Remote Sensing Solutions for Estimating Runoff and Recharge in Arid Environments

Adam M. Milewski
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REMOTE SENSING SOLUTIONS FOR ESTIMATING RUNOFF AND RECHARGE IN ARID ENVIRONMENTS

by

Adam M. Milewski

A Dissertation
Submitted to the
Faculty of The Graduate College
in partial fulfillment of the
requirements for the
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Dr. Mohamed Sultan, Advisor

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Adam M. Milewski
REMOTE SENSING SOLUTIONS FOR ESTIMATING RUNOFF AND RECHARGE IN ARID ENVIRONMENTS

Adam M. Milewski, Ph.D.

Western Michigan University, 2008

Efforts to understand and to quantify the interplay between precipitation, runoff, and recharge are often hampered by the paucity of appropriate monitoring systems. We developed 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, AVHRR, and AMSR-E,) using the arid Sinai Peninsula (SP; area: 61,000 km$^2$) and the Eastern Desert (ED; area: 220,000 km$^2$) of Egypt as our test sites. A two-fold exercise was conducted. Temporal 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 from 1998-2006. This was accomplished by using an automated cloud detection technique to identify the presence of clouds during the identified precipitation events, and by examining changes in soil moisture (extracted from AMSR-E data) following the identification of clouds. 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 km$^2$) and then used to provide a continuous simulation (1998-2006) of the overland flow, channel flow, transmission losses, evaporation, evapo-transpiration, and groundwater recharge for the major (area $\geq 2000$ km$^2$) watersheds in the SP and the ED covering 48% and 51% of the total areas, respectively. For the investigated watersheds in the SP, the average annual runoff, and average annual recharge through transmission losses were found to be: $80.5 \times 10^6$ m$^3$ (10.3% total precipitation (TP)) and $87.3 \times 10^6$ m$^3$ (11.2% TP), respectively, whereas in the ED these values are: $17.5 \times 10^6$ m$^3$ (4.1% TP) and $86.1 \times 10^6$ m$^3$ (20.1% 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 approach is not a substitute for traditional methodologies that rely on extensive datasets from rain gauge and stream flow networks, but rather a tool for providing first order estimates for rainfall, runoff, and recharge over large sectors of the world.
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1.1 Motivation and Contributions

The demand for freshwater resources in arid environments is increasing at alarming rates due to limited water supplies and increasing population. This situation is exemplified in the Middle East where demand is now exceeding the supply. As a result, many countries are beginning to develop programs to explore and utilize alternative renewable water resource strategies. Unfortunately, efforts to understand and to quantify the interplay between precipitation, runoff, and recharge are often hampered by the absence of appropriate monitoring systems (e.g., stream flow gauges, rain gauges). Therefore, traditional programs that are data-intensive and expensive, for assessing groundwater potential are non-applicable to many areas worldwide. The Middle East is one of these areas. Fortunately, with the increasing number and versatility of remote sensing satellites, applications for first order estimates of groundwater potential are now within reach.

I have developed methodologies for rainfall-runoff and groundwater computations that heavily rely on observations extracted from a wide range of global remote sensing data sets (e.g., TRMM, AVHRR, AMSR-E) using the Eastern Desert (ED) of Egypt and the Sinai Peninsula (SP) as my test sites. I performed a two-fold exercise: First,
precipitation events were identified from TRMM data and qualitatively verified using the presence of clouds throughout the investigated event and soil moisture difference images (from AMSR-E) extracted from those acquired before and after the selected precipitation events. Second, a calibrated catchment-based continuously distributed (over the 9 years) hydrologic model was adopted to quantify the spatial and temporal distribution of surface runoff and groundwater recharge for the alluvial aquifers in the study areas. Due to the absence of streamflow data in the Eastern Desert, calibration of the model was accomplished using streamflow data from Israel, where the geologic and hydrogeologic settings are similar to those of the Eastern Desert and the Sinai Peninsula and can readily be applied to these areas using physical catchment descriptors.

The topographic, climatic, geologic, and hydrogeologic conditions of the Eastern Desert and Sinai are replicated along the Red Sea Hills, in Sudan, Somalia, Saudi Arabia, and Yemen, and are collectively known as the Arabian-Nubian Shield. Therefore, regional applications of these methodologies in North Africa, in the Arabian Peninsula, and in similar arid areas elsewhere are clear. These methodologies are ideal for applications elsewhere in the arid and hyper-arid parts of the world, providing integrated innovative techniques to conduct enhanced hydrologic modeling on regional scales. The methodologies provide alternatives to understand and to quantify the partitioning of precipitation between runoff, losses, and recharge in the less examined parts of the world.
1.2 Thesis Road Map

Chapter 2 provides a brief overview of the hydrogeologic and geologic characteristics of the research site. It also provides an overview of hydrologic modeling particularly the development and use of the Soil Water and Assessment Tool (SWAT) model.

Chapters 3 and 4 of this thesis are written as independent studies based on manuscripts that have already been submitted for publication in scientific journals. Therefore, it is possible to read these chapters independently without having to read the other chapters first.

Chapter 3 is primarily concerned with reporting the results of the major research activities I conducted in its entirety. Specifically, it discusses the geological and hydrogeologic settings of the test area, the identification and verification of satellite-based rainfall estimates, and the setup, calibration, and simulation results of the hydrologic model. Lastly, it discusses the potential applications of the developed methodologies for groundwater development in arid environments. This chapter presents the material that was submitted (March, 2008) to the Journal of Hydrology for consideration for publication (Milewski et al., 2008, In Review).

Chapter 4 discusses an innovative computer program that was developed to handle the large amounts of remote sensing data sets that are required to run the models
described in Chapter 3. These datasets take up large amounts of storage space (>10TB) and require long processing times. The Remote Sensing Data Extraction Model (RESDEM) is an IDL-based computer program that processes global remote sensing data sets, specifically those used in Chapter 3. This manuscript was submitted (May, 2008) to the Journal of Computer & Geosciences (Milewski et al., 2008).

Chapter 5 provides a summary of the thesis and suggestions for future work.
CHAPTER 2

BACKGROUND

2.1 SWAT Modeling

The main objective of this exercise is to develop and calibrate methodologies that heavily rely on remote sensing data sets (e.g., TRMM, SSM/I, SRTM, Landsat TM, AVHRR) in conjunction with field observations (e.g., soil maps, groundwater table, stream flow, etc.) for conducting continuous rainfall-runoff and groundwater recharge calculations using the Eastern Desert of Egypt and the Sinai Peninsula as test sites.

There are very few modeling studies that have taken place in the test areas. Again, this is due to the lack of data in this area that is traditionally required for modeling applications. Gheith and Sultan (2002) conducted a GIS-based rainfall-runoff model for four watersheds (Qena, Tara, Asyuti, and Hammamat) in the Eastern Desert. Precipitation estimates were obtained using spatial interpolation techniques between the limited (~10) rain gauge stations in the Eastern Desert. Though the model produced first-order estimates of runoff and recharge, there were a few limitations to their model. The model was not calibrated against existing stream flow data, but rather a less sophisticated approach of measuring water levels in weirs and roads. No attempt was made to show the similarities between the different watersheds and the
ability to apply catchment specific parameters to the various watersheds. Also, their model was not a continuous model.

The activities described within this thesis build on these earlier findings and methodologies for recharge and runoff calculations in arid areas (Gheith and Sultan, 2002). They also recognize the uncertainties arising from scarcity of one or more of the following data sets: temporal and spatial rainfall depths, stream flow data, and field data. In this thesis, a catchment-based, semi-distributed hydrologic model was developed for continuous simulation of surface runoff and potential recharge to the groundwater systems. For this purpose, The Soil & Water Assessment Tool (SWAT) model developed by the Blackland Research Team at Texas A&M University was used. Stream simulated flows were calibrated against streamflow data, and meaningful spatial distribution of precipitation were extracted from 3-hourly TRMM data.

The SWAT model (Arnold and Fohrer, 2005) has proven to be an effective tool for water resource and pollutions applications. SWAT is watershed scale, distributed, continuous model that was designed to predict the impact of management practices on water, sediment, and agricultural yields in ungauged watersheds. 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. More importantly, SWAT has gained international acceptance as a robust watershed modeling tool as evidenced by international conferences and hundreds of SWAT-related articles in peer-reviewed journals (Gassman et al., 2007).
3.1 Introduction

To date, monitoring systems which are needed to estimate precipitation, runoff, and recharge are absent on a regional scale for the majority of the Earth’s surface and it is unlikely that such systems will be in place in the near future given the efforts and resources needed to construct and maintain such systems. This situation is making it difficult to characterize and to monitor the key reservoirs of, and fluxes to, the water cycles. Fortunately, recent advances in remote sensing hold the promise to address these apparent inadequacies. The developed methodologies for surface runoff and recharge computations heavily rely on observations extracted from a wide-range of global remote sensing data sets, procedures which could be readily applied to large sectors of the Earth’s surface. We chose the Sinai Peninsula (SP) and the Eastern Desert (ED) of Egypt, the desert to the east of the Nile River and west of the Red Sea (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. Moreover, Egypt’s climate, and hydrologic settings resemble those of surrounding areas in North Africa and the Arabian Peninsula and hence, results will be applicable to neighboring countries and other similar arid settings as well (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 the totals tend to increase with elevation (Herschy 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 2006. 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 SSMI 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 SSMI-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
Figure 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 Figure 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 marked with the symbol “X” belong to the Arabian-Nubian Shield.
Figure 2. Average annual precipitation derived from TRMM 3B42.v6 three-hourly data over the study area and surroundings throughout the investigated period (1998 - 2006). Also shown are the centers of each of the TRMM footprints, each covering $0.25^\circ \times 0.25^\circ$ 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).
indication for light rainfall (Turk et al., 2003), a phenomena 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 2006 with the realization that the SSMI 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)).

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 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 landuse, 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 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 from a calibrated watershed to neighboring surrounding catchments.

3.2 Site Description

Most of the SP and the ED are classified as arid to hyper-arid terrains. Rainfall is generally less than 35 mm/yr 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. Figure 2 shows the average annual precipitation extracted from TRMM over Egypt from 1998 to 2006. Despite the paucity of the rainfall events, many flash floods 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 crops out along the Red Sea coastline and in southern Sinai, 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 Precambrian basement complex in Egypt is part of the Arabian-Nubian Shield, a region of Neoproterozoic (550-900 Ma) crystalline rocks comprising the ED of Egypt, southern Sinai, western Saudi Arabia, and northeastern Sudan (David, 1984; Engel et al., 1980; Greenwood et al., 1980) (Inset Fig. 1). During the Oligocene, tectonic movement led to the uplift of the Arabian-
Nubian Shield, and in the Miocene the landscape of the ED and the SP were shaped during a period of intense erosion (Said, 1990).

The major stratigraphic units along E-W and N-S-trending cross sections in the ED and the SP are shown in Figure 3 and the locations of these cross sections (AA’ and BB’) are plotted on Figure 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 Nubian Sandstone and Eocene 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 and the deeper underlying limestone, sandstone, and fractured basement aquifers (Sultan et al., 2007).

The Wadi deposits are of variable composition and include clasts of Precambrian rocks and Eocene limestone (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 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-
Figure 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), respectively.
Arish, Kharit, Qena, Tarfa, Asyuti, 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 regional precipitation and flash floods having modern meteoric to evaporated meteoric compositions ($\delta^D$ and $\delta^{18}O$ 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 intervening dry climatic periods (e.g., present) (Sultan et al., 2007). This hypothesis is supported by the patterns of modern precipitation. 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.
3.3 Methodology

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 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° x 0.25° footprint from 1998-2006, (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° x 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.

3.3.1 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.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 (1999) and Hijazi (2001).

The pre-processing step for the large (>3TB) 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 them 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 (1998-2006) 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 2 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, those exceeding the threshold value were then verified 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. 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. RESDEMI was also used to accomplish this verification step (Milewski et al., 2006).
3.3.2 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 3-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 ($R^2 = 0.94$; Fig. 5a) was observed between the average annual precipitation (1998-2000) from five rain gauge stations (Aswan, Asyuti, Ismalia, El-Suez, and Minya) (EMA, 1996) in the ED (Fig. 2) and average annual precipitation from the TRMM picture elements encompassing the same stations. Similarly, the precipitation during individual storm events reported from six rain gauge stations (Asyuti, Aswan, Minya, Sohag, Ras-Benas, and Kosseir) were found to be in good correspondence ($R^2 = 0.77$; 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° x 0.25°). 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 (<0.5mm/hr) (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 precipitation especially in arid areas where events tend to be short and intense (Morrissey and Janowiak, 1996). Results show that precipitation in the ED is underestimated by ~23% (Fig. 5b) 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 up to 20-30%. Next, we describe the procedures we adopted to address these two potential sources of error.

Figure 5b. Comparison of TRMM-derived precipitation to rain gauge data in the ED. (b) Rain gauge precipitation data (Asyuti, Aswan, Minya, Sohag, and Kosseir) for individual events versus precipitation from TRMM data for the same events (black diamonds). Also shown in black circles are TRMM-derived false positive rainfall events (not included in reported regression). Dashed lines represent 1:1 relationships and solid lines represent the linear correlation relationships.

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 (1.23) to bring the TRMM values to match those observed at the rain gauges
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, 2007). Microwave observations are sensitive to soil moisture content due to the large differences in dielectric constant values for liquid water (~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. Figure 6 demonstrates an example for a verified precipitation event that occurred on 1/6/04. Examination of TRMM data indicated 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.

3.4 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.

3.4.1 Database Generation Using GIS

The initial step in the development of our hydrologic model was the generation of a database incorporating digital mosaics from various sources. We generated the following digital mosaics covering the entire ED and the SP that were used as model inputs: (1) temporal, calibrated rainfall data (3-hourly precipitation data: 1998-2006) extracted from TRMM, (2) a geologic mosaic from ten 1:500,000 geologic maps, each covering 2° latitude by 3° longitude (scale 1:500,000), (3) landuse 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.
Figure 6. Validation of TRMM-derived precipitation event over the ED on 1/6/04. (a) Soil moisture content extracted from AMSR-E acquired on 1/5/04. (b) Soil moisture on 1/6/04. (c) Soil moisture difference image: (1/6/04 image minus 1/5/04 image). (d) AVHRR image showing minimal cloud coverage on 1/5/04. (e) AVHRR image acquired on 1/6/04 showing extensive cloud coverage (white areas). Also shown on 6e is TRMM-derived precipitation (colored areas).

(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: 15m) (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. ASTER scenes with minimal to no cloud coverage acquired during the summer months (July though September) were selected for DEM extraction. DEM extraction was enabled through a series of steps within the PCI OrthoEngine module (Hijazi, 2001). 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 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).

3.4.2 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 subbasins and subbasins 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 subbasin and routed through channel networks to subbasin outlets and ultimately to the watershed outlet.

Initial losses and direct overland flows in HRUs were estimated using the U.S. 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 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; Gheith and Sultan, 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 routed partially as 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 to take advantage of the available daily precipitation data (cumulative 3-hourly TRMM data over periods of 24 hours) and applying monthly average values for temperature, wind speed, relative humidity, and solar radiation as daily estimates.

3.5 Calibration
Simulation using the process-based SWAT model to estimate hydrologic processes 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 km$^2$) 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 the Israeli Hydrologic Service. The Girafi watershed like the majority of all other investigated watersheds in the ED and SP has four main soil types/outcrop units: Quaternary Alluvium (36.3% of watershed area),
Cretaceous sandstone (43.2%), Eocene limestone (9.6%), and Precambrian volcanics (10.9%). The watershed receives an average of 25 mm of precipitation or less per year and precipitation events are infrequent and intense (Crouvi et al., 2006). Table 1 provides a summary for the dates of the events that produced runoff at the Bottleneck station over the past nine years (1998-2006). The table also provides: (1) precipitation (extracted from TRMM) data throughout the examined period, the events that produced runoff and others that did not, and (2) a comparison between the observed and simulated flows.

3.5.1 Parameter Specification

Automatic calibration processes often become time consuming and less practical with increasing number of parameters to be calibrated. Using the Shuffled Complex Evolution method, Eckhardt and Arnold (2001) found that approximately 18,000 runs were required to achieve convergence if eighteen parameters were to be calibrated within the SWAT domain. An attempt was made to reduce the number of parameters to be calibrated by identifying the most sensitive of these parameters, the ones that had the largest influence on predicted runoff. Sensitivity analysis was conducted using the LH-OAT method; parameters were varied to assess the corresponding level of change in outputs. The LH-OAT method combines the Latin Hypercube (LH) sampling method (McKay, 1988; McKay et al., 1979) with the One-factor-At-a-Time
Figure 7. Location of the calibration site (Wadi Girafi watershed), similar watersheds (color filled watersheds with streams delineated) that were modeled using SWAT, and dissimilar watersheds (transparent watersheds, streams not delineated) that were not modeled. The latter include watersheds with relatively low elevation (mean elevation: < 300 m a.s.l.; e.g., S1 & S2), watersheds receiving relatively high precipitation (>75 mm/yr; e.g., S3), relatively small (<2000 km²) watersheds (e.g., S4 & S5), and watersheds that comprise relatively large areas covered by soil types not represented in the Wadi Girafi watershed (e.g., S6 & S7 watersheds; approximately 15% of their areas are covered by sabkha deposits).
<table>
<thead>
<tr>
<th>Day</th>
<th>Precipitation from TRMM (10^6 m^3)</th>
<th>Observed volume (10^6 m^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>1.17</td>
<td>0.00</td>
<td>0.00</td>
<td>0.80</td>
</tr>
<tr>
<td>3/20/2000</td>
<td>3.55</td>
<td>0.00</td>
<td>0.00</td>
<td>0.45</td>
</tr>
<tr>
<td>10/16/2000</td>
<td>7.64</td>
<td>0.85</td>
<td>10.10</td>
<td>9.68</td>
</tr>
<tr>
<td>12/9/2000</td>
<td>16.70</td>
<td>0.10</td>
<td>2.14</td>
<td>1.26</td>
</tr>
<tr>
<td>12/10/2000</td>
<td>0.00</td>
<td>0.54</td>
<td>5.38</td>
<td>6.66</td>
</tr>
<tr>
<td>1/24/2001</td>
<td>4.01</td>
<td>0.00</td>
<td>0.00</td>
<td>0.68</td>
</tr>
<tr>
<td>4/5/2001</td>
<td>5.47</td>
<td>0.27</td>
<td>5.61</td>
<td>4.01</td>
</tr>
<tr>
<td>12/19/2001</td>
<td>2.77</td>
<td>0.00</td>
<td>0.00</td>
<td>0.81</td>
</tr>
<tr>
<td>2/21/2002</td>
<td>1.75</td>
<td>0.00</td>
<td>0.00</td>
<td>0.35</td>
</tr>
<tr>
<td>11/2/2002</td>
<td>9.51</td>
<td>1.18</td>
<td>5.97</td>
<td>5.98</td>
</tr>
<tr>
<td>12/4/2002</td>
<td>0.89</td>
<td>0.00</td>
<td>0.00</td>
<td>0.12</td>
</tr>
<tr>
<td>1/23/2003</td>
<td>2.74</td>
<td>0.10</td>
<td>0.72</td>
<td>2.12</td>
</tr>
<tr>
<td>3/26/2004</td>
<td>2.38</td>
<td>0.00</td>
<td>0.00</td>
<td>0.07</td>
</tr>
<tr>
<td>11/20/2004</td>
<td>3.69</td>
<td>0.00</td>
<td>2.78</td>
<td>3.34</td>
</tr>
</tbody>
</table>

Table 1. TRMM-based precipitation (1998-2006) over the Wadi Girafi watershed and discharge (simulated and observed) produced at the Bottleneck Station.

(OAT) method (Morris, 1991). LH sampling was used to generate input data for each parameter from the assigned distributions and ranges. Using the OAT method, the impacts of changes of individual parameters on model outputs were evaluated. The LH simulation performs random sampling functions similar to those described by Monte Carlo simulations, but applies simplified sampling routines which significantly reduce the number of simulation runs (Van Griensven et al., 2006). Throughout the sensitivity analysis, attempts were made to match to a first order modeled runoff with observed stream flow data collected for the Girafi watershed. Initial parameter values and ranges were largely extracted from SWAT databases and are consistent with reported and/or expected values for arid and semiarid environments (Table 2). In the selection of these values, we were also guided by site specific data (e.g., soil type
distribution, hydraulic conductivities, etc.) assembled in a GIS database generated for
the study area
(http://ims.esrs.wmich.edu/website/IMS_UNDP/viewer.htm).

Outputs of the sensitivity analysis, eleven parameters ranked in a descending order
reflecting model sensitivity and performance, are given in Table 2. Omitted from the
list, are parameters that are irrelevant or least relevant to the examined setting.

<table>
<thead>
<tr>
<th>Parameter*</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>0.04%</td>
<td>Baseflow alpha factor (days)</td>
<td>Groundwater</td>
<td>2</td>
</tr>
<tr>
<td>SUFLAG</td>
<td>0.5</td>
<td>28</td>
<td>4</td>
<td>Surface runoff lag coefficient</td>
<td>Runoff</td>
<td>2</td>
</tr>
<tr>
<td>SOL AWC*</td>
<td>0</td>
<td>1</td>
<td>Varies</td>
<td>Available water capacity of the soil layer (mm/mm soil)</td>
<td>Soil</td>
<td>1</td>
</tr>
<tr>
<td>SOL K*</td>
<td>0</td>
<td>100</td>
<td>Varies</td>
<td>Soil conductivity (mm/hr)</td>
<td>Soil</td>
<td>5</td>
</tr>
<tr>
<td>CH N*</td>
<td>0.01</td>
<td>0.3</td>
<td>0.014</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>0</td>
<td>Maximum canopy index</td>
<td>Runoff</td>
<td>8</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>31</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>

Table 2. Inputs (initial values and ranges) and outputs of the Sensitivity Analysis
conducted in SWAT.

Examples include, parameters describing snow formation, melting, and
evapotranspiration. Also omitted, are the “insensitive parameters”, parameters whose
variations have negligible impact on modeled runoff. Examples include the BLAI,
the leaf area index for crops, and REVAPMNN, the threshold depth of water in the
shallow aquifer for 'revap' to occur. A parameter is designated as being insensitive if upon changing its value by 50%, only insignificant (<1%) variations are introduced in modeled runoff. The eleven selected parameters were used for model calibration; these parameters largely control processes of overland flow, interception, soil storage/routing, channel routing, and groundwater recharge.

3.5.2 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.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Initial Values</th>
<th>Final Value</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>CN (Alluvial)</td>
<td>67</td>
<td>64</td>
<td>SCS Curve Number</td>
</tr>
<tr>
<td>CN (Sandstone)</td>
<td>77</td>
<td>74</td>
<td>SCS Curve Number</td>
</tr>
<tr>
<td>CN (Limestone)</td>
<td>98</td>
<td>94</td>
<td>SCS Curve Number</td>
</tr>
<tr>
<td>CN (Precambrian)</td>
<td>98</td>
<td>96</td>
<td>SCS Curve Number</td>
</tr>
<tr>
<td>ALPHA BF</td>
<td>0.9</td>
<td>1.0</td>
<td>Baseflow alpha factor (days)</td>
</tr>
<tr>
<td>CH_K</td>
<td>100.0</td>
<td>80.0</td>
<td>Effective hydraulic conductivity in channel alluvium (mm/hr)</td>
</tr>
<tr>
<td>SURLAG</td>
<td>10.0</td>
<td>15.0</td>
<td>Surface runoff lag coefficient (days)</td>
</tr>
<tr>
<td>SOL_AWC</td>
<td>Varies (0.05-0.60)</td>
<td>Varies (0.01-0.50)</td>
<td>Available water capacity of the soil layer (mm/mm soil)</td>
</tr>
<tr>
<td>SOL_K</td>
<td>Varies (0.5-10)</td>
<td>Varies (0.5-10)</td>
<td>Saturated hydraulic conductivity (mm/hr)</td>
</tr>
<tr>
<td>CH_N1</td>
<td>Varies (0.035-0.05)</td>
<td>Varies (0.035-0.05)</td>
<td>Manning's &quot;n&quot; value for the tributary channels</td>
</tr>
<tr>
<td>CH_N2</td>
<td>Varies (0.035-0.05)</td>
<td>Varies (0.035-0.05)</td>
<td>Manning's &quot;n&quot; value for the main channel</td>
</tr>
<tr>
<td>CANMX</td>
<td>0.0</td>
<td>0.0</td>
<td>Maximum canopy index</td>
</tr>
<tr>
<td>SOL_Z</td>
<td>Varies (1-1000)</td>
<td>Varies (1-1000)</td>
<td>Soil depth (mm)</td>
</tr>
<tr>
<td>GW DELAY</td>
<td>10.0</td>
<td>0.0</td>
<td>Groundwater delay time (days)</td>
</tr>
<tr>
<td>GWQMIN</td>
<td>2000.0</td>
<td>2000.0</td>
<td>Threshold depth of water in the shallow aquifer required for return flow to occur (mm H2O)</td>
</tr>
</tbody>
</table>

Table 3. Inputs and outputs of the Automatic Calibration conducted in SWAT.

3.5.2.1 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 subbasin 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/hr). 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/hr). 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 (98) and the Neoproterozoic volcano-sedimentary rocks (98) (Table 3).

SURLAG, the surface runoff lag coefficient, is a lag factor for subbasins 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 subbasin, 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).
3.5.2.2 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 100 mm/hr. In absence of direct measurements for hydraulic conductivities (CH_K) for channel beds in the study area, we compared the extracted conductivities to those reported from pumping tests within the study area (Wadi Asyuti alluvial deposits; Fig. 7). Our values fall within the range of the reported conductivities (20 mm/hr to 350 mm/hr)(Sultan et al., 2007).

Manning’s coefficient, n, the estimated mean stream roughness value for streams and channels, ranges from 0.015 to 0.05 in natural desert landscape. Chow (1959) adopts the following n values: (1) 0.05 for mountainous areas, areas characterized by rugged drainage, sharp ridges, and narrow steep canyons, (2) 0.015 for valleys with uniform drainage and gentle slopes, and (3) 0.03 for foothills characterized by rolling drainage, rounded ridges, and moderate side slopes. Examination of digital elevation data over the calibration site, allowed assignment of areas within the watershed to one of the three landforms (mountainous, valleys, foothills) described above and all reaches of streams within a designated landform were assigned Chow’s “n” value for that specific landform type. The majority of the tributary channels were found in
mountainous areas and the majority of the main channels were in the valleys and foothills. No further refinements were pursued for the "n" values using manual calibrations.

3.5.2.3 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).

3.5.2.4 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/hr; sandstone: 5 mm/hr; limestone: 1 mm/hr; and volcano-sedimentary: 1 mm/hr) 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.

3.5.3 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.

3.5.4 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 m³/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 water balance was 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
Figure 8. Calibration results. Calculated versus observed flow at the Bottleneck Station in Wadi Girafi for the time period 1998 through 2006. Dashed line represents the 1:1 relationship and solid line is the regression line. Results indicate a high correlation between observed and calculated flow ($R^2 = 0.93$).

The correspondence between observed and modeled discharge. An $R^2$ value of 0.93 and a COE value of 0.91 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).
3.6 Discussion and Results

A physically-based SWAT model was used to construct the ED and SP watershed model 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 by 50%. 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) by 50% 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 semiarid 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 subbasin. Similarly, SURLAG is well
constrained using data from the GIS database including subbasin 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 semiarid 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.

Catchment-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 (9 watersheds occupying 51% of the ED) and the SP (4 watersheds occupying 48% of Sinai). These watersheds share similar climatic and topographic conditions, soil types, and sizes. Precipitation over selected watersheds is sparse (<100 mm/yr) and generally occurs during the winter season (December through March) originating from northwest winds coming off the Mediterranean Coast (Brookes, 2003). These watersheds are found in topographically high elevations with average elevations ranging from 300 to 900m; 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 landuse classification (Southwestern 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 km$^2$ <10,000 km$^2$) to large (area: 10,000 km$^2$ - 30,000 km$^2$) 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 km$^2$) and Kharit (area: 28,632 km$^2$) 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 Figure 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 75 mm/yr (e.g., S3; Figs 2 and 7), small watersheds with areas less than <2000 km$^2$ (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 sabkha 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 (1998-2006) 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 Shentsis, 2001; Schwartz, 2001; Shentsis et al., 1999; Sorey and Matlock, 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 that over the SP watersheds, being 428.7 x 10^6 m^3 and 778.2 x 10^6 m^3, respectively. Of this precipitation, an average of 87.3 x
10^6 m^3 (11.2% of total the SP precipitation) and 86.1 x 10^6 m^3 (20.1% total ED precipitation) is partitioned as recharge in the SP and the ED, respectively. Though the ED receives similar amounts of recharge per year to that in Sinai, it is more spatially distributed. A comparison of the area occupied by the investigated watersheds in the SP (30,000 km^2) to that of the selected watersheds in ED (111,000 km^2) suggests that the SP probably 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 groundwater 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 worldwide 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.
4.1 Introduction

Remote sensing data provide quantitative observational parameters over large domains and thus can potentially present cost-effective alternatives or supplements to extensive field campaigns. Throughout the past two decades, there has been a dramatic increase in the number and types of space-borne sensors that were deployed, enabling new and enhanced applications in various scientific disciplines ranging from geology, to hydrology, forestry, atmospheric sciences, and oceanography. The development of these new data sets and the accumulation of extensive temporal measurements has opened new research opportunities and at the same time posed new challenges for scientists attempting to retrieve, assimilate, and analyze these large data sets. In this manuscript, we discuss the impacts of such advances on one of these fields, the field of hydrogeology. We examine the problems that hydrogeologists face as they attempt to utilize remote sensing data sets in their investigations and provide solutions to assist in such applications.

Monitoring systems which are needed to estimate precipitation, runoff, and recharge are absent on a regional scale for the majority of the Earth’s surface and it is unlikely that such systems will be developed in the near future given the resources that are needed to build and maintain such systems. This situation is making it difficult for
hydrogeologists to monitor the key reservoirs of, and fluxes to, the water cycles. Observations from recent deployments of new remote sensing sensors in conjunction with observations extracted from earlier sensors are now enabling researchers to address some of these apparent inadequacies (Milewski et al., 2005). Examples of such recent and earlier deployments include: (1) the Moderate Resolution Imaging Spectroradiometer (MODIS; launch date: 2002), (2) the Advanced Microwave Scanning Radiometer (AMSR-E: 2002), (3) the Tropical Rainfall Measuring Mission (TRMM; 1998), and (4) the Advanced Very High Resolution Radiometer (AVHRR: 1978).

Until recently, users had to resort to rainfall station data to extract precipitation over areas of interest. Because the distribution of such stations over the majority of the Earth’s surface is sparse, spatial rainfall distributions extracted from these stations could be questionable. For example, Figure 9 shows a limited number (<20) of rain gauge stations over extensive areas in the Sinai Peninsula (SP) and the Eastern Desert (ED) of Egypt, a situation that is typical of many of the World’s surfaces. Currently, users can freely download digital TRMM and Special Spectral Measuring Imager (SSM/I) precipitation data from the Earth System Science Data Center provided by National Aeronautics and Space Administration (NASA). The downside to this free product is that it is provided in a format that is prohibiting its use by many users. In
Figure 9. Average annual precipitation derived from TRMM 3B42.v6 three-hourly data over Egypt and surroundings from 1998 – 2006 using RESDEM. Also shown are the centers of each of the TRMM footprints, each covering $0.25^\circ \times 0.25^\circ$ and the locations of climatic stations that collect atmospheric data (e.g., precipitation, relative humidity, temperature, solar radiation, and wind speed).
order for users to quantify rainfall they are required to read the data using programming codes in a variety of programming languages. Similarly, the processing of AVHRR data which is widely used for land use-land cover observations, vegetation intensity, atmospheric studies, fire detection, and aquatic studies, has become labor-intensive for users looking at data acquired over long time spans and large domains (i.e., the data is organized as individual time slices, where data through time at one locations is used as model inputs). We address these obstacles through the development of the Remote Sensing Data Extraction Model (RESDEM) that simplifies the tedious manual processes needed to process raw satellite data and by selecting adequate hardware to enable processing and archiving of these large data sets. Next, we briefly describe the remote sensing data sets analyzed by RESDEM, and provide examples for applications now enabled by RESDEM with emphasis on hydrogeologic investigations.

4.2 Datasets

RESDEM processes the following sets of remote sensing data: (1) TRMM 3B42.v6 rainfall (1998-Present); (2) AHVRR (1978-Present); (3) AMSR-E (2002-Present); (4) MODIS (2002-Present); (5) SSM/I (1987-Present); and (6) NASA’s Quick Scatterometer (QuikSCAT) wind speed data (2002-Present). Table 5 summarizes the fundamental characteristics of the remote sensing data sets used in this study.
4.2.1 TRMM

The TRMM is a joint mission between the National Space Development Agency (NASDA) of Japan and the National Aeronautics and Space Administration (NASA) of the United States as part of the Earth Observing System (EOS). TRMM provides global (50°N-50°S) data on rainfall using microwave and visible-infrared sensors. Instantaneous rainfall estimates are obtained every three hours with a 0.25° x 0.25° footprint. Launched in 1997, TRMM provides continuous coverage from 1998-present. The primary rainfall instruments of TRMM are the precipitation radar, TRMM microwave imager, and the visible/infrared scanner (Kummerow, 1998). The TRMM 3B42.v6 products were downloaded from NASA’s Distributed Active Archive System (DAAC) at http://daac.gsfc.nasa.gov for its entirety (1998-Present).

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Operation Time</th>
<th>Data sets</th>
<th>Temporal Resolution</th>
<th>Spatial Resolution</th>
<th>Spectral Resolution</th>
<th>Products</th>
</tr>
</thead>
<tbody>
<tr>
<td>TRMM</td>
<td>1998 - Present</td>
<td>3B42.v6</td>
<td>3-hourly</td>
<td>0.25 x 0.25 degrees</td>
<td>VIR, Microwave (Passive, Active)</td>
<td>Instantaneous Rainfall</td>
</tr>
<tr>
<td>AVHRR</td>
<td>1981 - Present</td>
<td>Level 1B</td>
<td>Sub-daily</td>
<td>1km, 4km, and 8km</td>
<td>5 Bands: 1-2 = visible; 3-5 = infrared</td>
<td>Cloud detection, NDVI</td>
</tr>
<tr>
<td>AMSR</td>
<td>2002 - Present</td>
<td>AE_Land3</td>
<td>Daily</td>
<td>Microwave: 6.9 - 89.0 GHz</td>
<td>Vegetative Water Content &amp; Soil Moisture</td>
<td></td>
</tr>
<tr>
<td>SSM/I</td>
<td>1987 - Present</td>
<td>GPROF</td>
<td>4-6 hourly</td>
<td>Microwave: 19.4 - 85.5 GHz</td>
<td>Rainfall</td>
<td></td>
</tr>
<tr>
<td>MODIS</td>
<td>2002 - Present</td>
<td>Various MOD##</td>
<td>Sub-daily</td>
<td>36 Bands: VNIR, SWIR, TIR</td>
<td>Land &amp; Ocean Products</td>
<td></td>
</tr>
<tr>
<td>QuikSCAT</td>
<td>1999 - Present</td>
<td>Standard Wind Product</td>
<td>Twice daily</td>
<td>Microwave: 13.4 GHz</td>
<td>Wind Direction &amp; Speed</td>
<td></td>
</tr>
</tbody>
</table>

Table 5. Overview of the general characteristics of remote sensing sensors that are commonly used in hydrogeological investigations.

4.2.2 AVHRR

The AVHRR is a cross-track scanning system, five-channel scanning radiometer with 1.1km resolution in the visible and near-infrared wavelength region. The temporal
resolution depends on the observation period. The AVHRR sensor is on board the National Oceanic & Atmospheric Association (NOAA) satellite series. With the vast number of satellite sensors now in orbit, AVHRR is providing global coverage and multiple coverages on daily basis for the majority of the Earth’s surface. AHVRR products were obtained from the NOAA CLASS website at http://class.noaa.gov (CLASS, 1978).

4.2.3 AMSR-E

The AMSR-E on the EOS’ Aqua satellite launched on May 4, 2002, is a conically scanning total power passive microwave radiometer that measures microwave radiation (brightness temperatures) across 12 wavelength regions (12 channels) and at frequencies ranging from 6.9 to 89.0 GHz. Both horizontal and vertical polarized radiations are measured separately at each frequency (Njoku et al., 2003). The input brightness temperature data, corresponding to a 56 km mean spatial resolution, are resampled to a global cylindrical 25 km Equal-Area Scalable Earth Grid (EASE-Grid) cell spacing. The Aqua orbit is sun-synchronous with equator crossings at 1:30 P.M. and 1:30 A.M. The AMSR-E data was downloaded from NASA’s Distributed Active Archive System (DAAC) at http://daac.gsfc.nasa.gov.

4.2.4 SSM/I

The SSM/I is a seven channel passive microwave radiometer operating at four frequencies onboard the Defense Meteorological Satellite Program (DMSP) series of
polar orbiting satellites. SSM/I provides instantaneous rain rates on a global coverage at a 0.5 x 0.5 spatial resolution from 1987-Present. The SSM/I data was downloaded from ftp://lake.nascom.nasa.gov/data/TRMM/Ancillary/ssmi.

4.2.5 MODIS
The MODIS is aboard the Terra and Aqua Earth Observing Satellites launched in 1999. MODIS has a temporal resolution of 1 to 2 days and a spatial resolution of 250m - 1km. MODIS uses 36 spectral bands to provide data on global dynamics and processes occurring on the land, in the oceans, and in the lower atmosphere. MODIS products were downloaded from http://modis.gsfc.nasa.gov/.

4.2.6 QuikSCAT
QuikSCAT is a polar orbiting satellite that provides high resolution measurements of near-surface winds over global oceans approximately twice daily. The spatial resolution of QuikSCAT is 25km. The data can be downloaded at http://manati.orbit.nesdis.noaa.gov/quikscat/

4.3 Programming Environment
We developed routines using the Interactive Data Language (IDL)(IDL, 1999). IDL was selected because it is a powerful, array-based, programming language that integrates image processing techniques with simple graphical user interfaces packages(GUI)(IDL, 1999). Moreover, the use of IDL allowed us to take advantage
of, and integrate, the image processing capabilities of ENVI (The ENvironment for Visualizing Images) package (ENVI, 1998). The latter, also written in IDL, provides a library of procedures and programming tools for user functions to handle input/output, sub-routines, and file management. Using our IDL scripts, standard ENVI functions were modified to handle the majority of the pre- and post-processing steps such as input/output, georeferencing, and file management before and after implementing a particular user function.

The storage requirements that are needed for processing the remote sensing data sets discussed above will vary depending on the size of the particular data set under consideration, and the format and the available temporal range for the data set. For example, to extract TRMM, SSMI, and AMSR-E over an area of interest, one has to retrieve the global set in its entirety and subset the global data to the area of interest. For the TRMM, the global set is 200 GB in size, the SSM/I is 1 TB, and the AMSR-E is 150 GB. For the remaining two data sets (AVHRR and MODIS), one does not need to work with the global data sets in their entirety, but with individual images covering the areas of interest. A user investigating cloud coverage, vegetation intensity, soil moisture, or wind directions over the entire African continent could assemble a full coverage (mosaic of images) of the continent using 3-5 AVHRR images (150 MB each) and 3-5 MODIS scenes (200 MB each), respectively. If these mosaics were to be acquired over the entire operational periods for the individual sensors, approximately ~10 TB will be required for the AVHRR stack of images and
~3.5 TB for the MODIS stack of images. Therefore, for users conducting applications on regional or continental scales, the recommended minimum requirements for hard drive space is ~10 TB (our system is 14TB); space requirements should be scaled down for local applications over smaller areas and vice versa. In our case, images were processed on a Windows XP operating system with a 1.8GHz Intel processor with 2 GB of RAM. Naturally, faster processors and larger RAM would speed computations.

4.4 RESDEM Development

The use of public domain global remote sensing data sets (e.g., TRMM, SSMI, AVHRR) to assess complex environmental and hydrologic problems worldwide is hampered by the effort, time, and expertise needed to extract and process such data sets, and the technical obstacles that users face in attempting to retrieve and process these data. Specifically, these difficulties could be attributed to: (1) media storage requirements; computations often require downloading and processing of Terabytes worth of data that are generated by each of the targeted space-borne data sets, (2) computing time requirements; the processing time of certain functions for each image let alone thousands of images is extensive and such difficulties are compounded if processing is conducted manually, (3) raw data formats; each sensor acquires and stores binary data in specific formats (e.g., AMSR-E: HDF-EOS) and thus various codes are required for reading the individual remote sensing data sets and subsets, (4) image calibration (specifically for AVHRR and MODIS scenes); raw satellite data are
stored in digital numbers and need to be converted to other measurable units (e.g., space reflectance, radiance) to allow comparisons to be made between images acquired under different viewing geometries, (5) georeferencing; the viewing geometries of individual images vary considerably and thus images should be re-projected to a common projection to allow comparisons to be made between images acquired at different times over the same approximate areas, (6) non-site specific data sets; many of the remote sensing raw data sets (e.g., TRMM) are global data sets that are not specific to a region of interest and thus the data should be subset to areas of interest, (7) large temporal frequency of satellite sensors; global remote sensing data sets are now being acquired over the same areas as frequently as possible to capture temporal variations on daily or even hourly basis (e.g., TRMM: 3-hourly data; SSMI: 4-hourly data) and thus the data should be subset to the time span and time step (e.g., for TRMM: every 3 hours, 6-hours, 9 hours, etc.) of interest, and (8) quality control issues; for example in the case of TRMM data, the noise could be mistaken for low levels of precipitation and thus only the rainfall events that exceed the noise levels should be considered.

The challenges outlined above were addressed by developing RESDEM to simplify the tedious manual processes needed to process raw satellite data and by selecting computationally intensive, cost-effective hardware with adequate memory resources to enable adequate processing and archiving of these large data sets.
RESDEM addresses the difficulties outlined above by performing the following functions: (1) read the raw binary data and export data into unified image and database formats (Section 4.1.1), (2) pre-process images to bring them to a common projection and to eliminate spectral variations (within and between scenes) related to differences in sun angle elevations (Sections 4.2.1 – 4.2.3), (3) subset remote sensing data sets over user-defined spatial and temporal domains (Section 4.3.1 and 4.3.2), and (4) apply user defined functions (e.g., Cloud Detection Module, Section 4.4).

4.4.1 Data Import

4.4.1.1 Read_In.pro, Step1_TRMM.pro, Step1_SSMI.pro

These programs allow the user to read the initial individual databases for each of the utilized remote sensing data sets that are usually stored in a wide range of formats. All data import programs require images to reside in the same directory. The images that do not have a set image size (AVHRR, MODIS, QuikSCAT) are imported using Read_In.pro (Figure 10), whereas the images with a set number of columns and rows (i.e., global data set) (e.g., TRMM and SSM/I) are imported using simpler routines that are specific to each of these data sets (Read_TRMM.pro, Read_SSMI.pro, and Read_AMSR.pro). Most files are output into .TIFF files with the original name. In the case of the TRMM and SSM/I, the files are also exported into database files for ease of use in hydrologic models. For example, for every picture element (pixel) a database file is created along with a database file containing the list of stations IDs and names. This allows direct import into many of the existing hydrologic models.
such as the Soil Water and Assessment Tool (SWAT) and the Groundwater Modeling System (GMS); both programs require separate database files for each rain gauge location. In our case these correspond to locations of TRMM or SSMI picture elements.
4.4.2 Pre-Processing

4.4.2.1 Calibrate.pro

This program allows the user to calibrate the remote sensing raw data. Calibration of AVHRR images converts the digital numbers (DN) of the thermal bands (Channels 3 and 4, and 5 when present) to temperature values and the visible bands (Channels 1 and 2) to albedos. AVHRR images are first calibrated before applying any of the post-processing (e.g., Spatial Extraction, User Functions) steps using RESDEM's calibration programs (Calibrate.pro). Similarly, MODIS images are converted to albedo and temperature values using Calibrate.pro. Outputs of this program are calibrated image files.

4.4.2.2 Georeference.pro

Following the calibration step, AVHRR and MODIS images are georeferenced and set to a common projection before proceeding with the post-processing steps. In this program the AVHRR geometry (latitude and longitude), solar zenith angles, and sensor zenith angles for each pixel are computed. The input to this routine are AVHRR level 1b files. Built in ENVI functions (ENVI_GOREFERENCE_DOIT; ENVI, 1998) were modified to allow automatic batch georeferencing of raw AVHRR and MODIS images. The input bands are resampled and reprojected to a common output projection and pixel size. TRMM, SSM/I, and AMSR_E images are automatically georeferenced in the data import programs (Read_TRMM.pro,
Read_SSMI.pro, Read.AMSR-E.pro). Outputs are calibrated georeferenced image files.

4.4.2.3 Layer_Stacking.pro

Layer stacking is the process of building up an image cube of referenced images with increasing temporal range. This program builds a multi-band file from georeferenced images of similar pixel sizes, and projections, where each band represents a time slice. However, the areal extent of each of the stacked images could vary as is the case with AVHRR and MODIS data sets. The satellite images are stacked during this pre-processing step to facilitate the spatial and temporal data extraction steps (Figure 10). Outputs are stacked image files with the MODIS and AVHRR files being calibrated and georeferenced.

4.4.3 Spatial and Temporal Data Extraction

4.4.3.1 Lat/Long_Mask.pro

This program allows the user to specify in a graphical user interface (GUI) the spatial extent of the data set(s) to be subset. The user identifies the geographical coordinates (in degrees of latitude and longitude) of the area of interest by selecting a start and end point; the coordinates are used to create a mask covering the area of interest. Figure 11a shows the latitude/longitude mask created over an area within the Eastern Desert of Egypt. The mask could then be used to subset any of the investigated remote sensing data sets. Figure 11b shows a subset of TRMM precipitation event in
Figure 11. Identification and validation of a TRMM-derived precipitation event over the ED on 1/6/04 using RESDEM functions. (a) User defined mask to be used for sub-setting global data sets to a specific region of interest. (b) TRMM precipitation data acquired on 1/6/04 that was subset using the user-defined mask. (c) Distribution of precipitation (purple areas) during the 1/6/04 event that exceeds a user-defined threshold value (2 mm). (d) AVHRR image acquired on 1/6/04 showing extensive cloud coverage (white areas) and TRMM-derived precipitation (colored areas). (e) AVHRR image showing minimal cloud coverage on 1/5/04. (f) VWC difference image extracted from AMSR-E showing an increase in VWC following the 1/6/04 precipitation event. (g) NDVI difference image extracted from AVHRR showing an increase in NDVI following the 1/6/04 precipitation event. (h) Soil moisture difference image showing an increase in soil moisture following the 1/6/04 precipitation event.
the Eastern Desert. For MODIS and AVHRR, the output file is a stack of raster images that is subset to the boundaries of the area of interest, whereas a stack of database files is generated for each of the TRMM, SSMI, and AMSR-E data sets.

4.4.3.2 Timerange.pro

This program allows the user to specify in a graphical user interface (GUI) the temporal extent of the data set(s) to be subset. Outputs from the Lat/Long_Mask.pro are inputs to this program. The output file is a stack of raster images (e.g., AVHRR and MODIS data sets) or database files (TRMM and SSM/I, AMSR-E) that are subset to the area and the temporal range of interest. For the latter data sets, the user is prompted to specify the time step of interest (e.g., 3-hourly, 6-hourly, daily). This function allows users to generate input files for various hydrologic models that respond to specific time step requirements dictated by the model of choice. For example, the SWAT rainfall runoff model requires that precipitation data (e.g., TRMM or SSMI) to be re-sampled at daily steps (e.g., TRMM 3-hourly and SSM/I 6-hourly are summed up to daily totals).

4.4.4 User Defined Functions

In this section, a number of routines which allow the user to screen data and perform quality control assessment on data sets by integrating multiple fused data sets have been developed.
4.4.4.1 Event_Logger.pro

The event logger program allows users to screen data sets to identify areas or individual pixels that exceed a defined threshold value. The event logger serves many purposes including minimizing false positives and reducing computational time. For example, the TRMM sensors can misidentify a variety of Earth surfaces for precipitating clouds (e.g., Bauer et al., 2002) giving a false indication for light rainfall (<0.5mm/hr) (Turk et al., 2003). Many of the light precipitation events (<2mm) are unlikely to produce runoff or recharge (Gheith and Sultan, 2002). Thus, users conducting continuous rainfall runoff modeling could set an appropriate threshold value for precipitation (e.g., 2mm; Milewski et al., 2005) to minimize false positive precipitation events and to reduce computational time by eliminating the low precipitation events that are unlikely to produce recharge or runoff. Similar applications include identifying wind speed events exceeding a certain magnitude using QuikSCAT data sets.

The program generates two products: (1) an image of all the pixels exceeding the threshold value (Figure 11c), and (2) a database log file that incorporates all dates in which a threshold value was exceeded. If a pixel in an image exceeds the user-defined threshold level, the program exports the date of that image to a database log file. A subroutine arranges the dates chronologically and removes duplicate dates.
4.4.4.2 Cloud Detection Module

The cloud detection module (CDM) identifies the presence and spatial distribution of clouds in AVHRR data sets. This program checks for one of two requirements that are adopted to verify a precipitation event that was extracted from TRMM data. The first requirement that is checked by this program is the presence or absence of clouds on the day the TRMM precipitation was observed. A precipitation event is verified if it was associated with cloud coverage (observed in AVHRR data). The CDM calculates the percentage of picture elements covered by clouds (cloud pixels) within a user-defined mask (typically covering 1° x 1° in dimension). The mask moves across the entire AVHRR image (bands 1 or 2) and at each location, the number of bright picture elements with reflectance values greater than the user defined threshold value (typically > 0.70) is identified as being covered by clouds. A log file is created with the date and cloud % for all of the processed mask locations for all examined AVHRR files. If the cloud % for a given date is greater than 50%, the precipitation event is verified and the precipitation values in the TRMM database with the same date and mask location is left unchanged. If the cloud % for a given date and a given mask location is less than 50%, this could indicate absence of precipitating clouds or fast cloud movement following a precipitation event. To distinguish between these two possibilities, the cloud detection methodology described above is repeated using a user-defined larger mask (typically, 2° x 2° in dimension). If the cloud % for a given date is greater than 25% in the larger mask, the precipitation values in the TRMM database with the same date and mask location is left unchanged. If, on the other
hand the cloud pixels are less than 25% of the mask area, the corresponding precipitation values in the TRMM database are considered to be unverified and are set to zero in the modified TRMM database. Outputs are both images files and database files.

4.4.4.3 VWC_SM.pro

Because not all clouds produce precipitation, additional verification tools (i.e., integration of other data sets) are required to verify TRMM- or SSMI-based rainfall events. The increase in vegetative water content (VWC) or soil moisture following precipitation events were used for such purposes. In the study area, we find that soil moisture image products show an immediate increase following a precipitation event that are detectable for a few days following rainfall events, whereas the VWC image products show an increase within a few days following the precipitation event and are detectable for several days to weeks following the event. The VWC_SM.pro program extracts surface soil moisture and vegetation/roughness water content, as well as brightness temperatures from the gridded Level-3 land surface product (AE_Land3) (Njoku et al., 2003). Microwave observations are sensitive to soil moisture due to the large contrast of the dielectric constants of liquid water (~80) and dry soils (<4)(Njoku and Kong, 1977). Brightness temperatures are largely controlled by the volumetric soil moisture, the vegetation water content (VWC), and the surface temperature. Outputs include Vegetative Water Content and Soil Moisture raster files over the area and time period of interest.
Unfortunately, the VWC and soil moisture products described above became available only recently (2002-present) as the AMSR-E sensor was deployed around that time. Thus, for time periods predating the deployment of such sensors, one has to resort to other remote sensing products that detect changes in surface properties associated with precipitation events. One such product is the Normalized Difference Vegetative Index (NDVI) that could be extracted from AVHRR data available as early as 1978. The NDVI is the difference between Near-Infrared and visible red divided by the summation of Near-Infrared and visible red electromagnetic radiation (Gallo et al., 2004). The NDVI is indicative of the intensity of vegetation. In the study area, we find that the NDVI product shows an increase within a few days from the event, and is detectable for several days to weeks following the event. The NDVI.pro program generates NDVI images from calibrated and georeferenced AVHRR or MODIS images. Outputs include raster files displaying NDVI values for the selected area and times of interest.

The Rose_Diagrams.pro program is used to generate wind rose diagrams showing both the prevailing wind direction and wind speed from QuikSCAT data. This program also allows the user to define the temporal range (e.g., daily, monthly,
seasonal, yearly) for the generated rose diagrams. Outputs include wind rose diagram image files.

4.4.4.6 Tiff_gen.pro

Tiff_gen.pro exports images into a widely recognized and accepted file format (.tiff). This is done to ensure that the end products of all of the functions can be readily used with existing image processing software programs (e.g., ENVI, ArcGIS).

4.5 Implications for Hydrologic Investigations

In this section, we provide an example of how RESDEM is being utilized to address the growing need (e.g., Melesse et al., 2007) to use many of the remote sensing data sets listed above in hydrologic investigations. RESDEM was selected (Milewski et al., 2005) as our preferred platform to conduct continuous rainfall-runoff and groundwater recharge computations in the arid Sinai Peninsula (SP; area: 61,000 km²) and the Eastern Desert (ED; area: 220,000 km²) of Egypt.

A two-fold exercise was conducted. Firstly, temporal remote sensing data (TRMM, AVHRR and AMSR-E) were extracted from global data sets over the test sites using RESDEM and were then used to identify and to verify precipitation events throughout the past nine years (1998-2006). The use of RESDEM enabled speedy and efficient analysis of global remote sensing data sets; a total of 25,000 TRMM, 25,000 SSM/I, 2,000 AVHRR, and 2,000 AMSR-E scenes were processed. The labor and storage
space was greatly reduced using RESDEM as our preferred platform for analysis of remote sensing data (Table 6). Secondly, a catchment-based, continuous, semi-distributed hydrologic model (Soil Water and Assessment Tool model; SWAT) was used to provide a continuous simulation (1998-2006) of the overland flow, channel flow, transmission losses, evaporation on bare soils and evapo-transpiration, and groundwater recharge for the major (area ≥ 2000 km²) watersheds in the SP and the ED, respectively (Figure 12). RESDEM allows for speedy analysis of global TRMM data sets to extract more reliable spatial rainfall distributions than those extracted from a limited number of existing rain gauges in the study areas (<20 stations in the ED & the SP; Figure 9).

<table>
<thead>
<tr>
<th>Dataset</th>
<th># of files</th>
<th>Original Hard Drive Space</th>
<th>After RESDEM</th>
</tr>
</thead>
<tbody>
<tr>
<td>TRMM</td>
<td>~25,000</td>
<td>200 GB</td>
<td>170 MB</td>
</tr>
<tr>
<td>SSM/I</td>
<td>~25,000</td>
<td>1.0 TB</td>
<td>400 MB</td>
</tr>
<tr>
<td>AVHRR</td>
<td>~2,000</td>
<td>250 GB</td>
<td>75 GB</td>
</tr>
<tr>
<td>AMSR-E</td>
<td>~2,000</td>
<td>100 GB</td>
<td>50 GB</td>
</tr>
</tbody>
</table>

Table 6. Comparison (in number and in size) between the original and output files that were processed by RESDEM for the purpose of conducting hydrologic investigations in ED and the SP.

A mask (Fig. 11a) was created using Lat/Long_Mask.pro to subset remote data sets over the study area. Figure 11b shows one of such data sets, global TRMM data acquired on 1/06/2004, that was subset over the specified region of interest (ED & SP) using the created mask. No temporal sub-setting (using Timerange.pro) was applied to the spatially subset data since the entire temporal range (1998-2006) of the
global data set was utilized. Precipitation events that exceeded a pre-defined threshold value (2 mm) were then identified using the Event_Logger.pro for the investigated time period. Applying the 2 mm threshold value to the precipitation event shown in Fig. 11b yielded the precipitation distribution displayed in Figure 11c. The selected events, the ones exceeding the threshold value were then verified, first by using the CDM that tests for the presence of clouds followed by additional tests to verify increases in VWC, soil moisture, or NDVI following the precipitation event in question. A precipitation event was verified if substantial cloud coverage and an increase in soil moisture or VWC associated with the investigated event was detected. For events preceding 2002, VWC and soil moistures images were replaced by NDVI images. Events that did not meet these criteria were omitted. Figure 11 demonstrates an example for a verified precipitation event that occurred on 1/6/04. Examination of TRMM data indicated precipitation along a NE-SW trending zone extending across the Eastern Desert and Sinai (Fig. 11d). Extensive clouds were detected from AVHRR on 1/6/04 (Fig. 11d), but were minimal in the preceding day (1/5/04)(Fig. 11e). Examination of the difference images (VWC: Figure 11f; NDVI: Figure 11g; and Soil Moisture: Figure 11h) showed an increase in each of these three parameters following the precipitation event under investigation. As described earlier, we find that precipitation produces a more rapid response on soil moisture content image product compared to the vegetation image products, and thus, the soil moisture difference images are more reliable and predictable methods for verifying rainfall events compared to vegetation products (i.e., VWC, NDVI). For the investigated
Figure 12. Distribution of the major watersheds >2000 km² (color filled watersheds with streams delineated) that were modeled using SWAT.
period, 232 of 303 events were verified in the SP, and 191 of 318 in the ED. During this study it was concluded that the recharge potential in the SP is approximately sub-equal (average annual recharge: $85 \times 10^6 \text{m}^3$) to that of the ED despite the fact it is 1/4 of the size of the ED.

4.6 Conclusions
The increasing versatility and number of satellite sensors that are becoming available is providing unprecedented opportunities for new applications in various scientific disciplines. The utilization of these images is also presenting challenges for the scientific community as these large temporal satellite data sets often come in varying formats, are usually uncalibrated, and are not georeferenced. Moreover, they require substantial computer processing time and large storage space. We have developed RESDEM to address problems cited above to enable the utilization of relevant temporal remote sensing observations in hydrogeologic research on regional and global scales, and to integrate/fuse multiple data types to check the quality of the results.

Using the SP and the ED of Egypt, we demonstrated in Milewski et al., (2005) how RESDEM could be used to enable hydrogeologic research over large spatial domains and throughout extensive temporal time frames. Precipitation was extracted from temporal TRMM data, verified using cloud detection techniques and induced differences in soil moisture and vegetation intensity. The verified precipitation events
were then used in conjunction of available field data (e.g., soil maps, stream gauge, and aquifer characteristics) to quantify to a first order, the magnitude of runoff and recharge for extensive areas in the SP and the Eastern Desert of Egypt. Prior to this work such applications could have not been accomplished due to the lack of adequate field data (e.g., rain gauge networks), and the large extent and inaccessibility of the investigated area. These problems are not restricted to the study areas, but are rather typical of the majority of Earth’s land surface.

RESDEM applications are not restricted to hydrogeological investigations. For example, RESDEM was used to determine the seasonal wind directions and magnitude from QuikSCAT data for the Cape Cod region. Using this data together with temporal aerial photography and ages from optically stimulated luminescence dating, Forman et al., (2008) concluded that the recent (20th century) deforestation and strong winds from the W-NW are the major forcing parameter behind dune mobilization in the Cape Cod area. Although we restricted our analysis to the applications of RESDEM in hydrological investigations, it should be evident that it can provide an adequate platform for monitoring and modeling terrestrial and aquatic systems on regional and global scales.
5.1 Conclusions

For a detailed description of all of the major conclusions of this work refer to Chapter 3 Section 3.6 and Chapter 4 Section 6. All of the conclusions of this thesis were already mentioned in these sections.
BIBLIOGRAPHY


