~4) (Njoku and Kong, 1977).

A precipitation event was verified if substantial cloud coverage and change in soil moisture was associated with the investigated event; other events that did not meet these criteria were omitted. Fig. 6 demonstrates an example of a verified precipitation event that occurred on 1/6/04. Examination of TRMM data indicated
The initial step in the development of our hydrologic model was the generation of a database incorporating digital mosaics from various sources. Recently released GIS-based SWAT modules (ArcSWAT: SWAT, 2007) can readily display and query geospatial information in a GIS environment and use GIS databases as inputs to the SWAT model. We generated the following digital mosaics covering the entire ED and the SP that were used as model inputs: (1) temporal, calibrated rainfall data (three-hourly precipitation data: 1998–2007) extracted from TRMM, (2) a geologic mosaic from 10 1:500,000 geologic maps, each covering 2° latitude by 3° longitude (scale 1:500,000), (3) land use maps extracted from the USGS 1 km global Land Use and Land Cover database generated from AVHRR data (acquisition date: April 1992–March 1993) (Anderson et al., 1976) data that is being used for a wide-range of environmental and modeling applications (e.g., Loveland et al., 2000), (4) a mosaic of three quadrants (each covering 5° by 6°) from the NASA Landsat GeoCover Dataset 2000 (Landsat GeoCover Orthorectified Thematic Mapper Dataset 2000; spatial resolution: 15 m) (Tucker et al., 2004), (5) climatic parameters including solar radiation, wind speed, air temperature, and relative humidity obtained from the Egyptian Meteorological Authority's Climatic Atlas (EMA, 1996) and (6) digital elevation model mosaic from ~100 ASTER scenes at 30 m resolution. The data sets described above, originally in various projections, were co-registered to a reference map (NASA Landsat GeoCover Dataset 2000) and re-projected to a common projection (UTM-Zone 36, WGS84).

ASTER data provides nadir and backward looking scenes, which enable extraction of digital elevation data using automated procedures that take advantage of ASTER's stereoscopic capabilities. The PCI OrthoEngine module (Hijazi, 2001), a geospatial image processing software package was chosen for this application. ASTER scenes with minimal to no cloud coverage acquired during the summer months (July–September) were selected for DEM extraction. DEM extraction was enabled through a series of steps within the PCI OrthoEngine module. Using the extracted DEM, the Topographic Parameterization (TOPAZ) program was then applied to identify water accumulation patterns, distribution of watersheds, stream networks, as well as geometric properties (areas, slope, lengths, etc.) for the main basins and valleys (Garbrecht and Martz, 1995). The geology mosaic was used to identify and map soil types and the Landsat Thematic Mapper (TM) mosaic was used to validate and refine the DEM-based distribution for watersheds and stream networks. Average monthly climatic data (e.g., minimum temperature, maximum temperature, solar radiation, and wind speed) were extracted from the Global Historical Climatology Network (GHCN) global climatic dataset (EarthInfo, 1998–2005) and the Egyptian Meteorological Authority (EMA, 1996). These average monthly datasets are available for seven stations in the SP and twelve stations in the ED (Fig. 2).

**SWAT model setup**

The hydrologic model of the ED and SP was constructed within the SWAT framework to simulate the hydrologic processes using its physically-based formulations. Watersheds were divided into sub-basins and sub-basins were further subdivided into hydrologic response units (HRUs) with each HRU possessing unique land use and soil type attributes. Water partition and balance in each HRU were calculated; flows from all HRUs were summed for each sub-basin and routed through channel networks to sub-basin outlets and ultimately to the watershed outlet.

Initial losses and direct overland flows in HRUs were estimated using the US Department of Agriculture’s-Soil Conservation Service method (SCS, 1972). The SCS method was successfully applied to ephemeral watersheds in southwestern United States, areas that bear resemblances in their climatic, hydrologic, topographic, landscape, and soil and landuse types to those in the ED and the SP (Gheith and Sultan, 2002; Osterkamp et al., 1994). The bulk of precipitation along a NE–SW trending zone extending across the Eastern Desert and Sinai (Fig. 6e). Extensive clouds were detected from AVHRR on 1/6/04 (Fig. 6e), but were minimal in the preceding day (1/5/04) (Fig. 6d). Examination of soil moisture products before (Fig. 6a) and after (Fig. 6b) the examined event together with the soil moisture difference image (Fig. 6c) showed an increase in soil moisture content following the precipitation event under investigation.

**Model construction**

The SWAT model provides a continuous simulation of the overland flow, channel flow, transmission losses, evaporation on bare soils and evapo-transpiration on vegetated canopy, and potential recharge to the shallow alluvial aquifers (Arnold and Fohrer, 2005; Arnold et al., 1998). SWAT was selected because it is a continuous model, allowing rainfall–runoff and groundwater-recharge estimates to be made over extended periods of time and it is compatible with GIS data formats allowing us to import the existing GIS databases for the ED and SP into the model.

**Database generation using GIS**

The initial step in the development of our hydrologic model was the generation of a database incorporating digital mosaics from
the physical properties of the HRUs in each sub-catchment was extracted from existing databases that we generated for soils, land cover, and land use types throughout our previous studies (Gheith and Sultan, 2001, 2002). Initial losses are largely dictated by the curve numbers (CN); the latter is a function of the antecedent moisture condition (AMC), the land use, the hydrologic condition, and the hydrologic soil type (SCS, 1985).

Initial losses were assumed to enter the soil profile after interception of canopy storage; losses were then routed using a soil–water storage/routing method adopted in SWAT that partitions initial losses through processes including transpiration, soil water evaporation, infiltration, lateral flow, and groundwater recharge. Evaporation on bare soils and transpiration on vegetated canopy was calculated using the Penman–Monteith method (Monteith, 1981). Water exceeding soil field capacity throughout the soil profile was routed to the shallow aquifer at each time step and partitioning from the latter to the deep aquifer was assumed to be negligible (Scanlon, 1994). A simplified top soil profile was employed in the model with soil properties dictated by the assigned land use and soil type. In our case, the “Southwestern US Arid Range” provided by SWAT database was the selected land use type across the entire study area.

Channel flows were estimated using the Muskingum routing method (McCarthy, 1938), whereby the Manning’s coefficient for uniform flow in a channel was used to calculate the rate and velocity of flow in a reach segment for a given time step. Channel flows were subject to transmission losses, a partitioning that depends on the channel geometry, upstream flow volume, duration of flow, bed material size, sediment load, and temperature (Neitsch et al., 2005). We assumed negligible losses from channel flows to transpiration or evaporation for the following reasons: (1) vegetation is scarce or absent under the prevailing arid to hyper-arid conditions, (2) flows are short-lived, typically not lasting for more than a day with cloudy conditions typically prevailing throughout storm events, and (3) alluvial deposits flooring the valleys have high hydraulic conductivities.

Simulations were performed at daily time steps, the smallest time steps allowed by SWAT using cumulative three-hourly TRMM data over periods of 24 h and applying monthly average values for temperature, wind speed, relative humidity, and solar radiation as daily estimates.

Calibration

Simulation using the process-based SWAT model to estimate hydrologic response involves calibration of some forty parameters. Calibration involved: (1) parameter specification using sensitivity analysis, (2) initial parameter estimation, and (3) final automatic calibration.

Stream flow data for calibration purposes is only available at the outlet (Bottleneck station) of the Wadi Girafi watershed (Fig. 7; outlined in green), an E–W trending, medium size (area: 3656 km²) watershed that collects precipitation from the highlands of central Sinai and flows eastwards towards Israel. The reported stream flow data (from 1998 to 2006) was measured by...
Parameters estimation

Following the identification of the most sensitive parameters, manual calibrations were conducted to estimate inputs for the automatic calibration step, namely the initial values. In conducting these calibrations, one parameter was adjusted at a time to match modeled average annual watershed runoff against existing stream flow observation data for the Girafi watershed. Initial values and ranges for this step are essentially those used for the sensitivity test (Table 2). Adjustments were then applied to these values throughout the adopted manual calibrations. Manual calibrations were applied to the most sensitive of the eleven parameters, namely CN2 (SCS curve number), ALPHA_BF (baseflow alpha factor), CH_K (effective hydraulic conductivity in channel alluvium), SURLAG (surface runoff lag coefficient), and SOL_AWC (available water capacity of the soil layer). For the remaining six parameters:
SOL_K (soil conductivity), CH_N (Manning’s roughness coefficient), CANMX (maximum canopy index), SOL_Z (soil depth), GW_DELAY (groundwater delay), and GWQMN (depth of water in shallow aquifer required for return flow to occur) that had a lesser impact on modeled runoff, we adopted reported values for these parameters that were applied to areas with similar climatic and hydrologic settings. Outputs of the manual calibration step, the estimated initial values for the automated calibration step are listed in Table 3.

### Parameters for overland flow

The SCS curve number (CN2) and surface runoff lag coefficient (SURLAG) are two of the identified sensitive parameters that significantly affect the overland flow. The values for these two parameters are largely dependant on soil type, land use, and sub-basin characteristics.

As described earlier, four soil types crop out in the study area: Quaternary alluvial valley deposits, Tertiary limestone, Cretaceous sandstone, and Neoproterozoic volcano-sedimentary rocks. Quaternary deposits are well-drained sand and gravel, with low runoff potential and high infiltration rates; they were classified as type A soils (infiltration rate >10 mm/h). Sandstones have moderate infiltration rates, fine to coarse textures, and relatively well-drained soils; we classified the sandstones as type B soils (infiltration rate 5 mm/h). Soil cover is generally absent on the massive limestone and on the volcano-sedimentary rocks, leaving the bedrock surface exposed. Infiltration capacity is extremely limited in these areas, and runoff is very high. Outputs (CN2 values) of the manual calibrations reflect differences in soil types described above: CN2 values for the Quaternary alluvial (67) and the Cretaceous sandstone (77) are considerably lower than those for the Tertiary limestone (96) and the Neoproterozoic volcano-sedimentary rocks (96) (Table 3).

SURLAG, the surface runoff lag coefficient, is a lag factor for sub-basins that controls surface runoff storage by lagging a portion of the runoff that would have otherwise been released to the main channel. For a given time of concentration in a sub-basin, more runoff is released to the channel as the value of SURLAG increases (Neitsch et al., 2005). Using SWAT’s default range of 0.5–28 days, which amounts to 5–99% of total available surface runoff allowed to enter the main channel without delay, and adopting SWAT’s initial value (4 days), a refined SURLAG value of 10 days was extracted from manual calibrations (Table 3).

### Parameters for channel routing

The effective hydraulic conductivity in channel alluvium (CH_K) and the manning’s roughness coefficient for channels (CH_N) are two of the identified sensitive parameters that largely affect the magnitude of transmission losses as well as the amount and timing of the channel flow.

Manual calibrations yielded CH_K values of 130 mm/h. In absence of direct measurements for hydraulic conductivities (CH_K) for channel beds in the study area, we compared the extracted

---

### Table 1

TRMM-based precipitation (1998–2006) over the Wadi Girafi watershed and discharge (simulated and observed) produced at the Bottleneck Station.

<table>
<thead>
<tr>
<th>Day</th>
<th>Precipitation from TRMM (Mm^3)</th>
<th>Observed volume (Mm^3)</th>
<th>Observed average discharge (m^3/s)</th>
<th>Calculated average discharge (m^3/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1/28/1999</td>
<td>1.17E+06</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>3/20/2000</td>
<td>8.14E+06</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>12/9/2000</td>
<td>2.83E+07</td>
<td>0.103</td>
<td>2.135</td>
<td>2.27</td>
</tr>
<tr>
<td>12/10/2000</td>
<td>4.82E+06</td>
<td>0.54</td>
<td>5.383</td>
<td>5.49</td>
</tr>
<tr>
<td>1/24/2001</td>
<td>7.48E+06</td>
<td>0</td>
<td>0</td>
<td>0.11</td>
</tr>
<tr>
<td>4/5/2001</td>
<td>1.16E+07</td>
<td>0.267</td>
<td>5.605</td>
<td>2.81</td>
</tr>
<tr>
<td>12/19/2001</td>
<td>1.35E+06</td>
<td>0</td>
<td>0</td>
<td>0.58</td>
</tr>
<tr>
<td>11/2/2002</td>
<td>2.58E+07</td>
<td>1.184</td>
<td>5.974</td>
<td>6.67</td>
</tr>
<tr>
<td>12/4/2002</td>
<td>5.33E+06</td>
<td>0</td>
<td>0</td>
<td>0.29</td>
</tr>
<tr>
<td>1/23/2003</td>
<td>9.49E+06</td>
<td>0.098</td>
<td>0.722</td>
<td>0.91</td>
</tr>
<tr>
<td>3/26/2004</td>
<td>1.64E+06</td>
<td>0</td>
<td>0</td>
<td>0.19</td>
</tr>
<tr>
<td>10/30/2004</td>
<td>1.32E+07</td>
<td>0.15</td>
<td>1.631</td>
<td>1.64</td>
</tr>
<tr>
<td>11/20/2004</td>
<td>4.09E+06</td>
<td>0.001</td>
<td>2.778</td>
<td>3.34</td>
</tr>
<tr>
<td>2/16/2006</td>
<td>1.79E+06</td>
<td>0.119</td>
<td>0.931</td>
<td>0.21</td>
</tr>
</tbody>
</table>

### Table 2

Inputs (initial values and ranges) and outputs of the sensitivity analysis conducted in SWAT.

<table>
<thead>
<tr>
<th>Parametera</th>
<th>Min.</th>
<th>Max.</th>
<th>SWAT initial value</th>
<th>Definition</th>
<th>Process</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>CN2 (alluvial)</td>
<td>35</td>
<td>98</td>
<td>39</td>
<td>SCS curve number</td>
<td>Runoff</td>
<td>1</td>
</tr>
<tr>
<td>CN2 (sandstone)</td>
<td>35</td>
<td>98</td>
<td>61</td>
<td>SCS curve number</td>
<td>Runoff</td>
<td>1</td>
</tr>
<tr>
<td>CN2 (limestone)</td>
<td>35</td>
<td>98</td>
<td>74</td>
<td>SCS curve number</td>
<td>Runoff</td>
<td>1</td>
</tr>
<tr>
<td>CN2 (precambrian)</td>
<td>35</td>
<td>98</td>
<td>80</td>
<td>SCS curve number</td>
<td>Runoff</td>
<td>1</td>
</tr>
<tr>
<td>ALPHA_BF</td>
<td>0</td>
<td>1</td>
<td>0.048b</td>
<td>Baseflow alpha factor (days)</td>
<td>Groundwater</td>
<td>2</td>
</tr>
<tr>
<td>CH_K</td>
<td>0</td>
<td>150</td>
<td>0.50c</td>
<td>Effective hydraulic conductivity in channel alluvium</td>
<td>Channel</td>
<td>3</td>
</tr>
<tr>
<td>SURLAG</td>
<td>0.5</td>
<td>28</td>
<td>4</td>
<td>Surface runoff lag coefficient</td>
<td>Runoff</td>
<td>4</td>
</tr>
<tr>
<td>SOL_AWCa</td>
<td>0</td>
<td>1</td>
<td>Variesb</td>
<td>Available water capacity of the soil layer (mm/mm soil)</td>
<td>Soil</td>
<td>5</td>
</tr>
<tr>
<td>SOL_K</td>
<td>0</td>
<td>100</td>
<td>Varies</td>
<td>Soil conductivity (mm/h)</td>
<td>Soil</td>
<td>6</td>
</tr>
<tr>
<td>CH_N</td>
<td>0.01</td>
<td>0.3</td>
<td>0.014d</td>
<td>Manning’s roughness coefficient</td>
<td>Channel</td>
<td>7</td>
</tr>
<tr>
<td>CANMX</td>
<td>0</td>
<td>3</td>
<td>Maximum canopy index</td>
<td>Runoff</td>
<td>8</td>
<td></td>
</tr>
<tr>
<td>SOL_Z</td>
<td>0</td>
<td>3000</td>
<td>Varies</td>
<td>Soil depth (mm)</td>
<td>Soil</td>
<td>9</td>
</tr>
<tr>
<td>GW_DELAY</td>
<td>0</td>
<td>100</td>
<td>31e</td>
<td>Groundwater delay (days)</td>
<td>Groundwater</td>
<td>10</td>
</tr>
<tr>
<td>GWQMN</td>
<td>0</td>
<td>5000</td>
<td>0</td>
<td>Depth of water in shallow aquifer required for return flow to occur (mm)</td>
<td>Groundwater</td>
<td>11</td>
</tr>
</tbody>
</table>

---

*SOL_K (soil conductivity), CH_N (Manning’s roughness coefficient), CANMX (maximum canopy index), SOL_Z (soil depth), GW_DELAY (groundwater delay), and GWQMN (depth of water in shallow aquifer required for return flow to occur) that had a lesser impact on modeled runoff, we adopted reported values for these parameters that were applied to areas with similar climatic and hydrologic settings. Outputs of the manual calibration step, the estimated initial values for the automated calibration step are listed in Table 3.*

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*a* Distributed parameters that are varied according to a relative (+/-50%) that maintain their spatial relationship (Van Griensven et al., 2006).

*b* Neitsch et al. (2002).

*c* Sangrey et al. (1984).

*d* Smedema and Roycroft (1983).

*e* Lane (1983).

*f* Chow (1959).
Parameters for groundwater

The baseflow recession constant (ALPHA_BF), the threshold water levels in shallow aquifer for base flow (GWQMN), and the delay time for groundwater recharge (GW_DELAY) are sensitive groundwater parameters that dictate the amount as well as the timing of water flow released from or recharged to the shallow aquifer. Due to the lack of site-specific data for the study area, these parameters were first assigned SWAT default values and ranges (Table 2), and then adjusted using manual calibration. The manually calibrated values for the ALPHA_BF, GWQMN, and GW_DELAY parameters are 0.9 days, 2000 mm of water, and 10 days, respectively (Table 3).

Parameters for soil storage/routing and interception

The available water capacity in the soil layer (SOL_AWC), soil saturated conductivity (SOL_K), and thickness of soil layer (SOL_Z) are three of our sensitive parameters that govern the process of soil storage and routing in the soil profile. Maximum canopy storage (CANMX) is another sensitive parameter that largely controls the canopy interception prior to infiltration in soil.

SOL_AWC values were manually calibrated for the investigated four soil types by subtracting the fraction of water present at permanent wilting point from that present at field capacity using expressions (Neitsch et al., 2005) and reported (Rawls and Brakensiek, 1985) ranges/constants for percent clay and bulk density for our soil types. The SOL_AWC values obtained from manual calibrations for the alluvium, sandstone, limestone, and volcano-sedimentary soil types are 0.10, 0.05, 0.02, and 0.02 mm of water per mm of soil respectively. Adopted soil saturated hydraulic conductivity (SOL_K) values for these rock types (alluvial: 10 mm/h; sandstone: 5 mm/h; limestone: 1 mm/h; and volcano-sedimentary: 1 mm/h) were based on site-specific data extracted from our GIS database and published (e.g., Rawls and Brakensiek, 1985) values for similar rock units. The thickness of the soil profile (SOL_Z) was assumed to be less than 3.5 m, a thickness that is consistent with our field observations and those reported for many soil profiles in arid and semi-arid environments (FAO, 1998). As described earlier, the vegetation in the study area is negligible, and thus interception by plants is very limited. Accordingly, CANMX was assigned a value of 0.

Automatic calibration

An automatic calibration was performed to further refine the model parameters extracted from the initial manual calibration. This calibration uses a multiplier for each parameter to adjust the parameter while retaining the relative spatial pattern generated in data-processing module for all sub-basins. The shuffled complex evolution method (SCE) (Duan, 1991; Sorooshian et al., 1993) implemented in SWAT (Van Griensven, 2002) was used to calibrate the parameter multiplier. The SCE algorithm was used to conduct a global probabilistic search for multiplier values for the entire watershed. The parameters for each sub-basins were scaled up or down by the derived multiplier. The objective function used in the automatic calibration was utilized to minimize the mean square error between observed and simulated stream discharge. A total of over 2000 runs were simulated before achieving the best possible result.

Calibration evaluation

Twenty-four precipitation events were extracted from TRMM data over the watershed. Only fourteen of these events produced runoff. A comparison between observed and simulated discharge (Fig. 8 and Table 1) shows a good correspondence. Simulated runoff from seven of these fourteen events was recorded at the Bottleneck Station, whereas the modeled runoff from each of the remaining seven events was insignificant (<1 m$^3$/s). This explains why no runoff was reported from the Bottleneck Station for any of the remaining events (Fig. 8). The model parameters were calibrated in a SWAT domain using procedures outlined above until the overall simulated values for discharge were close to the observed values. Table 3 lists the parameters that were adjusted to achieve the best
correlation between observed and simulated discharge at the Wadi Girafi site. The coefficient of determination ($R^2$) and the coefficient of efficiency (COE) Nash and Sutcliffe (1970) were used to evaluate the correspondence between observed and modeled discharge. An $R^2$ value of 0.86 and a COE value of 0.85 indicate high degrees of correlation between the observed and computed values of discharge and were determined to be sufficient for accepting model results (Fig. 8).

**Discussion and results**

A physically-based SWAT model was used to construct the ED and SP watershed models and was calibrated through processes involving parameter specification, estimation, and automatic calibration. In the calibration process, the eleven most sensitive parameters were identified and adjusted to maximize agreement between simulated and observed runoffs at the Girafi watershed. Because of the limited field data (e.g., stream flow data) and potential uncertainties in the calibrated values of a few of the sensitive parameters (e.g., groundwater depth/delay time, canopy storage, and soil profile characteristics), errors could potentially be introduced with the extrapolation of catchment-specific parameters from the gauged watershed to others in the SP and the ED. These potential sources of errors were assessed by varying (increase or decrease) each of the calibrated sensitive parameters within the SWAT default range listed in Table 2. The change in model outputs was found to be less than 5% for: SOL_K, SOL_Z, CH_N, CANMX, GW_DELAY, and GWQMIN and 12% for SOL_AWC. Varying the most sensitive of our parameters (CN2, ALPHA_BF, CH_K, and SURLAG) within the specified range listed in Table 2 on the other hand, produced significant (>25%) impact on model outputs. Such significant uncertainties are unlikely to occur because these parameters are well constrained by site-specific data (assembled in the GIS database) and because the adopted calibrated values are consistent with those reported for similar arid and semi-arid environments. CN2 is well constrained by soil types, landuse, and hydrologic parameters. Throughout the automatic calibration step, CN2 is adjusted globally even though calibration is only conducted on one sub-basin. Similarly, SURLAG is well constrained using data from the GIS database including sub-basin characteristics, soil types, and landuse types. The calibrated value for CH_K is consistent with pumping test results conducted for shallow alluvium at the Asuyti basin in the ED. The calibrated value for ALPHA_BF is 1 indicating no significant return flow from channel storage, consistent with the nature of flash flood events in arid and semi-arid environments, being short-lived and quick and consistent with values (0.9–1) reported from arid areas elsewhere (Neitsch et al., 2005). Thus, we believe that extrapolation of catchment-specific parameters from the gauged watershed to others in the SP and the ED could provide reasonable outputs for regional analysis of watersheds in the ED and SP.

Cathment-specific parameters from the only gauged watershed in the Red Sea Hills in the SP and the ED were extrapolated to similar watersheds in the ED (nine watersheds occupying 51% of the ED) and the SP (four watersheds occupying 48% of Sinai). These watersheds share similar climatic and topographic conditions, soil types, and sizes. Precipitation over selected watersheds is sparse (<150 mm/year) and generally occurs during the winter season (December through March) originating from southeast winds coming off the Mediterranean Coast (Brookes, 2003). These watersheds are found in topographically high elevations with average elevations ranging from 300 to 900 m; they originate from the Red Sea Hills and adjoining limestone platforms and drain towards the adjacent water bodies in the lowlands (e.g., Mediterranean Sea, Red Sea, Gulf of Suez, Gulf of Aqaba, Nile River). The selected watersheds share the same land use classification (Southwestern

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**Table 4** Modeled average annual (1998–2007) values of hydrologic variables for the investigated watersheds.

<table>
<thead>
<tr>
<th>Watershed</th>
<th>Area km²</th>
<th>Precipitation x 10³ m³</th>
<th>Initial losses</th>
<th>Surface runoff</th>
<th>Transmission losses</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>$\times 10^6$ m³ (%)</td>
<td>$\times 10^6$ m³ (%)</td>
<td>$\times 10^6$ m³ (%)</td>
</tr>
<tr>
<td><strong>Eastern Desert</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Qena</td>
<td>15,738</td>
<td>140.1</td>
<td>107.3 (76.6)</td>
<td>5.1 (3.6)</td>
<td>27.7 (19.8)</td>
</tr>
<tr>
<td>Hammamat</td>
<td>7,745</td>
<td>27.1</td>
<td>20.6 (76.0)</td>
<td>3.6 (13.4)</td>
<td>2.9 (10.6)</td>
</tr>
<tr>
<td>Asyut</td>
<td>6,073</td>
<td>43.1</td>
<td>32.2 (74.7)</td>
<td>1.5 (3.5)</td>
<td>9.4 (21.8)</td>
</tr>
<tr>
<td>Tarfa</td>
<td>4,931</td>
<td>66.1</td>
<td>50.8 (76.9)</td>
<td>3.6 (5.3)</td>
<td>11.7 (17.8)</td>
</tr>
<tr>
<td>El-Quffa</td>
<td>4,596</td>
<td>40.9</td>
<td>34.5 (84.4)</td>
<td>1.7 (4.0)</td>
<td>4.7 (11.6)</td>
</tr>
<tr>
<td>El-Batur</td>
<td>6,809</td>
<td>36.8</td>
<td>30.6 (83.1)</td>
<td>0.6 (1.7)</td>
<td>5.6 (15.2)</td>
</tr>
<tr>
<td>Kharit</td>
<td>28,632</td>
<td>229.1</td>
<td>155.2 (67.7)</td>
<td>19.8 (8.6)</td>
<td>54.1 (23.6)</td>
</tr>
<tr>
<td>Hodein</td>
<td>11,578</td>
<td>90.3</td>
<td>46.8 (51.8)</td>
<td>26.1 (28.8)</td>
<td>17.4 (19.4)</td>
</tr>
<tr>
<td>Allaqi</td>
<td>25,126</td>
<td>133.2</td>
<td>80.0 (60.0)</td>
<td>15.8 (11.9)</td>
<td>37.4 (28.1)</td>
</tr>
<tr>
<td>Total</td>
<td>111,228</td>
<td>806.7</td>
<td>558.0 (69.2)</td>
<td>77.8 (9.6)</td>
<td>170.9 (21.2)</td>
</tr>
<tr>
<td><strong>Sinai</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Watir</td>
<td>3536</td>
<td>192.7</td>
<td>158.0 (82.0)</td>
<td>3.4 (1.7)</td>
<td>31.3 (16.3)</td>
</tr>
<tr>
<td>El-Arish</td>
<td>22,030</td>
<td>257.8</td>
<td>1708.0 (66.2)</td>
<td>488.4 (18.9)</td>
<td>381.6 (14.9)</td>
</tr>
<tr>
<td>Dahab</td>
<td>2014</td>
<td>110.6</td>
<td>73.7 (66.14)</td>
<td>10.4 (9.14)</td>
<td>26.5 (24.0)</td>
</tr>
<tr>
<td>Awag</td>
<td>2083</td>
<td>74.2</td>
<td>45.6 (61.4)</td>
<td>5.3 (7.2)</td>
<td>23.3 (31.4)</td>
</tr>
<tr>
<td>Total</td>
<td>29,663</td>
<td>2,955.5</td>
<td>1985.3 (67.2)</td>
<td>507.5 (17.1)</td>
<td>462.7 (15.7)</td>
</tr>
</tbody>
</table>

Numbers in parenthesis represent the percentage of total precipitation.
US Arid Range) and soil types as well. Namely basement, limestone, sandstone, and alluvial soil types, that constitutes more than 95% of the total area of each of the selected watersheds. The selected watersheds are medium (>2000 < 10,000 km²) to large (area: 10,000–30,000 km²) size watersheds. Examples of the former are Watir, Dahab, and Awag and Hammamat, Asyuti, and Tarfa watersheds in the SP and the ED, respectively and examples of the latter are El-Arish (area: 22,030 km²) and Kharit (area: 28,632 km²) watersheds in the SP and the ED, respectively (Fig. 7). Watersheds that did not meet one or more of the criteria identified above were omitted from the selection. Examples of such watersheds are outlined in Fig. 7. These include watersheds with average elevations less than 300 m a.s.l. (e.g., S1, S2), watersheds that receive exceptionally high precipitation exceeding 150 mm/year (e.g., S3; Figs. 2 and 7), small watersheds with areas less than <2000 km² (e.g., S4, S5), and watersheds that incorporate relatively large amounts (>5%) of soil types other than the major four soil groups. For example, S6 and S7 watersheds (Fig. 7) comprise relatively large areas (>5% watershed area) that are covered by sabbka deposits covering more than 15% and 20% of these two watersheds, respectively.

Model results, including the average annual amount of precipitation, surface runoff, initial losses (e.g., infiltration–evaporation), transmission losses, and shallow aquifer recharge throughout the investigated period (1998–2007) are summarized in Table 4. Recharge for the investigated watershed’s shallow alluvial aquifers was estimated as a sole function of the transmission losses. This assumption is supported by earlier findings from arid and semiarid environments showing: (1) negligible (<4% of infiltration) evaporation from channel reaches during flash floods (e.g., Abdulrazzak and Sorman, 1994; Ben-Zvi and Shentis, 2001; Schwartz, 2001; Shentis et al., 1999; Sorey and Matlick, 1969) and (2) minimal (<4% of precipitation) recharge through initial losses from studies in the arid southwest of the United States (e.g., Flint et al., 2000), the Nevada Basin (Dettinger, 1989), and Western Saudi Arabia (Bazuhair and Wood, 1996).

Inspection of Table 4 shows that the average annual precipitation over the selected watersheds in the ED is approximately one third that observed over the SP watersheds, being 807 × 10⁶ m³ and 2955 × 10⁶ m³, respectively. Of this precipitation, an average of 171 × 10⁶ m³ (21.2% of the total ED precipitation) and 463 × 10⁶ m³ (15.7% of the SP precipitation) is partitioned as recharge in the ED and the SP, respectively. The larger volume of recharge in the SP together with the smaller area of its watersheds (investigated watersheds: SP: 29,663 km²; ED: 111,228 km²; Table 4) suggests that the SP holds more promise for groundwater exploration and development.

We have demonstrated how a wide-range of readily available, global remote sensing data sets could potentially be used applying protocols developed in this work to address apparent inadequacies in monitoring systems (e.g., temporal and spatial rainfall depths, stream flow data). Our protocols also reduce uncertainties arising from scarcity of one or more of these data sets and provide reliable quantitative tools for conducting regional-scale rainfall–runoff modeling. Implications for applying the developed methodologies to obtain first-order estimates of surface runoff and ground water recharge using limited gauge data coupled with inferences from remote sensing of the less examined parts of the Earth’s surface are clear.

Applications of the developed methodologies in the study areas and elsewhere world-wide will contribute to our understanding of the regional scale variability and the fluxes and storages of the terrestrial hydrosphere. The applications of these methods are especially valued for arid and hyper-arid parts of the world, where demand for freshwater supplies is on the rise due to increasing populations and limited water supplies.

Acknowledgements

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References
