AN INTEGRATED ASSESSMENT OF GROUNDWATER SCARCITY AND RISK CONDITIONS IN THE ARAB MIDDLE EAST AND NORTH AFRICA REGION

by

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(Under the Direction of ADAM MILEWSKI)

ABSTRACT

Water crises have been ranked as the top global risk to economies, environments, and people in the 21st century. Nonetheless, the lack of continuous groundwater data availability and inadequate monitoring networks has been a challenge to the development of accurate and representative assessments of groundwater scarcity and risk conditions, especially in developing countries. This characterization is all the more discernible in arid environments and developing localities, such as the Arab Middle East and North Africa (MENA) region. Recent technological advancements, however, have provided the scientific community with hydrologic remote sensing datasets and GIS models, whose integration allows for systematic and detailed assessments of groundwater resources that have been traditionally lacking. Consequently, the following dissertation focuses on the combined use of remote sensing technology and GIS-models to achieve two main objectives: First, the spatio-temporal assessment of groundwater reserves and storage changes between 2003 and 2014, using a distributed ArcGIS model, parameterized with current gridded datasets. Second, the development, construction, and evaluation of a Groundwater Risk Index *GRI*, as a regional screening tool, to identify cold spots/hot spots of groundwater depletion risk, as a function of hydrological systems and political and socio-economic considerations. The results indicate vast groundwater reserves in the MENA region, averaging 1.28 million km^3. Groundwater storage changes between 2003 and 2014, highlighted groundwater declines in areas beneath or in close proximity to urban and demographic concentrations and potential effects of climate change and human impacts. Moreover, results also highlighted the potentiality of recharge occurring in deep sedimentary aquifers within desert areas, albeit at constrained rates. Relative to the large groundwater reserves, groundwater storage changes between 2003 and 2014 are negligibly minimal and do not represent an immediate threat to the region. Similarly, groundwater risk conditions are unevenly distributed, with good governance and high income countries displaying low groundwater risk, and vice versa. *GRI* results show a strong dependency between groundwater risk, and governance and food security, whereas groundwater reserves were indeterminate of groundwater risk. Sensitivity analysis of the *GRI*, affirm the index's insensitivity to alternative methodological choices in relation to subindicator selection, and choice of normalization and aggregation methods.

INDEX WORDS: FOOD SECURITY, GOVERNANCE, GRACE, GROUNDWATER RESERVES, GROUNDWATER RISK INDEX, GROUNDWATER STORAGE CHANGE, MENA, SENSITIVITY ANALYSIS

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DEDICATION

I dedicate my work to the PEOPLE OF THE ARAB REGION.

You have been with me in heart and spirit.

May you be blessed with peace and prosperity that you have long since deserved.

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CHAPTER 1

INTRODUCTION

1.1 Background

From time immemorial to our current time, the prosperity and progress of countries and societies has relied significantly on the availability of sufficient and accessible freshwater resources, capable of meeting the demands of our complex and ever-growing human communities. Secure, reliable, and economic sources of freshwater have often been one of the major linchpins of socio-economic development, (inter-)national food security, socio-political stability, and public health and safety. Indeed, freshwater availability and management are essential considerations, since long-term sustainable economic growth can be effectively hindered by a lack of adequate water supplies. According to *Sanctuary et al.* [2004], improved freshwater supplies not only greatly contribute to economic growth and poverty eradication, but are also often cost effective, insofar that the economic benefits of improved water supply outweigh that of investment costs. Depending on the region and the available technology, economic benefits could range between USD 3 to 34 USD per USD 1 invested. Moreover, improved freshwater supplies translate into increased production and productivity within different economic sectors.

Freshwater resources, however, are not uniformly distributed and vary significantly regionally and nationally. While some countries, such as Canada and Russia are 'water rich', with some of the largest per capita water endowments in the world, one third of the world lies in dry arid environments, characterized with varying levels of freshwater scarcity. Not all freshwater resources are renewable, especially in arid environments. According to *Gleeson et al.* [2016], less than six percent of the of the earth's groundwater is renewable within the scale of a human lifetime. This is especially pertinent in arid environments, where large non-renewable sedimentary aquifers are extensively located, often as the only major freshwater source. The Middle East and North Africa (MENA) region is a perfect example of a (hyper-) arid locality, where the dominance of the fossil groundwater is the most striking hydrogeological phenomenon [*Burdon*, 1982].

According to the *World Economic Forum* [2015], water crises are the top short-term and long-term global risk to industry and society. In arid environments generally, and the MENA region specifically, groundwater scarcity and its associated risk to countries and societies constitute a serious challenge to the region. This is all the more urgent given that the MENA region, with 6% of the world's population and yet 1% of its freshwater resources, is and will be experiencing a growing gap between freshwater demand and supply, as a function of increasing demand due to population growth and higher living standards on one side, and decreasing water supplies driven by climate change effects on the other. Facing and mitigating groundwater depletion necessitates the development of groundwater management strategies and policies in alignment and with the backing of rigorous and accurate scientific and interdisciplinary assessments of groundwater scarcity and risk conditions.

1.2 Study Area

Physical Settings

The Arab Middle East and North Africa (MENA) region is a continuous land mass extending over an area of approximately 14 million km^2, situated between the 18° and 37° north latitudes, and between 15° west and 60° east longitudes (Fig.1). The region extends from the Atlantic Ocean in the west to the Arab – Persian Gulf in the east, and from the southern shores of the Mediterranean Sea in the north to Sub-Saharan Africa in the south.

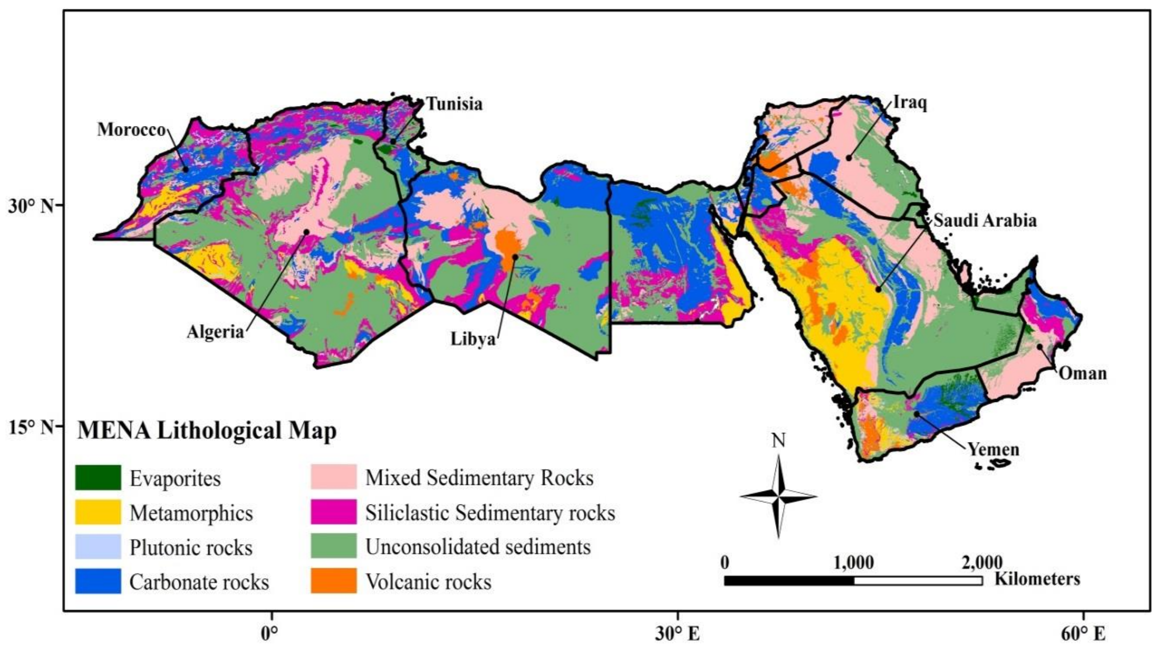

Figure 1.1. Lithological Map of the MENA region (modified from Hartmann and Moosdorf [2012]). Some MENA countries are labeled for reference.

As a consequence of the region's geographical location and the global atmospheric circulations patterns dry, warm deserts cover the greater part of the study area [*Shahin*, 2002], with the world's two largest hot deserts (Sahara Desert, Arabian Desert) being included within the region. The Sahara desert (7×10^6 km^2) covers most of Northern Africa, and extends from the east of Morocco to the west of Egypt. On the other hand the, the Arabian Desert is located in western Asia and occupies most of the Arabian Peninsula with the Rub'al-Khali, the largest continuous sand desert at its center [*Shahin*, 2007]. Other smaller desert ecosystems include (but are not limited to) the Nubian Desert east of the Nile river, and the Badeyat Esh'Sham Desert between Iraq and Syria.

Another distinctive physiographic feature characterizing the MENA region are mountain chains extending along the Mediterranean Sea and Red Sea. This includes the Atlas Mountain Range in northwest Africa, the Arabian Shield mountainous heights along the Arabian Peninsula and Egypt on the eastern and western shores of the Red Sea respectively, and the Eastern and Western Lebanon mount ranges in the Levant [*Shahin*, 2007]. In addition to coastal mountain ranges, The MENA region is also pocketed by some protrusions of volcanic lava and crystalline basic rocks. Examples of these inland heights are the Al-Hoggar Mountains at 2,900 meters in Algeria, the Tibesi Mountains at over 3000 meters in Libya, and the Uweinat Mountains at 1,850 meters between Libya, Egypt, and Sudan.

Alternatively, and in addition to coastal and inland heights, the Arabian physiography also contains expressions of erosional relief expressed in the forms of oases, flat depressions, and sebkhas [*Parsons and Abrahams*, 1994]. Some of the large depressions characterizing the region are Wadi Araba in Jordan, Wadi Tharthar in central Iraq, and Wadi Qattara in northwest Egypt [*Cooke et al.*, 2006]. Moreover some the MENA's largest and most prolific Oases are found in the Western Desert in Egypt (e.g. Siwa, Farafra, and Kharga and Dakhla oases) and in Libya (e.g. Al-Kufrah, Jalo, and Al-Jaghbub oases).

Geological Setting

The Arab MENA Region's geology backdates to the Precambrian Age (~ 500 Ma) with the formation of the Arabian shield which occupies the central Najd-Hijaz and Asir Highlands in Saudi Arabia, the Arabian Sea coast, and Yemeni Plateau [*Shahin*, 2007]. In the Oligocene (~ 34 to 24 Ma), the split of the Arabian part of the shield from the Nubian part occurred and resulted in the formation of the Red Sea – the major water body separating the MENA region between its African and Asian (Arabian Peninsula and Levant) equivalents.

In the Arabian Peninsula, two major structural provinces are discerned. The first structural feature is the relatively stable Precambrian basement, which occupies approximately one third of the Arabian Peninsula, and forms, with its vast extent of igneous and metamorphic rocks, the basis for sedimentary depositions on the eastern side of the Peninsula [*Powers et al.*, 1966]. The second structural geologic feature are the extensive belts of depositional sedimentary rocks to the east, which have been deposited at depths of approximately 5,500 meters between the Cambrian and the Pliocene [*Powers et al.*, 1966]. In close proximity to the Precambrian basement in northwestern and northcentral Arabia, older lower Paleozoic rocks consisting predominantly of coarse-grained sandstones at depth of 2,000 meters are exposed. The lower Paleozoic strata are succeeded by approximately 1,000 m of upper Permian and Triassic rocks consisting of Shallow-water limestone (Khuff Formation) and overlying non-marine clastics [*Nairn and Alsharhan*, 1997]. In central Arabia, Jurassic carbonate sediments, which contain billion n of barrels of oil reserves, are exposed in central Saudi Arabia. Overlying the Carbonate sequence are lower and middle Cretaceous sandstones, upper cretaceous and Eocene limestone and dolomite facies, and Miocene and Pliocene marly sandstone and sandy limestone [*Powers et al.*, 1966]. Unconsolidated quaternary deposits conclude the geologic sequence with sand deserts and gravel sheets that blanket most of southern Arabia [*Beydoun*, 1966]. The thickest sedimentary accumulations occurring on the eastern side of the Arabian Peninsula gradually thin out in a northwesterly direction until its pinches out in Northern Syria [*Shahin*, 2007].

In northern Africa, the Precambrian crystalline shield was overlain by sediments with thicknesses ranging between one kilometer in the south part of the Saharan platform, and 9 kilometers along the North African Mediterranean coast [*Peterson*, 1986]. Deposition during the Paleozoic era, deposition, controlled global sea-level changes, climate, and epeirogenic movements, was dominated by continental and shallow marine clastic-sediments [*Tawadros*, 2011]. Epeirogenic movements during the Paleozoic were primarily responsible for the formation of topographic lows; later be filled with Paleozoic sediments to form the sedimentary basins in which the bulk of the region's fossil groundwater is located. During the Mesozoic, carbonate deposition prevailed in northwest Africa and northern Sinai, as part of the open marine facies belt in the north [*Tawadros*, 2011]. Meanwhile, in the south, continental clastic deposition of fluvial and deltaic sediments dominated [*Tawadros*, 2011]. Tertiary sediments are primarily marine carbonate and fine clastic deposits deposited by a marine transgression between the late Cretaceous and early tertiary that extended as far south as central Egypt and south Libya [*Peterson*, 1986]. Finally, in the Quaternary period, the regression of the Mediterranean shoreline of North Africa was associated with the deposition of dunes, alluvial sand, and fine clastic units on the Saharan Platform [*Peterson*, 1986]. In summary, rock from all geologic rocks are present on the Saharan platform and the northern Mediterranean border, with marine stratigraphic sections dominating in the north and northwest as a function of marine transgression since the early Paleozoic; and epicontinental sediments dominating in the south, close to the clastic-source area.

Climate

Two major climate systems characterize the Arab MENA region. The first is the dry 'desert' climate that overwhelmingly dominates the region, specifically the inland stretches of land separated from the Mediterranean Sea and Atlantic Ocean by coastal topographic high reliefs [*Shahin*, 2007]. The second climate system more is strictly geographically defined to coastal strips adjacent to either the Mediterranean Sea or Atlantic Ocean [*Shahin*, 2002].

The preponderance of the dry desert climate in the MENA region relates to its proximity to the Tropics of Cancer, near which areas have characteristically high average daily temperatures due to longer sun exposure and lack of clouds year round [*Shahin*, 2007].

The existence of a dry desert climate in the MENA region relates to multiple factors. The most determinant of those factors relates to the earth's complex air-circulation patterns (coupled with the Coriolis Effect) which are responsible for the preponderance of descending cold and dry air masses moving away from the equator [*Shuttleworth*, 2012]. Moreover, the rain shadow effect and continentality (distance from oceans) factor also play an essential role in dry climate and desert formation [*Rakhecha and Singh*, 2009]. Coastal topographic highs (i.e. Atlas Mountains), characteristic of the MENA region, are responsible for the orographic lifting of moisture laden air masses, which consequently releases moisture on the windward side of the mountain range and create arid areas in the lee of the mountains [*Shahin*, 2007]. Additionally, in North Africa and the Arabian Peninsula, the effects of continentality play a marked role in dry climate formation, given the vast inward stretches of land on the leeside of coastal mountain formations. Along with the orographic effect of coastal mountain ranges which account for most of the moisture depletion and precipitation drops, the traversing of air current into deep continental areas will ensure the loss of any remaining moisture.

According to the aridity index – defined as the ratio between precipitation and reference evapotranspiration – the vast majority of region is considered as hyper-arid (< 0.05) given short rainy seasons and high evaporation rates. Moreover, a clear pattern of gradation from semi-aridness (0.21 - 0.5) to very and hyper-aridness can be noticed as we move from the coastal and/or mountain formations towards inland desert expanse.

In terms of climatic systems, the North Atlantic Oscillation (NAO) strongly affects the degree and extent of precipitation in Northwestern Africa, whereas the East Atlantic (EA) pattern and the El Nino Southern Oscillation (ENSO) are central in driving much of the precipitation patterns in the eastern Mediterranean, where NAO's effect is weak [*Lionello et al.*, 2006]. On the other hand, the coasts along the Arabian Peninsula are affected primarily by Monsoonal climatic systems which occur in the summer with the arrival of torrential rains from the Arabian Sea [*Karamouz et al.*, 2012].

Water Resources

The two most striking regional – scale hydrological phenomena occurring in the MENA region are the extreme scarcity of renewable groundwater resources due to prevalent low precipitation and high evapotranspiration rates , and the predominance of fossil groundwater resources formed during pluvial periods, the most recent of which ended approximately 5000 BC [*Burdon*, 1982]. The outlined hydrological phenomena are clearly reflected in the overall distribution of groundwater resources in the MENA region of which renewable freshwater resources – primarily centered within coastal mountain formations and transboundary Perennial

River systems – only account for 13.7% of total water resources as opposed to non-renewable fossil groundwater resources accounting for the remaining 86.3% of the existing water resources [Klingbeil and Al-Hamdi, 2010].

Surface Water Resources

Consistent with the overall conditions of low rates of precipitation and high rates of potential evapotranspiration, surface flows in the MENA Arab region are very limited. As such Perennial Rivers are very rare. The greater permanent rivers that do transect the study area – Nile and Tigris and Euphrates – originate outside the Arab region in areas of higher precipitation, and belong to transboundary basins shared by two or more states [*Shahin*, 1989].

The Nile river basin has a total surface area of 2.88 million km^2, of which 326,751 km^2 lies in Egypt [*Shahin*, 1989]. The two main tributaries feeding the Nile River are the White Nile river system sourced from the Equatorial Lake Plateaus, and the Blue Nile river system sourced from the Ethiopian highlands [*Melesse*, 2011]. As the only outflow from Lake Victoria in Uganda, which is fed by thousands of streams, the White Nile River originates from the northern shores of the Lake and crosses the Uganda-Sudan border to flow in southern Sudan [*Shahin*, 2007]. The average annual flow of the White Nile river in Southern Sudan between 1905 and 1983 was estimated at approximately 3.3 billion cubic meters (BCM) with a variation coefficient of 0.4 [*Elwan et al.*, 1995]. The White Nile flows northwards through the Sudanese Sudd region until it converges upstream with the Blue Nile arising from the Ethiopian Plateau at elevations ranging between 2000 and 3000 meters a.m.s.l. The Blue Nile is estimated to have an average flow of 48.7 BCM (1912 – 97) within Sudan. Approximately 370 km from the Sudan – Ethiopia Border, the Blue Nile converges with the White Nile near Khartoum [*Melesse*, 2011]. The main

Nile river flows another 800 miles before it reaches the Aswan Dam in Egypt at an annual flow rate of 85 BCM of which 10 BCM is lost to evaporation and seepage [*Shahin*, 2007]. The remaining natural supply is divided between Egypt (55 BCM) and Sudan (18 BCM).

The Tigris and Euphrates rivers, with their respective tributaries, traverse Iraq and Syria and constitute the major water supply for both countries. While the southern slopes of the Torus Mountain range in Turkey act as the source of the Tigris River, approximately 83% of its total length runs with Iraqi territory [*Shahin*, 2007]. The flow of the Tigris River is dependent on three sources: rainfall, snowmelt, and flow from linked tributaries. Flow in the Tigris River rises between December and the beginning of July as a response to precipitation in December and July which is consequently augmented by snow melting coupled with spring rainfall between April and May [*Shahin*, 2007]. Based on figures in the period 1958-75 the average annual flow of the Tigris River is 2 BCM. Similarly, the Euphrates River originates in the high grounds (> 3000 a.m.s.l) of Northeastern Turkey. The bulk of the Euphrates's river flow is from rainfall and snowmelt in the mountains of Armenia – long term average discharge of 26.8 BCM – with some rainfall generated runoff (2.5 BCM) with Syria [*Shahin*, 2007]. The Tigris River and Euphrates River join together in southeastern Iraq to form the Shatt al-Arab River which discharges into the Arab – Persian Peninsula.

In addition to the aforementioned permanent river basins, there exist a number of local scale rivers originating within the MENA region. The Jordan, Yarmouk, Orontes, and Litani Rivers are some examples of national scale river fed by springs from limestone and basalt aquifers [*Burdon*, 1982]. Another example are perennial streams originating within the Atlas Mountains in northwest Africa [*Lévêque*, 1995].

Groundwater Resources

Groundwater resources are extremely important in arid locations such as the MENA region. In the context of scarce surface water resources, groundwater is the primary source of freshwater in most Arab countries. Groundwater is extracted from various hydrogeological settings in the MENA region. In areas with exposed Precambrian crystalline rock, water is extracted from fissure and joint systems within igneous and metamorphic rocks, in addition to weathered basement rocks [*Shahin*, 2007]. But the water is rarely quantitatively or qualitatively suitable for large-scale utilization. Groundwater is also extracted heavily from coastal aquifer systems. Due to the concentration of demographic populations and associated areas of groundwater over abstraction, coastal aquifers are threatened by salt water intrusion, with saline intrusion ranging between 10 km inland from the coast near the Libyan capital of Tripoli, to 60 km inland in the Nile delta [*Steyl and Dennis*, 2010]. Finally, groundwater extraction occurs deep in hyper-arid desert continental areas, where the bulk of the region's non-renewable fossil groundwater is located. The existence of fossil groundwater is traced back to many periods in the quaternary – especially the Abbasia and Mousterian Pluvial – where there was abundant precipitation over the Sahara and Arabia. Isotopic testing of water samples from major groundwater reservoirs indicate that groundwater recharge during pluvial periods took place over outcrop areas with direct infiltration from river flow, lakes, and precipitation along vast areas [*Burdon*, 1982]. While these resources have been used to support relatively small-scale agricultural activities and domestic water demand, the high economic cost of groundwater extraction from deep water tables, and conveyance of long distances to population centers, have so far prohibited the over exploitation of these significant groundwater reserves. The only exception to this Saudi Arabia, which has significantly over depleted its non-renewable groundwater storage in pursuit of expansive wheat production projects to achieve food self-sufficiency [*Elhadj*, 2004]. Due to its unsustainability, wheat production was completely stopped in 2016.

In the following paragraphs, we briefly outline the major groundwater systems in the MENA region, and their properties.

The three largest groundwater basins in North Africa are the Nubian Sandstone basin (1,800,000 km^2), the North-Western Sahara Basin (1,060,000 km^2), and the Murzuq Basin (350,000 km^2). The Nubian Sandstone Basin (NSAS) is largest transboundary fossil aquifer system in the world, extending within four countries: Chad, Libya, Sudan, and Egypt. The aquifer's thickness is variable and ranges between 500 meters in Libya to over 2000 m in Egypt. NSAS is dominated by sandstones of epicontinental origin, which are overlain by fissured marine limestones rocks, with transmissivity values ranging between 100 m^2 d^{-1} in the south and 15,000 m^2 d^{-1} in the north [*Shata*, 1982]. NSAS's groundwater reserve estimates vary from a conservative estimate 87,000 km^3 [*Richey et al.*, 2015a] to a liberal estimate of 373,000 km^3 [*Bakhbakhi*, 2006]. The Northwestern Sahara Aquifer System (NWSAS) stretches along Algeria, Tunisia, and Libya. The NWSAS is characterized as a multilayered hydrogeological system constituted of the superimposition of the shallower Complex Terminal (CT) aquifer over a deeper Continental Intercalary (CI) aquifer. The CT is an unconfined to semi-confined multilayered reservoir with carbonaceous and sandstone formations at depths ranging from 100 to 400 m [*Shahin*, 2007]. Conversely, the CI aquifer is a deep confined aquifer at depths ranging from 400 up to 2000 m. the CI consists of an interlayering of different lithologies, primarily continental sandstone with marine and clay formations. The average transmissivity values and effective porosity values is 43.2 m^2 d^{-1} and 0.2 respectively [*Gischler*, 1979]. Like the two preceding systems, the Murzuq basin is another transboundary system that underlies Algeria, Chad, Libya, and Niger. It consists of two aquifer systems separated by a carboniferous aquitard: a lower Devonian aquifer and an upper Jurassic and Cretaceous aquifer, with transmissivity values ranging between 500 and 2,500 m^2 d^{-1}, and storativity values from 0.005 to 10^{-4} [*Shahin*, 2007].

The Arabian Peninsula is underlain by approximately 10 shared aquifer systems. The Saq-Ram aquifer and the Wajid aquifer are two Paleozoic sandstone aquifer systems shared by Saudi Arabia (SA) with its neighboring countries. The Saq-Ram aquifer between SA and Jordan is a porous sandstone aquifer extending over 308,000 km^2. Its thickness varies between 250 and 700 m [*UN-ESCWA*, 2013], whereas its transmissivity varies between 35 m^2 d^{-1} and 23,000 m^2 d^{-1} [*Shahin*, 2007].Moreover groundwater reserves are estimated at 475 km^3. Similarly, the Wajid aquifer system, located between SA and Yemen, is a porous sandstone system with a thickness ranging between a 100 and 900 m. Aquifer transmissivity has been estimated at between 50 to1750 m^2 d^{-1}, , whereas aquifer reserves were estimated at 430 km^3. Groundwater in the Arabian Peninsula is also sourced from Mesozoic aquifer systems such as the Wasia-Biyadh-Arumah aquifer system (WBAS). WBAS is an immensely large groundwater reservoir extending from Yemen and Oman in the south, to Iraq in the north. It is also inclusive of Kuwait, Qatar, and the UAE .The aquifer system is dominated by sandstones with some marls and siltstones, and of a thickness ranging between 250 m and 1230m [*Shahin*, 2007; *UN-ESCWA*, 2013]. The range of transmissivity values ranges between 122 m^2 d^{-1} and 8400 m^2 d^{-1}. WBAS's groundwater reserve estimate is approximately 500 km^2. Another extensive aquifer system is the Cenozoic Umm er Radhuma-Dammam Aquifer system (URDAS), which extends along most of the length of the Arabian Peninsula. Unlike Paleozoic and Mesozoic systems, URDAS is a fractured/karstic aquifer system, mainly formed of limestones and dolomites with some evaporites [*UN-ESCWA*, 2013]. The 'Dammam' is found at depths from 140 m to 230 m, and with an average thickness of 83 m, meanwhile, the 'Umm er-Radhuma' formation is found at depth between 240 m and 600 m, with maximum thickness of 700 m [*Shahin*, 2007].

In the Levant and near east region of our study area, aquifer systems are more limited geographically, highly complex, and display significant differences in hydrogeological characteristics to easily classify within the context of this section. Geologically, aquifer systems in the Levant could be either porous, fracture/karstic, or both. Moreover, aquifers in the Levant differ drastically than their counterparts in North Africa on two accounts. First, most aquifers in the Levant are renewable with various degrees of recharge rates, and second, they are hydraulically connected to surface water. Examples of such aquifers are the Coastal Aquifer Basin (Egypt, Israel, Palestine), Basalt Aquifer System (Jordan, Syria), and Anti-Lebanon Aquifer System (Lebanon, Syria) [*UN-ESCWA*, 2013].

1.3 Review of Regional Groundwater Assessments

The central role of groundwater resources in the healthy functionality of the MENA region necessitates the development, planning, and implementation of integrated and sustainable management practices and policies. However, the limitations of data paucity and the extensive spatial extent of the region are pivotal in hampering our understanding of the nature, distribution, and accessibility of water resources in the region. According to *Shiklomanov et al.* [2002], hydrological monitoring capacity has declined rapidly, with only 50% of the continental land mass being monitored. This dilemma is exacerbated in North African groundwater aquifers, where conceptualizing the general distribution is made difficult due to data paucity [*Giordano* *and Villholth*, 2007]. Moreover the lack of operational, organizational, and financial capacity, coupled with unstable political and security conditions, makes it highly unlikely to establish extensive monitoring programs on large swaths of continental mass – the North African Sahara alone is of an area equivalent to that of the contiguous United States.

Faced with extreme data paucity in the MENA region, analysis of groundwater scarcity – the volumetric availability of water supplies – and the implementation of water-related sustainable solutions require a comprehensive quantitative assessment of groundwater systems in the MENA region. The literature review addresses existing models designed for regional water resources assessments, followed by a discussion of similar assessments pertaining to the MENA region specifically.

Traditionally, the long-term water balance method, which is based on a simple lumped bucket model, has been used in water assessments with temporal scales equivalent to or exceeding one year [*Xu and Singh*, 2004]. Water resources in this model are calculated by relating changes in long term average precipitation to that of long term average evapotranspiration. While this method is computationally efficient, feasibly applicable with lesser parameters and easy to set up, it does suffer from two major disadvantages. Firstly, the model's integral response limits any verification and calibration against any spatially distributed observations. Secondly, it does not account for spatial and temporal variability which are inherent in hydrogeologic and climatic parameters. Alternatively, physically based, semi-(distributed) models have been used in regional water assessments, but to a much lesser extent. Process-based models simulate physical processes and their interactions within hydrological and hydrogeological domains, through the use of mathematical algorithms, such as partial differential equations [*Grayson et al.*, 1992; *Wada et al.*, 2012]. However, physical models suffer from several limitations, especially with regional scale modeling. In addition to requiring enormous amounts of information for parameterization, their assumptions and algorithmic base are rendered invalid or questionable, largely as a function of the lack of understanding and knowledge of fundamental hydrologic processes [*Grayson et al.*, 1992; *Rakhecha and Singh*, 2009].

The advent of computer processing capabilities coupled with the formation of Geographic Information Systems (GIS) has led to the creation of GIS-supported spatial hydrology models (e.g. r.water.fea, AVSWAT, PCRASTER). While process-based models and GIS-based models are distributed and require that equations and parameters be physically relevant, they diverge on issues of scale. While physical models were developed primarily for small catchments, GIS-based models are usually applied to large areas, which necessitate the use of fewer model parameters and require some form of generality and averaging in the parameterization process and in the formalization of governing equations [*Xu and Singh*, 2004]. The extensive and widespread use of GIS-supported modeling in regional water assessments has been motivated by the operational and technological feasibility of estimating spatial variability over large areas at different resolutions, as well as to the added capability of accounting for the effects of land-use and climate change over large geographical domains [*Xu and Singh*, 2004].

With the exception of a recent study by Droogers *et al.*, *"a complete analysis on water demand and water shortage over the coming 50 years based on combined use of hydrological and water resources models, remote sensing, and socio-economic changes has never been undertaken for the MENA region"* (Droogers, 2012). In his paper, Droogers uses a physically-based, distributed hydrological model (PCR-GLOBWB) to assess internal and external renewable water resources currently and in the future on a regional scale (Droogers, 2012).

While this is the first time that the MENA region has been hydrologically modeled at high spatial (10 KM) and temporal (daily) resolutions (Droogers, 2012), Drooger's water assessment presents some drawbacks. The first relates to the physical model used and its suitability for a mostly hyper arid region. According to the creators of the PCR-GLOBWB model at Utrecht University, it is used on a regional scale to examine the influence of wetland hydrology on methane emission in arctic regions, study water availability, and to quantify sediment and nutrient flux [*Utrecht University*, 2014]. The provided description poses legitimate questions on whether the model correctly simulates hydrologic process in the MENA region. Conceptually, Drooger's water assessment only accounts for renewable surface water (i.e. runoff) and groundwater (i.e. recharge) and does not take in consideration non-renewable (fossil) groundwater aquifer reserves. As discussed by [*MacDonald et al.*, 2012], fossil groundwater in Africa has an estimated volume of more than a 100 times the estimate of renewable freshwater resources, where the largest groundwater aquifers are found in large sedimentary lithologies in North African countries such as Egypt, Libya, and Algeria. This paradigm extends to the Arabian Peninsula and governs most of the MENA region.

1.4 Review of Water Scarcity/Stress Indices

Since the late 1980's we have witnessed the development of numerous water availability/stress indices as tools for quantifying concepts that cannot be directly measured, such as water scarcity or vulnerability [*Sullivan*, 2002]. Due to the acceptability and simplicity of these indices, a large number of indicators are used by policymakers to guide their decision-making processes, especially on regional scales. The multi-faceted nature of water resources problems is reflected in multiplicity of index 'types' and the criteria by which they are assessed.

Generally, water vulnerability/scarcity indices are categorized into three main categories. The first category is based on human water requirements, where freshwater scarcity is defined as a function of available water resources and human population. The most widely used of those indicators is the *Falkenmark Indicator*, which defines water scarcity according to the number of people sharing available total annual runoff [*Falkenmark*, 1990]. While the Falkenmark indicator sheds light on the most basic aspects of water scarcity – amount of available water to meet each person's needs – it fails to consider differences in water needs across different cultures, societies, nations, and regions [*Brown and Matlock*, 2011]. Given the role of technology and socio-economic institutions in the facilitation of adaptive capacity to water scarcity, *Ohlsson* [2000] departed from Falkenmark's indicator to consider societal, economic, and technical variables' role in accounting for the ability to adapt to water stress by creating a *Social Water Stress Index*. Ohlsson employs the UNDP's Human Development Index to assess societal variables and their effect on adaptive capacity. The *Falkenmark Indicator's* simplicity fails to account for the complex interactions between natural water system and anthropogenic structures in satisfying water needs. For example, empirical evidence clearly displays the role of political and socioeconomic institutions in successfully meeting societal water demand in arid to hyper-arid regions, such as Australia and the western contiguous US. Conversely, humid regions such as sub-Saharan and central Africa are endowed with a surplus of natural water resources, but lack the infrastructure and institutions required for successful utilization, thus suffering from 'economic water scarcity'. As such the *Social Water Stress Index* better captures the conjunctional causes of water scarcity.

The second category of water scarcity indices is positioned around water resources vulnerability to water demand. This category addresses the major weakness in the former category– to consider the differences in water usages among different societies, countries, or regions – by focusing on the *used* amount of available natural water, as opposed to the total endowments of natural water, as is the case with the Falkenmark indicator. The centerpiece of the water resources vulnerability category is the *WTA* (water to availability) *indicator*, which is defined as the ratio of annual water withdrawals to annual water availability [*Raskin et al.*, 1997]. For example, according to the WTA indicator, annual withdrawals exceeding 40% of the annual renewable water supply are indicative of severe water scarcity. Variations of the WTA indicator exist to include varying criteria (i.e. water reuse, consumptive versus non consumptive use) at different scales.

The evolution in the 1990s of the viewpoint that ecological systems are water users themselves, and therefore demand an allotment of water, put forth a third category of water indices that complement the aforementioned ones by incorporating environmental water requirements. This category is the most holistic approach to integrated water scarcity assessment, "*linking social and economic development with the protection of natural ecosystems"* [*Savenije and Van der Zaag*, 2008]. The most widely accepted and used indicator in this category is the *Water Poverty Index* (WPI). *WPI* is unique in the multiplicity of approaches to calculating it. Calculation methodologies could range from a conventional composite index approach to the gap method which measures the deviation of water provision and its uses from a predetermined standard [*Sullivan*, 2002]. The flexibility in determining the choice of components and choice of the governing formula makes *WPI* the optimal tool for measuring water scarcity/poverty without oversimplifying what are quintessentially multi-layered complex interactions. However, the index's points of strength are simultaneously its source of limitation. While *WPI* can incorporate qualitative and quantitative water parameters with social and economic indicators, it is often extremely difficult or impossible to acquire comprehensive datasets to support the chosen criteria. Another important consideration lies with weighing the designated criteria and providing a supporting basis and assumptions for it.

Despite the variability of water scarcity and vulnerability indices, a major overarching limitation is their failure to address groundwater resources. This failure is attributable to prevailing data scarcity as a consequence of a multitude of factors. Assessment methods of groundwater are more complex and more expensive than those for surface water, given the significant spatial distribution and vertical depth of those resources. Moreover, existing technical groundwater data are diffusely stored in thousands of local and personal databases [*Marcus Wijnen*, 2012], which renders it difficult to access them. Furthermore, the quality of groundwater data tends to be highly variable and unstandardized. All the aforementioned reasons contributing to data paucity, often translate to neglect of groundwater research.

Most of the indices in place are designed to only address renewable surface water resources, and overlook groundwater resources. The few indices that do address groundwater resources use relatively inaccurate proxy indicators such as water use estimates as the basis of their parameters. The following reality makes most of these indicators unsuitable for the Middle East, where the bulk of water demand is met by deep, productive fossil groundwater aquifers. The advent of the Gravity Recovery and Climate Experiment (GRACE) mission enables the indirect measurement of groundwater changes, and as a consequence facilitates the formation of indices that accurately reflect the conditions of groundwater resources, especially in hyper-arid and developing areas such as the MENA region.

Moreover, available water indices have focused primarily on measuring water scarcity and stress as opposed to water risk. To clarify, water "scarcity" refers to an objective measurement of volumetric abundance of water supplies. Despite the multiplicity of indices highlighting water scarcity and stress, the inverse is true with the development of indices measuring "risk", as the probability of an entity experiencing detrimental water related events. It is essential to note that the authors are focusing on quantitative deleterious events, primarily groundwater depletion. This is opposed to qualitative water events such as contamination and pollution which have numerous tools designed to evaluate water pollution potential such as the DRASTIC index [*Aller et al.*, 1987]. Global demographic and economic growth in the 21st century will exacerbate scarcity and stress conditions on groundwater systems, the majority of which are being depleted at unsustainable rates that threaten freshwater availability [*Gleeson et al.*, 2012; *Richey et al.*, 2015b; *Vaux*, 2010]. This necessitates the development of tools designed to evaluate and pinpoint hotspots that are highly susceptible to groundwater depletion and the associated adverse socio-economic and security effects.

1.5 Research Question and Objectives

Building on what has been outlined and discussed above; the following **research questions** are formulated:

1. Can the development and use of distributed GIS models parameterized with current gridded datasets, and remote sensing datasets, such as the Gravity Recovery and Climate Experiment's (GRACE) gravimetric datasets, provide better quantitative assessments of groundwater resources in the MENA region than present assessments?

2. What are the drivers behind groundwater risk in arid environments such as the MENA region? Is groundwater risk determined by either physical hydrogeological systems, social-adaptive factors, or both?

Based on the preceding research questions, it is hypothesized that estimations and assessments of groundwater scarcity and risk are inaccurate and distorted, as a consequence of the lack of spatially and temporally detailed characterizations of groundwater systems, due to data paucity in arid and developing regions, such as the MENA region.

The **overall objective** of this research is to advance and improve groundwater resources assessments in the MENA region and similar environments, by integrating gridded satellite, model-based, and/or in-situ datasets into GIS-based models on a regional scale. Specific objectives include:

1. Evaluating and estimating regional groundwater resources in the MENA region by integrating modeled groundwater reserves estimates with groundwater storage changes, quantified using GRACE–based terrestrial water storage data and GLDAS–derived land surface parameters.
2. Developing and constructing a *Groundwater Risk Index* (GRI) designed for assessing and visualizing the spatio-temporal vulnerability of MENA countries to groundwater depletion, as a function of hydrogeological characterizations of groundwater systems on one hand, and social adaptive criteria (e.g. governance) on the other.
3. Testing the robustness and validity of GRI's results by conducting a sensitivity analysis, examining the impact of different methodological choices, within the development process, on GRI country scores and ranks.

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CHAPTER 2

A QUANTITATIVE ASSESSMENT OF GROUNDWATER RESOURCES IN THE MIDDLE EAST AND NORTH AFRICA REGION

Lezzaik, K.A., and A.M. Milewski (2015), A Quantitative Assessment of Groundwater Resources in the Middle East and North Africa Region, *Journal of Arid Environments (Submitted).*

Abstract

The Middle East and North Africa (MENA) region is by far the most water stressed region; with its countries constituting 15 of the 20 most water stressed nations worldwide. As a consequence of data paucity, comprehensive regional-scale assessments of groundwater resources in the MENA region have been lacking. The following study addresses this issue by using a distributed ArcGIS model, parametrized with gridded datasets, to estimate groundwater storage reserves in the region on the basis of generated saturated thickness and effective porosity estimates. Furthermore, monthly gravimetric data (GRACE) and land surface parameters (GLDAS) were used to quantify changes in groundwater storage between 2003 and 2014. Total groundwater reserves in the region were estimated at 1.28 million km^3 with an uncertainty range between 816,000 and 1.93 million km^3. The majority of the reserves were located within the large sedimentary basins of North Africa and the Arabian Peninsula; with Algeria, Libya, Egypt, and Saudi Arabia accounting for approximately 75% of the region's total reserves. Alternatively low groundwater reserves were found in fractured Precambrian basement exposure. As for groundwater changes between 2003 and 2014, only 8 out of the 16 MENA countries (e.g. Algeria, Iraq, and Saudi Arabia) exhibited a decline in groundwater changes. Nonetheless, the great majority of the nations in the region exhibit a clear decline in groundwater trend that could signal potential future depletion, including in countries with a currently balanced groundwater budget. Given the large groundwater reserve estimates groundwater changes between 2003 and 2014 are fractionally minimal and represent no immediate short-term threat to the MENA region. However this study recommends the development of sustainable and efficient groundwater management policies to optimally utilize the region's groundwater resources, especially in the face of climate change, demographic expansion, and socio-economic development.

2.1 Introduction

Amongst the serious challenges faced by the Middle East and North Africa (MENA) region, freshwater scarcity ranks the highest given its impact on food security, development and poverty reduction, and socio-political stability. Natural water scarcity defined by the predominantly (hyper-) arid environment of the MENA region is exacerbated by increased water demand consistent with population growth, urbanization, and economic development. The projected doubling of the MENA region's population in the next fifty years is expected to decrease per capita water availability by forty percent in the most water scarce region in the world [*Terink et al.*, 2013].

The central role of groundwater resources in the healthy functionality of the MENA region is derived from the fact that 76% of freshwater resources are primarily sourced from groundwater systems of which 65.6% are non-renewable fossil aquifers [*Klingbeil and Al-Hamdi*, 2010]. According to a study by the British Geological Survey (BGS), fossil groundwater resources in Africa have an estimated volume of more than a hundred times the estimate of renewable freshwater resources, with the largest groundwater aquifers found in the large sedimentary lithologies in North African countries such as Egypt, Libya, and Algeria [*MacDonald et al.*, 2012]. This paradigm extends to the Arabian Peninsula and most of the Levant.

Given the dependence of the region on non-renewable subterranean freshwater resources; the development, planning, and implementation of future sustainable water management practices and policies should be dependent on an accurate characterization of groundwater resources and of changes in water table levels driven by climatic and anthropogenic factors.

However, the limitations of data paucity and the extensive spatial extent of the MENA region hamper scientific efforts designed to understand the nature, distribution, and accessibility of groundwater resources within our study area. In the past 20 years, we have witnessed a reduction of long-term baseline high quality water datasets due to the continuing disintegration of monitoring networks, with a marked 90% decline in the number of active discharge stations [*Vörösmarty et al.*, 2001].

The constraints of data unavailability and inaccessibility in the MENA region are arguably the main causes behind the limited number of studies and publications addressing water resources, specifically groundwater resources. However the advent of satellite-based remote sensing has given rise to global and regional scale, high resolution, and gridded datasets to counter in-situ data paucity [*Milewski et al.*, 2009]. These technological developments lead to a number of studies in the MENA region. An excellent example is the advent of NASA's Gravity Recovery and Climate Experiment (GRACE) satellite mission in March 2002, which has offset the historical lack of groundwater monitoring programs and long-term hydrological datasets in data sparse areas such as the MENA region by providing spatially and temporally continuous measurements of terrestrial water storage change [*Tapley et al.*, 2004].

In a study for the World Bank, *Droogers et al.* [2012] used a physically – based, distributed, hydrological model to assess internal and external renewable freshwater resources in the MENA region under current and future conditions (2001 – 2050). This study *"is the first time that a hydrological model has been developed capturing the entire MENA region at high spatial and temporal resolutions"* to offer *"a complete analysis on water demand and water shortage over the coming fifty years based on combined use of hydrological and water resources models, remote sensing, and socio-economic changes"* [*Droogers et al.*, 2012]. A revised version of the

PCRaster Global Water Balance (PCR-GLOBWB) hydrological model was used to assess current and future water availability. Unlike most previous modeling studies, the PCR-GLOBWB not only focused on streamflow inputs, but also parametrized all the relatable components of the water cycle (i.e. soil, land cover, topography, groundwater recharge, and runoff) and their variability on a grid and sub-grid level. It used a suite of global and regional datasets constructed primarily from remote sensing data and modeling approaches. Despite being the first to model water resources in the MENA region at high spatial (10 km) and temporal (daily) resolutions, Drooger's study has a major conceptual limitation – the water assessment only accounts for renewable surface water (runoff) and groundwater (recharge) resources and does not incorporate groundwater reserve estimates in fossil groundwater aquifers which constitute the backbone of freshwater supplies in the MENA region.

The limitations of the aforementioned study are appropriately addressed by *MacDonald et al.* [2012], who developed a quantitative aquifer storage map for the entire African continent on the basis of a comprehensive review of available maps, publications and datasets. Groundwater storage estimates were calculated by multiplying saturated aquifer thickness with effective porosity. Saturated thickness values were obtained from acquired hydrological and geological reports and datasets, whereas effective porosity values were estimated by relating the flow and storage characteristics of different lithologies to analogous lithologies with measured effective porosity values [*MacDonald et al.*, 2012]. This study successfully attempted to bridge the informational gap of African groundwater resources by using the best available data on a continental scale for Africa, without failing to discuss the limitations posed by the lack of good quality hydrological maps and studies specifically in North Africa. The assessment of groundwater resources in North Africa (> 5 million km^2) on the basis of 6 local studies, 17 regional studies, and qualitative maps [*MacDonald et al.*, 2012] renders the results vulnerable to over extrapolation and generalization.

Despite successfully addressing their objectives on regional and continental scales with the use of multiple informational sources, datasets, and methodologies; both *Droogers et al.* [2012] and *MacDonald et al.* [2012] make no attempt at quantifying changes in predominantly 'fossil' groundwater storage. To clarify, *Droogers et al.* [2012] generated water shortage estimates in MENA countries by using a supply-demand model, parametrized with modelled total renewable water resources on one hand, and water demands supplied by FAO's Aquastat database on another. However, his study did not attempt to quantify groundwater changes specifically and its effects on groundwater volumes in major basin and aquifer systems.

The GRACE satellite has enabled experts to quantify and delineate groundwater depletion on a global scale through the use of integrated measurements and modeling of terrestrial water mass [*Wahr et al.*, 1998], thus giving rise to numerous studies aimed at characterizing groundwater depletion worldwide [*Feng et al.*, 2013; *Joodaki et al.*, 2014]. In reference to the Middle East, a study by *Voss et al.* [2013] used GRACE to estimate groundwater depletion in the Euphrates-Tigris river basin between 2003 and 2009 by isolating the groundwater component of total water storage from variations in land surface water components (i.e. surface water, soil moisture). Similarly, a study by *Longuevergne et al.* [2013] utilized analogous methods to determine GRACE-derived groundwater change estimates in the lower Nile and Euphrates-Tigris river basin. While the aforementioned GRACE-based studies have allowed for consistent spatial and temporal assessments of groundwater changes in certain river basins in the MENA region, comparisons between groundwater changes and groundwater reserves have not been conducted. Consequently, the relative impact of groundwater storage change and depletion on the overall conditions of what are predominantly fossil groundwater resources in the MENA region remains unexamined.

In this study we attempt to assess and characterize groundwater resources in the MENA region by integrating groundwater reserve estimates with GRACE-derived groundwater storage change estimates by developing a distributed, conceptually lumped, hydrogeological model parameterized with a suite of accurate and up-to-date gridded remote sensing datasets and models.

2.2 Study Area

The Arab MENA region is a land mass covering a surface area of approximately nine million km^2, situated between 18° and 37° north latitudes, and between 15° west and 60 east longitudes (Figure 2.1). Deserts form the greater part of the surface area of the region – Great Sahara desert (7×10^6 km^2) covers most of North Africa – due to the region's dry desert climate which is caused by global wind circulation patterns. Given the (1) current conditions of low precipitation and high evapotranspiration, and (2) evidence of many pluvial periods in the quaternary, the predominance of fossil groundwater resources is the most salient regional scale hydrogeological phenomenon in the MENA region [*Burdon*, 1982]. The mass of groundwater resources in the region are found in post-Cambrian lower Paleozoic sandstones and Quaternary unconsolidated sediments (i.e. sand dune, alluviums) [*Burdon*, 1982]. In the Gulf Cooperation Countries and Libya, groundwater is used as the primary source of freshwater; whereas in the remaining countries especially Algeria, Egypt, and Iraq groundwater is still utilized as a secondary source [*Shahin*, 2007]. However, climate change assessments for the MENA region show a 15% to 20% decrease in average annual precipitation for the majority of the countries

[*Terink et al.*, 2013]. These changes are bound to stress surface water resources and increase the reliance on groundwater resources in the region.

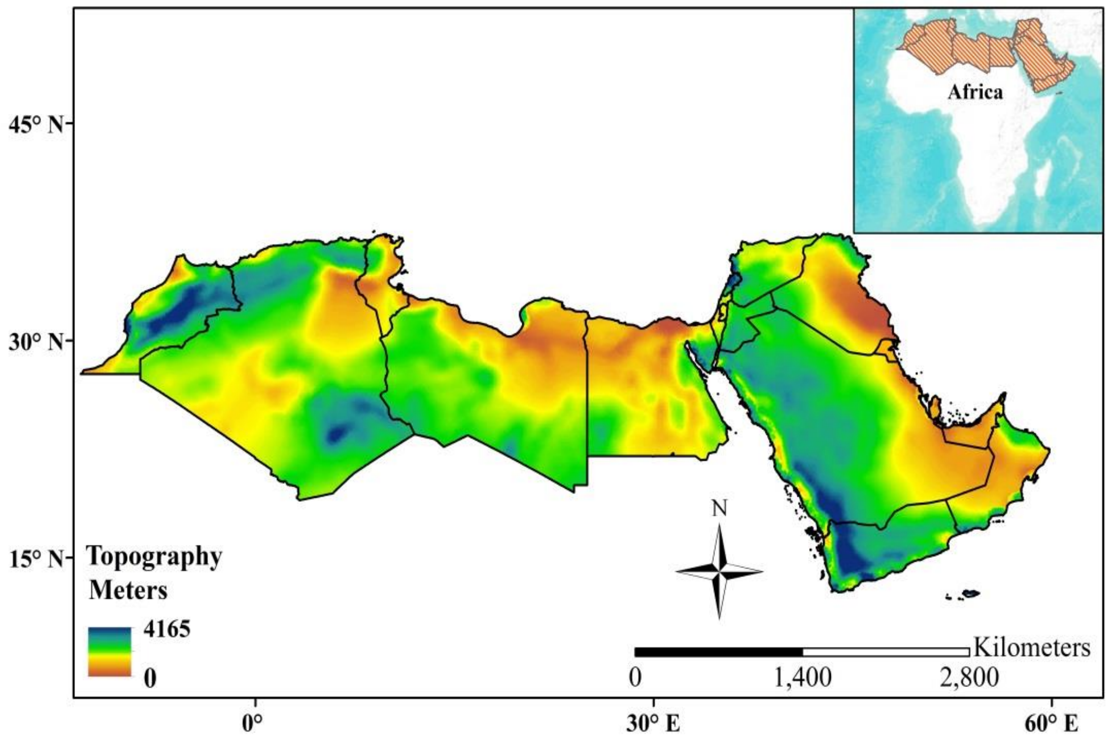

Figure 2.1. Topographic map displaying the spatial extent of the MENA region and the political boundaries of the 16 MENA countries addressed in this study.

According to the *World Bank* [2013], the MENA region is home to 345.4 million people (2% annual growth rate), of which 60% live in urban concentrations. The projected doubling of the population by 2050 is expected to exacerbate water stress.

2.3 Data

Water Table Depth

To calculate aquifer saturated thickness, depth to water table (WTD) was determined using a global water table pattern map developed by *Fan et al.* [2013]. The map was constructed using WTD observations at well sites worldwide. To fill in large data gaps in data sparse regions (i.e. Africa, MENA), a groundwater model parameterized with the present climate, terrain, and sea level parameters was used to simulate groundwater movement in 1 x 1 km grid cells to determine WTD. For the purpose of this study, the map was aggregated to a 0.25 x 0.25-degree resolution (Figure 2.2).

Sediment Thickness

For the purpose of calculating aquifer saturated thickness, sediment thickness estimates were obtained from a 1 x 1-degree global crustal model (CRUST1.0) developed by *Laske et al.* [2013]. Crustal thickness was obtained from a compilation of active sources experiments, receiver functions, and published Moho maps [*Laske et al.*, 2013]. In areas with no seismic and gravity data, sediment thickness was acquired by extrapolating the averages of crustal properties in each crustal type [*Laske et al.*, 2013]. For this study, the sediment thickness map was resampled to a 0.25 x 0.25-degree resolution (Figure 2.2).

Lithology

A global lithological database *GLiM* developed by *Hartmann and Moosdorf* [2012] was used to develop an effective porosity map by obtaining the geophysical characteristics of rocks given its important role in the development of groundwater resources. *GLIM* is the most recently published vector-based global lithological map, developed from 92 regional lithological maps of the highest available resolution. For this study, the lithological map was rasterized to a 0.25 x 0.25-degree resolution (Figure 2.2).

Effective Porosity

Effective porosity values of lithological sedimentary units, which constitute 87% of the MENA region, were derived from [*McWhorter and Sunada*, 1977]. Effective porosity estimates were indirectly calculated by subtracting the field capacity estimates of soils, derived via physical methods; from the total porosity values obtained indirectly from measuring soil densities. Mean, minimum, and maximum effective porosity values were assigned to respective lithologies to account for the natural variability inherent in geologic parameters. In addition to the type of the lithological sedimentary unit, sediment grain size was also accounted for (if available) when designating effective porosity value to different units.

GRACE-Derived Terrestrial Water Storage (TWS) Variations

Terrestrial water storage change (TWS) values between January 2003 and November 2014 were acquired from GRACE satellite observations of the earth's gravity field. We used level three Release-05 monthly land mass grids (1 x 1-degree) from the JPL, CSR, and GFZ processing centers [*Landerer and Swenson*, 2012; *Swenson and Wahr*, 2006]. GRACE land data were processed by Sean Swenson, supported by NASA MEaSUREs Program, and is available at http://grace.jpl.nasa.gov. Level three TWS grids were multiplied by a scale factor raster [*Landerer and Swenson*, 2012], provided by the GRACE Tellus website, to account for the signal attenuation caused by sampling and post-processing of GRACE observations. Following scaling, the long-term baseline average between 2003 and 2014 was calculated and then removed from each monthly land mass grid to allow for their use with other data.

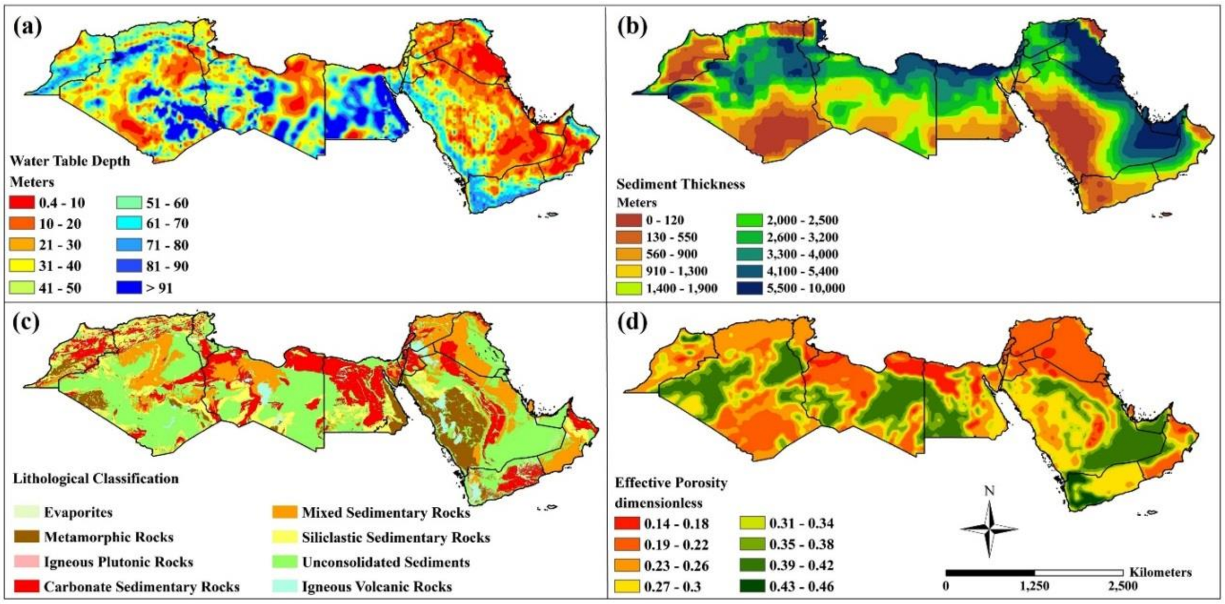

Figure 2.2. Analysis input datasets: **(a)** depth to water table (modified from Fan et al., 2013), **(b)** sediment thickness (modified from Laske et al., 2013), **(c)** lithological classification (modified from Hartmann and Moosdorf, 2012), and **(d)** effective porosity.

To minimize uncertainty in Level three TWS data, we adopted the approach presented by [*Sakumura et al.*, 2014]. According to the authors, ensemble GRACE data sets produced from the arithmetic mean of JPL, CSR, and GFZ TWS solutions are most effective in reducing noise and minimizing uncertainty. Consequently, an ensemble solution was used to generate TWS datasets for this study. TWS total errors estimates were computed from measurement and leakage errors using a least squares estimation [*Swenson and Wahr*, 2006].

Global Land Data Assimilation System (GLDAS) Outputs

Hydrological data is essential for isolating groundwater storage change (GWS) from GRACE-based TWS. Given data scarcity in the MENA region, we used outputs from NASA's Global Land Data Assimilation System (GLDAS) [*Rodell et al.*, 2004] to quantify surface water components: soil moisture, snow water equivalent, and canopy storage. GLDAS is a system that generates land surface states and fluxes by parametrizing satellite and ground-based observational data into advanced land surface models [*Rodell et al.*, 2004]. For this study, we used monthly, 1 x 1-degree, version one land surface parameters simulated by NOAH 2.7.1 in GLDAS [*Hua-lan*, 2011].

2.4 Methodology

Estimating Groundwater Storage Capacity

The calculation of groundwater storage capacity is dependent on the geometry and the hydrogeologic characteristics of the aquifer system. Groundwater storage capacity has been estimated by combining effective porosity values with the saturated thickness of aquifer systems and their areal extent. The equation used for this purpose is:

$$\boldsymbol{V_{sc} = A.H_{sat}.\varphi_e} \qquad \text{Equation 2.1}$$

Where V_{sc} is groundwater reserves (km^3), A is surface areal extent (km^2), H_{sat} is saturated thickness (km), and φ_e is effective porosity (dimensionless).

Saturated thickness (H_{sat}) was generated on a 0.25 x 0.25-degree grid by subtracting WTD estimates [*Fan et al.*, 2013] from sediment thickness estimations [*Laske et al.*, 2013].

Effective porosity (φ_e) was also generated on a 0.25 x 0.25-degree grid by assigning φ_e estimates to their assigned lithological units as developed and mapped by [*Hartmann and Moosdorf*, 2012].

Given the difficulty of establishing regional-scale distributed hydrological models, especially in ungauged domains such as the MENA region, the adopted methodology above attempts to balance the analytical complexity in estimating groundwater storage capacity with the reality of data paucity at such regional scales. As a result, the methodology allows for first order estimations of storage capacity using limited input datasets while presenting some limitations that need to be addressed. One limitation requiring mitigation is the proclivity for overestimating saturated thickness by subtracting depth to water table from sediment thickness estimations from a crustal model. The adopted approach assumes that water saturates the entire vertical column of sediments (~ 10 km) all the way down to the Precambrian crystalline basement. If left unaddressed, this assumption will generate hyperbolized storage capacity estimates that are unfeasible and inconsistent with the presented literature. Therefore to modulate our results an upper limit of two kilometers was established for our saturated thickness estimates. The limit was selected based on *Shahin* [2007] who argues that groundwater resources in zones below sea or ocean levels with a depth of 2000 meters are not abstracted in the MENA region, which withdraws groundwater from zones entirely in the upper earth's crust (up to a depth of 400 meters). Finally to better constrain saturated thickness, previously published saturated thickness estimates and isopach maps from existing reports and literature were incorporated into our results. In the Arabian Peninsula, deterministic values for aquifer saturated thickness were obtained from the *Economic And Social Commission For Western Asia* [2013]. Saturated thickness of the North-Western Sahara Aquifer System (NWSAS) was obtained from isopach maps from the *Sahara and Sahel Observatory* [2004]. In the Nubian Sandstone Aquifer, saturated thickness was obtained from isopach map in *Thorweihe* [1990]. Finally, saturated thickness of the Kufra and Sirte basins were obtained from isopach maps provided by *Wright et al.* [1982].

Another limitation that was addressed pertains to the assigned porosity values and their relationship to depth. Given that storage capacity is defined by effective porosity and saturated aquifer depths of up to two kilometers, the authors in this study found it necessary to incorporate the effects of depth on effective porosity values. Consequently, depth was integrated into assigned porosity values by averaging reduced porosity values at 250-meter intervals. To clarify, in a grid with a saturated thickness of 750 meters, the effective porosity value used would be the average of effective porosities at depths at 0, 250, 500, 750 meters. These calculations are based on porosity-depth relationships in sandstones as discussed by *Magara* [1980].

Estimating Groundwater Storage Change (GWS)

GRACE-derived TWS represent the combined effects of surface water and groundwater storage changes. Separately estimating groundwater storage changes requires isolating it by quantifying surface water storage parameters (e.g. soil moisture) and removing them from GRACE's TWS observations [*Chen et al.*, 2014; *Joodaki et al.*, 2014; *Leonard F. Konikow*, 2015]. Due to the lack of ground-based measurements in our area of study, model estimates from GLDAS were used to account for surface water storage components [*Rodell et al.*, 2004]. GWS was calculated using the following:

$$\boldsymbol{GWS = TWS - SM - SWE - CW} \qquad \text{Equation 2.2}$$

Where SM is soil moisture, SWE is snow water equivalent, and CW is canopy water storage. All units are expressed as a vertical water column in cm.

Based on the calculation of GWS from GRACE and GLDAS datasets, the associated errors in GWS were estimated as follows [*Voss et al.*, 2013]:

$$\boldsymbol{\sigma_{GWS}} = \sqrt{(\boldsymbol{\sigma_{tws}})^2 + (\boldsymbol{\sigma_{sm}})^2 + (\boldsymbol{\sigma_{swe}})^2 + (\boldsymbol{\sigma_{canop}})^2} \qquad \text{Equation 2.3}$$

Where σ_{tws} is the error of GRACE-derived total water storage change;σ_{sm}, σ_{swe}, and σ_{canop} are the errors of GLDAS-computed soil moisture, snow water equivalent, and canopy storage respectively.

Calculating σ_{tws} required decorrelating nearby pixels for both leakage and measurement errors before computing σ_{tws} using a least squares estimation [*Swenson and Wahr*, 2006]. Errors for soil moisture, snow water equivalent, and canopy storage are the mean monthly standard deviation of each respective surface water parameter.

Integrating Groundwater Reserves with Groundwater Storage Anomalies

To account for changes in groundwater storage capacity, GRACE – derived groundwater storage anomalies were quantitatively incorporated into those estimations. A simple arithmetic approach was adopted where aggregate groundwater storage anomalies between January 2003 and November 2014 were added to storage capacity estimations. The calculations were performed using raster analysis in ArcGIS to provide a spatial representation of storage capacity changes within the MENA region. For example, a grid with a storage capacity of 100 km^3

experiencing a total groundwater depletion of one km^3 would be shown to exhibit a 1% decrease in storage capacity with a resultant storage capacity of 99 km^3 in 2014.

2.5 Results and Discussion

Groundwater Storage Capacity (Reserves)

First – order estimations of groundwater reserves in the MENA region were generated by integrating saturated thickness and effective porosity (Figure 2.3). The estimation of total groundwater volume in the MENA region is approximately 1.28 million km^3 with an uncertainty range between 816,000 and 1.93 million km^3 (Figure 2.3, Table 2.1). The bulk of the region's groundwater was found in the large sedimentary basins of the Sahara desert and the Arabian Peninsula. Consequently countries with vast areal extent overlying primarily sedimentary basins accounted for the biggest share of the region's groundwater storage. For example, Algeria, Libya, Saudi Arabia, and Egypt have storage capacities of 360, 250, 249, and 93 (10^3) km^3 respectively (Table 2.1). Together the four countries alone account for 74 % of the MENA region's total storage capacity. Alternatively, areas with the least storage (equivalent to 0 – 5 m water depth) were located in predominantly the Precambrian basement which exhibit effective porosity values and thin sedimentary columns. Three main examples are the Arabian Shield in Saudi Arabia, the Hoggar region in southern Algeria, and the Atlas Mountains region in Morocco. Aquifer capacity within fissured crystalline rocks is almost nil and their potential are expected to be very weak [*Shahin*, 2007]. Countries with the lowest reserves are Lebanon, Qatar, and Kuwait. It is worth noting that reserve estimates in those countries are less a function of lithology which is predominantly sedimentary, and more a result of their limited surficial area.

Establishing the validity and reliability of our results through comparison is difficult, given the overall lack of data and publications on groundwater reserves in the MENA region with the exception of the study by *MacDonald et al.* [2012] and a more recent publication by *Richey et al.* [2015]. A comparison of ground water reserve estimates in North African countries shows that our results are relatively higher than MacDonald's. The differences in groundwater reserve estimations are mostly attributed to the approaches followed in establishing saturated thickness estimates. While the study by MacDonald estimated saturated thickness using available hydrogeological reports and data, this paper adopted an approach dependent on spatially and temporally consistent remote sensing datasets with an inherent proclivity to inflate estimates, as discussed in the methodology section. To elaborate, our study's reserve estimates for Algeria, Libya, Egypt, Tunisia, and Morocco are 4, 2.5, 1.6, 2.5, and 8 times respectively higher than the MacDonald study. The lower differences in reserve estimates in the former four countries can be explained by the fact that they overlie the Nubian, North Western Sahara, and Kufra and Sirte basins that have been constrained with isopach maps. However in the case of Morocco, the significantly larger differences in storage estimations can be justifiably linked to the fact that no constraining data was found to modulate the saturated thickness results obtained from the remote sensing approach. While this paper approaches the estimation of groundwater reserves using the same methodology followed by *MacDonald et al.* [2012], it diverges in its selection of datasets by relying on a suite of remote sensing data that attempt to address a limitation in Macdonald's study represented by the lack of quality hydrological maps in North and West Africa.

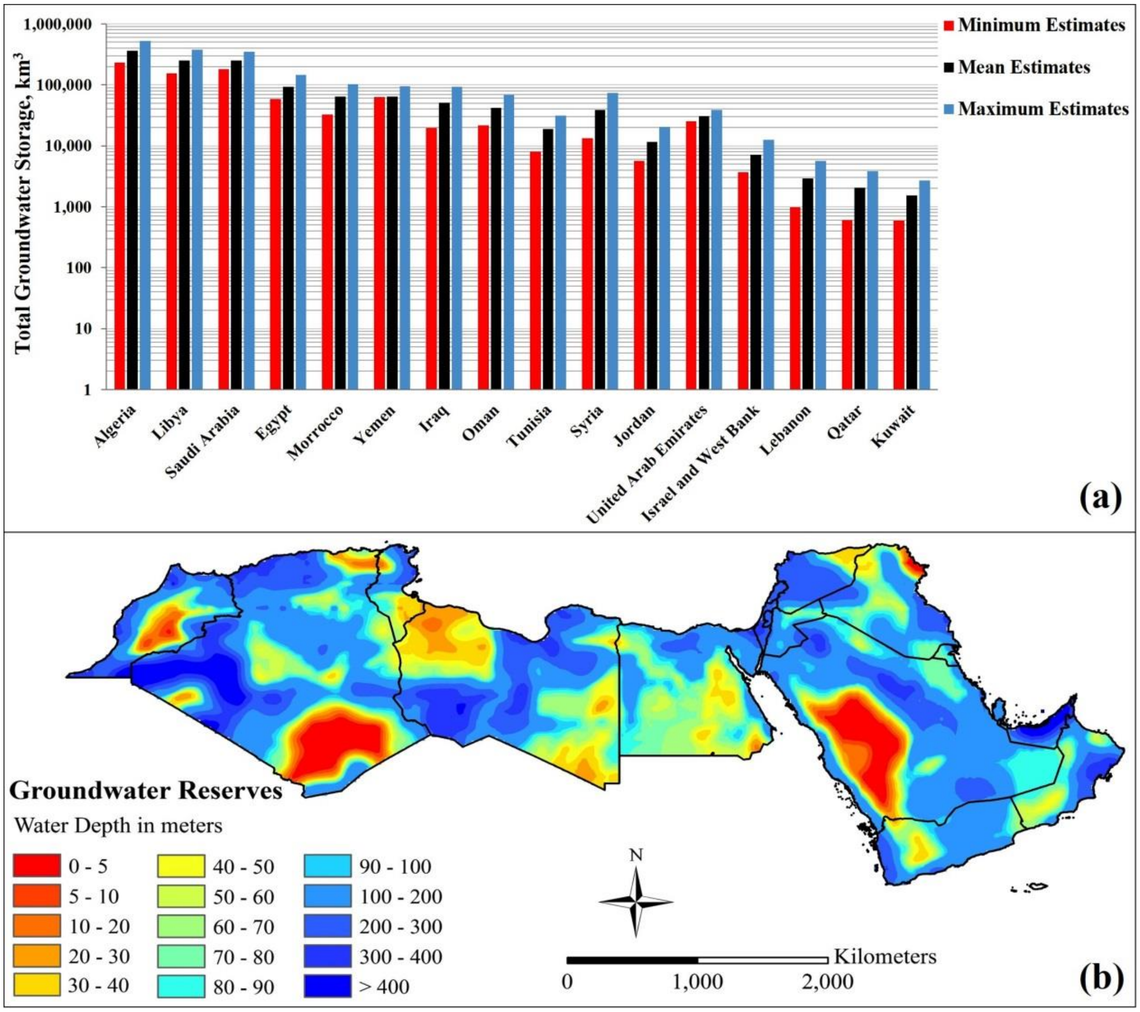

Figure 2.3. Groundwater reserve estimates for the MENA region based on effective porosity and saturated aquifer thickness: (a) bar graph showing minimum, mean, and maximum estimates of volumetric groundwater storage in each country. Conservative and liberal estimates of storage capacity are calculated by using a range of effective porosity values to account for margins of error. (b) Map of groundwater storage expressed in meters.

Table 2.1. Country-level estimates of groundwater reserves, groundwater storage changes, and changes in groundwater reserves.

Country	Groundwater Storage Capacity (km^3)		Groundwater Storage Change (km^3)		Δ Groundwater Capacity (%)[b]
	Average Estimate	Range[a]	Annual Change	Total change (2003 - 2014)	
Algeria	361,327	231,204 - 522,763	-0.24	-2.83	0
Egypt	92,863	58,304 - 144,483	1.42	17.01	0.02
Iraq	50,963	19,391 - 92,946	-0.72	-8.67	-0.02
Israel and West Bank	7,134	3,646 - 12,417	-0.16	-1.86	-0.03
Jordan	11,618	5,680 - 20,216	0.11	1.29	0.01
Kuwait	1,543	588 - 2,698	0.03	0.40	0.03
Lebanon	2,929	985 - 5,590	0.005	-0.65	-0.02
Libya	249,469	154,076 - 375,209	0.82	9.83	0
Morocco	64,279	32,199 - 102,154	0.53	6.33	0.01
Oman	42,167	21,709 - 67,816	-0.34	-4.06	-0.01
Qatar	2,038	605 - 3,828	0.02	0.18	0.01
Saudi Arabia	248,159	178,822 - 348,777	-0.85	-10	0
Syria	38,872	13 246 - 72,848	-0.11	-1.32	0
Tunisia	18,944	7,930 - 31,140	-0.26	-3.13	-0.02
United Arab Emirates	30,826	25,322 - 39,000	0.07	0.87	0
Yemen	64,383	62,319 - 94,642	1.04	12.54	0.02

[a] Range was determined by recalculating groundwater storage using minimum-maximum spectrum of effective porosity values.
[b] Percent change to groundwater storage capacity between is January 2003 and November 2014 is generated by comparing GRACE- derived groundwater storage change to initial estimates of storage capacity.

Table 2.2. Study comparison of groundwater storage capacity in the Arabian Aquifer System, Nubian Aquifer System, and Northwestern Sahara Aquifer system.

Aquifer	Source	Total storage Capacity (km^3)	
		Value	Time period
Arabian Aquifer System	This Study	min: 198,948 mean: 278,906 Max: 407,537	-
	[Richey et al., 2015]	500000	2015
	[Al-Ibrahim,1991]	500000	1985
Nubian Aquifer System	This Study	min: 50,421 mean: 73,497 Max: 106,004	-
	[Richey et al., 2015]	87,000	2015
	[Gossel et al., 2004]	135,000	2004
	[Bakhbakhi, 2006]	373,000	2006
NW Sahara Aquifer System	This Study	min: 59,368 mean: 99,088 Max: 145,206	-
	[Richey et al., 2015]	43,000	2015
	[CEDARE, 2014]	60,000	2014

Moreover a more recent study by *Richey et al.* [2015] also allows for another comparison. Unlike the MacDonald study, *Richey et al.* [2015] uses historical and regional estimates to estimate groundwater capacity in major groundwater aquifer including the three largest aquifer systems in the MENA region: Arabian Aquifer System (AAS), Nubian Sandstone Aquifer System (NSAS), and the North Western Sahara Aquifer System (NWSAS). Upon comparison with the Richey study and other regional publications and reports (Table 2.2), groundwater storage estimates displayed a close convergence within uncertainty ranges in the NSAS and NWSAS with other available estimates. In the case of the AAS, our produced estimates were smaller than one available estimate of 500,000 km^3. Given that our limited knowledge of groundwater aquifers systems produces uncertainty ranges across order of magnitude [*Richey et al.*, 2015] – for example, groundwater storage for the NSAS ranges between 15,000 km^3 and 373,000 km^3 [*Richey et al.*, 2015] – the aforementioned country-level and aquifer-level comparisons support our groundwater storage estimates and the methodologies and datasets from which they were produced.

While the study comparison (Table 2.2) shows that the large sedimentary basins in North Africa and the Arabian Peninsula (78% of the MENA region) are consistent and reliable, groundwater reserve estimates in remaining areas with no constraining data such as the Levant (Lebanon, Syria, Iraq, and Jordan), Oman, Yemen, United Arab Emirates and Morocco should be cautiously utilized while taking into consideration methodology limitations. It is worth noting that groundwater storage reserves do not equate to abstractable or utilizable water. "Abstractable volume" is a concept that extends beyond the various physical determinants such as transmissivity and water quality to technical, financial, legal, and political variables that are unique to different communities.

Notwithstanding the aforementioned uncertainties, estimated groundwater reserves (1.28 million km^3) represent a water resource of growing importance in a region where precipitation is projected to decrease (15 – 20 %), and evapotranspiration is forecasted to increase in the majority of the countries [*Terink et al.*, 2013]. Given that internal and external renewable water resources between 2000 and 2009 in the MENA region constituted only 250 km^3, with a projected annual decline of 0.6 km^3 by 2050 [*Droogers et al.*, 2012], these reserves serve as an important buffer against climate change that needs to be properly characterized to better guide their management and use in a manner that is socio-economically and environmentally optimal.

Groundwater Storage Change (2003 – 2014)

GRACE–derived datasets integrated with GLDAS land surface parameters were processed to produce spatially representative groundwater storage anomalies between January 2003 and November 2014. Figure 2.4a displays total groundwater change in the MENA region and highlights spatial variations within the study area. The results clearly show that the highest declines in groundwater storage were centered in the coastal areas in North West Africa stretching from Algeria to western Libya, and on the eastern Mediterranean coast (e.g. Lebanon, Syria). This is not surprising given the impact of coastal human population growth on the depletion and deterioration of coastal groundwater aquifers [*Ferguson and Gleeson*, 2012]. To demonstrate, Figure 2.4c displays population densities as being highest in coastal regions of North West Africa and the eastern Mediterranean, ranging between 500 and 3000 persons per km^2. In Algeria for example, 91% of the population lives along coastal areas representing approximately 12% of the country's total land mass [*Yearbook*, 2007]. In Libya, coastal groundwater depletion occurs particularly on or around major cities with high populations such as Tripoli (1.127 million) and Benghazi (650,629) [*Yearbook*, 2007]. Moreover we also detect spatially defined areas exhibiting a decline in groundwater storage and that underlie cities with major demographic concentrations. For example Riyadh in central Saudi Arabia, Jeddah, Muscat in Oman, Dubai in the United Arab Emirates, Alexandria in Egypt, and Baghdad in Iraq all overlie or reside next to areas (displayed in yellow) exhibiting five to fifteen centimeter decline in groundwater storage. Based on our observations there seems to be a strong relationship between the decline in groundwater storage and areas of high population density, specifically when exceeding 500 persons per square kilometer.

The exceptions to this observation, however, are the Nile river valley and the Moroccan Coast. The Nile River exhibits no significant decline in groundwater storage despite accommodating approximately the entirety of the Egypt's populace of 82 million. This can be explained by the fact that groundwater only accounts for 4% of Egypt's water supply given it reliance on the Nile waters which represent approximately 86% of the water supply [Abdel-Shafy and Aly, 2002]. Actual increases in groundwater storage change in the Nile river valley are attributable to seasonal groundwater recharge by the Nile river of up to 240 km^3/yr [*Bonsor et al.*, 2009]. In the case of the Moroccan Coast, Recharge rates between 10 and 15 cm (over 12 years) can be explained by the relatively high precipitation rates induced by the orographic effect of the Atlas Mountains on approaching saturated air masses. Naturally higher precipitation rates should account for more aquifer recharge and more constrained rates of groundwater decline, especially in Morocco where groundwater use is secondary (25% of total water use) [*Bzioui*, 2004].

While the findings confirm the effect of demographic concentrations on groundwater depletion, they also present results that challenge some of the assumptions on groundwater conditions in the MENA region. Given that our study area is in a predominantly hyper-arid region with negligible precipitation and very limited surface water, it was assumed that the region would exhibit significant groundwater depletion across the spatial domain.

However Figure 2.4a presents a more nuanced image of groundwater storage change that indicates possible groundwater recharge, including within aquifer systems that are traditionally defined as "non-renewable" or "fossil" aquifer systems. Desert expanses, stretching from the southern Algeria in the West to Sinai and Jordan in the East, exhibit increases in groundwater storage ranging anywhere between one and fifteen centimeters over a twelve year span. These observations have been the center of many scientific publications that have been attempting to quantify groundwater recharge in arid environments such as the MENA region and reexamining the categorization of "fossil" groundwater systems.

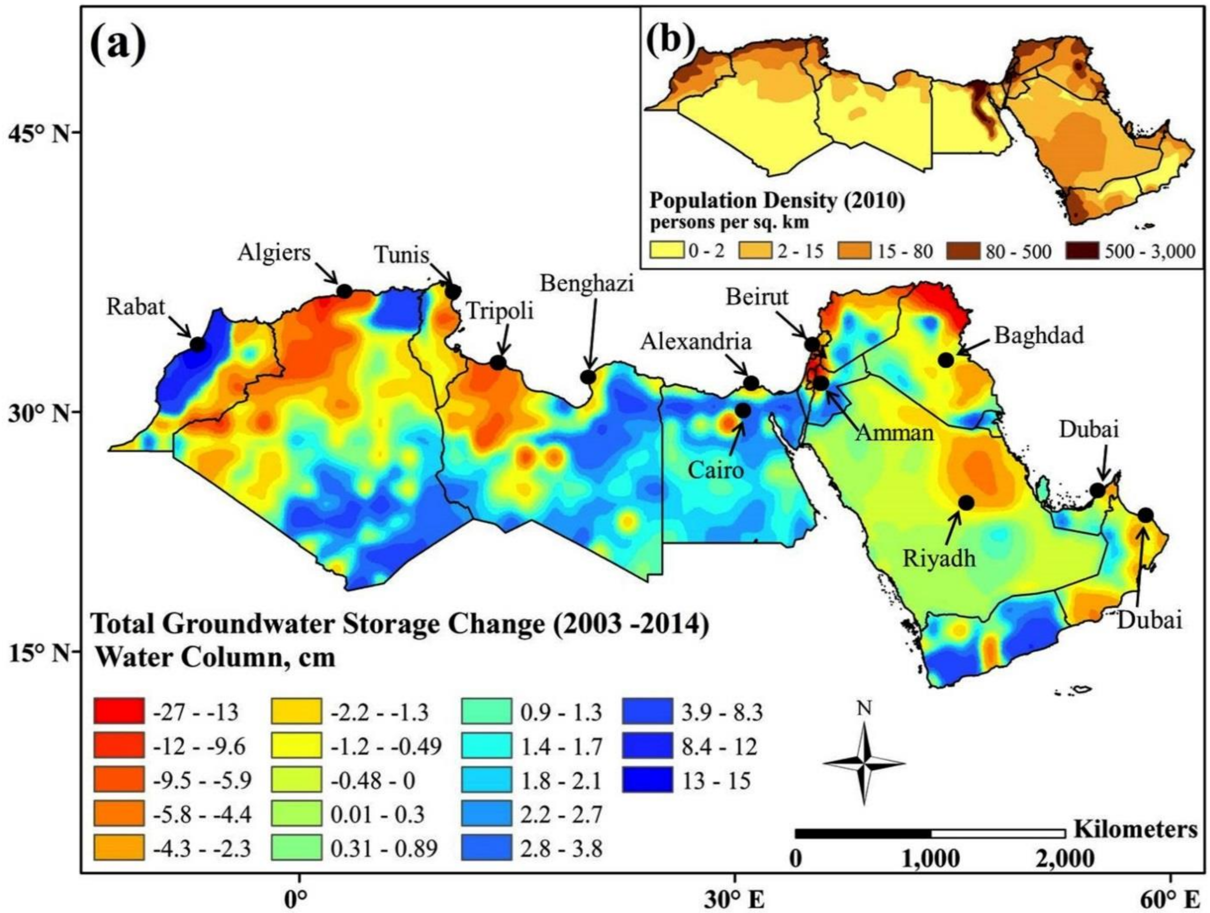

Figure 2.4. (a) Total groundwater storage change in the MENA region between January 2003 and November 2014 and **(b)** Population density map [CIESIN, 2005].

Another factor that could potentially explain the lack of pervasive groundwater decline expected in "fossil" aquifer systems in inland desert expanses pertains to the local scale of groundwater cones of depression and the low resolution of the GRACE satellite used to monitor those changes. Given the large extent of aquifer systems in inland desert areas such as the

Sahara, and the low population densities in those areas (0 – 15 persons/km^2), groundwater abstraction activities tend to concentrate in spatially small areas around towns and agricultural projects, which result in local scale declines in groundwater levels. The GRACE data sets used to monitor these groundwater changes however are limited by a coarse spatial resolution of 300 to 400 km [*Ramillien et al*., 2008] that potentially prevent it from detecting spatially limited change in groundwater storage, as opposed to detecting storage changes induced by large scale diffuse recharge. It should also be noted that the assumption of pervasive groundwater depletion could also be a product of sampling bias, which occur (sampling) in concentrated and defined areas of groundwater abstraction next to agricultural projects and population centers. The limitation of sampling in these locations often forwards the observation of groundwater depletion that is then extrapolated to the rest of an aquifer system. The assessment of groundwater conditions based on such sampling bias can also account for the lack of consideration of possible aquifer recharge in literature, publications, and international reports.

Area-averaged groundwater storage change estimates between 2003 and 2014 (Table 2.1) were also generated at country level, and then compared to the first – order groundwater reserve estimates by generating percent change in groundwater storage as a function of GRACE-derived changes in groundwater (Figure 2.5). Eight out of the sixteen countries in the MENA region exhibited a decline in groundwater storage change between 2003 and 2013, with the rest displaying a rise in groundwater storage at varying rates (Table 2.1). The three countries with the highest rates of groundwater depletion are Saudi Arabia (-10 km^3, -0.04%), Iraq (-8.67 km^3, -0.02%), and Oman (-4.06 km^3, -0.01%). Unexpectedly Saudi Arabia did not exhibit significant declines in groundwater storage as was expected given available literature [*Leonard F Konikow and Kendy,* 2005]. This can be attributable to renewable water resources specifically occurring within the Arabian Shield which covers about a third of the country [*Elhadj*, 2004]. To provide an estimate of renewable groundwater in Saudi Arabia, *Abderrahman* [2006] estimates groundwater recharge in Saudi Arabia at approximately 4 km^3/yr, of which 2.7 km^3 occur in the Arabian Shield. This estimation, which amounts to a recharge of 48 km^3 between 2003 and 2014, could explain for reserved groundwater depletion estimates displayed in Saudi Arabia. The decline in groundwater in Iraq is a consequence of a larger regional drought that occurred for four hydrological between 2007 and 2010 in the Levant generally and the northern Mesopotamia region specifically [*Kaniewski et al.*, 2012]. The effects of this drought extend beyond Iraq to Syria, Lebanon, Israel and Palestinian Territories, Jordan, and Kuwait. This is clearly visible in figure 2.6 where stabilized groundwater storage changes suddenly start significantly declining after 2007 in the aforementioned countries. These declines are a consequence of increased groundwater abstractions as a result of declining levels of surface water storage [*Voss et al.*, 2013].

Groundwater storage change time series (Figure 2.6) clearly show prevalent significant declines in groundwater storage from 2003 to 2014 in the Levant region, and to a lesser extent in Northwest African countries. In the Arabian Peninsula, seasonal or annual groundwater storage trends are relatively unchanging or show much modulated levels of decline. In the case of the small gulf countries (i.e. UAE, Qatar) along the Arab – Persian Gulf, the coarse resolution of the GRACE satellite could account for the inability to detect changes in groundwater within very limited spatial areas.

A review of cumulative groundwater changes and their trends between 2003 and 2014 demonstrates that countries with both net positive (i.e. Egypt) and negative (i.e. Syria, Iraq) groundwater levels demonstrate an overall decline in groundwater storage over time. Egypt is an excellent example, where the positive net change in groundwater storage change between 2003 and 2014 is a reflection of the rise in groundwater storage between 2003 and 2008 after which groundwater change starts following a negative dipping trend.

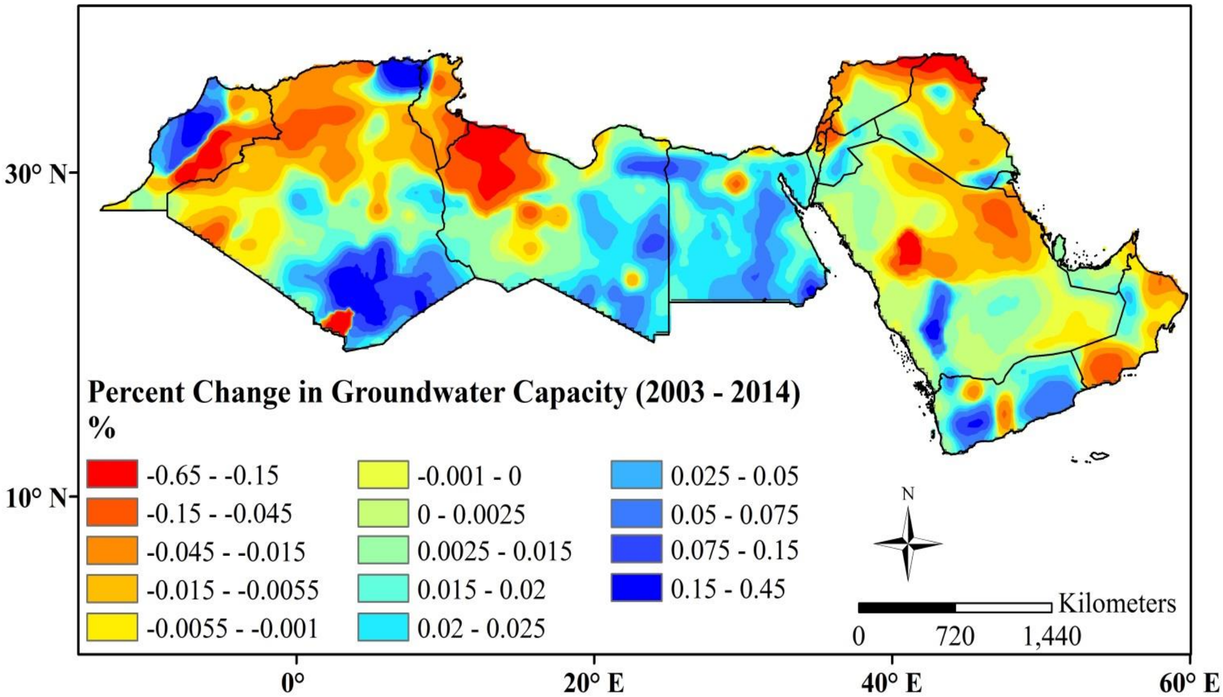

Figure 2.5. Percent change in estimated groundwater storage capacity (Fig. 2.3) as a function of GRACE-derived total groundwater storage anomalies between January 2003 and November 2014.

In both cases of minute and significant groundwater storage changes, changes to groundwater reserves range from the modest (i.e. Iraq, Tunisia, Lebanon) to the negligible (i.e. Algeria, Libya, United Arab Emirates) with percent change to groundwater reserves not exceeding 0.5% in any of the 16 countries. Changes to groundwater reserves represented in figure 2.5 are consistent with the observations made on the variability of total groundwater anomalies in Figure 2.4, with the most drastic depletion of groundwater reserves occurring in northwestern Africa and within areas of demographic concentrations such as the Mediterranean coast, Riyadh in central Saudi Arabia, Muscat in eastern Oman, and the United Arab Emirates. Alternatively areas exhibiting the highest recharge rates appear to be concentrated in areas with exposed Precambrian basement rock as is the case in Southern Algeria in the Hoggar region, and in the Arabian shield on the western flank of the Arabian Peninsula. This observation could relate to the initial low groundwater reserve estimates within these Precambrian exposures given the lack of thick sedimentary cover and very low effective porosity values within the Precambrian basement. It is also a function of the higher topographic levels and their proximity predominantly near water bodies with saturated air masses.

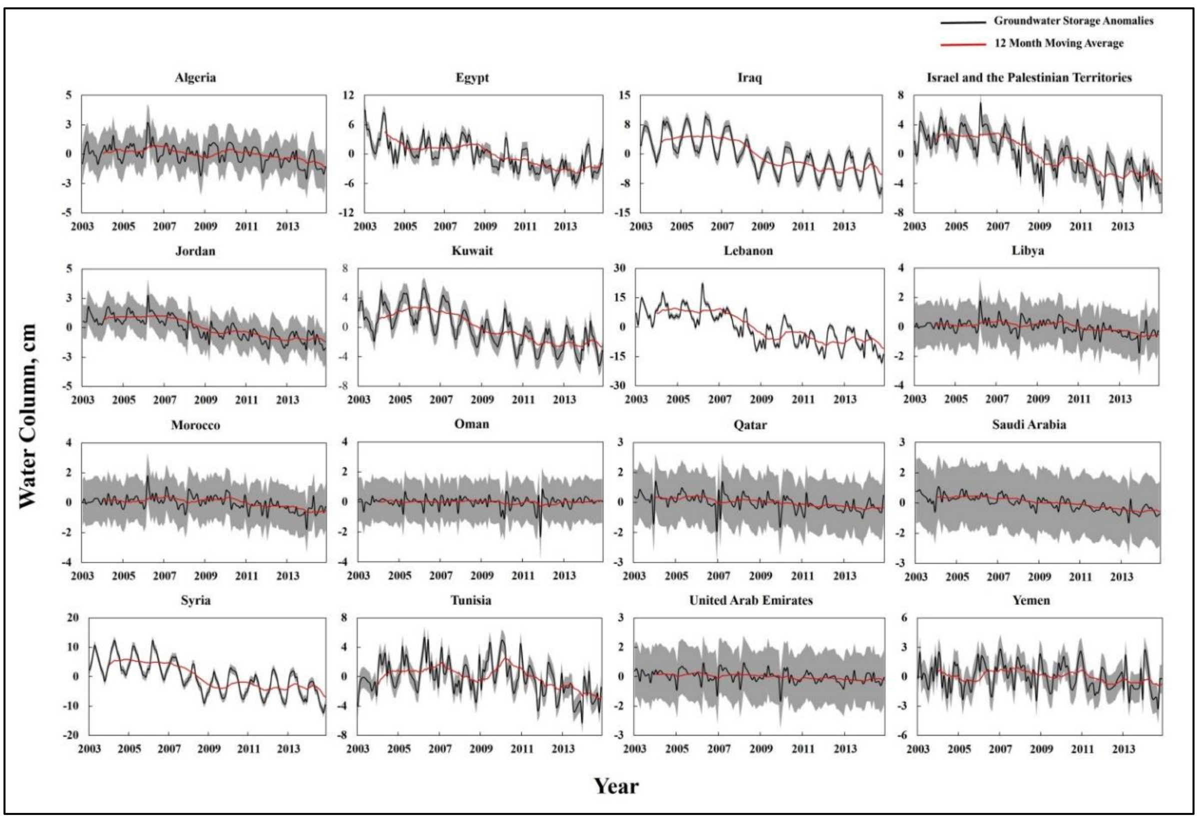

Figure 2.6. Time series of GRACE-derived groundwater storage change in the 16 MENA countries. Grey Shaded bands indicate ranges of uncertainty.

2.6 Conclusion

In an attempt to better characterize and quantify groundwater resources in the MENA region, first – order estimates of groundwater reserves were calculated using a distributed ArcGIS model parametrized with a suite of remote sensing datasets. Moreover, GRACE-derived datasets were used to calculate changes occurring in groundwater storage between January 2003 and November 2014 in order to construct an image of the recent conditions of groundwater resources in the MENA region. Consistent with the available literature, groundwater storage reserves were highest in the deep sedimentary basins of Northern Africa and the Arabian Peninsula that were recharged during previous fluvial periods. Alternatively the lowest estimates were found in the Precambrian basement exposure. Results on groundwater storage change, however, offer more complex observations than the general assessment of overall depletion of groundwater resources in the MENA region. The association between areas of groundwater depletion and urban concentrations with high population densities ascertains the effects of anthropogenic demand on groundwater depletion. On the other hand, observations of increases in groundwater storage over desert regions, primarily in the Sahara desert, indicate a possibility of recharge occurring in territories containing aquifers that are naturally characterized as "non-renewable". While only half of the countries in the MENA region experienced a net loss in groundwater storage between 2003 and 2014, the overall majority of the countries display a clear downward trend in groundwater storage change that could indicate potential future groundwater depletion even within countries that are currently experiencing a net gain in groundwater storage.

Given the large groundwater reserves underlying the region, groundwater changes between 2003 and 2014 represent only a small fraction of available water resources and pose no immediate threats to water supply. However the impact of climate change, demographic expansion, and socio-economic development necessitates the development of sustainable and efficient water management policies to address future challenges in one of the driest regions in the world.

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CHAPTER 3

THE GROUNDWATER RISK INDEX: DEVELOPMENT AND APPLICATION IN THE MIDDLE EAST AND NORTH AFRICA REGION

Lezzaik, K., A. Milewski, and J. Mullen (2016), The Groundwater Risk Index: Development and Application in the Middle East and North Africa Region, *Earth-Science Reviews* (*submitted).*

Abstract

The advent of mobile and cheap pumping technology in the past 40 years has enabled the extensive use of groundwater resources in promoting economic development and poverty alleviation, especially in developing countries in the Middle East and North Africa (MENA) region. However, overreliance on predominantly non-renewable groundwater resources and their subsequent depletion, has been giving rise to adverse environmental, political, economic, and social effects. The high costs of groundwater depletion are exacerbated by the notable absence of tools designed to identify and diagnose areas at risk of groundwater degradation. In this study, a Groundwater Risk Index (*GRI*) was developed as a multi-disciplinary regional screening tool, designed to identify regions most susceptible to groundwater depletion, as a function of physical characteristics (e.g., hydrological systems), and political and socioeconomic factors (e.g., governance, food security, and groundwater extraction costs). Examination of annual *GRI* results indicates a strong dependency of groundwater risk on governance and food security. Surprisingly, groundwater storage reserves were characteristically indeterminate of groundwater risk conditions. Given the centrality of food security and its provision through effective governance, MENA governments are recommended to enhance food security conditions through reliable and secure virtual water transfers, in the form of agricultural trade, as opposed to unsustainability exploiting finite water resources for short-term food sufficiency.

3.1 Introduction

Global Context of Groundwater Vulnerability

According to a global risk report by the World Economic Forum [2015], water crises caused by disruptions to water supplies were deemed to be one of the four risks most likely to pose the most devastating threats globally. Within the framework of intense pressures of growth in population, food demand, and economic conditions; freshwater availability is increasingly becoming a major obstacle to achieving food security on one hand and poverty alleviation on another, especially in semiarid and arid environments where a high proportion of renewable water resources are already being used [*FAO*, 2011].

The role of groundwater resources in the development of human systems cannot be emphasized enough. Fifty percent of the world's potable water is extracted from groundwater systems, with half of the world's megacities being fully dependent on it [*Giordano*, 2009]. However, in terms of significance and scale, agriculture has been the main beneficiary of groundwater utilization. In conjunction with the third agricultural revolution, groundwater extraction in the 1970s has contributed significantly to the expansion of global irrigated areas and the growth of agricultural production [*Shah et al.*, 2007]. Consequently, groundwater utilization was and remains a major factor in the improvement of the livelihood of millions of rural farmers, and in the achievement of (inter-)national food security. Beyond its role in socio-economic development, freshwater scarcity plays an essential role in inter and intra-state security and stability. According to the *Global Water Security Intelligence Community Assessment* by the National Intelligence Council [2012], water problems will result in higher risks of instability and state failure, as a function of countries' inability to produce food, generate energy, and achieve economic growth. Nations are already in conflict over access to freshwater resources and future conflicts are likely, given the maldistribution and accentuating scarcity of freshwater resources [*Gleick*, 1993].

However, overreliance on groundwater resources due to easy and economic access to pumping technology has led to a global scale groundwater depletion problem with adverse repercussions to dependent communities [*Döll et al.*, 2014; *Gleeson et al.*, 2012a; *Konikow*, 2011; *Wada et al.*, 2012]. The social and economic impacts of groundwater depletion are directly tied to the environmental effects they present. For instance, lowering of groundwater levels often translates into greater capital investments in well construction and pumping plants associated with pumping from greater depths [*Pereira et al.*, 2009]. The consequent increased cost of water delivery to end users imposes economic costs on society's different sectors. Most notably, farmers reliant on groundwater for irrigation state the rise in electricity costs required to pump groundwater from ever-growing depths as being the primary reason behind the economic unviability of their agricultural activities [*World Bank*, 2009]. Moreover the overuse of aquifers also accrues social costs, especially on poor urbanites and rural dwellers, by forcing them to invest increasing amounts of time on finding alternative sources of water within a framework of competition that could optimize conflict conditions. Land subsidence associated with groundwater depletion also damages public infrastructure and private property, consequently imposing economic costs related to damage repairs born by official organizations and individuals [*Pereira et al.*, 2009]. In addition to the large economic and social costs arising from measures taken to re-equilibrate human systems to the "new normal [depleted] groundwater conditions", groundwater degradation, and subsequent competition over it, generates societal instability by forcing migration and creating underemployed and restive demographics as a function of rendering their economic activities unviable [*Moench*, 2002]. Given the vulnerability of countries and communities to groundwater depletion and degradation, effective policies for groundwater development and management must be aligned, backed up, and informed by rigorous and interdisciplinary scientific assessments of groundwater risk and susceptibility to depletion.

Conventional Assessments of Water Scarcity and Stress

Since the 1980s, we have witnessed the development of freshwater indices as tools designed to measure relative, non-measurable, and dimensionless concepts such as water scarcity and stress [*Gogu and Dassargues*, 2000; *Sullivan*, 2002]. The multi-dimensionality of water resource issues is reflected not only in the multiplicity of indices that are currently in use, but also by the differing criteria with which they are assessed.

The first of those indicators was the *Falkenmark Indicator* [*Falkenmark et al.*, 1989] which expressed water stress as the fraction of total annual runoff available for human use. Recognizing the importance of technology and institutions on the effects of limited water resources, *Ohlsson* [2000] departed from Falkenmark's indicator by creating a *Social Resource Water Stress Index* to incorporate the roles society, economics, and technology play in assessing water stress. The significance of Ohlsson's index lies not only in its consideration of the complex interactions between physical freshwater systems and anthropogenic constructs, but also in its examination of the conjunctional causes of water scarcity which extend beyond the natural climatic and hydrogeological conditions in a given area. *Criticality ratio* indices were subsequently developed to assess water stress and scarcity conditions as a function of water withdrawals relative to renewable freshwater resources [*Raskin et al.*, 1997]. Given their propensity to overestimate scarcity conditions, *criticality ratio* indices were followed by consequent assessments such as the *Physical and Economic Water Scarcity* [*Brown and Matlock*, 2011] and the *Index of Relative Water Use* [*Vörösmarty et al.*, 2005] to address the limitation of overestimating water stress by accounting for the role of water technology, infrastructure, and water reuse, respectively in affecting water scarcity conditions. *Index of Relative Water Use* accounts for water reuse using a ratio of total water use over river discharge. Whereas, the

Physical and Economical Water Scarcity Index, makes an important distinction between physical and economic water scarcity to highlight the effect of human systems on water scarcity.

The development of a nuanced conceptualizations of water scarcity/stress and the interdisciplinary conjunctional causes that define it led to the advancement of a category of indices that provided a holistic approach to water scarcity, linking physical water systems, socioeconomic conditions and ecosystem health in integrated and dynamic interactions [*Asheesh*, 2007; *Chaves and Alipaz*, 2007; *Sullivan*, 2002]. An appropriate representation of this holistic approach to water scarcity is *Sullivan* [2002] *Water Poverty Index,* which uses a disaggregated approach to assessing water stress and scarcity by examining the interactions and relationships between macro-scale physical estimates of water availability and micro-scale socio-economic variables.

Limitations of Conventional Water Scarcity Assessments

Notwithstanding advancements in the past 30 years, available water scarcity indices suffer from two major limitations that severely restrict their use within the present day's framework. Firstly, the majority of existing indices examine water scarcity/stress solely from the perspective of renewable surface water resources, with a disregard of groundwater resources. This is attributable to prevailing groundwater data scarcity which is caused by the more complicated and expensive nature of groundwater assessments, in addition to the decentralized diffuse storage of unstandardized groundwater data in thousands of local and personal databases (*Marcus Wijnen*, 2012). The exclusion of the groundwater component in water scarcity assessments reduces the accuracy and validity of available indices at best, and renders them inapplicable at worst, especially in arid environments where groundwater constitutes the major source of freshwater.

Secondly, available water indices have focused primarily on measuring water scarcity and stress as opposed to water risk. To clarify, water "scarcity" refers to an objective measurement of volumetric abundance of water supplies. The *Falkenmark index* and *water scarcity index* [*Gleick*, 1996] are adequate examples of indices measuring water scarcity. On the other hand, water "stress" is a more holistic and inclusive concept that refers to the capacity to meet human and ecological water demands and needs, in which water "scarcity" is but one of many constituent variables (e.g. governance, infrastructure, climate change) that determine water "stress". Ohlsson's [2000] *Social Resource Water Stress Index* and Sullivan's [2002] *Water Poverty Index* are primary examples of water stress indices. Although there are multiple indices highlighting water scarcity and stress, there are few indices measuring "risk", or the vulnerability of an entity experiencing deleterious or degradational effects. It is essential to note that the authors are focusing on quantitative deleterious events, primarily groundwater depletion. This is opposed to qualitative water events such as groundwater contamination which have numerous tools designed to evaluate water pollution potential such as the DRASTIC index [*Aller et al.*, 1987]. Global demographic and economic growth in the 21st century will exacerbate scarcity and stress conditions on groundwater systems [*Gleeson et al.*, 2012b; *Richey et al.*, 2015b; *Vaux*, 2010]. This necessitates the development of tools designed to evaluate and pinpoint hotspots that are highly susceptible to groundwater depletion and the associated adverse socio-economic and security effects.

Groundwater Risk Index

The driving aim behind this paper is the development of a *Groundwater Risk Index* (GRI) designed to evaluate the vulnerability of entities to groundwater depletion. A distributed GRI is developed using an overlay and index method, and constructed using ArcGIS 10.3 to allow for spatio-temporal characterization and visualization of groundwater depletion risk, at a level of detail lacking in composite indices with average based assessments.

GRI's assessments are dependent upon two main sets of parameters: hydrogeological characterizations of groundwater systems on one hand, and socio-economic conditions and capacities of communities on the other. The nature of groundwater risk assessment provided by *GRI* as relative, non-measurable, and dimensionless concept determines the ultimate objective of our composite index: the provision of policy-makers, water managers, and academics with a comparative risk assessment aimed at highlighting areas or entities most at risk (vis-à-vis other areas) of depleting their groundwater resources. As such, *GRI*'s function of summarizing complex and multi-dimensional phenomenon, such as groundwater depletion, allows for focused attention on high risk areas, in either forms of more extensive studies by academics or mitigation efforts by water managers and policy-makers.

Following its development, *GRI* was applied in the Middle East and North Africa (MENA) region (Fig. 3.1), where groundwater scarcity and stress conditions are at their highest globally. Given its extensiveness and the diversity of socio-economic capacities and environmental conditions, that largely determine groundwater policy and management [*Antonelli and Tamea*, 2015], the MENA region can serve as an informative case study for other regions. Moreover the region is experiencing the same conditions that increase freshwater demand and drive groundwater depletion in other parts of the world. These conditions include population growth [*Roudi-Fahimi and Kent*, 2007], economic and rising living standards, and the impact of climate change on the region's heavily stressed freshwater resources and arable land.

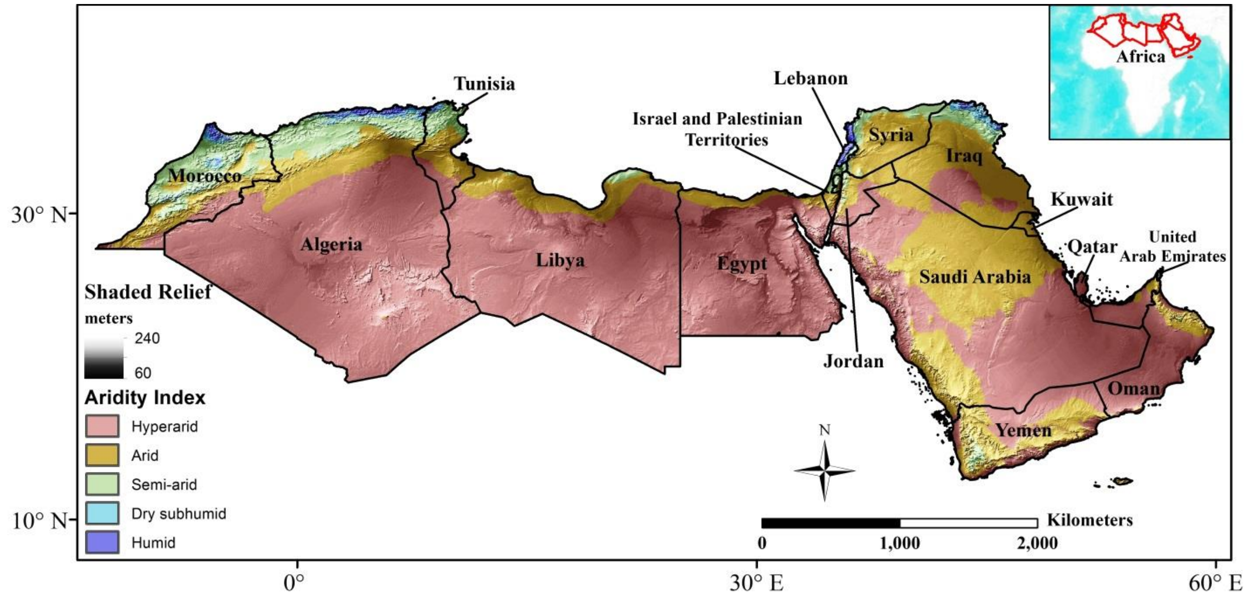

Figure 3.1. Shaded relief and aridity index map highlighting the Arab Middle East and North Africa (MENA) region and the political boundaries of the 16 MENA countries included in this study. The country of Bahrain was excluded by cause of its negligible area rendering a reliable risk assessment unfeasible.

3.2 Groundwater Risk Index Development

This section presents and expounds upon the sequential steps followed in the development of the Groundwater Risk Index (*GRI*), from the selection of the constituent variable components, their weighting and their aggregation to the final index. Consequently, a detailed methodological section (Fig. 3.2) serves to provide clarity and justification at each developmental stage of the *GRI* to different end-users that may scrutinize and examine the developmental process, and contribute to further improvements and amendments in the future. A sensitivity analysis of the *GRI* is provided in [*Lezzaik and Milewski*, 2016].

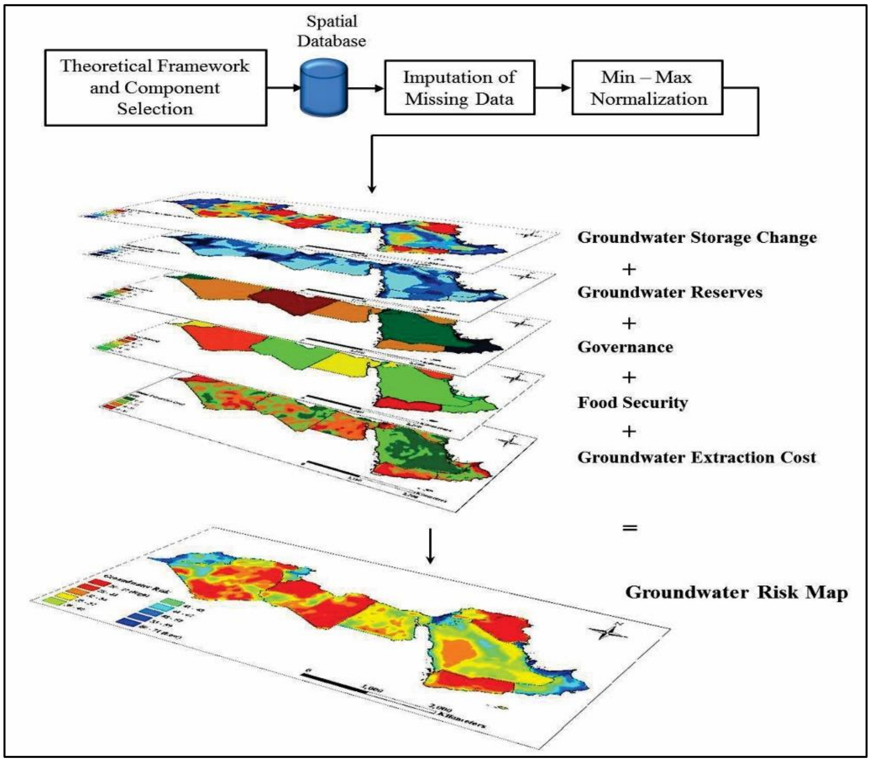

Figure 3.2. Flowchart outlining the main developmental stages involved in constructing the Groundwater Risk Index.

3.2.1 Theoretical Framework and Index Component Selection

The first and most essential process in the construction of an index is the provision of a conceptual basis for the selection of a combination of variables (components) involved in understanding and measuring the multidimensional phenomenon being assessed – the likelihood or risk of an entity or domain to face groundwater depletion. This section discusses the relevance and justification behind the inclusion of each of the variables into the composite index, in addition to the strengths and limitations of each component. It also illustrates each of the components' data sources and the associated methodology involved in developing them for aggregation into an overall composite index. Upon examination of the literature on groundwater depletion challenges, the following components were selected for inclusion in the *GRI* index:

3.2.1.1 Groundwater Reserves and Storage Change

Justification

The nature, processes, and limitations of groundwater systems constitute the principle framework within which groundwater risk can be conceptualized and characterized. Groundwater risk is a function of numerous components, the most central of which is groundwater scarcity – the volumetric availability of groundwater supplies. As such, an accurate quantitative characterization of groundwater systems, as an objective physical reality, is a pivotal determinant in groundwater risk assessments.

Characterized by short-lived or lack of surface water resources, non-renewable groundwater resources are the dominant viable and economic freshwater source in arid environments such as the MENA region. In the MENA region 76% of freshwater resources are primarily sourced from groundwater systems, of which 65.6% are non-renewable fossil aquifers [*Klingbeil and Al-Hamdi*, 2010]. The majority of the MENA's renewable groundwater systems are located along the region's lengthy coastal plain of North Africa, the eastern Mediterranean, and the Arabian Peninsula. Despite their importance to coastal urban concentrations, renewable freshwater resources are minor relative to the fossil groundwater reserves, which are stored in deep sedimentary basins, and constitute the dominant source of freshwater in the MENA region [*Edmunds and Wright*, 1971; *Shahin*, 2007; *E Wright et al.*, 1982]. According to a study by the British Geological Survey (BGS), fossil groundwater resources in Africa have an estimated volume of more than a hundred times the estimate of renewable freshwater resources, with the largest groundwater aquifers found in the large sedimentary lithologies in North African countries such as Egypt, Libya, and Algeria [*MacDonald et al.*, 2012]. This paradigm extends to the Arabian Peninsula and most of the Levant.

Due to their importance for energy and food security, public health, and socio-economic development, groundwater aquifers are being overburdened by human demand. According to a study by *Richey et al.* [2015a], over a third of the world's largest aquifers are overstressed. A more recent study by *Gleeson et al.* [2016] used numerical simulations parametrized by geochemical, geologic, and hydrological geospatial datasets to demonstrate that less than six percent of global groundwater is modern (< 50 years old). In relation to the Middle East, studies have shown alarmingly large negative trends in total water storage due to significant declines in groundwater storage [*Richey et al.*, 2015b; *Voss et al.*, 2013].

A review of hydrogeological literature of arid environments generally, and the MENA region specifically, reveals two essential observations. First, a minority of groundwater reserves are dynamic – regularly replenished by recharge – within a human lifetime [*Margat and Van der Gun*, 2013]. Second, aquifer systems are overstressed due to groundwater depletion as a natural and unavoidable consequence of groundwater withdrawals [*Konikow and Kendy*, 2005]. Therefore, an assessment of groundwater water scarcity, as an integral component of the groundwater risk index, necessitates the quantitative characterization of both groundwater reserves (volumetric storage) and changes occurring within them.

Methodology

Groundwater reserves were estimated by combining effective porosity values derived from [*McWhorter and Sunada*, 1977] with saturated thickness estimates and the areal extent of aquifer systems (Fig. 3.3). The following equation was used [*MacDonald et al.*, 2012]:

$$\boldsymbol{V_{sc} = A.H_{sat}.\varphi_e} \qquad \text{Equation 3.1}$$

Where V_{sc} is groundwater reserves (km^3), A is surface areal extent (km^2), H_{sat} is saturated thickness (km), and φ_e is effective porosity (dimensionless).

Aquifer saturated thicknesses (H_{sat}) were determined by subtracting gridded depth-to-water table estimates [*Fan et al.*, 2013] from sediment thickness estimations [*Laske et al.*, 2013]. Gridded effective porosity estimates (φ_e) were spatialized by assigning φ_e estimates to their assigned lithological units as developed and mapped by [*Hartmann and Moosdorf*, 2012]. For detailed information on data and methodology, please refer to *Lezzaik and Milewski* [2015].

Terrestrial water storage change (TWS), derived from gravimetric product datasets from the Gravity Recovery and Climate Experiment mission *GRACE* [*Adam*, 2002], were used in conjunction with Global Land Data Assimilation System *GLDAS* outputs [*Hua-lan*, 2011; *M Rodell et al.*, 2004] to generate estimates of groundwater storage change (GWS) (Fig.3). Given that GRACE-derived TWS represents the combined effect of surface and groundwater storage change, separately estimating GWS requires isolating the components by quantifying surface water storage components (e.g. green water) using *GLDAS* followed by their removal from TWS observations [*Chen et al.*, 2014; *Joodaki et al.*, 2014; *Konikow and Kendy*, 2005; *Matthew Rodell* *et al.*, 2009]. For detailed information on data and methodology, please refer to *Lezzaik and Milewski* [2015].

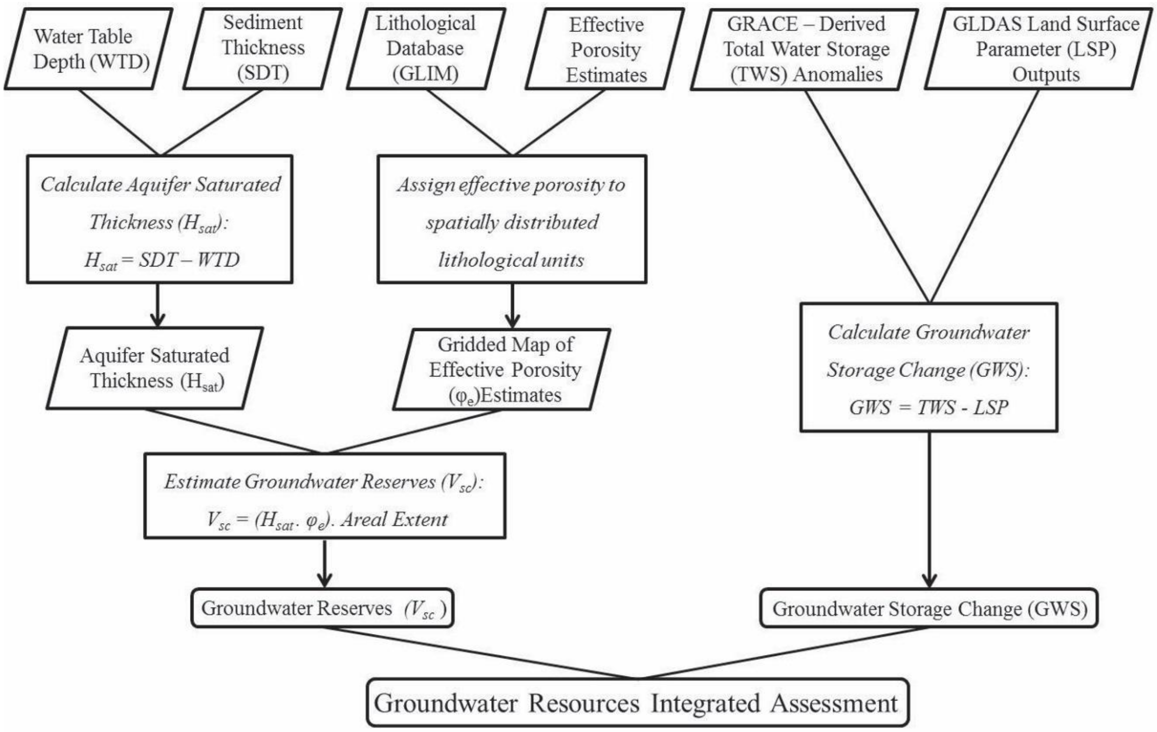

Figure 3.3. Flowchart displaying the methodology behind groundwater reserves assessments and storage change estimates in the MENA region.

3.2.1.2 Governance

Justification

A study by *Srinivasan et al.* [2012] conducted a qualitative comparison analysis on 22 study cases of coupled human-water systems to identify the driving factors behind different water resources system outcomes. The major pathway to groundwater depletion was determined to be unregulated decentralized pumping for irrigation purposes by farmers [*Lichtenthäler*, 2003; *Shah et al.*, 2000] and domestic use by urban dwellers. According to *Srinivasan et al.* [2012], the two underlying drivers behind decentralized pumping are governance related. The first driver is the *"ineffective control over water rights or instream flows (CNTRL)"*, manifesting itself in the lack of extraction limits, poor enforcement of groundwater abstraction, and inadequate and corrupt administrative capacity. The second driver is the *"presence [or lack of] of reallocation mechanisms (REALLOC)"* in the form of water markets, reliable interbasin transfers, and effective water efficiency programs.

It is also essential to examine the role of governance and arrangement capacity in overcoming water scarcity as a driver of further groundwater depletion. A report by *Falkenmark et al.* [2007] highlights policy solutions necessary to ameliorate or overcome real water scarcity. For instance, tackling blue water scarcity requires overarching governance components that would facilitate the best possible utilization of basic water resources, such as reallocation, raw water interbasin transfers, and virtual water imports. These measures fall within the purview of REALLO, one of the main determinants of decentralized pumping as proposed by *Srinivasan et al.* [2012]. Moreover, overcoming water scarcity requires the enforcement of strict demand management measures such as reducing wasteful water use and cutting leaks and losses in the water system [*Falkenmark et al.*, 2007].

While good governance factors are unquestionably essential in ensuring efficient, optimal, and equitable use of groundwater resources; the discipline of groundwater governance, as a newcomer to the water sector, is lacking in any serious discourse on how governance concepts can be directly used to implement effective groundwater management policies [*Biswas and Tortajada*, 2010]. This primarily relates to definitional challenges of governance as a broad multi-dimensional concept with no agreed upon definitions. As a consequence, overall definitions of governance are usually framed according to the specific biases, perceptions, and perspectives of the international organizations and institutions. To illustrate, let's consider the four most well recognized and used government indicators in development literature: the International Country Risk Guide (ICRG) [*PRS Group*, 2001], the World Bank [*World Bank*, 2013], Freedom House [*Freedom House*, 2014], and Transparency International [*Transparency International*, 2011]. Freedom House and Transparency International assess governance through the lens of political rights and civil liberties, and corruption respectively. On the other hand, the ICRG and World Bank consider governance within the framework of financial, economic, and political risk and their effect on international business operations. While some measure of governance is provided, the aforementioned indices all suffer from a lack of transparency, a basis in perception as opposed to actual objective metrics, selection bias, and spatial and temporal comparability issues. More importantly, the theoretical and structural framework of available governance indicators more often poorly reflect water governance effectiveness and offers little practical insight into managing the water sector.

Nevertheless, in relation to groundwater governance, *Ostrom* [2015] offers a general approach to governing common pool resources such as groundwater resources. First, voice and accountability are necessary through governmental recognition of the rights of communities and stakeholders to organized resource. Second, rule of law is required to ensure any collective arrangement for stakeholder participation in the decision-making process. Third, regulatory quality and effectiveness, and control of corruption are pivotal for monitoring groundwater use mechanisms that have been agreed upon and organized through inclusive decision-making processes. They are equally responsible for insuring sanctions on those who violate those rules and mechanisms. Given the multi-layered institutional requirements for groundwater governance as laid by *Ostrom* [2015], the World Bank's *Worldwide Governance Indicators* are best suited for use in our Groundwater Risk Index, since they include five dimensions of governance ranging from the mechanisms of government to efficiently and effectively implement policies (e.g. government effectiveness, regulatory quality) to accountability and rule of law.

Methodology

The overall governance indicator used in *GRI* was developed as a composite of the five governance dimensions considered above: Voice and accountability, government effectiveness, regulatory quality, rule of law, and control of corruption [*Kaufmann et al.*, 2011]. Annual country – level governance datasets between 2003 and 2014 were obtained from the World Bank's open access webpage (http://info.worldbank.org/governance/wgi/index.aspx#reports, accessed on 2/12/2016). The five governance dimensions were then arithmetically averaged to produce the overall governance data, which was then rasterized (0.25-degree) to allow for spatial aggregation with the other indicators composing the risk index.

3.2.1.3 Food Security

Justification

In a globalized and trade-driven economic order, the concept of "virtual water" as developed by *John Allan* [1998], plays an essential role in alleviating water stress conditions prevalent in (semi-)arid environments. In conformity with dominant international trade theory, virtual water trade ensures optimal and efficient water use by allowing water-rich nations (e.g. Canada, Russia) with a comparative advantage in the production, of primarily agricultural products, to export their goods to water-scarce countries at a comparative disadvantage in production. As a consequence, the import of water-use products into arid and water-stressed countries could contribute towards a reduction in the demand for groundwater irrigation and reduce pressures on water-scarce nations' own groundwater resources [*Bouwer*, 2000; *Global Water Partnership*, 2012; *Hoekstra*, 2003].

Scientific and technological advancements played a central role in the spectacular increase in groundwater irrigation in the past fifty years, especially in (semi-)arid countries [*Llamas and Martínez-Santos*, 2005]. As a result, agricultural irrigation accounts for 70% and 85% of groundwater abstractions globally and in the MENA region respectively. Given that agricultural production accounts for the outstanding majority of groundwater abstractions, a *Food Security Indicator* was developed as a proxy measure of entities' capacity to engage in exogenous virtual water trade to supply their populations' dietary and nutritional requirements, as opposed to relying on their predominately stressed and unsustainable fossil groundwater resources.

This paper adopts the FAO's definition of food security as the *"...physical, social, and economic access to sufficient, safe, and nutritious food that meets their dietary needs and food preferences…"* [*World Food Summit*, 1996]. Consequently our food security indicator is based on three main pillars: availability, as a supply concept (do countries have enough physical food supplies to feed a given population?); Affordability, as a concept of economic access (do people have enough income to purchase food?); and quality, as a nutritional concept (do the people have a diversified healthy nutritional profile?). Food availability and affordability were weighed highly given their central and dominant role in determining food security.

The relationship between food security levels and groundwater depletion risk appears to be inverse in nature, given one specific assumption: acceptance of decision and policy –makers in the MENA region that the achievement of national food security through self-sufficiency (i.e. satisfying food demand entirely with domestic food production) is unfeasible – due to extreme physical limitations imposed by arable land and water – but rather requires an integration with global food trade networks with the objective of facilitating efficient, reliable, and secure virtual water transfers. Some argue that the economic basis of the assumption ignores food's role in promoting domestic social stability and justifying government legitimacy [*Lagi et al.*, 2011]. Notwithstanding the truthfulness of these concerns, the authors find that recent assessments of food policy in the MENA region fall in line with our assumption. The MENA region already imports 50% of its food [*Kamrava*, 2005]. The region is the largest importer of wheat in the world at 27% of all globally traded wheat [*Faostat*, 2009; *B Wright and Cafiero*, 2011]. Moreover MENA countries have engaged in the past ten years in expanding their grain storage capacity, shoring up their strategic reserves, and increasing storage-to-use ratios [*Larson et al.*, 2013]. The surge in agricultural commodity prices between 2008 and 2011 – due to high energy prices and demand for biofuels – has energized these efforts as evidenced by the fact that a region with five percent of the world's population now stores approximately 13 percent of global wheat stocks. A recent study by *Antonelli and Tamea* [2015], concluded that most MENA countries are already large net food importers of agricultural products and food commodities.

According to our analysis, reliance on global food trade networks as the backbone of food security policies, as is the case in the MENA region, results in lower demand pressure on its groundwater resources. Countries with higher food security levels are deemed at less of a risk of depleting their groundwater resources as opposed to countries with relatively lower food security.

Methodology

Therefore the food security indicator is a function of affordability, availability, and dietary diversity. Sub-indicators for each pillar of food security were selected based on their impact and their annual data availability between 2003 and 2014. The *Global Food Security Index* by the *Economist Intelligence Unit* [2012] offers the most reliable and informed disaggregation of food security variables, since they were determined, assessed, and weighted via a peer panel process that involved 44 experts on food security issues. Metrics that were weighed highly by the peer committee and to which annual data was available were included as a sub-indicator in our food security index. The authors would like to clarify that while, according to our assessment, the *Global Food Security Index* offers the most detailed and comprehensive measure of food security, its temporal range only extends from 2012 to 2015. Moreover, the Economist's index does not account for a number of countries in the MENA region, such as Libya. Therefore, we created our own index that would provide annual food security assessments between 2003 and 2014 for each MENA country.

Affordability was measured using gross domestic product (GDP) per capita (PPP, USD), obtained from the *World Bank* [2016] and United Nations database (http://data.un.org/, access date: 11/30/2015), to reflect the ability of average individuals to purchase food. Data on food consumption as share of household expenditure and on the proportion of population under the global poverty line are also highly weighted measures of food affordability; however they were not included due to the lack of consistent reliable data for MENA countries. Availability assessments were composed of two sub-indicators: average food supply by intake and volatility of domestic agricultural production .Average food supply by intake (calorie/day/person), as the most direct estimate of the amount of food available for human consumption, was obtained from

Faostat [2016]. Volatility of domestic agricultural production, on the other hand, was calculated by computing the variation coefficient of total domestic agricultural production over the most past 40 years as provided by the *World Bank* [2016]. Average food supplies examine the question as to whether there are enough food supplies in the country to meet food demand, whereas volatility of agricultural products addresses the detrimental impact of agricultural output fluctuations have on managing food supplies, with more fluctuations negatively affecting food availability and security [*Economist Intelligence Unit*, 2012]. A country's agricultural infrastructure, such as crop storage facilities, roads and ports are also an important determinant of food availability. However since infrastructure data was specifically lacking (> 50% missing data), they were not included. Finally, nutritional diversity was measured using estimates of percent of energy coming from non-staples on one hand and a Modified Shannon Entropy on another obtained from *Remans et al.* [2014]. While the former accounts for non-staple foods that tend to be more nutritious, the Modified Shannon Entropy weighs not only the diversity of the food items, but also the diversity nutritional profile amongst those food items [*Remans et al.*, 2011].

To generate the food security indicator, the aforementioned datasets were rasterized into 0.25-degree grids and then inputted into a weighted sum model with a weighting of 44%, 40%, and 16% for food availability, affordability, and dietary diversity respectively as recommended by the *Economist Intelligence Unit* [2012] peer panel recommendation.

3.2.1.4 Groundwater Extraction Energy Cost

Justification

Energy and freshwater resources share mutual dependencies globally and specifically within the MENA region's economic and hydrologic framework, which is often referred to as the "energy – water nexus". As such, water managers and policy – makers should specifically account for energy's impact on water demand and groundwater extraction, especially within the context of arid environments with finite freshwater resources. In the MENA region, the energy-water nexus is highly skewed given the scarcity of freshwater resources and the abundance of energy resources. The wide variation between water and energy resources in the region translates into a disassociation of energy from water supplies, with limited dependence on freshwater in the energy chain from fossil fuel production and refining to electricity generation [*Siddiqi and Anadon*, 2011]. Alternatively, water abstraction, desalinization, and wastewater treatment are highly energy intensive processes responsible for significant energy consumption [*Siddiqi and Anadon*, 2011].

Given that groundwater resources constitute 76% of total freshwater resources in the MENA region, the energy indicator formulated in this paper focuses on quantifying the cost of the required energy needed to extract groundwater from specific depths, and establishing the effect they (energy prices) have on mitigating or exacerbating groundwater depletion risk.

The establishment of a relationship between energy prices and groundwater depletion risk requires a characterization of the response of groundwater extraction rates to changes in energy price. A significant number of studies indicate a strong inverse correlation between increasing energy prices and groundwater demand and extraction. In a study by *Zhu et al.* [2007], a global water and food model used to assess the effect of energy prices on groundwater extraction at global and basin level, found that on average the doubling and tripling of energy prices from a baseline scenario led to a 7.5 percent and 9.1 percent decline in groundwater depletion, respectively. In one case in the Dong Nai Basin in Vietnam, the response of total groundwater withdrawals to the doubling and tripling of energy prices was a decline in groundwater abstraction by 42 percent and 56 percent, respectively. Another study by *Pfeiffer and Lin* [2014], which examined the effect of energy prices on agricultural groundwater extraction in the High Plains aquifer, concluded that high energy prices decreased groundwater use and demand – a response of 3.6% decline in groundwater extraction to a 13.6% rise in energy prices. According to *Shaheen and Shiyani* [2007], increasing energy costs reduces groundwater pumping and achieves prolonged energy as well as groundwater sustainability. It is essential to note that the analysis is predicated upon the assumption that energy prices are the primary variable controlling groundwater extraction and use. The authors are aware of the influence of other factors such as national agricultural policies, crop prices, and the availability of alternative freshwater sources on groundwater use and abstraction. While the inelasticity of groundwater demand to energy prices is affected by other factors, such as crop prices and access to alternative water resources, the fundamental inverse correlation between increasing energy prices and groundwater demand and extraction is sustained.

The developed energy indicator measures the control energy prices and groundwater depths exert on groundwater extraction rates and depletion risks. Based on our analysis, deeper groundwater depths and higher energy prices translate into lower risk of depleting groundwater resources. As groundwater extraction costs rise, groundwater shareholders will have a greater incentive to conserve water (e.g. consumption reduction, adoption of efficient technology) and to resort to alternative sources for economic goods (e.g. virtual water) [*Charalambous*, 2014].

Methodology

To obtain first-order estimates of groundwater cost-of-extraction in the MENA region, groundwater depth data was needed. For this study, we used a global groundwater table (WTD) pattern map developed by *Fan et al.* [2013], which provides 1-km gridded map with depth to groundwater data, generated with a groundwater model parametrized with present climate, terrain, and sea level parameters. The map was aggregated to a 0.25-degree resolution and masked over the MENA region. The amount of energy (kilowatt-hour, kWh) needed to lift water was calculated by multiplying the weight of water with meters of lift [*Réth† áti*, 1983]. A 70% pumping efficiency was assumed. Assuming the pumping was done with diesel pumps, the computed lift energy was then converted into the amount of diesel fuel that would be needed to extract water from different depths. The conversion required two steps. First, the multiplication of the heat rate of diesel (Btu per kWh) by the fuel heat content of diesel (Btu per gallon) required to generate the amount of diesel fuel needed to affect one kWh of energy. Annual heat rate and fuel heat content for diesel were obtained from the U.S. Energy Information Administration's open access database (http://www.eia.gov/electricity, access date: 12/9/2015). Second, the generated datasets in the previous step were multiplied by the gridded map of lift energy in kWh required to extract water from different depths. The final step consisted of monetizing the amounts of diesel required for groundwater abstraction using the World Bank's pump price for diesel fuel by country [*World Bank Group*, 2016]. Given that the prices are given in nominal terms, country-level consumer price indices (CPI) provided by the *World Bank Group* [2016] were used to deflate diesel cost from nominal values to real values.

3.2.2 Imputation of Missing Data

Missing or incomplete datasets are often a frequent hindrance to the development of composite indicators. The problem is more acute in the social science disciplines and in developing regions. Therefore missing data imputation – the process of replacing missing data with substituted values – was a necessary junction in the development of the *GRI*. Fortunately, very limited to no imputation was required with the exception of the food security and governance indicators.

When faced with an incomplete dataset, the first course of action involved searching for alternative reliable sources to fill the gaps in it. For instance, when the GDP per capita dataset from the *World Bank* [2016] was missing values for Syria from 2008 to 2014, values made available by the *United Nation's Statistics Division* were used to fill in the gaps. In other cases, data gaps in some countries were filled by assigning values from other countries in the region with similar typologies (e.g. political, economic, and demographic). For example, missing data on food availability for Qatar were filled with values from Kuwait, given that both countries are gulf monarchies with rich oil-exporting economies and low demographic populations of similar cultural backgrounds. If no reliable alternative sources of data were available; multiple imputation, a general-purpose approach to dealing with missing data, was used to replace each missing value with plausible estimates. The procedure involves running *n* number of iterations and imputing *n* values for each missing cell in your data matrix and creating *n* "complete" datasets. Across the completed datasets, the observed values are the same, however the missing values are filled with a distribution of imputations reflecting the uncertainty in the missing data [*Rubin*, 1979; *Schafer*, 1999; *Schafer and Olsen*, 1998]. An Expectation-Maximization model with bootstrapping model was used to impute missing values given its ease of use, capability of running multiple iterations, and lenient assumptions in relation to data distributional normality [*J Honaker et al.*, 2015]. Its capacity to reduce bias and increase efficiency renders multiple imputation techniques preferable to listwise deletion when dealing with missing data [*James Honaker et al.*, 2011].

3.2.3 Normalization

Prior to integrating the separate indicators into the final composite index, data transformation of the selected variable indicators by way of data normalization was required. To render them comparable, datasets with incommensurate scales and measurement units are transformed into a common scale or measurement unit, in addition to aligning the directional influences of the data on the final outcome [*Booysen*, 2002; *M Nardo et al.*, 2005]. In our index, a Min-Max transformation method was used to normalize our data on a [0, 100] range:

$$x_{i,0\ to\ 100} = \frac{x_i - x_{min}}{x_{max} - x_{min}} \times 100 \qquad \text{Equation 3.2}$$

Where $x_{i,\ 0\ to\ 100}$ is the normalized value, x_i is the original value, x_{max} is the maximum value and, x_{min} is the minimum values across countries. In indicator datasets with a spatial component (groundwater reserves, storage changes and extraction costs), x_i is normalized relative to the highest value x_{max} and lowest x_{min} value within the spatially distributed dataset, with all spatially distributed values between x_{max} and x_{min}, across the MENA region. Whereas, indicators with country-level point datasets (governance and food security), x_{max} and x_{min} are represented by countries with the highest and lowest values, respectively, with county-level x_i normalized between x_{max} and x_{min}.

In addition to being consistent with our data's defined bounds, min-max normalization as a linear transformation preserves the relationships between the data's original values [*OECD*, 2008]. Moreover, the formulation of index data on a [0, 100] range allows for a more intuitive visualization and interpretation of index results for different end-users [*OECD*, 2008].

3.2.4 Weighting and Aggregation

Determining the relative importance of constituent index components requires the assignment of explicit weights during the aggregation process. Following an examination of the various weighting techniques available, it was decided to adopt an equal weighting (EW) scheme for the groundwater risk index. Conventional normative weighting, characterized by ad hoc, expert and consultation based weighting are often singled out for their arbitrariness and their lack of theoretical and/or empirical support [*Booysen*, 2002]. The paucity of subjective weights in index development is ubiquitous since most indices contain components reflecting a unique set of disciplines and perspectives [*Sharpe and Andrews*, 2012].

Moreover the subjective nature of the weighting scheme makes it difficult for experts from different backgrounds to reach a consensus on a given weighting scheme. Multivariate techniques (e.g. PCA), on the other hand, counteract the subjectivity of normative weighting with more empiricism and objectivity. However they suffer from conceptual rigidity by not allowing for control over the selection and weighting of index components [*Ginsburg et al.*, 1986]. As a consequence, index flexibility, which is often preferred in composite indices, is sacrificed. Beyond the limitations of normative and statistical weighting methods, the index's theoretical framework offers no basis for either weighting schemes. Although the data selection process above provides evidence on which components affect groundwater depletion, it does not offer detailed quantitative characterizations ideal for calculating particular weights objectively. In accordance with *Hagerty and Land* [2007], and *Babbie* [1989] the paper argues that in the absence of subjective weightings and adequate justification for particular weighting schemes, EW should be the norm, especially in many of the early composite indices. This assessment is supported by the fact that most indicators rely on EW [*OECD*, 2008]. Some notables examples of indices with EW are the Human development index [*Anand*, 1994] and some versions of the Water Poverty Index [*Sullivan*, 2002].

After the assignment of weights to each component index and weighting them accordingly, component scores required aggregation into a composite score. The two major aggregation methods are linear additive aggregation and non-linear multiplicative aggregation. Additive and multiplicative models have fundamentally different properties as outlined by *Choo and Wedley* [2008], however the choice of aggregation method is determined by whether an index's theoretical framework and choice of components allows for compensability, that is the possibility of an offsetting the bad performance in some dimension with an outstanding performance in another dimension. Linear additive aggregation assumes full compensability, whereas non-linear multiplicative aggregation allows for partial or lower compensability [*Michela Nardo et al.*, 2005; *OECD*, 2008]. This paper argues that a linear additive method is most suitable for the groundwater risk index, based on an assumption of full compensability within the different indicators (i.e. high levels food security and affordability can offset the high risk of groundwater depletion caused by limited physical groundwater reserves). However the use of linear aggregation entails one condition, which is the preferential independence of the variable components constituting the index [*Joint Research Centre-European Commission*, 2008]. Therefore multicollinearity tests between the index's variables were executed to identify any possible conflicts or synergies among the selected phenomena driving groundwater depletion risk. The resultant correlation coefficients, consistently displayed weak to no linear relationships between the variables, ensuring that the aforementioned condition is met, with no inclusion of two or more highly correlated variables ($r > 0.5$) in our groundwater index.

Notwithstanding the issue of component compensability, the paper also argues that weighted additive aggregation is superior to multiplicative aggregation insofar that it renders the index effective and easier for end-users to interpret and use as a function of its simpler construction [*Babbie*, 1989; *Booysen*, 2002].

3.3 Results

The Groundwater Risk Index (*GRI*) was implemented in the MENA region to establish a preliminary first – order holistic measure of groundwater depletion risk. GRI results are presented in a rank score order. Countries scoring highest on the [0,100] scale and lowest on the rank order are identified as experiencing least risk to groundwater depletion. For example, based on an averaged index score over 12 years, Israel and the Palestinian territories are identified as least at risk with a score of 68 (/100) and a rank of one (/sixteen countries). Conversely, Iraq, with a score of 26 and a rank of 16, was designated most at risk.

The four highest ranking (GRI score) countries with extremely low groundwater risk were small, high-income, energy-exporting OPEC countries in the gulf region, in addition to Israel as another high-income OECD country (Fig. 3.4, 3.5). On the opposite end of the ranking spectrum, countries with high risk to groundwater depletion are middle to low income countries with characteristically low governance scores: Syria, Libya, Yemen, and Iraq. Within the two extremes, lie an array of differing countries such as high-income Gulf States (Saudi Arabia, Oman), and high to low middle income countries such as Lebanon and Morocco respectively.

Given the spatially distributed nature of GRI, inter- and intra- country variations in groundwater risk are also presented (Fig. 3.6). Beyond corroborating the aforementioned risk comparisons between MENA countries, the groundwater risk map provides observations into groundwater risk variations within individual countries, as a function of the three spatially distributed index variable components: groundwater reserves, groundwater storage change, and groundwater extraction cost. Moreover, the map highlights the contribution or influence of input factors to risk estimations by country. The influence of each individual indicator on country level groundwater risk outputs were determined using a component inclusion/exclusion sensitivity testing, where GRI is run with the exclusion of one indicator at a time, followed by the comparison of the resultant scores from the testing with the original index scores with all five indicators. The pie charts provide indicator influence on risk estimations in proportional terms, and present an overall idea of what is driving groundwater risk in each respective country. Additionally, the paper also presents the effect of each individual indicator on groundwater risk quantitatively, by displaying the change to the original GRI scores as a function each indicator (Table 3.1). Figure 3.6 and Table 3.1 are integral in determining the best approach to mitigating groundwater risk by providing a breakdown of the driving forces behind it.

Since GRI was applied on an annual time step, changes in country-level groundwater risk rankings are available between 2003 and 2014 (Fig. 3.7). All of the 16 countries undergo varying degrees of change in rank. A comparison of risk ranking in 2003 and 2014 displays the largest shifts occurring in Kuwait (-4), Syria (-3), Jordan (+3), and Yemen (+3).

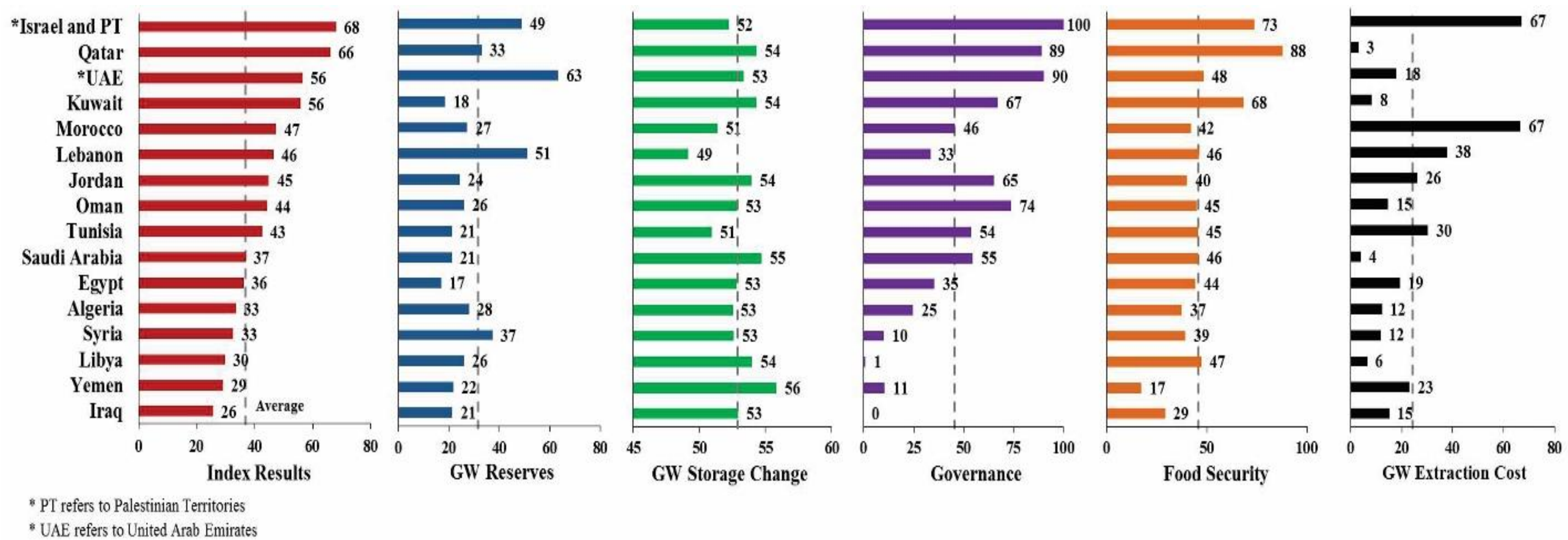

Figure 3.4. Average normalized scores of the final GRI results and its constituent variable components between 2003 and 2014. Higher normalized scores indicate lower groundwater depletion risk (e.g. Qatar). Lower normalized scores correspond to higher groundwater depletion risk (e.g. Yemen). The dashed grey lines indicate the 12-year average regional score.

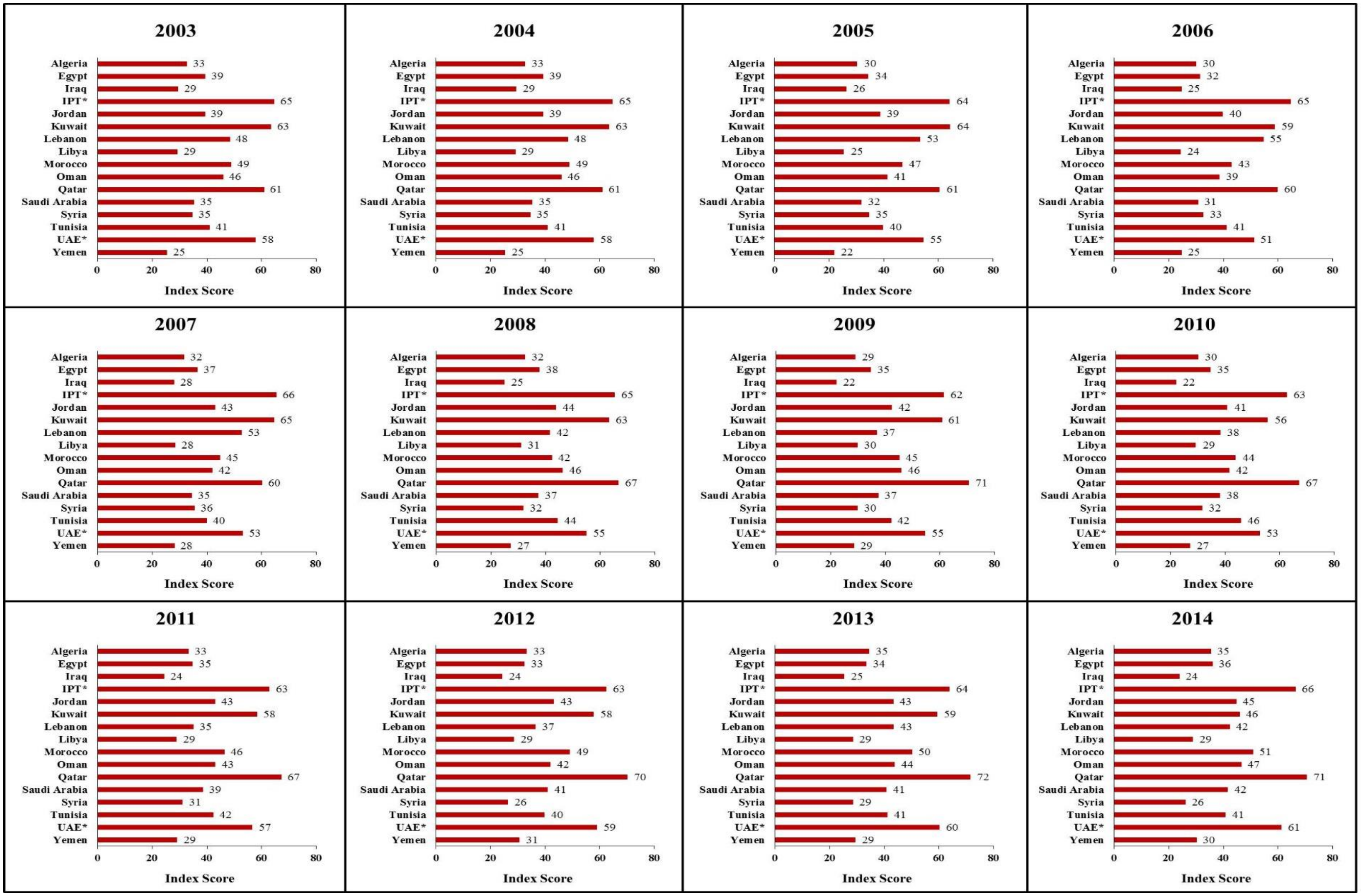

Figure 3.5. Annual normalized groundwater risk scores for MENA countries.

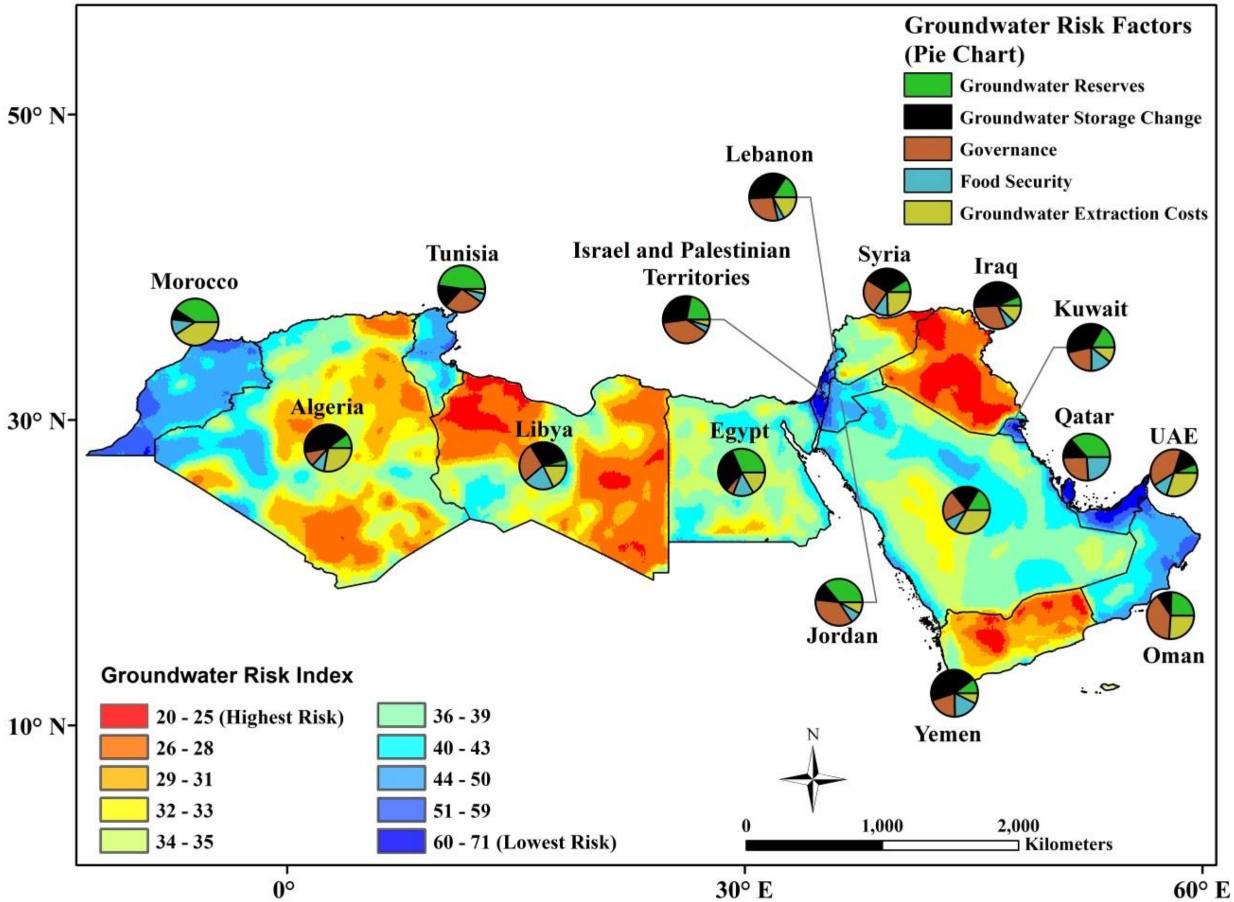

Figure 3.6. Average spatial variations in groundwater depletion risk across the MENA region between 2003 and 2014. The pie charts represent the impact of individual indicators on groundwater risk outcomes in each country as determined by component inclusion/exclusion sensitivity analysis.

Table 3.1. Individual indicator impact on country groundwater risk outcomes as determined by indicator inclusion/exclusion testing. Indicator impact is quantified using percentage change to original GRI scores caused by the inclusion/exclusion of each indicator from the baseline GRI configuration. The +/- signs determine the directionality of the impact with positive percentages indicating a positive contribution towards higher scores, and vice versa.

Country	GW Reserves	GW Storage Change	Governance	Food Security	GW Extraction Cost
Algeria	-3.5%	14.6%	-3.6%	3.0%	-9.5%
Egypt	-12.8%	13.0%	2.2%	5.8%	-6.8%
Iraq	-4.0%	27.4%	-18.9%	3.9%	-7.6%
Israel & PT	-6.0%	-8.3%	10.7%	1.3%	1.2%
Jordan	-12.1%	4.1%	12.2%	-2.6%	-2.7%
Kuwait	-5.5%	-12.2%	7.1%	4.7%	-3.5%
Lebanon	2.1%	4.6%	-3.7%	0.6%	2.3%
Libya	-3.1%	20.8%	-19.3%	14.8%	-12.6%
Morocco	-11.1%	1.6%	0.4%	-3.0%	11.1%
Oman	-11.0%	4.4%	17.8%	0.2%	-11.7%
Qatar	-16.7%	-6.3%	11.7%	10.9%	0.0%
Saudi Arabia	-10.3%	12.2%	13.7%	5.8%	-21.0%
Syria	4.6%	16.4%	-12.3%	5.1%	-12.5%
Tunisia	-13.1%	4.2%	7.5%	1.7%	-0.9%
United Arab Emirates	2.4%	-5.2%	14.6%	-4.1%	-11.3%
Yemen	-5.8%	25.1%	-11.4%	-9.8%	4.1%

PT refers to Palestinian Territories; GW refers to groundwater

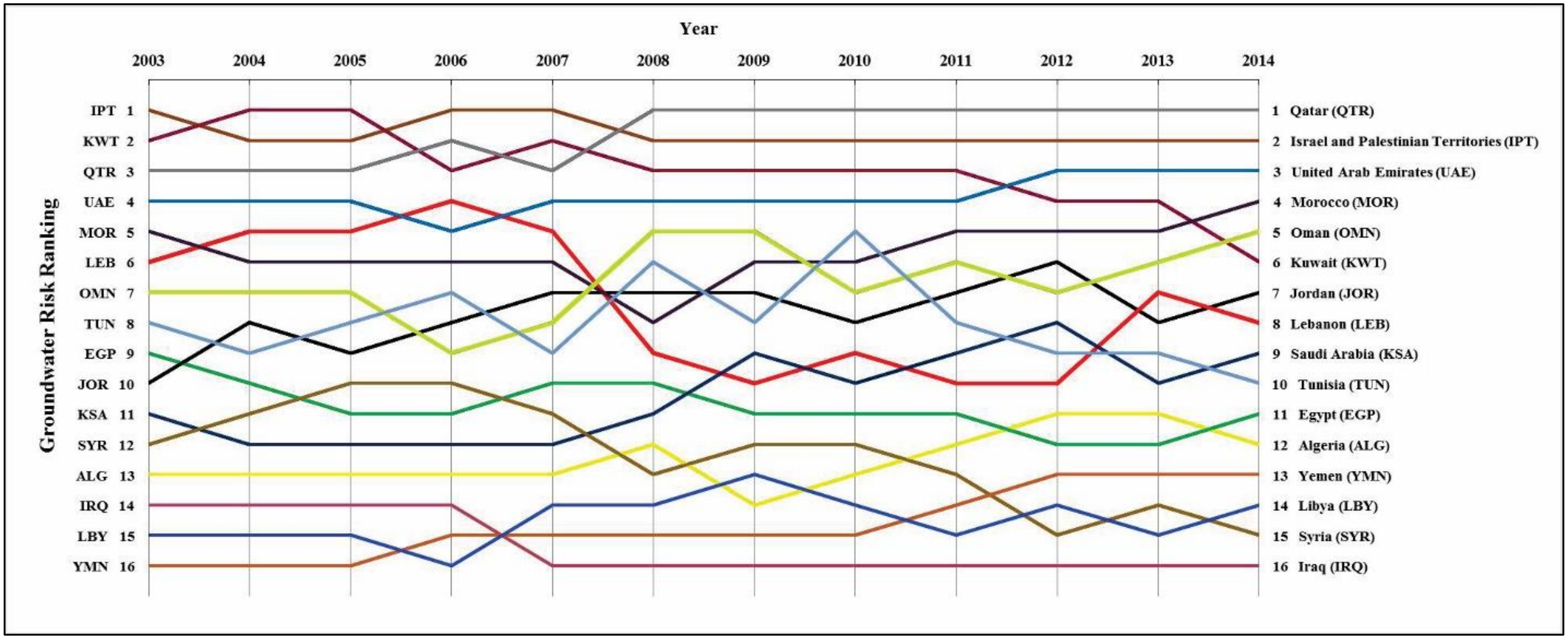

Figure 3.7. Bump graph displaying annual temporal changes in groundwater risk rankings for MENA countries between 2003 and 2014.

Moreover, a closer observation of risk ranking shows a stable period of relatively minor changes between 2003 and 2007, followed by heightened levels of rank change post 2007 in countries located within the middle section of the ranking spectrum such as Saudi Arabia, Lebanon, Tunisia, and Egypt (Fig. 3.7).

3.4 Discussion

The authors' discussion of the study examines identifiable relationships and patterns between groundwater risk outcomes and the index's independent variables. Consequently, a conceptual framework is necessary to advance our understanding of the causes, controls, and solutions to groundwater depletion risk. As a corollary, the authors propose the identification of typologies – nominal level categorizations that summarize two or more variables – to organize the interpretive process and to facilitate comparative analysis essential for identifying the causal processes involved in exacerbating or ameliorating groundwater risk. The authors identified typologies based on characterizations of groundwater systems and of political economies.

Given the predominance of fossil groundwater systems in the MENA region, countries are organized into 2 major groups: those with rich versus poor non-renewable groundwater allocations. The categorization is based on total groundwater reserves as estimated by *Lezzaik and Milewski* [2015], with the MENA regional average as a threshold – countries with higher than regional average groundwater allotments are considered groundwater rich, and vice versa (Fig. 3.8).

From a political economy perspective, countries were categorized by their average gross national income between 2003 and 2014, as provided by the *World Bank Group* [2016] into three major categories: high income (e.g. Kuwait, Oman), middle income (e.g. Lebanon, Libya), and low income (e.g. Syria, Yemen) countries. Also, granted the strong positive correlation (r = 0.7) between income and governance, these income classifications accounted for governance levels, with higher income countries reflecting higher governance levels, and middle to low income countries reflecting lower governance capacity.

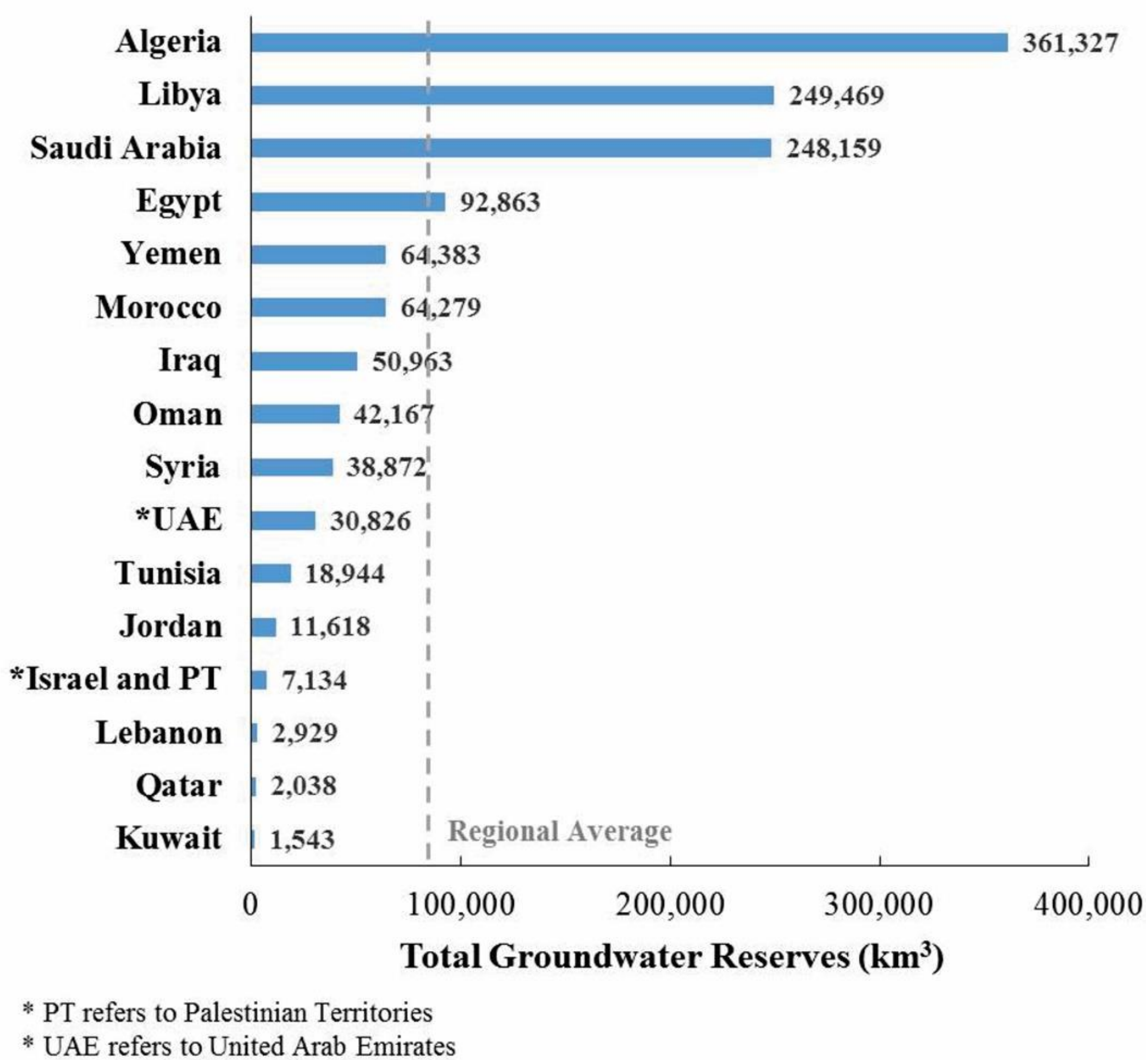

Figure 3.8. Total Groundwater Reserves by MENA country. The grey dashed line represents the regional average.

According to our typology of the MENA region, countries were organized into five distinct groups (Fig. 3.9). High income countries with responsive governance systems and poor groundwater systems (group 1) consistently demonstrated the least groundwater risk in the region. Saudi Arabia (group 2) stands out as an anomaly since its designation as a high income country is further supported by its large groundwater endowment. Analysis of the *GRI*'s variables reveals that Saudi Arabia's governance score is slightly above the regional average score but significantly behind the governance scores of high income countries in group 1 such as Israel and Qatar. Moreover, Saudi Arabia's lower GNI per capita at approximately $17,000 – vis-à-vis Kuwait and Israel, for example, at $42,000 and $27,000 respectively – compromises affordability as a main determinant of food security, thus bringing down its score down to the regional average. Lower governance and food scores are further exacerbated by Saudi Arabia's second lowest groundwater energy extraction costs due to its entrenched domestic energy subsidies program [*Alyousef and Stevens*, 2011]. All these considerations combined account for the moderately high risk of groundwater depletion in Saudi Arabia despite its massive underground aquifers.

As we shift our examination to low and middle income countries with less responsive governance institutions (group 3, 4, and 5), we immediately notice higher levels of groundwater risk. Middle income countries with low groundwater endowments (group 3) display some variance in their risk ranking. For example, Morocco displayed moderately low levels of groundwater risk – despite relatively poor groundwater resources and constrained governance and food security scores – as a function of having the highest groundwater extraction costs in the region due to its status as a major energy importer. This category is also shared by countries with higher risk such as Tunisia.

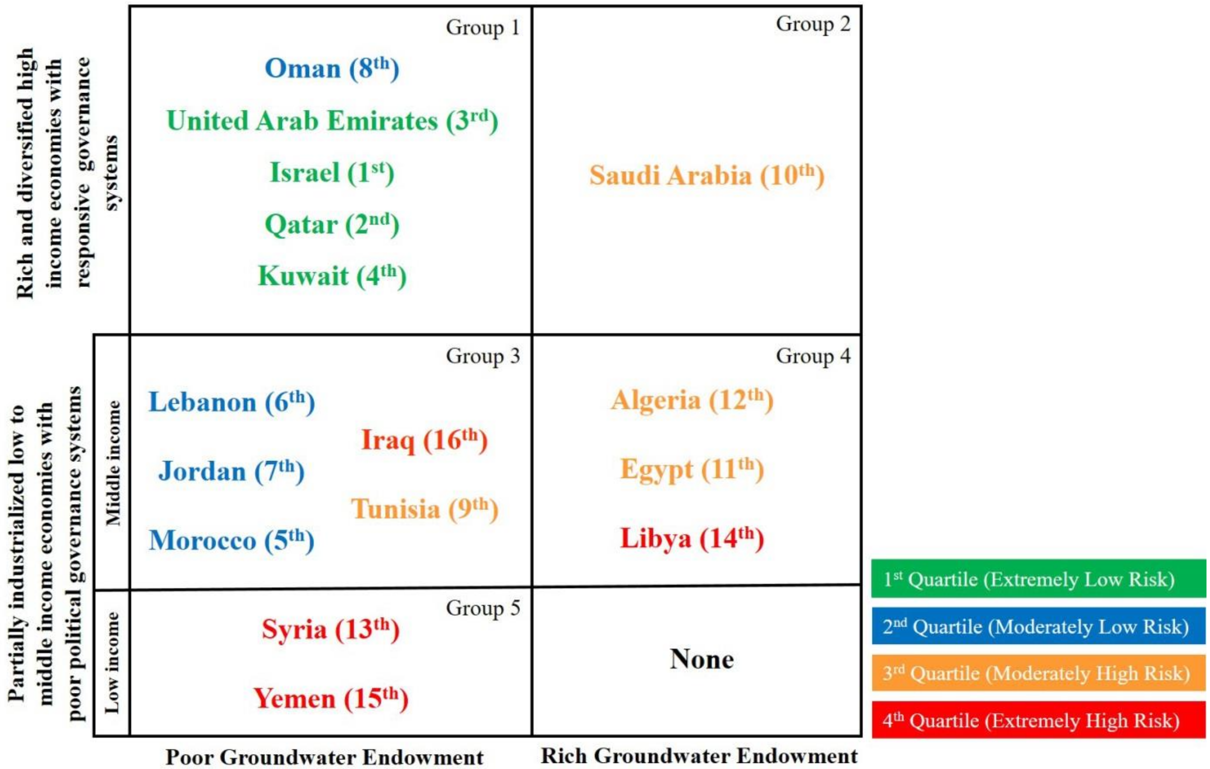

Figure 3.9. A typology of MENA countries by hydrological systems and political economies, useful for interpreting patterns of groundwater risk. Each country is placed in its group classification with its respective overall rank amongst the 16 MENA countries.

Another intriguing observation is the relatively high levels of groundwater risk in group 4 with middle income countries with corresponding extensive groundwater resources such Algeria and Egypt (Fig. 3.8), due to lower governance and food security levels on one hand and low energy extraction costs on the other (Fig. 3.4). Last but not least; Iraq and Libya, despite their middle income categorization, have the highest groundwater risk in the entire region. Not surprisingly this relates to the ongoing breakdown of these nations' states, institutions, and governance capacity following the second Gulf war in 2003 and the Libyan civil war in 2011, respectively. The same applies to less developed Syria and Yemen (group 5) that have been embroiled in destabilizing domestic conditions and conflicts since the “Arab Spring” in 2011. Gaps in governance translate into lower level of food security given the centrality of national scale governance in food production, consumption, and trade [*Pinstrup-Andersen et al.*, 2001], which in turn further exacerbates groundwater risk estimates.

The organization of the interpretive process using the aforementioned typology presents us with three fundamental key points explaining the causal factors impacting groundwater risk. Firstly, groundwater allocations are an ineffective determinant of groundwater risk. This is clearly observable within the various typological categories (Fig. 3.9). For example, countries displaying the lowest groundwater risk are consistently the least endowed in terms of groundwater reserves (Fig.7), such as Qatar and Kuwait. Alternatively, Algeria, Egypt, Libya, and Saudi Arabia exhibit moderate to extreme high risk, despite collectively accounting for approximately 75% of the region’s total groundwater reserves. The preceding point is supported by strong evidence that groundwater endowments do not determine the manner with which they are utilized and managed [*A Allan*, 2007]. It is such realizations that led, for example, to the development of concepts of physical and economic water scarcity which differentiate between the natural inability to meet water demands and the “anthropogenic” inability to meet that demand due to the lack in institutional capacity, investment in water infrastructure, and other various factors.

If groundwater allocations are poor determinants of groundwater risk, then what are good determinants? As demonstrated by group 1 (Fig. 3.9), a combination of competent and efficient governance, and developed high income economies appears to be the best prescription to mitigating groundwater risk. The provision of good governance allows for not only developing supply-side engineering (e.g. recharge enhancement) and demand side interventions (e.g. water savings measures), but also allows for the selection and implementation of different management instruments such as macro-policy adjustments (e.g. reducing pumping energy subsidies) and regulatory provisions (e.g. groundwater access and use codes) [*Foster et al.*, 2009]. It is essential to note however that the translation of governance capacity into actionable plans requires political will to exercise control of excessive groundwater abstraction, which sometimes might not be present, as is the case in some gulf countries. Economic and fiscal strength allows for the circumvention of the constraints posed by limited freshwater resources and arable land, via greater integration with international trade to access “virtual water” crop imports. High income economies, not only address affordability as an essential backbone of food security, but also allows for the dispensation of resources to enhance food availability by investing in strategic reserves, agricultural infrastructure, and agricultural research and development. The third and last key point extends the previous argument to ascertain the centrality of governance in groundwater risk determination. As clearly indicated in typological groups 3 to 5 (Fig. 3.9), the worst scored and ranked countries in terms of groundwater risk, governance and, food security scores are also ranked as one of the most vulnerable by the *Failed States Index* [*Haken et al.*, 2014]. According to the index; Syria, Libya and Yemen – all falling within the “Alert” category – visibly display a worsening in the provision of public services after domestic destabilization following 2010. These observations are supported by a sharp drop in governance scores, food security scores, and in overall worsening of groundwater risk rankings after 2010 with Syria and Iraq dropping three and two ranks respectively between 2003 and 2014 (Fig. 3.7). The rank rise in Yemen and Libya is a relative change in ranking due to the worsening of conditions in Syria and Iraq, and does not represent actual improvement in conditions pertaining to groundwater risk.

Notwithstanding the peculiarity of conditions within individual MENA countries, our reading and analysis of *GRI*'s results in the MENA region helps outline overall policies necessary to not only mitigate groundwater depletion risk, but also to facilitate socio-economic growth and prosperity within the context of limited groundwater resources here and worldwide. As a consumer of 85 percent of withdrawn freshwater in the MENA region, food production is central to water management in the MENA region. Given the region's inability to sustainably grow its own food using its limited water resources and arable land, the authors argue for addressing groundwater risk through economic systems in addition to through hydrological systems, with the placement of a premium on secure, efficient, and reliable agricultural trade. From a physical hydrologic perspective, countries can mitigate their groundwater depletion risk by artificial recharge, exploration of untapped groundwater potentialities [*Sultan et al.*, 2011] , utilize and develop freshwater lens [*Milewski et al.*, 2014], and investigate potential weather and climatic shifts [*Milewski et al.*, 2015]. With wheat constituting the major staple commodity in the region, water-scarce MENA countries are at an advantage, given the highly subsidized and effected nature of global wheat trading system [*J A Allan*, 1997]. However, there is room for enhancing MENA food security in light of future challenges. One such challenge is the expected continuation of high and volatile food prices as a function of demand factors such as increased consumer demand and growth in biofuels, and of supply factors such as natural resources scarcity. In dealing with agri-trade price volatility, MENA governments can attempt to either intervene to reduce price volatility or accept price volatility and set coping mechanisms in place. One course of action involved in decreasing price volatility is the establishment of early warning systems and enhanced market information systems to allow for early planning by governments and the private sector to address any disruptions in food supplies associated changes in food supplies [*FAO*, 2012]. These agri-trade information networks, in enabling the tracking of information ranging from agricultural production forecasts to food prices and markets, would allow MENA governments to assess their needs, facilitate and finance food safety nets, and organize emergency food reserves in a timely fashion[*FAO*, 2012]. Conversely, MENA governments can cope with food price volatilities through the expansion of their strategic food buffer stocks, which can be released when global food supplies are low and prices high, and built up with reverse conditions. Following the 2007 – 2008 food crisis, many MENA countries became aware of their vulnerability to grain markets, and as a consequence have embarked upon investing in the expansion of their strategic grain reserves capacity and in increasing their food storage-to-use ratio [*B Wright and Cafiero*, 2011]. All the preceding recommendations require effective and strong governance as a precursor to greater policy planning and predictability essential for mitigating price volatilities. Developmental economics is as essential. Since low-income countries are more vulnerable to unstable food prices than high income countries, given that the former spend a larger share of their income on food consumption than the latter, equitable macroeconomic growth is recommended as a long term-solution to food security in low-income countries, such as Syria and Yemen. Meanwhile oil-exporting high-income countries in the Gulf should proceed from proclamations on economic diversification, to the actual implementation of these economic reforms if they are to sustainably maintain their food security.

3.5 Conclusion

The study presented here is unique in terms of constructing a spatially-variable composite index, designed to assess and evaluate groundwater depletion risk by combining different data, models, and tools. *GRI* sets a precedent by being the earliest index to approach multi-dimensioned groundwater risk evaluations from environmental and politico-economic perspectives. The strength of our index lies in its consistent methodology that allows for inter-country comparisons without being affected by differences in approach. The drawback of *GRI* results in the MENA region specifically, lies in the difficulty of validating the theoretical framework and methodological constructs of the, index due to a lack of access to meaningful engagement and significant input from officials, stakeholders and experts in the MENA region, specifically with regards to issues on governance, food security, and the water-energy nexus. Moreover the regional scale of this study would make any possible validation less detailed than would be possible with smaller areas and/or had a mono-disciplinary approach been followed.

Results from the study clearly show that for the MENA region, groundwater reserve characterizations are poor determinants of groundwater risk conditions. Contrary to expectations, countries with high groundwater endowments such as Saudi Arabia, Algeria, and Libya often displayed higher levels of risk as a consequence of offsetting low performances in the areas of governance, food security, and water energy extraction costs. Alternatively, good governance consistently predicted low levels of groundwater risk. In addition to the reallocating groundwater resources and enforcing limitations on groundwater extractions, effective governance allows for better food security. Due to the high correlation between them, governance often translates into higher economic incomes that not only enhance food affordability and availability, but also allows for structural shifts from water-intensive agricultural based economies to more water-efficient industrialized economies. To summarize, the achievement of food security via effective governance, economic growth, and integration into global agricultural trade markets and agreements, is the most efficient and optimal way to mitigating groundwater depletion with the hydrogeological and socio-economic context of the MENA region.

In this study, the authors designed, developed, and implemented *GRI* as a preliminary tool to help academics, governmental institutions, and policy-makers alike to spatially screen, assess, and evaluate groundwater depletion within water scarce (semi-)arid environments. Advancement beyond these preliminary stages should focus on the verification and validation of the index's conceptual framework, component selection, methodology, preferably by a multi-disciplinary and sectoral peer committee of experts, academic, and policy-makers. To aid in this process, the authors would also recommend applying *GRI* at a national-level, where the index can be further constrained with more consistent and accurate national datasets.

Given the index's theoretical framework, which was based on a comprehensive and multidisciplinary conceptualization of the determinants of groundwater depletion, the index can easily be used in globally in groundwater-dependent regions. Moreover the the structural flexibility of the groundwater risk index, would allow for modifications and alterations to suit specific circumstances outside our study area. Consequently, the groundwater risk index, is a unique screening tool for policy-makers, allowing them to not only highlight areas and communities vulnerable to groundwater depletion, but also aids them in mitigating it by deconstructing the causes driving groundwater degradation.

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CHAPTER 4

SENSITIVITY ANALYSIS OF THE GROUNDWATER RISK INDEX IN THE MIDDLE EAST AND NORTH AFRICA REGION

Lezzaik, K.A., and A.M. Milewski (2016), Sensitivity Analysis of the Groundwater Risk Index in the Middle East and North Africa Region, *Water Resources Research (Submitted).*

Abstract

Composite indicators have become increasingly popular tools for assessing and measuring multidimensional phenomena, and comparing performances between countries. Yet critics of composite indicators often highlight doubts about the robustness of resulting country scoring and ranking, and the associated risk of recommending erroneous and misinformed policy messages. This paper discusses the methodological judgements made during the development of the Groundwater Risk Index (GRI), by using a one-factor-at-a-time (OFAT) sensitivity analysis to examine the impact of different methodological choices on GRI scores, as well as the associated changes in rank. The focus is on GRI's output sensitivity to the selection of subindicators, choice of normalization scheme, and choice of aggregation method. OFAT sensitivity results clearly display GRI's independence from either the selection of constituent subindicators or the choice of alternate normalization schemes, thus affirming the index's robustness. Conversely, GRI proved to be highly sensitive to arithmetic and multiplicative aggregation methods, given the methodological difference in how they conceptualize, reward, and penalize subindicator performance, interactions, and tradeoffs. The execution of the index using both arithmetic and geometric means, results in outputs that are complementary to each other and highlight different perspectives on groundwater depletion risk. Consequently, the authors highlight the importance of accurately understanding and conceptualizing the modes of interaction between different subindicators in determining groundwater risk – reflected in the choice of aggregation method – in developing coherent and representative theoretical framework.

4.1 Introduction

Composite indicators, often referred to as indices, have witnessed a dramatic expansion in the past decade as a result of their increased use by governments, think tanks, and national and international organizations for assessing multi-dimensional and interdisciplinary concepts such as human development, governance, and environmental degradation [*Foa and Tanner*, 2012]. A review is available by *Saisana and Tarantola* [2002]. Moreover, composite indices have become popular tools for policymaking in wide ranging fields by allowing for a platform for comparative analysis and the benchmarking of countries' performances on elusive policy issues [*Cherchye et al.*, 2006]. A survey of inter-country composite indices by *Bandura* [2008], found that of the approximately 180 indices developed, 50% were in the previous five years alone, as opposed to less than 20% before 1990.

Composite indicators are calculated by combining well-chosen subindicators into a single index, on the basis of a conceptual framework dictated, by what is being measured, under what conditions, and for what intended purpose. The construction of an index and the computation of a final index score is most often achieved by normalizing the subindicators' values, weighting subindicators' scores, and aggregating them into a final index using an additive mathematical function.

Notwithstanding their favorability amongst different organizations, Composite indicators remain a point of contention between their supporters and critics, with both sides arguing the pros and cons of using them. A discussion by *Saisana and Tarantola* [2002] accurately summarizes both perspectives. The popularity of composite indices is primarily explained by their ability to provide the big picture by effectively summarizing complex multi-dimensional issues. Moreover the provision of a single score or estimate of whatever is being measured, makes composite indices have a significant ease of interpretation vis-à-vis the use of multiple benchmarks [*Foa and Tanner*, 2012]. Furthermore, indices enable progress assessment over time, and the performance of meaningful international comparisons. Consequently, indices functionally provide support for decision makers, and facilitate communication and debate with the general public [*López-Claros*, 2010]. On the other hand, critiques of composite indices focus primarily on the consideration of the relationship between methodological decisions and outcomes taken in their construction. Some scientists argue that poorly constructed and misinterpreted indices may propose misleading and non-robust policy messages, whereas others point out to the risk of extrapolating simplistic policy recommendations on the basis of simple big picture summarizations of complex phenomena [*Saisana et al.*, 2005]. Yet, most critics cite the underlying developmental methodological process of composite indices as the fundamental reason behind their unreliability as policy-informing tools [*Cherchye et al.*, 2006; *López-Claros*, 2010; *Saisana and Tarantola*, 2002]. Despite some similarities with mathematical or computational models, composite indices involve more stages where subjective judgements have to be made, compared to other models were scientific rules are more universally accepted [*Cherchye et al.*, 2006]. Key decisions, informed by subjective judgments and decision-making, are made at the different stages of index design and construction, ranging from the selection of subindicators to the selection of a normalization method, weighting scheme, and aggregation approach for the composite index.

As a result of their increased use and influence within different organizations at national and international levels, composite indicators and their various methodologies have been receiving substantial attention and demand to address the aforementioned issues. Indeed, according to *Saisana and Tarantola* [2002], the consideration of sensitivities associated with the data and methodology is discussed in very few composite indices.

In this paper, the Groundwater Risk Index will be considered as a case study. The Groundwater Risk Index (GRI) was created by *Lezzaik et al.* [2016], as an acknowledgment that sole assessments and characterizations of hydrological systems, mechanics, and limitations are not enough to capture and assess groundwater risk – the probability of an entity to experience detrimental degradation of groundwater resources, primarily groundwater depletion. Under that assertion, the GRI operationalized the concept of groundwater risk by combining hydrogeological assessments of groundwater reserves and storage changes, with governance, food security, and energy costs into a composite index. The authors aim to provide an answer as to whether individual subindicators, and alternate normalization and aggregations methods in the development of the composite indicator (e.g. the original *Groundwater Risk Index*) provide a biased picture of countries' risk ranking, and to what extent do they affect the countries' ranks with respect to the original GRI. This paper analyses the robustness of this measure, by assessing the impact of different methodological choices on both GRI country scores and associated rank changes.

First we briefly review the methodological judgements and choices that were incorporated in the building of the GRI, i.e. subindicator normalization, weight assignment, and aggregation methods. Second, we performed a sensitivity analysis on all decisions that are justifiable neither by theoretical reasons nor by data properties.

4.2 Review of GRI Methodological Choices

Theoretical Framework and Subindicator Selection

The GRI is a composite indicator that was developed and is described in detail by *Lezzaik et al.* [2016]. The paper argues that groundwater risk extends beyond the physical characterizations and limitations of groundwater systems, to include societal adaptive capacity criteria. The GRI composite indicator was designed to help countries to spatially and temporally assess hotspots of groundwater depletion risk in semi-(arid) environments. Moreover, it enables countries to compare and benchmark groundwater risk and its determinants, by allowing them to assess their position relative to others. GRI advances itself as a national or regional screening tool that provides easily interpretable assessments on the basis of a single composite measure. Indeed, GRI results are to be followed up by individual country-level analysis of the factors driving groundwater risk. The design of the index reflects two key concerns. The first is determination of the dominant determinant factors underlying groundwater risk (is it physical groundwater endowments, politico-economic adaptive capacity, or both?). The second is the comparison of groundwater risk levels across all countries, and the possible identification and extrapolation of policy recommendations, especially to poorly ranked, high risk countries. To accomplish this, GRI focuses on five dimensions:

a) **Groundwater Storage Reserves:** characterized as groundwater supply availability, constitute the principle and objective natural framework on which groundwater risk can be conceptualized and measured. An accurate quantitative characterization of groundwater reserves was achieved by integrating distributed saturated aquifer thickness estimates with gridded effective porosity values [*Lezzaik and Milewski*, 2015].

b) **Groundwater Storage Changes:** as a consequence of human consumption, groundwater is overburdened, where 30% of the world's largest aquifers are overstressed and undergo little to no natural replenishment [*Richey et al.*, 2015a; *Richey et al.*, 2015b]. Groundwater storage change estimates were calculated by disaggregating GRACE-derived terrestrial water storage data, using GLDAS-generated land surface parameters [*Lezzaik and Milewski*, 2015].

c) **Governance:** decentralized pumping, caused by poor governance, is one of the primary drivers of groundwater depletion. *Srinivasan et al.* [2012] argues that poor governance translates into a lack of water reallocation mechanisms, and an ineffective control over water rights and flows, which consequently drives decentralized pumping by rural and urban dwellers. The World Bank's *Worldwide Governance indicators* [*Kaufmann et al.*, 2011] were used to generate aggregate governance scores, based on five different dimensions (e.g. rule of law, government effectiveness).

d) **Food Security:** with the globalization and internationalization of trade, food security – translated as a secure and effective reliance on global food trade networks – results in reduced demands and pressures on local, national and regional groundwater resources. The food security subindicator is a proxy measure of countries' capacities to rely on exogenous virtual water trade to meet a population's caloric requirements by relying on domestic food production based on the stressing limited local groundwater resources. The three pillars of food security – affordability, availability, and dietary diversity – were calculated, using data from the *World Bank* [2016], *Faostat* [2016], and independent studies, followed by their integration into an overall measure of country-level food security.

e) **Groundwater Extraction Cost:** within an energy-water nexus framework, where groundwater abstraction, conveyance, and treatment are highly energy intensive processes responsible for significant energy consumption, energy costs influence groundwater extraction rates and affect associated groundwater risk. Numerous studies have established a negative correlation between increasing energy prices and groundwater extraction rates [*Pfeiffer and Lin*, 2014; *Zhu et al.*, 2007]. The developed subindicator measures groundwater extraction costs as a function of country-level diesel energy prices provided by *World Bank Group* [2016] and groundwater table depths modelled by *Fan et al.* [2013].

A detailed explanation of the underlying methodologies for each dimension is found in *Lezzaik et al.* [2016].

Normalization

A selection of different subindicators always presents a typical feature in most composite indices, i.e. the display of the various subindicators in diverse measurement units. GRI's authors dealt with this problem by *normalizing* the original data, using a linear transformation method that re-expresses the original value for each subindicator on a unitless scale from 0 to 100, with the following formula:

$$\boldsymbol{N_{q,c} = \frac{x_{q,c} - min(x_q)}{range(x_q)} \times 100} \qquad \text{Equation 4.1}$$

Where $N_{q,c}$ represents the normalized value of the subindicator q for country c, *and* $x_{q,c}$ represents the raw value of the subindicator q for country c.

Weighting

GRI attaches equal weights to each dimension of groundwater risk, on the grounds that they are all worth the same. However, it should be noted that the assignment of relative importance to subindicators representing different perspectives on what is being measured, remains ones of the most difficult subjective assessments that are undertaken in building composite indices. The decision to use an equal weighting scheme is discussed in more detail later in the paper.

Aggregation

An additive simple arithmetic mean model was selected to aggregate the subindicators into a final index:

$$\boldsymbol{CI_c = \sum_{i=1}^{n} W_q N_{q,c}} \qquad \text{Equation 4.2}$$

Where CI_c represents the composite score of country c, $N_{q,c}$ represents the normalized value of subindicator q for country *c, and* Wq represents the weight of the subindicator q.

The aggregation method was selected on the basis of GRI's theoretical framework that allows for compensability and trade-offs between different subindicators [*Aguna and Kovacevic*, 2010]. Moreover, for the purpose of facilitating ease of interpretation, additive aggregation methods are superior to multiplicative methods, insofar as rendering the GRI effective and practical for use by different end-users.

4.3 GRI Sensitivity Analysis

In the preceding section, we briefly outlined the original GRI model ($GRI_{Original}$), as one that calculated groundwater risk from a set of subindicators that were rescaled using a *min-max normalization*, assigned an *equal weighting scheme*, and aggregated into a final composite index score using a *simple additive arithmetic mean function*. This section focuses on describing and discussing the steps undertaken to assess the robustness of the design behind $GRI_{original,}$ by formally considering the sources of sensitivity in the index's input factors, and their effect on the index's output values.

Firstly, we identified and assessed the sources of sensitivity. Generally, sensitivities in the development of composite indicators might arise from some or all of the following constructive steps involving subjective judgement and decision-making:

i. subindicator selection
ii. data selection and editing
iii. data normalization
iv. subindicator weighting scheme
v. index aggregation function

The determination of the relative importance and the proper balancing of the plurality of perspectives through explicit weighting of different subindicators, remains the most contentious problem in building composite indices. Conventional normative schemes, in which weights are assigned on the basis of ad hoc expert consultation, are markedly criticized for both their arbitrariness and lack of theoretical and empirical support [*Booysen*, 2002]. Moreover, agreement over subjective weighting in composite index development is rare, since most indices contain subindicators reflecting a disparate set of disciplines and perspectives [*Sharpe and Andrews*, 2012]. On the other hand, complex multivariate statistical analysis sacrifice the functionality and the objectives of composite indices by imposing a conceptual rigidity on the selection and weighting of subindicators, and by inhibiting any easy of interpretation of index results [*Cox et al.*, 1992; *Ginsburg et al.*, 1986]. Beyond the limitations of normative and statistical weighting methods, the authors of GRI were limited by lack of resources to access societal and expert viewpoints, necessary to assign weights using participatory approaches such as the Beneficiary Assessment or Analytic Hierarchy Process. Since alternative weighting schemes are unfeasible, given the practical obstacles (lack of access) to subjective weightings, and the conceptual impediments to multivariate analysis, sensitivity analysis dealing with subindicator weighting is unexecutable within this study.

In this work, we focus on three sources of sensitivity within the GRI building process: the selection of subindicators, the type of normalization, and the aggregation scheme.

Subindicator Selection

Composite indicators are developed and their components selected on the basis of the underlying theoretical framework and empirical observations of the phenomenon being assessed. Many composite indices, especially in their earlier phases, describe phenomena whose theories and conceptual frameworks are still under development, as is the case with GRI. As a consequence, GRI's component choices are potentially debatable and present a source of sensitivity to the underlying phenomenon being assessed.

To assess the sensitivity associated with the choice of subindicators, the authors exercised inclusion/exclusion of individual subindicators. The process involves a one-at-a-time exclusion of an individual subindicator, followed by an execution of the composite index, and an examination of the difference in the result index scores for each country between the original (baseline) and modified GRI scores:

$$\Delta\, \boldsymbol{score_c} = \boldsymbol{score_{original,c}} - \boldsymbol{score_{excl.\ q,c}} \qquad \text{Equation 4.3}$$

Where Δ *score*$_c$ represents the change in score for country c, *score*$_{original,\ c}$ represents the original GRI score for country c, and *score*$_{excl.\ q,c}$ represents the modified GRI score for country c after the exclusion of subindindicator q.

Additionally, shifts in country ranks will be explored, following the exclusion of individual subindicators:

$$\Delta\, \boldsymbol{rank_c} = \boldsymbol{rank_{original,c}} - \boldsymbol{rank_{excl.\ q,c}} \qquad \text{Equation 4.4}$$

Where Δ *rank*$_c$ represents the change in rank for country c, *rank*$_{original,\ c}$ represents the original GRI rank for country c, and *score*$_{excl.\ q,c}$ represents the modified GRI rank for country c after the exclusion of subindicator q.

The investigation of Δ *score*$_c$ and Δ *rank*$_c$ will be the scope of the sensitivity analysis, targeting the question raised in the introduction on the robustness of GRI's subindicator selection.

Selection of Normalization Scheme

In GRI$_{\text{original}}$, a Min-Max re-scaling (eq. 4.1) was adopted as the method of normalization to transform subindicator datasets into a common scale. The choice was based on multiple considerations. First, as a linear transformation, Min-Max rescaling preserves the data between the data's original values [*Joint Research Centre-European Commission*, 2008]. Second, the ease of communicating index data and outputs lying within an identical and bounded range [0,100] facilitates GRI's functionality by enabling ease of interpretation of index results and accessibility to the public.

However, since data normalization involves the transformation of data, the use of different normalization schemes could have an effect on index outputs. Therefore, an examination of the sensitivity posed by choice of normalization schemes is necessary.

In addition to Min-Max rescaling, there are two main methods of normalization [*Mazziotta*, 2013]: standardization (Z-score) and Indicization (distance to a reference). The standardization method converts the indicators to a common scale of mean zero and a standard deviation of one. Consequently, the Z-score method rewards exceptionally higher than average scores:

$$\boldsymbol{S_{q,c}} = \frac{\boldsymbol{x_{q,c} - mean(x_q)}}{\boldsymbol{std(x_q)}} \qquad \text{Equation 4.5}$$

Where $S_{q,c}$ represents the standardized value of the subindicator q for country c, *and* $x_{q,c}$ represents the raw value of the subindicator q for country c.

Indicization takes the ratio of an indicator for a specific country $x_{q,c}$ with respect to a reference country. In our case the highest scoring country will be taken as a reference, such that an indicator score for each country will be divided by the indicator score for the best ranking country. The 'distance-to-largest-value' (DLV) is calculated using the following formula:

$$\boldsymbol{DLV_{q,c}} = \frac{\boldsymbol{x_{q,c}}}{\boldsymbol{x_{q,ref}}} \qquad \text{Equation 4.6}$$

Where $DLV_{q,c}$ represents the normalized value of the subindicator x_q for country c, $x_{q,c}$ represents the raw value of the subindicator x_q for country c, and $x_{q,ref}$ represents the raw value of the subindicator x_q for the highest ranking reference country.

GRI was executed separately with different normalization schemes, as to assess normalization-related sensitivities in terms of shifts in country rank (eq. 4.7) $\mathrm{Gri}_{\mathrm{ming\text{-}Max}}$, and $\mathrm{GRI}_{\mathrm{Z\text{-}score}}$ and $\mathrm{GRI}_{\mathrm{DLV}}$:

$$\Delta\, \boldsymbol{rank_c} = \boldsymbol{rank_{Min-Max,c}} - \boldsymbol{rank_{Z-score/\,DLV,c}} \qquad \text{Equation 4.7}$$

Where $\Delta\ rank_c$ represents rank change in country c, $score_{Min\text{-}Max,c}$ represents the original GRI rank for country c using a min-max rescaling scheme, $score_{z\text{-}score/DLV,c}$ represents the modified GRI rank for country c using alternative normalization schemes.

Selection of Aggregation Method

The two main aggregation methods are additive arithmetic mean and multiplicative geometric mean. The methodological choice between the two models rest upon an index's theoretical framing of which kind of performances are awarded and penalized [*Nardo et al.*, 2005]. As mentioned in section 2.4, GRI aggregated its subindicators using an additive arithmetic mean model, based on the assumption of perfect substitutability, and the superiority of additive models insofar their effectiveness in facilitating ease of interpretation and adoption by experts and the public alike.

A geometric mean aggregation, however, reflects and awards trade-offs between different subindicators by allowing only for partial or imperfect substitutability, where a negative performance by one subindicator cannot fully compensate for a positive performance by another. Moreover, geometric aggregation rewards balanced scores between index dimensions, and severely penalizes poor performance in one or more particular dimensions [*Aguna and Kovacevic*, 2010].

To account for the sensitivity associated with aggregation methods, the authors executed the GRI using a geometric mean formula:

$$\boldsymbol{CI_c = \prod_{i=1}^{n} [q_c]^{1/n}} \qquad \text{Equation 4.8}$$

Where CI_c represents the composite score of country c, q_c represents subindicator q score for country c, and n represents the number of indicators aggregated. Sensitivities inherent to the choice of aggregation function were evaluated through shifts in country-level groundwater risk score and rank.

4.4 Results and Discussion

Sensitivity analysis is rarely reported in developed composite indices, and as a consequence, index robustness is questioned and adoption by end-users is compromised. In this study, sensitivity analyses at different stages within the development process were conducted to test and verify the robustness of the newly developed GRI. A one-factor-at-a-time (OFAT) sensitivity approach was adopted to examine the effects of subindicator selection, normalization schemes, and aggregation methods on country output groundwater risk scores and ranks.

Sensitivity results associated with subindicator choice, normalization schemes, and aggregation methods are presented in Tables 1, 2, and 3 respectively.

An analysis of the impact of GRI's subindicator selection on its final outcomes clearly shows that the original selection of constituent subindicators provides a robust measure that is not biased. This is evident by country ranks generated by different subindicator combinations (Table 4.1). Countries within the 75th percentile or higher group with very low groundwater risk (Israel and PT, Qatar, UAE, and Kuwait), were not sensitive to any subindicator, as they consistently ranked similarly within their quantile group with the exclusion of individual indicators. The same applies to the 25th or lower quantile group with Syria, Yemen, Libya, and Iraq slightly shifting positions within their quantile group with different subindicator combinations. A detailed examination of GRI's sensitivity to each individual subindicator, ascertains the preceding observations, with relatively small shifts in country rank, ranging between one to two positions, and little to no change in the overall ranking structure of the 16 countries in this study. The only exception is the governance indicator, whose exclusion led to larger shifts in country ranking than its counterparts (e.g. Saudi Arabia, Syria, and Libya). On the basis of average ranking shift across countries per subindicator exclusion, the GRI's sensitivity relative to its constituent subindicators is in the following decreasing order: GOV ($\Delta\ \overline{\text{Rank}}$ = 1.37), GWEC ($\Delta\ \overline{\text{Rank}}$ = 0.75), GWR ($\Delta\ \overline{\text{Rank}}$ = 0.75), FS ($\Delta\ \overline{\text{Rank}}$ = 0.25), and GWSC ($\Delta\ \overline{\text{Rank}}$ = 0.12). In addition to highlighting the sensitivity impact of the subindicator selection on GRI outcomes, average rank changes suggest that country rankings are overall robust towards the choice of each individual subindicator. This of course is no nullification of the sensitivity of individual countries to some indicators, as is the case with Saudi Arabia and Syria's sensitivity to governance, but rather a statement of their infrequency within GRI.

Table 4.1. Subindicator exclusion/inclusion sensitivity analysis results. The subindicators are as follows: groundwater reserves (GWR), groundwater storage change (GWSC), governance (GOV), food security (FS), and groundwater extraction cost (GWEC). GRI's sensitivity to the choice of subindicators is assessed according to country-level shifts in rank, relative to the original ranking (grey column) of GRI $_{original}$. Countries exhibiting an upward movement in rank are highlighted in green, and show the resultant final rank and number of rank changes in parentheses. Countries exhibiting a downward movement in rank are highlighted in red.

Country	GRI $_{original}$		GRI $_{excl. GWR}$		GRI $_{excl. GWSC}$		GRI $_{excl. GOV}$		GRI $_{excl. FS}$		GRI $_{excl. GWEC}$	
	Scores	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
Israel and PT*	68.1	1	72.2	2 (-1)	73.7	1	60.8	1	67.2	1	67.2	1
Qatar	66	2	77	1 (+1)	70.2	2	58.3	2	58.8	2	66	2
UAE**	56.4	3	55.1	4 (-1)	59.4	4 (-1)	48.2	4 (-1)	58.7	3	62.8	3
Kuwait	55.8	4	58.8	3 (+1)	62.6	3 (+1)	51.8	3 (+1)	53.1	4	57.7	4
Morocco	47.3	5	52.5	5	46.5	5	47.1	6 (-1)	48.7	5	42	10 (-5)
Lebanon	46.5	6	45.5	9 (-3)	44.3	6	48.2	5 (+1)	46.2	6	45.4	7 (-1)
Jordan	44.8	7	50.2	6 (+1)	43	7	39.3	7	46	7	46	6 (+1)
Oman	44.2	8	49	7 (+1)	42.2	8	36.3	10 (-2)	44.1	8	49.3	5 (+3)
Tunisia	42.5	9	48.1	8 (+1)	40.7	9	39.3	8 (+1)	41.8	9	42.9	9
Saudi Arabia	36.9	10	40.8	11 (-1)	32.4	10	31.9	15 (-5)	34.8	10	44.7	8 (+2)
Egypt	36.2	11	40.8	10 (+1)	31.5	11	35.4	12 (-1)	34.1	11	38.6	11
Algeria	33.5	12	34.6	12	28.6	12	34.7	13 (-1)	32.4	12	36.7	12
Syria	32.6	13	31	13	27.2	13	36.6	9 (+4)	30.9	14 (-1)	36.6	13
Libya	29.8	14	30.8	14	23.6	14	35.6	11 (+3)	25.4	15 (-1)	33.6	14
Yemen	28.9	15	30.6	15	21.7	15	32.2	14 (+1)	31.7	13 (+2)	27.7	15
Iraq	25.6	16	26.7	16	18.6	16	30.5	16	24.7	16	27.6	16

* PT refers to Palestinian Territories
** UAE refers to United Arab Emirates

In testing the robustness of the minimum-maximum rescaling scheme, GRI was executed using alternative normalization methods – Z-score standardization and Indicization – and alternative GRI outcomes were compared with the original results. Comparable country rank outcomes generated by the different normalization methods (Table 4.2), confirm the GRI's independence of normalization scheme selection, and affirm the robustness and unbiasness of the min-max rescaling method. Countries are more robust to the choice of normalization scheme, if it is among the best (75^{th} or higher quantile) or worst (25^{th} or lower quantile) performers, and relatively more sensitive to normalization schemes within the 25^{th} to 75^{th} quantiles. For instance, Lebanon and Morocco suffer three and two downward shifts in rank with Z-score standardization, and four and two downward shifts in rank with an indicization scheme respectively. A possible explanation behind the relatively higher sensitivity within the central quantiles could be the smaller differences in country scores within these quantiles as opposed to the score of the highest and lowest performing countries. Nevertheless average ranking shifts – relative to the original ranking with min-max rescaling scheme – caused by Z-Score standardization ($\Delta\ \overline{\text{Rank}} = 0.75$) and *DLV* Indicization ($\Delta\ \overline{\text{Rank}} = 0.93$), clearly indicate GRI's overall independence and insensitivity to the choice of normalization scheme.

A sensitivity analysis on the choice of aggregation formula was conducted by executing the index using a geometric mean aggregation method, and comparing its outcomes to those produced by the original GRI, with its arithmetic mean formula. Unlike subindicator selection and choice of normalization scheme, GRI outcomes were found to be sensitive to the selection of aggregation formula. This is not surprising given how both methods reflect subindicator substitutability, score balance, and performance differently [*Aguna and Kovacevic*, 2010].

Table 4.2. Sensitivity analysis results on the choice of normalization scheme. GRI's sensitivity to alternative normalization methods is evaluated according to country-level shifts in rank and quantile grouping, relative to the original ranking and quantile grouping (grey columns) of $GRI_{original}$. Countries exhibiting an upward movement in rank are highlighted in green, and show the resultant final rank and number of rank changes in parentheses. Countries exhibiting a downward movement in ranking are highlighted in red.

Country	Minimum - Maximum Normalization ($GRI_{original}$)			Z -Score Standardization			Indicization (divide by largest)		
	Score	Ranking	Quantile Rank	Score	Ranking	Quantile Rank	Score	Ranking	Quantile Rank
Israel and PT	68.1	1	75th or higher	2.4	1	75th or higher	47.4	1	75th or higher
Qatar	66	2	75th or higher	2.3	2	75th or higher	41.6	2	75th or higher
UAE	56.4	3	75th or higher	1.7	3	75th or higher	40	3	75th or higher
Kuwait	55.8	4	75th or higher	1.4	4	75th or higher	20.9	4	75th or higher
Oman	44.2	8	50th to 74th	0.7	5 (+3)	50th to 74th	20.3	5 (+3)	50th to 74th
Jordan	44.8	7	50th to 74th	0.6	6 (+1)	50th to 74th	20.2	6 (+1)	50th to 74th
Morocco	47.3	5	50th to 74th	0.4	7 (-2)	50th to 74th	16.1	7 (-2)	50th to 74th
Lebanon	46.5	6	50th to 74th	0.1	9 (-3)	25th to 49th	6.9	10 (-4)	25th to 49th
Tunisia	42.5	9	25th to 49th	0.3	8 (+1)	50th to 74th	13.1	8 (+1)	50th to 74th
Saudi Arabia	36.9	10	25th to 49th	0	10	25th to 49th	9	9	25th to 49th
Egypt	36.2	11	25th to 49th	-0.3	11	25th to 49th	1.7	11	25th to 49th
Algeria	33.5	12	25th to 49th	-0.6	12	25th to 49th	-1.5	12	25th to 49th
Syria	32.6	13	24th or lower	-0.8	13	24th or lower	-8.7	14 (-1)	24th or lower
Yemen	28.9	15	24th or lower	-1	14 (+1)	24th or lower	-7	13 (+2)	24th or lower
Libya	29.8	14	24th or lower	-1.1	15 (-1)	24th or lower	-12.4	15 (-1)	24th or lower
Iraq	25.6	16	24th or lower	-1.3	16	24th or lower	-16.3	16	24th or lower

Out of the 16 countries considered in GRI, 12 experienced a shift in rank. Moreover, 7 countries underwent a shift outside their quantile group into another, thus reflecting not only minor shifts in rank but an overall reconfiguration of groundwater risk ranking. To demonstrate, both Qatar and Kuwait which ranked highly in the 75th or higher quantile with low groundwater risk in the original GRI, experienced five downward movements in rank into lower quantile groups (Table 4.3), when using the geometric aggregation method. Meanwhile, their positions were replaced by Lebanon and Morocco, which experienced a rise in rank position of three and one into the highest quartile. This significant restructuring of the rank order pertains to how arithmetic and geometric mean aggregations reflect tradeoffs. For example, when an arithmetic mean aggregation was used, Qatar and Kuwait scored and ranked highly, despite scoring low on the groundwater reserve and storage change subindicators. This is explained by the compensability of very high scores in the latter subindicators pertaining to governance and food security, which offset the poor performance in the former subindicators. On the other hand, when a geometric mean aggregation was implemented, Qatar's and Kuwait's scores declined from 66 and 56, to 33 and 32 respectively, thus ensuring a downward movement in rank. This is explainable by the geometric mean's property that rewards balance and penalizes differences between subindicator values. Contrarily, Lebanon and Morocco, experienced upward movement in rank with the implementation of a geometric mean, as a function of their balanced subindicators and the lack of a distinctive poor performance in one or more of them. A general observation in Fig. 4.1 is that countries with well distributed subindicator performance, reflected in relatively lower in-group standard deviation values such as Lebanon, Tunisia, and Morocco, experienced a rise in rank of 5, 3, and 1. Inversely, countries displaying a poor performance in one or more subindicators (e.g. GW Reserves), with higher in-group standard deviation values, are penalized and experience a decrease in rank, such as Qatar, Kuwait, and Saudi Arabia. Rank changes are assessed relative to $GRI_{original}$ ranking results, generated using additive arithmetic aggregation.

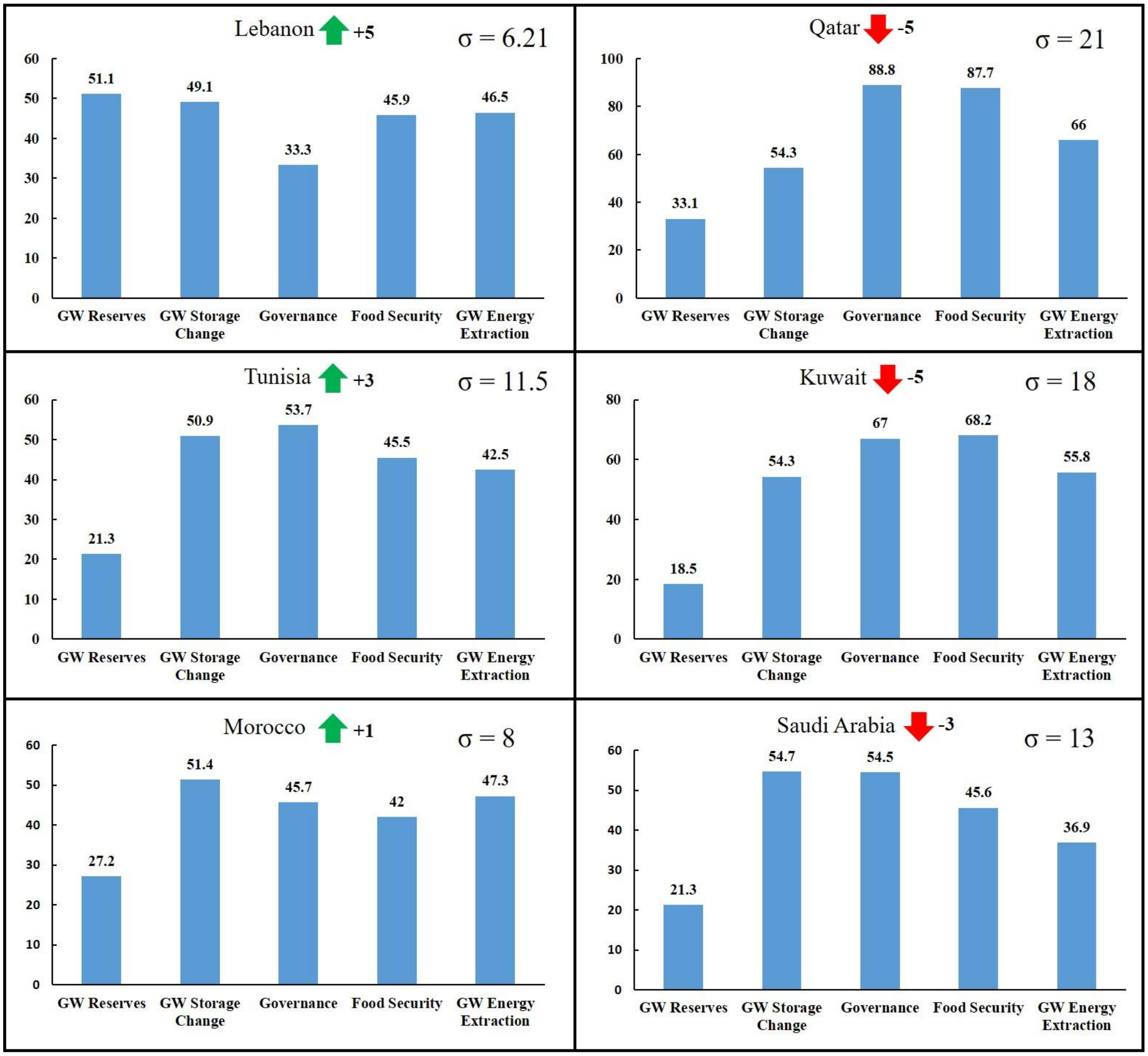

Figure 4.1. Bar graphs displaying the effects of 'balanced' subindicator performance on country-level score and rank when using multiplicative geometric mean aggregation.

Table 4.3. Sensitivity analysis results on the choice of aggregation method. GRI's sensitivity to weighted geometric mean aggregation is evaluated according to country-level shifts in rank and quantile grouping, relative to the original ranking and quantile grouping (grey columns) of $GRI_{original}$. Countries exhibiting an upward movement in rank are highlighted in green, and show the resultant final rank and number of rank changes in parentheses. Countries exhibiting a downward movement in ranking are highlighted in red.

Country	Weighted Arithmetic Mean ($GRI_{original}$)			Weighted Geometric Mean		
	Score	Rank	Quantile Rank	Score	Rank	Quantile Rank
Israel and PT	68.1	1	75th or higher	65.2	1	75th or higher
UAE	56.4	3	75th or higher	44.3	2 (-1)	75th or higher
Qatar	66	2	75th or higher	33.2	7 (+5)	50th to 74th
Lebanon	46.5	6	50th to 74th	43.7	3 (-3)	75th or higher
Kuwait	56	4	75th or higher	32.4	9 (+5)	25th to 49th
Morocco	47.3	5	50th to 74th	40.7	4 (-1)	75th or higher
Jordan	44.8	7	50th to 74th	36.5	5 (-2)	50th to 74th
Tunisia	42.5	9	25th to 49th	34.9	6 (-3)	50th to 74th
Oman	44.2	8	50th to 74th	33.2	8	50th to 74th
Egypt	36.2	11	25th to 49th	29.4	10 (-1)	25th to 49th
Saudi Arabia	36.9	10	25th to 49th	22.5	13 (+3)	24th or lower
Algeria	33.5	12	25th to 49th	24.9	12	25th to 49th
Syria	32.6	13	24th or lower	25.3	11 (-2)	25th to 49th
Yemen	28.9	15	24th or lower	22.5	14 (-1)	24th or lower
Libya	29.8	14	24th or lower	17.6	15 (+1)	24th or lower
Iraq	25.6	16	24th or lower	17.1	16	24th or lower

Indeed, countries that exhibited the most downward movement in rank with geometric aggregation are high-income, oil-rich gulf countries (e.g. Saudi Arabia, Kuwait, and Qatar), which under full compensability conditions, simulated by arithmetic aggregation, scored well due to the effect of wealth and governance on offsetting poor water endowments; but which were penalized for the imbalance between water resource allocations and adaptive capacity parameters with the application of a geometric mean. Similarly, countries with more balanced conditions to groundwater risk exhibited a rise in rank, as was the case with Lebanon and Tunisia. Developing a sound and coherent theoretical framework that reflects the complexity of what is being measured and the interaction between the different dimensions that create it, is the most pertinent step in the construction of a good composite index. The selection of an aggregation method relates directly to that framework, particularly when it pertains to understanding and assuming the interactions between different subindicators and perspectives in creating a specific phenomenon. In GRI's case, executing the index using both arithmetic and geometric means, results in outputs that are complementary to each other and highlight different perspectives on groundwater depletion risk. For instance, based on what has been discussed above, the penalizing effect of geometric aggregation on oil-rich gulf countries highlights the reliance on oil-income in mitigating groundwater risk, and raises inquiries on the sustainability low risk scores, produced by the index under full compensability conditions (arithmetic mean), if such incomes are not available in the future.

The preceding analysis examined the effects of different potential sources of sensitivity on GRI's output separately, with results displaying varying levels of sensitivity by subindicator selection and choice of normalization and aggregations schemes. For a complete sensitivity analysis, an aggregation of the potential sources of sensitivity or error was conducted. GRI country scores, generated with each preceding sensitivity testings, were arithmetically averaged into a modified GRI output ($GRI_{Modified}$) reflecting country scores and ranks, as defined by alternative subindicator, normalization scheme, and aggregation method selection. The results (Table 4.4) clearly display the robustness of GRI and its insensitivity to the discussed methodological alternatives. In terms of country scores, modified GRI values are negligibly different than original ones (Δ GRI Score) with the score shifts not exceeding 6 points on a [0, 100] scale, as is the case with Libya and Israel and the Palestinian Territories. In terms of country ranks, modified GRI values were also negligible, with 11 out of 16 countries experiencing no rank change (Δ GRI Rank). The remaining 5 countries only exhibited one shift in rank, with the exception of Lebanon, which fell two ranks. Moreover, GRI's modified results did not significantly alter the overall analysis, interpretations, and conclusions of the original GRI results in the MENA region, as presented by *Lezzaik et al.* [2016]. In *Lezzaik et al.* [2016], the authors interpreted GRI's results through the framework of a typological classification (Fig. 4.2) that grouped countries according to both their groundwater resource allotments, and their governance and income levels. According to their interpretation, countries with effective governance and high incomes ranked amongst the lowest in terms of groundwater risk, meanwhile countries with poor governance and low incomes were conversely high on groundwater risk. Meanwhile, groundwater allotments proved inconsequential in determining risk conditions. The results of the modified GRI are consistent with the above analysis as displayed by Fig. 4.2. Of the 5 countries that experienced a shift in rank, none moved outside their quantile group, thus maintaining the ranking overall structure of the ranking order and the primary interpretation underlying it. Consequently, GRI's modified results affirm the index's insensitivity to alternative subindicator selections, normalization schemes, and aggregation methods.

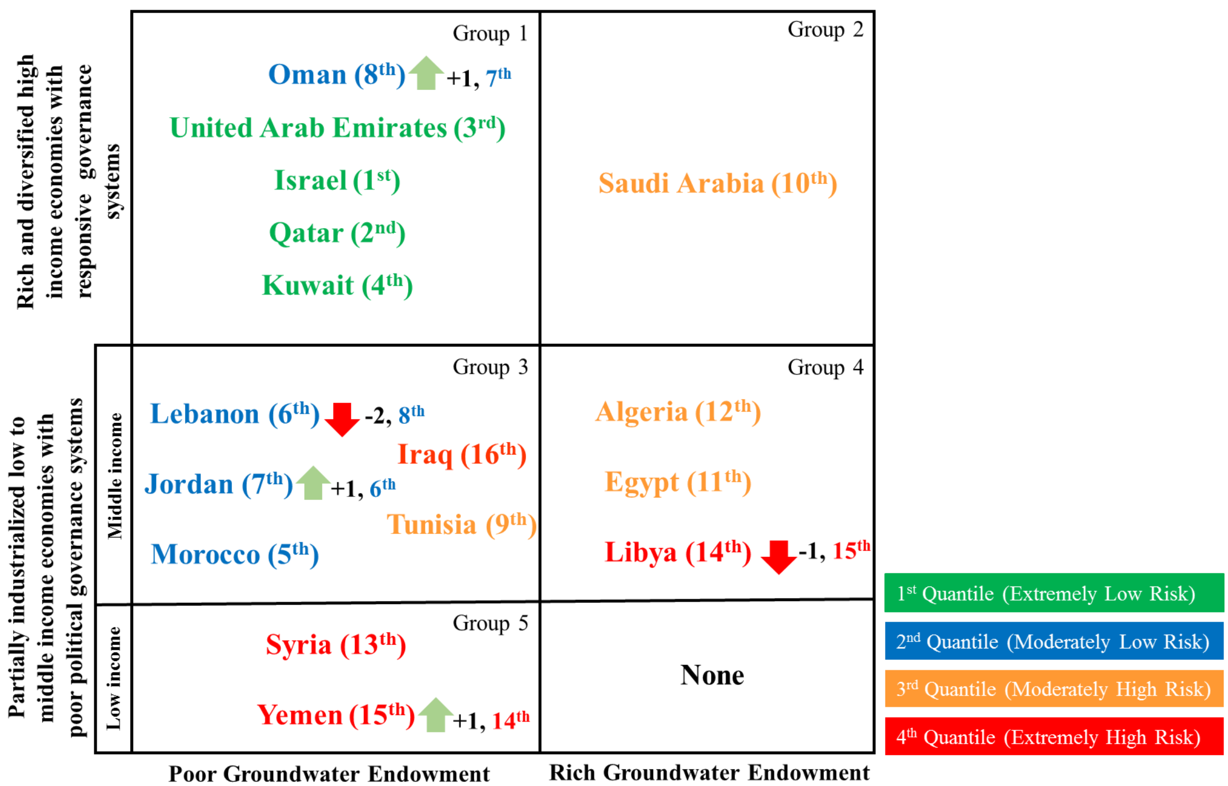

Figure 4.2. A modified typology of MENA countries by hydrological systems and political economies. The figure shows $GRI_{original}$ country rank (in parenthesis). Countries experiencing a rank shift with a $GRI_{modified}$ are denoted with an arrow, followed by the number of shifts and the modified rank.

Table 4.4. Summary of GRI sensitivity analysis score results. $GRI_{Modified}$ scores and ranks were generated from the arithmetic mean of sensitivity analysis results, to measure the combined impact of alternative methodological choices on $GRI_{original}$ score and rank.

Sensitivity Analysis		ALG	EGY	IRQ	IPT	JOR	KWT	LEB	LIB	MOR	OMN	QTR	SDA	SYR	TUN	UAE	YMN
Subindicator Exclusion/Inclusion	$GRI_{\text{excl. GWR}}$	35	41	27	72	50	59	46	31	53	49	77	41	31	48	55	31
	$GRI_{\text{excl. GWSC}}$	29	32	19	74	43	63	44	24	47	42	70	32	27	41	59	22
	$GRI_{\text{excl. GOV}}$	35	35	31	61	39	52	48	36	47	36	58	32	37	39	48	32
	$GRI_{\text{excl. FS}}$	32	34	25	67	46	53	46	25	49	44	59	35	31	42	59	32
	$GRI_{\text{excl. GWEC}}$	37	39	28	67	46	58	45	34	42	49	66	45	37	43	63	28
Normalization Scheme	Min - Max	33	36	26	68	45	56	46	30	47	44	66	37	33	43	56	29
	Z - Score	19	26	0	100	51	72	36	4	46	54	99	35	12	43	81	7
	Indicization	23	28	0	100	57	58	36	6	51	58	91	40	12	46	88	14
Aggregatio n Method	Arithmetic Mean	33	36	26	68	45	56	46	30	47	44	66	37	33	43	56	29
	Geometric Mean	25	29	17	65	36	32	44	18	41	33	33	23	25	35	44	22
$GRI_{Original}$ Score		34	36	26	68	45	56	47	30	47	44	66	37	33	43	56	29
$GRI_{Original}$ Rank		12	11	16	1	7	4	6	14	5	8	2	10	13	9	3	15
$GRI_{Modified}$ Score		30	34	20	74	46	56	44	24	47	45	69	36	28	42	61	25
$GRI_{Modified}$ Rank		12	11	16	1	6	4	8	15	5	7	2	10	13	9	3	14
Δ GRI Score		**4**	**2**	**6**	**-6**	**-1**	**0**	**3**	**6**	**0**	**-1**	**-3**	**1**	**5**	**0**	**-5**	**4**
Δ GRI Rank		**0**	**0**	**0**	**0**	**1**	**0**	**-2**	**-1**	**0**	**1**	**0**	**0**	**0**	**0**	**0**	**1**

ALG (Algeria); EGY (Egypt); IRQ (Iraq); IPT (Israel and Palestinian Territories); JOR (Jordan); KWT (Kuwait); LEB (Lebanon); LIB (Libya); MOR (Morocco); OMN (Oman); QTR (Qatar); SDA (Saudi Arabia); SYR (Syria); TUN (Tunisia); UAE (United Arab Emirates); YMN (Yemen).

4.5 Conclusion

This paper studied the sensitivity of the GRI to the methodological judgements that were made during its development, by examining the effects of alternate methodological methods on country-level groundwater risk scores and rank. A one-factor-at-a-time sensitivity analysis was used to measure the robustness of subindicator selection, choice of normalization scheme, and choice of aggregation method. The results have shown that the GRI provides a robust measure that is not biased by neither the choice of subindicators constituting the index, nor by the choice of normalization scheme, with relatively little to no change in country score and rank. On the other hand, the choice of aggregation methods between an additive arithmetic mean and a multiplicative geometric mean, presented a source of significant sensitivity to GRI, as was expected given the differences in how they reflect the interactions and tradeoffs between different factors involved in the index. GRI's sensitivity to the choice of aggregation method affirms the need of a representative theoretical framework that correctly simulates the interactive process between different factors contributing to groundwater risk. Overall, however, the GRI index is explicitly insensitive to the discussed alternative methodological choices. The implication of our sensitivity analysis is significant, as it allows for the customized use of the GRI index outside the MENA region, in which alternative methodological choices, taken to fit unique regional conditions, do not significantly distort GRI's outcomes. In the future, the authors recommend variance-based measures of sensitivity that explores and accounts for simultaneous variations and interactions between different input factors.

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CHAPTER 5

SUMMARY AND CONCLUSIONS

In this research, distributed GIS models parameterized with integrated timely and current gridded remote sensing, modelled, and in-situ datasets, were used to assess spatio-temporal groundwater scarcity and risk in the Arab Middle East and North Africa (MENA) region between 2003 and 2014.

Firstly, a regional-scale characterization of groundwater resources in the region was completed by integrating estimated groundwater reserves with calculated changes in groundwater storage. Groundwater reserves were estimated by combining effective porosity values with the saturated thicknesses of aquifer systems – as determined from sediment thickness and water table depth gridded datasets. On the other hand, monthly groundwater storage changes between 2003 and 2014 were estimated by quantifying and isolating GLDAS-derived surface water storage parameters (e.g. soil moisture) from GRACE satellite's total terrestrial water storage change datasets. Subsequently, aggregate groundwater changes between 2003 and 2014 were added to groundwater reserve estimations to generate a groundwater scarcity assessment.

Secondly, a groundwater risk index was designed and developed to assess spatio-temporal cold/hotspots of groundwater depletion in the MENA region. Given the nature of groundwater risk as a relative, non-measurable, and multi-dimensional concept, the composite index was composed of two sets of variable components: sensitivity parameters governed by hydrogeological characterizations provided by the aforementioned estimations of groundwater reserves and storage changes on one hand; and vulnerability parameters governed by adaptive criteria such as governance, food security, and energy systems. Moreover, to assess the robustness of the groundwater risk index, sensitivity testing was conducted to assess the vulnerability of the index's output country scores and ranks to alternate methodological choices and judgements along different phases of the construction process

The following major conclusions were drawn from this research:

Assessment of Groundwater Scarcity

1. Regional groundwater reserves in the MENA region range between 816,000 km^3 and 1.93 million km^3, with an average estimate of 1.28 million km^3.
2. Analogous to oil, groundwater in the region is unevenly distributed with Algeria, Egypt, Libya, and Saudi Arabia accounting for approximately 75% of the total groundwater resources.
3. Geologically, groundwater reserves were most concentrated in the deep sedimentary basins of North Africa and the Arabian Peninsula, and least concentrated in fractured and weathered Precambrian basement exposures. The hydrogeological distribution of groundwater resources explains the result outlined in (**2)**.
4. The largest declines in groundwater storage between 2003 and 2014 occurred along coastal areas with high demographic concentrations in North West Africa and the eastern Mediterranean. Declines in groundwater storage were also observed within close proximity to large cities elsewhere, such as in Riyadh in central Saudi Arabia, Muscat in Oman, and Baghdad in Iraq. The only exceptions

to these observations are demographic concentrations along the Nile River Valley and the Moroccan coast, which exhibit no significant declines due to their reliance on surface water supplies.

5. Groundwater storage change results indicate a possibility of groundwater recharge occurring in deep continental sedimentary aquifers, which have been traditionally categorized as fossil or non-renewable groundwater systems. The presence and rate of recharge in desert aquifer systems is an ongoing debate within the scientific community and remains unresolved. However, multiple factors could account for such observations, ranging from the coarse spatial resolution of GRACE satellite's datasets and sampling bias, to the very low population densities and abstraction rates in those areas coupled with intermittent recharge events.
6. Country timeseries display a decline in groundwater storage in 8 out of 16 MENA countries, with Saudi Arabia, Iraq, and Oman displaying the largest volumetric declines between 2003 and 2014. Moreover trends, across the region, display an overall decline in groundwater storage, albeit at varying rates between countries.
7. Storage changes of groundwater reserves range from the modest to the negligible, with percent changes in groundwater reserves not exceeding one percent in any MENA country.

Assessment of Groundwater Risk

8. The four best ranking countries with extremely low groundwater risk are high-income, energy-exporting countries in the Arabian Gulf (Kuwait, Qatar, and

UAE) and Israel. Conversely, low-income countries with bad governance rank the lowest in the region with extremely high groundwater risk.

9. Between 2003 and 2014, the largest shifts in groundwater risk rank occurred in Kuwait, Syria, Jordan, and Yemen; with the former two becoming more vulnerable to groundwater risk, and the latter two becoming less vulnerable to groundwater risk.

10. Shifts in country risk rank are driven either by changes in the objective conditions of risk determinants within either the country itself, other countries, or both. For example, Syria's worsening vulnerability to groundwater depletion reflects the deterioration of governance and food security as a consequence of the Syrian civil war; whereas Yemen's improved ranking is more a reflection of the worsening scores and ranking of countries within its quantile rank group such as Syria and Libya, as opposed to an objective improvement of risk determinants.

11. Analysis of identifiable relationships and patterns between groundwater risk outcomes and the index's component variables clearly shows that hydrogeological characterizations and groundwater endowments are a poor determinant of groundwater risk. To demonstrate, countries with extremely low risk are also consistently the least endowed in terms of groundwater reserves (e.g. Kuwait, Qatar). Conversely Algeria, Egypt, Libya, and Saudi Arabia display moderate to high levels of groundwater risk, despite for accounting for 75% of the region's groundwater resources.

12. A combination of effective governance and high income economies appears to be the best prescription to mitigating groundwater risk. The following recipe of

conditions not only allows for the selection and implementation of different management instruments, but also provides the capacity to rely on exogenous solution to groundwater depletion, primarily the achievement of food security through virtual-water trade.

13. The groundwater risk index is insensitive to either the selection of components or alternative normalization schemes. The index, however, was sensitive to the choice of aggregation method, given the difference in how arithmetic and geometric aggregation methods perceive, reward, and penalize tradeoffs between different index components.

This study establishes two important concepts. First, it demonstrates the potential of merged and integrated remote sensing, modeled, and in-situ datasets in providing accurate and detailed spatio-temporal assessments of groundwater resources, in regions of the world where data paucity is ubiquitous. This potential was materialized in the synthesis of the first of its kind assessment of groundwater resources in the entirety of the MENA region between 2003 and 2014. While our assessment confirmed groundwater depletion in the MENA region in areas with high demographic concentrations, it also provided insightful conclusions that can help inform the analysis and discourse on water resources in the MENA region: (1) the possibility of recharge within systems that have been traditionally categorized as being non-renewable, (2) and the negligibility of changes in groundwater changes relative to the vast reserves that exist beneath the region.

Second, is the development and creation of a unique groundwater risk index, designed to assess groundwater risk in the MENA region, on the basis of a comprehensive and multidisciplinary analysis of the factors that drive groundwater depletion. Given that the index's theoretical framework was based on a conceptualization of the determinants and drivers of groundwater depletion in arid environments, the index can be easily used in other dryland environments. Moreover, the structural flexibility of the groundwater risk index, would allow for modifications and alterations to suit specific circumstances outside our study area. Consequently, the groundwater risk index, is a unique screening tool for policy-makers, allowing them to not only highlight areas and communities vulnerable to groundwater depletion, but also aids them in mitigating it by deconstructing the causes driving groundwater degradation.