Review: Advances in groundwater potential mapping

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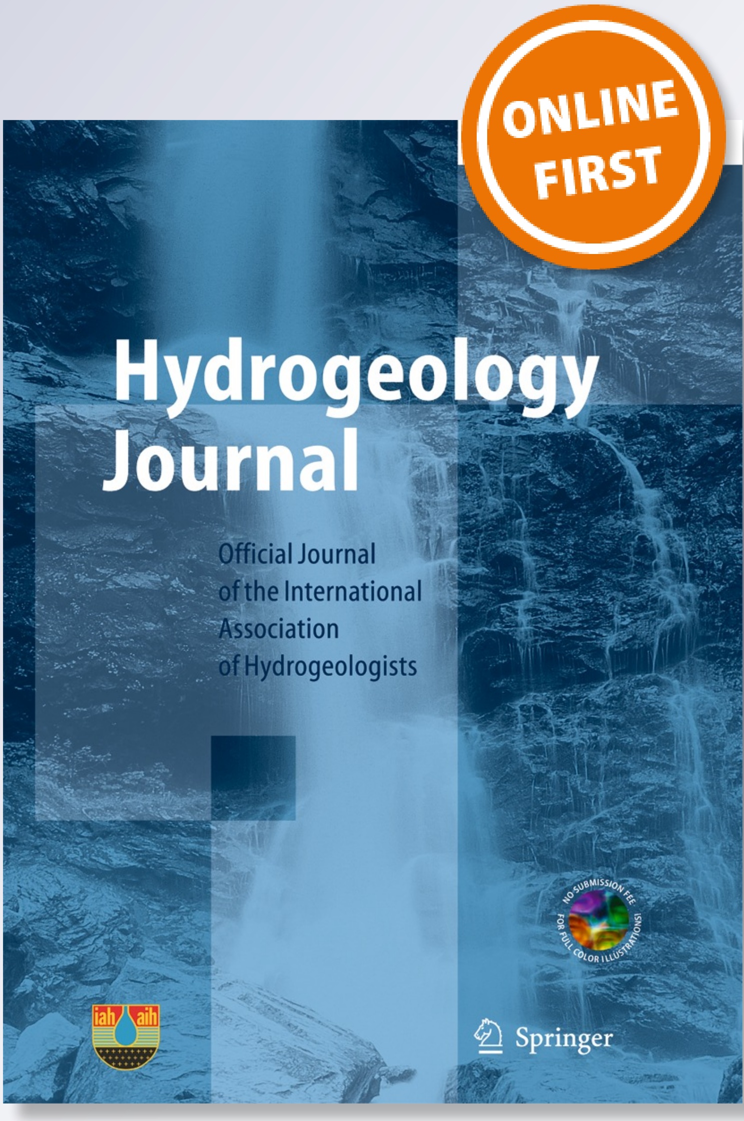

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PAPER

Review: Advances in groundwater potential mapping

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Abstract

Groundwater resources can be expected to be increasingly relied upon in the near future, as a consequence of rapid population growth and global environmental change. Cost-effective and efficient techniques for groundwater exploration are gaining recognition as tools to underpin hydrogeological surveys in mid- and low-income regions. This paper provides a state of the art on groundwater potential mapping, an explorative technique based on remote sensing and geographical databases that has experienced major developments in recent years. A systematic review of over 200 directly relevant papers is presented. Twenty variables were found to be frequently involved in groundwater potential investigations, of which eight are almost always present: geology, lineaments, landforms, soil, land use/land cover, rainfall, drainage density, and slope. The more innovative approaches draw from satellite images to develop indicators related to vegetation, evapotranspiration, soil moisture and thermal anomalies, among others. Data integration is carried out either through expert judgement or through machine-learning techniques, the latter being less common. Three main conclusions were reached: (1) for optimal results, groundwater mapping must be used as a tool to complement field work, rather than a low-cost substitute; (2) the potential of remote-sensing techniques in groundwater exploration is enormous, particularly when the power of machine learning is harnessed by involving human judgement; (3) quality assurance remains the main challenge ahead, as exemplified by the fact that a majority of the existing studies in the literature lack adequate validation.

Keywords Geographical information systems · Remote sensing · Decision support systems · Groundwater survey · Drinking water

Introduction

Groundwater is the largest available freshwater resource in the world. Aquifers provide drinking water to at least 50% of the global population, and account for 43% of all water used for irrigation. Furthermore, 2.5 billion people worldwide depend solely on groundwater resources to satisfy their daily needs (UNESCO 2015). Groundwater is particularly important in arid and semiarid climates, where droughts are frequent and where surface-water resources are often unreliable (Llamas and Martínez-Santos 2005). While crucial for human beings and ecosystems, groundwater resources suffer from the “hidden treasure” syndrome. Because groundwater is out of sight, aquifers are seldom well known, even in industrialized countries. This often leads to widespread contamination and dropping water tables, and hampers attempts to manage the resource in a sustainable manner.

Groundwater mapping has been defined as a tool for systematic development and planning of water resources (Elbeih 2015). Hydrogeological maps provide spatially distributed information about aquifers, including their geological, hydrogeological and hydrochemical characteristics. Groundwater maps may be used to develop strategies for sustainable management, allowing water planners to identify zones suitable for siting productive wells. Moreover, mapping contributes to understanding the vulnerability of aquifers and their associated ecosystems to contamination and overexploitation, to identify areas for artificial recharge, and to convey information to groundwater users. Furthermore, groundwater maps may reveal links between groundwater resources and human settlements (Ahmed and Sajjad 2018).

Inevitably, a conventional groundwater map is the synthesis of numerous variables. Field data can be problematic to obtain because surveys are typically time- and resource-intensive, particularly in the case of remote regions. In a world where a large share of the rural population relies on

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groundwater, and where millions still lack access to safe drinking supplies (Martínez-Santos 2017), this calls for alternative approaches to make groundwater exploration as efficient as possible. Consider remote sensing (RS) technologies. While satellite- and air-borne sensors are of limited use in groundwater surveys, they do provide valuable insights regarding certain hydrogeological processes and variables, particularly when combined with various other information sources. Remotely obtained data are especially important in developing regions, where hydrogeological monitoring is seldom systematic and where the potential of groundwater resources remains largely unknown. This is one of the reasons why many hydrogeologists worldwide have become accustomed to making use of remote sensing and geographic information systems (GIS). Jha et al. (2007) identified six major applications of RS/GIS in the field of groundwater, including the exploration and assessment of groundwater resources (Abdalla 2012; Fashae et al. 2014; Martín-Loeches et al. 2018), the selection of artificial recharge sites (Samadder et al. 2011), subsurface flow and/or pollution modelling (Leblanc et al. 2007), aquifer vulnerability and protection (Vias et al. 2005; Hernández-Espriú et al. 2014; Hadzic et al. 2015), estimations of natural recharge (Yeh et al. 2016; Mokadem et al. 2018) and hydrogeological data analysis and process monitoring (Crossman et al. 2012; Dailey et al. 2015; Sahoo et al. 2018). The number of applications of satellite information in groundwater science continues to grow. Take for instance the Gravity Recovery and Climate Experiment (GRACE), whose data have been used in recent times to monitor large-scale variations in groundwater storage (Feng et al. 2013; Lakshmi 2016).

This paper deals specifically with the first of these applications, i.e. groundwater potential mapping. As demonstrated in the following pages, interest in this topic has increased dramatically in recent years. Thus, the main aim of this paper is to provide a critical overview of the existing methods. To the authors' knowledge, there are only two precedents of this intent in the literature. The first one is the aforementioned review of RS/GIS applications to groundwater science provided by Jha et al. (2007), who touched upon the issue of groundwater potential mapping in the context of a broader study. The second one is the review carried out by Jasmin and Mallikarjuna (2011), which deals specifically with groundwater potential placing the emphasis on the Indian context. With this in mind, this contribution is two-fold. First, it provides an updated overview of groundwater potential methods based on a thorough review of the booming body of literature published in the last decade. This is perceived as a valuable addition in a field associated with rapidly evolving methods and technologies such as increasingly accurate satellite imaging and machine-learning techniques. Moreover, this work broadens the geographical focus, thus providing a global perspective on the state of the art.

Literature review

The following sections compile the findings of a literature review of over 200 papers, leading to two main conclusions. The first one is that the topic of groundwater potential mapping has drawn considerable attention among hydrogeologists in recent times. While a good number of earlier publications were found (Sander et al. 1996, Shahid et al. 2000, Jaiswal et al. 2003, Rao and Jugran 2004, Ravi Shankar and Mohan 2006, Solomon and Quiel 2006, Prasad et al. 2007, among many others), the truth is there has been a significant increase in the amount of groundwater potential research after 2010, more than 50% of the literature stemming from the years 2012–2018. The vast majority of these documents pertain to regional-scale case histories in the Middle East, Africa and South Asia (Fig. 1). A detailed classification revealed 22% to refer to sedimentary basins, 42% to crystalline terrains and 36% to mixed geological media. Climate-wise, over 95% of the literature deals with arid, semiarid or tropical domains.

The second conclusion has to do with the sheer extent of the available information. It would be fair to say that the proliferation of academic sources and online repositories rendered it impossible to perform a strictly exhaustive review. For practical purposes, however, this is only perceived as a minor drawback, as the investigation consistently failed to reveal new methodological information after the first 30 or 40 documents were analysed. This, coupled with the fact that the number of sources is considerable, suggests that the review was sufficiently comprehensive for practical purposes.

Defining groundwater potential

Interestingly, the search revealed neither a universal definition of groundwater potential, nor a standardized method or set of units to measure the outcomes. A closer look at the literature shows that groundwater potential mapping means different things to different authors. While most assume that a groundwater potential map provides an indication of variations in groundwater storage across a given region, others simply interpret it as a measure of how likely groundwater is to be found or as to where the highest yields may take place. A minority places the emphasis on delineating optimal locations to site boreholes at the local scale. Thus, even though there is a methodological consensus—groundwater potential maps are always developed based on a series of indirect indicators—it is also true that very few authors actually attempt to define "groundwater potential".

Broadly speaking, groundwater potential studies aim at identifying optimal zones for groundwater development. Since groundwater development presents a utilitarian component—groundwater is used "for something"—it makes

Groundwater potential variables	Source	Venkatesan et al (2010)	Dar el tal (2010)	Oh et al (2011)	Abdalla (2012)	Magesh et al (2012)	An et al (2012)	Nag and Ghosh (2012)	Agarwal et al (2013)	Gumma and Pavelic (2013)	Omosuyi et al (2013)	Nampak et al (2014)	Vishwakarma et al (2014)	Gabriel et al (2014)	García-Rodríguez et al (2014)
Country of application	Data type	IND	IND	KOR	EGY	IND	CHN	IND	IND	GHA	NGA	MYS	IND	NGA	MAR
Scale	L/A/R	A/R	A	A	A	A	A	A	A	L	R	A	A	A	R
Medium (predominant)	S/C/M	C	C	V	V	C	S	C	C	V	C	V	V	C	S
Lithology	M	●	●	●	●	●	●	●	●	●	●	●	●	●	●
Geomorphology	M/I/D	●	●					●	●	●			●	●	●
Soil[a]	M	●	●	●		●			●	●		●			
Land use/cover	M/I	●	●			●		●	●	●		●	●		
Proximity to water bodies	M/I			●									●		
Proximity to other features	M/I														
Paleo-drainage	I/D														
Lineament mapping	I/D/M		●	●	●	●		●	●			●		●	
Temperature-related variables	I														
Moisture- related variables[b]	I			●								●			●
Regolith vs outcrops	I														●
Clay presence	I														
Saturated/aquifer thickness	B										●				●
Pumping test data[c]	B			●			●								
Borehole depth	B														
Groundwater quality data	B						●								
Borehole success rate	B														
Groundwater level[d]	B/M	●		●			●		●		●		●		●
Topography	M/D		●	●	●	●		●		●		●			●
Drainage-related variables[e]	D			●	●	●			●	●		●	●		
Slope-related variables[f]	D	●	●	●	●	●		●	●	●		●			
Geophysical logs	O										●				
Aquifer recharge/rainfall	O	●				●	●		●	●		●	●		

Groundwater potential variables	Source	Konkul et al (2014)	Oikonomidis et al (2015)	Ali et al (2015)	Madani and Nayazi (2015)	Venkateswarana & Ayya. (2015)	Al-Abadi (2015)	Dinesan et al (2015)	Sternberg & Paillou (2015)	Adeyeye et al (2015)	Liu et al (2015)	Rahmati & Melesse (2016)	Kumar et al (2016)	Ibrahim-Bathis & Ahmed (2016)	Agarwal and Garg (2016)
Country of application	Data type	THA	GRE	IND	SAU	IND	IRQ	IND	MNG	NGA	CAN	IRN	LKA	IND	IND
Scale	L/A/R	R	A	A	A/R	A	A	A	A/R	A/R	A	A	A	A	A
Medium (predominant)	S/C/M	V	S	C	V	C	S	C	S	C	U	S	V	C	S
Lithology	M	●	●	●	●	●	●	●	●	●		●	●	●	●
Geomorphology	M/I/D			●	●	●		●	●				●	●	●
Soil[a]	M							●		●		●	●	●	●
Land use/cover	M/I				●		●	●				●	●	●	●
Proximity to water bodies	M/I							●		●		●			
Proximity to other features	M/I						●			●					
Paleo-drainage	I/D								●						
Lineament mapping	I/D/M	●	●	●	●	●	●			●	●	●		●	
Temperature-related variables	I														
Moisture- related variables[b]	I										●	●			
Regolith vs outcrops	I														
Clay presence	I														
Saturated/aquifer thickness	B														
Pumping test data[c]	B						●					●			●
Borehole depth	B						●								
Groundwater quality data	B	●										●			
Borehole success rate	B														
Groundwater level[d]	B/M	●	●				●	●		●					●
Topography	M/D	●					●				●	●		●	●
Drainage-related variables[e]	D	●	●	●	●	●				●	●	●		●	●
Slope-related variables[f]	D	●	●	●	●	●	●	●		●	●	●	●	●	●
Geophysical logs	O			●											
Aquifer recharge/rainfall	O	●	●		●									●	●

Groundwater potential variables	Source	Nicolas et al (2017)	Sultan et al (2017)	Díaz-Alcaide et al (2017)	Parks et al (2017)	Nanda et al (2017)	Akinlalu et al (2017)	Jenifer & Jha (2017)	Balamurugan et al (2017)	Naghibi et al (2017)	Govindaraj et al (2017)	Bashe (2017)	Hussein et al (2017)	Thapa et al (2017)	Mogaji & Lim (2018)
Country of application	Data type	IND	EGY	MLI	EGY	IND	NGA	IND	IND	IRN	IND	ETH	ETH	IND	MYS
Scale	L/A/R	A/R	A	L	A	A/R	R	A	A	A	A	A	A	A	A
Medium (predominant)	S/C/M	C	S	V	S	C	C	C	C	V	C	V	V	C	V
Lithology	M	●	●	●	●	●	●	●	●	●	●	●	●	●	●
Geomorphology	M/I/D					●	●	●	●		●	●	●	●	
Soil[a]	M					●		●			●	●	●	●	
Land use/cover	M/I	●				●	●		●	●	●	●	●	●	
Proximity to water bodies	M/I							●		●					
Proximity to other features	M/I														
Paleo-drainage	I/D				●										
Lineament mapping	I/D/M	●	●		●	●	●		●		●	●	●		
Temperature-related variables	I				●										
Moisture- related variables[b]	I				●					●					
Regolith vs outcrops	I														
Clay presence	I											●			
Saturated/aquifer thickness	B			●	●		●								●
Pumping test data[c]	B			●	●										●
Borehole depth	B			●											●
Groundwater quality data	B			●											
Borehole success rate	B			●											
Groundwater level[d]	B/M	●		●			●		●						●
Topography	M/D		●		●	●	●		●	●	●			●	
Drainage-related variables[e]	D	●	●			●	●	●	●	●	●	●	●	●	
Slope-related variables[f]	D	●	●							●	●		●	●	
Geophysical logs	O		●				●								●
Aquifer recharge/rainfall	O			●		●		●				●	●	●	

Groundwater potential variables	Source	Nsiah et al (2018)	Martín-Loeches et al (2018)	Nasir et al (2018)	Bayewu et al (2018)	Al Shaheeb et al (2018)	Chen et al (2018)	Abrams et al (2018)	Patra et al (2018)	Jahan et al (2018)	Magaia et al (2018)	Misi et al (2018)	Ahmed and Sajjad (2018)	Sener et al (2018)	Siddah and Sahu (2018)
Country of application	Data type	GHA	ANG	PAK	NGA	JOR	CHN	ARE	IND	BGD	MOZ	ZWE	IND	TUR	IND
Scale	L/A/R	A	A/R	A	R	A	A	L	A	A/R	A/R	A/R	A	A	A/R
Medium (predominant)	S/C/M	S	C	V	C	V	V	V	S	V	C	C	V	S	S
Lithology	M		●	●	●	●		●	●	●	●	●	●	●	
Geomorphology	M/I/D		●						●	●					
Soil[a]	M			●		●	●		●				●	●	
Land use/cover	M/I			●	●	●	●	●	●	●		●	●		
Proximity to water bodies	M/I						●								
Proximity to other features	M/I						●								
Paleo-drainage	I/D														
Lineament mapping	I/D/M		●	●		●		●		●	●		●	●	
Temperature-related variables	I							●							
Moisture- related variables[b]	I		●				●	●	●		●	●			
Regolith vs outcrops	I		●												
Clay presence	I		●												
Saturated/aquifer thickness	B	●													
Pumping test data[c]	B	●										●			●
Borehole depth	B	●													
Groundwater quality data	B											●			●
Borehole success rate	B	●													
Groundwater level[d]	B/M	●		●					●				●		●
Topography	M/D			●		●	●	●	●		●	●	●		
Drainage-related variables[e]	D		●			●	●	●	●	●		●	●	●	
Slope-related variables[f]	D		●	●		●	●	●	●	●	●	●	●	●	
Geophysical logs	O		●		●						●				
Aquifer recharge/rainfall	O			●		●		●	●	●		●	●	●	

Fig. 1 Key variables involved in groundwater potential studies and outcomes of the literature review (selection of documents published after 2010). Legend: M preexisting cartographic sources, D digital elevation model, I satellite image, B:borehole or well data, O other; L large (>10,000 km^2), A medium (100–10,000 km^2), R local (<100 km^2); S sedimentary, C crystalline, V variable (mixed), U unknown. [a] May refer to soil texture, type, depth and/or infiltration potential. [b] May include evapotranspiration, soil moisture, NDVI and/or topographic wetness index. [c] May include hydraulic conductivity, specific capacity, storage coefficient, transmissivity and/or well/borehole yield, also derived parameters such as groundwater velocity. [d] May include well, borehole and/or spring data; may also refer to whether the aquifer is confined or unconfined. [e] May include drainage density, runoff and/or erosion-related coefficients. [f] May include steepness, orientation, curvature and/or others. Sources: Venkatesan et al. (2010), Dar et al. (2010), Oh et al. (2011), Abdalla (2012), Magesh et al. (2012), An et al. (2012), Nag and Ghosh (2012), Agarwal et al. (2013), Gumma and Pavelic (2013), Omosuyi et al. (2013), Nampak et al. (2014), Vishwakarma et al. (2014), Gabriel et al. (2014), García-Rodríguez et al. (2014), Konkul et al. (2014), Oikonomidis et al. (2015), Ali et al. (2015), Madani and Niyazi (2015), Venkateswaran and Ayyandurai (2015), Al Abadi (2015), Dinesan et al. (2015), Sternberg and Paillou (2015), Adeyeye et al. (2015), Liu et al. (2015), Rahmati and Melesse (2016), Kumar et al. (2016), Ibrahim-Bathis and Ahmed (2016), Agarwal and Garg (2016), Sultan et al. (2017), Diaz-Alcaide et al. (2017), Parks et al. (2017), Nicolas et al. (2017), Nanda et al. (2017), Akinlalu et al. (2017), Jenifer and Jha (2017), Balamurugan et al. (2017), Naghibi et al. (2017), Govindaraj et al. (2017), Bashe (2017), Hussein et al. (2017), Thapa et al. (2017a), Mogaji and Lim (2018), Nsiah et al. (2018), Martín-Loeches et al. (2018), Nasir et al. (2018), Bayewu et al. (2018), Al Shaheeb et al. (2018), Chen et al. (2018), Abrams et al. (2018), Patra et al. (2018), Jahan et al. (2018), Magaia et al. (2018), Misi et al. (2018), Ahmed and Sajjad (2018), Sener et al. (2018), Siddha and Sahu (2018)

sense to bring purpose into the definition. In this context, what works for rural water supplies in low-income countries does not necessarily work for large irrigation developments in industrialized regions, neither in terms of yield, nor in terms of water quality. Certain authors thus refer their studies to a particular use or set of uses. For instance, Siddha and Sahu (2018) took into account multiple water quality and pumping test parameters to develop a groundwater potential map to underpin domestic water supplies in Gandhinagar, India. Similarly, Martín-Loeches et al. (2018) developed a groundwater potential map for the specific purpose of siting drinking water boreholes for rural communities in Caimbambo, Angola.

From a language point of view, the term "potential" refers to a latent quality or ability that may or may not be actualized. In other words, the idea of potential has to do with the probability of something happening. With this in mind, a groundwater potential map was defined as a spatially distributed estimate of the physical capacity of the terrain to yield enough groundwater for a given use based on a series of indirect indicators. This conceptualization recognizes (1) the spatial component intrinsic to groundwater resources, and (2) that no single source of information is failsafe, which means thatas many as possible are needed to be integrated to minimize the uncertainties inherent to groundwater exploration. Furthermore, by speaking of potential, the hypothetical nature of the intent (and of its results), i.e. that a groundwater potential map is essentially a hydrogeologist's "best estimate" is acknowledged. This holds true even in the case of maps checked against ground truth, as these are typically validated on limited datasets.

Relevant sources and variables in groundwater potential studies

Each document in the database was examined for the purpose of identifying the key elements involved in groundwater potential mapping. Over 20 parameter groups were identified, approximately 40% of which were found consistently across most studies (Fig. 1). These include lithology (geology), geomorphology, soil, land use/land cover, topography, lineaments, drainage- and slope-related variables, rainfall and groundwater recharge. The main factor determining the kind of information involved in each study seems to be whether the map was carried out a priori, that is, in the absence of groundwater data, or a posteriori, that is, with access to it. The former were found to rely almost exclusively on parameters that can be obtained without direct presence on the field (digital elevation models, preexisting cartography, satellite images), whereas the latter invariably banked on additional information sources such as groundwater levels, borehole yields and drilling success rates.

Another key factor is the scale of work. The relevance of local variables such as certain landforms or lineaments, is lost when developing maps that span several thousands of square kilometres. Conversely, the spatial variation of rainfall and recharge may be close to meaningless when dealing with a scale of a few square kilometres (largely because of the absence of actual spatially distributed information at that scale). All these factors explain why maps very rarely, if ever, consider all variables in Fig. 1.

All variables were classified in five categories as per their source of information—cartography, satellite images, digital elevation models, borehole data, other. Note that some papers were found to use a given parameter that was not listed explicitly. For instance, using a preexisting geological map implicitly means relying on the borehole/geophysical data that were used to produce it, even if this was not mentioned in the study. Moreover, in some cases it was found that the authors described a given variable, although it is unclear whether they actually used it; thus, the outcomes presented in Fig. 1 should be interpreted with some leniency.

Cartographic sources

Geology is the single most important factor determining groundwater occurrence. Since the geology of groundwater has been discussed extensively in the literature (Freeze and Cherry 1979, Fetter 1993, Younger 2007, among many others) only a schematic description will be provided here. Groundwater can only be stored and circulate within the rock's fractures and voids, which implies that it is the porosity and permeability of the materials that ultimately constrain groundwater potential. In practice the challenge typically consists in identifying those formations which are more likely to hold water. These include, but are not limited to, nonunconsolidated deposits, weathering products and fissured and soluble sedimentary rocks.

Groundwater is near ubiquitous in the case of unconsolidated sediments. These present intergranular porosity and a wide range of textures and permeabilities, which means that they usually make up either aquifers or aquitards. Under certain circumstances, the accumulations of unconsolidated materials can be hundreds or thousands of meters thick, making them highly interesting from the hydrogeological standpoint, even in those cases where the average permeability may be low. Similar considerations apply to alluvial fans, except that these typically make up shallow aquifers of limited potential. Consolidated sedimentary rocks such as limestone and sandstone also favour groundwater occurrence, particularly when heavily fractured and, in the case of limestone, when karstified. In such cases, groundwater flow takes place predominantly along fractures and conduits. These rocks can however be close to impervious if fracturing and/or karstification is either limited or altogether absent.

With the exception of some volcanic rocks, igneous and metamorphic materials do not constitute good aquifers. It is however possible to find moderate amounts of groundwater in coarse-grained weathering products overlying crystalline rocks, as well as in fractures. Because structural features play an important role in the infiltration and movement of groundwater (Chilton and Foster 1995; Meijerink 1996; Assatse et al. 2016), the definition of hydrogeological units is typically complemented by lineament mapping (Nag 2005; Bruning et al. 2011; Adeyeye et al. 2015; Varade et al. 2018). Lineaments are best described as elongated geological discontinuities associated with networks of fractures. These may extend over thousands of kilometres, and may be several kilometres wide and deep.

Traditionally, lineament maps were developed from aerial photographs. Nowadays they can also be discerned from digitally processed colour composites, radar data or digital elevation models (Dar et al. 2010; Wendt et al. 2016; Das et al. 2018). These may lead, for instance, to the identification of geological features associated with the presence of soil moisture or vegetation (Sahoo et al. 2018). Lineament mapping has proven valuable in numerous groundwater exploration surveys in the past (Teeuw 1995; Sander 2007). For instance, the classic paper by Sander et al. (1996) demonstrates how careful lineament mapping was instrumental in improving the borehole success rate in the Voltaian sedimentary basin, central Ghana. Nevertheless, lineament mapping has often been criticized for its reliance on intuition, which inevitably leads to nonrepeatable results. Reproducibility can be increased either by comparing and integrating the outcomes obtained by several operators in the same area or by using automated methods. Both alternatives present practical drawbacks (Sander et al. 1997; Meijerink 2007; Sander 2007), a combination of the two being the most recommendable approach to smooth out inconsistencies.

Sander et al. (1996) point out that a large proportion of the developing world is underlain by rocks where groundwater occurs chiefly in fracture zones. As many of these regions are subject to prolonged dry seasons and waterborne disease, groundwater is their only potable resource. This attests to the importance of appropriate lineament delineation in groundwater potential studies.

Geomorphology is the study of landforms and structural features of the landscape. Geomorphological maps are usually developed through field surveys, aerial photos and satellite images, and serve the purpose of identifying those features that may be favourable to infiltration, groundwater storage, or both. Alluvial fans, sand dunes, weathering mantles, floodplains and other accumulations of unconsolidated material typically rank among the most interesting geomorphological features from the point of view of groundwater (Venkateswaran and Ayyandurai 2015). Conversely, landforms such as inselbergs, scarps and ridges can be safely assumed to be of little practical use.

Soil data are routinely used in groundwater recharge and vulnerability studies (Vias et al. 2005, Samadder et al. 2011, Mokadem et al. 2018). This is mostly because soil permeability is directly related to effective porosity, grain shape and size, and void ratio, which means that soil type plays an important role in infiltration. For this reason, studies considering soil-related variables frequently do so together with rainfall and/or recharge (Nanda et al. 2017, Thapa et al. 2017b, Al Shaheeb et al. 2018). Typically, the higher infiltration potential is associated with sandy and gravelly soils, while clayey and silty soils rank among the least favourable. Fine sands and loamy soils can be expected to present moderate permeability.

Land use and cover play a similar role to soil type, for both are related to aquifer recharge. The integration of land use and land cover in groundwater potential studies attests to the fact that human activities can alter hydrological dynamics—for instance, cropland and forests are often considered favourable to groundwater occurrence because ploughing, root development and biological activity all favour infiltration. Areas in close proximity to permanent water bodies also tend to correlate with a higher groundwater potential (Naghibi et al. 2017; Singh et al. 2018). Conversely, hills, human settlements and wastelands are generally disregarded (Magesh et al. 2012; Martín-Loeches et al. 2018; Patra et al. 2018).

Despite its influence on some of the aforementioned aspects, attempts are usually made to consider aquifer replenishment as a stand-alone factor. This can be problematic because groundwater potential mapping is typically applied in data-scarce regions, where aquifer recharge is poorly characterized. Furthermore, the idea of groundwater potential mapping via RS/GIS is to develop predictive maps based on whatever is readily available, rather than to improve the existing knowledge about specific variables. Thus, even if the recharge mapping literature is rich (Selvam et al. 2015; Yeh et al. 2016; Mokadem et al. 2018), there are comparatively fewer examples of groundwater mapping studies using quantitative recharge estimates (An et al. 2012; Konkul et al. 2014; Oikonomidis et al. 2015). These tend to rely either on third-party information or on uncomplicated techniques (rainfall minus evapotranspiration, quantification of canal losses, etc.). In contrast, the use of rainfall is far more common (Nampak et al. 2014; Madani and Niyazi 2015; Bashe 2017; Panahi et al. 2017; Nanda et al. 2017; Jenifer and Jha 2017; Thapa et al. 2017; Hussein et al. 2017). Spatially distributed rainfall estimates are generally developed by geostatistical extrapolation of point-source information.

Digital elevation models

Satellites are equipped with remote sensors, that is, devices that can capture information about objects from far away. Remote sensors are either active or passive. The former send a signal in the direction of the object to be investigated, while the latter measure the radiation that naturally emanates from it (usually reflected sunlight). The majority of active sensors operate in the microwave portion of the electromagnetic spectrum, which makes them able to penetrate the atmosphere under most conditions. Conversely, most passive systems used in remote sensing applications operate in the visible, infrared, thermal infrared, and microwave portions of the electromagnetic spectrum. Examples of active sensors are radars, laser altimeters, laser radars, ranging instruments, scatterometers and sounders. Passive sensors include accelerometers, hyperspectral and imaging radiometers, spectrometers and spectroradiometers (NASA 2018a).

Satellite information is increasingly recognized as a cost-effective tool in many scientific domains. This is largely because its accessibility has become widespread in recent years, thus allowing scientific communities to develop applications within their respective fields. Digital elevation models (DEM) provide an excellent example of cross-discipline application. DEMs usually adopt the shape of raster files, and may be developed from many data sources, including field surveys. Currently, however, DEMs are mostly obtained from active sensor (radar, LIDAR) or passive optical sensor data. The radar-based Shuttle Radar Topography Mission (SRTM) and the optical Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) rank among those whose use is most widespread. Both are available for free and currently provide consistent information at the global scale for a spatial resolution of 1 arc-second (30 m) (Wendt et al. 2016).

In general, the application of DEMs to groundwater exploration relies on the assumption that shallow groundwater flow is partially driven by surface features, and parameterized by properties that can be inferred from surface data (Elbeih 2015); thus, topography may be used to identify lowlands, basins, closed depressions and other theoretically favourable settings. Furthermore, digital elevation information can be treated to gain additional insight (Liu et al. 2015)—for instance, slope provides important clues as to the nature of various geological and geodynamic processes, including groundwater recharge (Fashae et al. 2014; Kumar et al. 2016). Gentle slopes imply slow runoff, and thus, more time for infiltration, while, conversely, steeper gradients suggest greater erosion and short residence time. In groundwater potential mapping, this is frequently associated with a lesser probability of accumulation of unconsolidated sediments and recharge (Ibrahim-Bathis and Ahmed 2016).

DEMs may also be used to develop drainage density maps. Drainage density is computed as the total length of the streams per catchment unit area; thus, it represents how close together the stream channels are. A very high drainage density means that runoff can be evacuated quickly, and thus, that infiltration is less likely (Magesh et al. 2012; Fashae et al. 2014). There are, however, some exceptions, as groundwater can be expected to accumulate in alluvial sediments in the flatter areas of the catchment (Das et al. 2018). In addition, a high drainage density can be assimilated to a larger erosion potential. Parallelisms between drainage density and terrain permeability may be found in certain geological environments (Meijerink 2007).

Topography not only controls groundwater flow to some extent, but also plays an important role in the spatial distribution of hydrological variables such as infiltration potential or soil moisture. This can be reflected by parameters like the topographic wetness index (Beven and Kirkby 1979; Sorensen et al. 2006), which interprets the relation between the water that accumulates at any point of a given area and the gravitational force that drives water down slope. The topographic wetness index is calculated as a logarithmic ratio between the catchment area draining into a point of the drainage network and the average gradient. A higher index represents a lower slope and a larger area. Thus, groundwater occurrence and the topographic wetness index are positively correlated (Nampak et al. 2014; Rahmati and Melesse 2016; Misi et al. 2018). Other potentially useful parameters that can be inferred directly from topographic data include slope curvature, erosion indexes and runoff coefficients (Oh et al. 2011; Naghibi et al. 2017; Chen et al. 2018; Singh et al. 2018).

Satellite images

Rationale and image treatment procedures

Information from certain satellite images is classified and stored based on spectral response. Since each object presents a unique set of spectral responses, remote sensing may be used to identify different bodies (rocks, vegetation, roads, water) based on their specific signatures (Gupta 2018). Because each satellite presents a different spectrum of wavelengths, image size, spatial and temporal resolution, and historical records, the value of the data ranges from the local to the global scale, and may (or may not) be usable in studies spanning certain areas and/or periods of time. In this context, the selection of one information source over another may have critical implications on the results.

There are currently numerous satellite platforms which provide potentially useful information. These include Landsat 7 and 8, WorldView 4, Pleiades, QuickBird, KompSAT, IKONOS, ALOS or Sentinel 2, among others. Landsat is, however, the most widely used in groundwater studies., which is explained by several factors, including accessibility, long time series, a sufficiently broad wavelength spectrum and accurate spatial and temporal resolution. The most recent satellite in the Landsat program is Landsat 8, launched in 2013. Landsat 8's Operational Land Imager (OLI) captures spectral responses across nine discrete wavelengths along the electromagnetic spectrum, while its thermal infrared sensor (TIRS) includes two additional bands within the thermal infrared (Table 1; Barsi et al. 2014).

Satellite images may be treated to highlight the differences between spectral responses (Gupta 2018). Because images are made up of different wavelengths, their analysis typically seeks to find additional information by decomposing the image in separate bands (Bishop 2018). Common procedures include band composites, band ratios and principal component analyses (Wendt et al. 2016). These methods typically involve some subjectivity and trial-and-error, which means that the skill and experience of the technician may have a strong bearing on the results. Table 2 presents some commonly used composite combinations and band ratios for Landsat 8 images.

Spectral signatures are recorded at the scale of the image resolution (i.e. pixel scale). Since images may cover hundreds or thousands of square kilometres with a very high resolution, the volume of information stored in each one is enormous (Meijerink 2007). For practical purposes, this information

Table 1 Landsat 8 bands (after Barsi et al. 2014, NASA 2018a, b). *OLI* operational land imager, *TIRS* thermal infrared sensor

Band	Sensor	Wavelength (μm)	Pixel resolution (m)	Some applications
B1. Coastal aerosol	OLI	0.433–0.453	30	Coastal and aerosol studies
B2. Blue	OLI	0.450–0.515	30	Bathymetry, soil and vegetation (evergreen vs deciduous)
B3. Green	OLI	0.525–0.600	30	Plant vigour
B4. Red	OLI	0.630–0.680	30	Vegetation variations
B5. Near infrared (NIR)	OLI	0.845–0.885	30	Biomass content, shorelines
B6. Short-wave infrared (SWIR1)	OLI	1.560–1.660	30	Soil moisture content and vegetation
B7. Short-wave infrared (SWIR2)	OLI	2.100–2.300	30	Soil moisture content and vegetation
B8. Panchromatic	OLI	0.500–0.680	15	Higher resolution images
B9. Cirrus	OLI	1.360–1.390	30	Cirrus clouds
B10. TIRS 1	TIRS	10.600–11.190	100	Thermal and soil moisture mapping
B11. TIRS 2	TIRS	11.500–12.510	100	Thermal and soil moisture mapping

typically needs to be clustered, which may be achieved through unsupervised or supervised methods (Elhag 2017; Huang et al. 2018). In an unsupervised classification, in-built algorithms are used to classify the information based on similarities in pixel scores, with no human intervention beyond determining which algorithm to use. In contrast, a supervised classification involves the operator more directly. A number of sample pixels that can be considered representative of the variable at hand (rock, vegetation, etc) are selected based on ground-truth and expert knowledge (Aydav and Mizn 2015; Burton-Johnson et al. 2016). Then these are used as "training sites" for the computer to identify those pixels in the image that present similar properties, usually with some degree of tolerance. As a rule of thumb, supervised classification based on field data is preferable to unsupervised classification; however, unsupervised classification may prove invaluable for initial screening in complex and large areas (Elhag 2017).

Applications

While satellite surveillance does not penetrate deep into the ground, it does provide useful information as to those features of the landscape that may be associated with shallow groundwater. Vegetation is a classic example. Multispectral imagery at high spatial resolution has been used, for instance, to monitor crop biophysical parameters and water use (Calera et al. 2017). In the context of groundwater potential studies, the presence of vigorous vegetation at the end of the dry season can be interpreted as a proxy for a permanent spring or a shallow water table.

Many vegetation-related indices have been proposed over the years, including the ratio vegetation index (RVI), the vegetation index number (VIN), the differenced vegetation index (DVI), and the normalized difference vegetation index (NDVI; Bannari et al. 1995; Xie et al. 2008). The latter is perhaps the most widely used, largely due to its ease of calculation and to its sensitivity to temporal changes in vegetation patterns (Xue and Su 2017). NDVI banks on the principle that chlorophyll content generates a highly absorptive response in the visible red, but is reflective in the infrared wavelength. Since live green plants typically appear dark in terms of their photosynthetically active radiation and bright in the infrared, the contrast can be used as an indicator of vegetation status (Xie et al. 2008).

Table 2 Commonly used Landsat 8 band combinations and ratios (own elaboration from Wendt et al. 2016 and various other sources). Applications may differ from humid to dry climates

Band composite	Application	Band ratio	Application
432	Natural colour image	4/5	Rock vs vegetation
543	Vegetation type, moisture, water	5/7	Argillic vs Fe^{3+}
564	Land vs water	5/3	Fe^{2+} vs Fe^{3+}
567	Regolith vs outcrop	$(5-4/5+4)$	NDVI
571	Shallow water, vegetation	6/2	Iron vs non-iron
632	Landforms in dry environments	6/5	Argillic vs Fe^{2+}
652	Irrigated vs natural vegetation vs barren land	7/6	Argillic vs non-argillic
752	Geology	–	–
753	Land vs water vs vegetation	–	–
764	Urban environments	–	–

NDVI is typically used for the purpose of assessing vegetation vigour. NDVI values range from −1 to +1. Pixel-scale ratings are ultimately dependent on the image, which means that they may fluctuate from one setting to another. However, there is a more or less general consensus that rock and bare soil typically present low positive values, whereas water and snow are in the negative. In contrast, dense vegetation exceeds +0.5, and shrub lands and grasslands result in intermediate positive values. NDVI may be sensitive to variables such as soil brightness, colour, atmosphere and cloud shadows (Xue and Su 2017).

Because not all vegetation types present the same spectral signature, vegetation-related indexes may be used to distinguish among plant communities. This can be useful in the context of groundwater studies, where the presence of different species may have practical implications—for instance, the existence of a shallow water table may be inferred from the proliferation of phreatophytes. Halophytic species also point at shallow groundwater, but suggest a high degree of salinity, while xerophytes imply that groundwater is either "deep" or altogether absent (Jha et al. 2007; Jasmin and Mallikarjuna 2011). Other indicators such as evapotranspiration or soil moisture can provide similar information to vegetation (Ndou et al. 2017; Gokool et al. 2018).

Due to the thermal inertias of water stored underground, temperature anomalies in land surface may also be used as an indicator of the presence of groundwater. This is particularly true of arid and semiarid environments subject to long dry spells. Cool thermal anomalies have been defined as locations where land surface temperatures are lower than those of surrounding locations under normal conditions. These can be associated with discharge of groundwater through fracture systems, infiltration or groundwater accumulation (Abrams et al. 2018). Whenever dealing with temperature-related variables, care must be taken to discriminate the effects of cloud cover and recent rainfall and runoff, as well as that of shadows and vegetation canopies.

Satellite information has also proven useful in delineating rock types in numerous occasions (Simon et al. 2016; Ducart et al. 2016). Wendt et al. (2016) and Gupta (2018) provide an excellent discussion of the most prominent features of major rock types in satellite images, a selection of which is provided in Table 3. While rock type may be inferred from spectral response to some extent, there are mineral components with specific spectral signatures can be common to very different rocks (Meijerink 2007). Moreover, the spectral response of given rock can vary significantly depending on whether it is fresh or weathered; thus, spectral assessment needs to be complemented with other information (DEM, landforms, drainage) for optimal results. Some degree of field work is inevitable to ensure an adequate calibration of the results, but the RS approach can help keep it to a minimum. Classification-wise, a combination of supervised and unsupervised methods is typically appropriate. Image processing techniques such as edge detection methods are sometimes applied on satellite images to detect lineament density (Al Saud 2010; Panahi et al. 2017).

Relevant hydrogeological features might be buried. Radar waves are able to penetrate the ground down to a few meters, although this is strongly dependent on soil moisture. In desert regions, for instance, the space-borne low-frequency synthetic aperture radar (SAR) has proven an invaluable aid in revealing paleo-hydrological and tectonic structures hidden under aeolian sands (Molina et al. 2017). This allows for the delineation of alluvial fans, paleo-channels, paleo-lakes and paleo-shorelines, which may constitute preferential flow paths or reservoirs of groundwater (Sternberg and Paillou 2015). Radar techniques may also contribute to penetrate dense vegetation canopies, thus providing information as to which types or rocks are beneath (Gupta 2018).

Borehole and geophysical data

The aforementioned sources provide surface-level information, but fail to capture the vertical component of groundwater systems (i.e. depth). Because groundwater is by definition stored underground, borehole and geophysical logs must be sought whenever possible. Borehole logs provide undisputable evidence of the presence (or absence) of groundwater. Borehole databases typically have information on yield, depth and static groundwater level (DNH 2010; DGEP 2016), and may also include pumping test and water quality data, as well as the location and flow rate of springs (Nsiah et al. 2018; Saha et al. 2018).

In monotonous settings, consistently high success rates and similar groundwater levels throughout suggest the existence of a regional water table. In contrast, the value of borehole records is limited in highly anisotropic media, where the conditions underground may change significantly over just a few meters. Furthermore, water level/depth data are useful to develop water-table maps in order to determine the main recharge and discharge areas of an aquifer, while lithostratigraphic logs may be used to derive valuable information on aquifer thickness. Joint interpretation of all these variables can render a highly accurate picture of the hydrogeological conditions in the field, thus contributing to the reliability of the end product (Jasrotia et al. 2016; Diaz-Alcaide et al. 2017; Nsiah et al. 2018). Unfortunately, the literature shows that the use of exhaustive borehole databases in groundwater potential studies is relatively uncommon.

The next most informative thing to a borehole log is a geophysical log. Geophysical techniques do not directly detect the presence of groundwater, but do provide

Table 3 Characteristics of selected types of rocks as featured in satellite images (after Wendt et al. 2016 and Gupta 2018)

Rock type	Rock subtype	Landforms	Vegetation	Spectral response	Additional comments
Sedimentary	General features	Compositional layering of different rock types, resulting in differential erosion, moisture content variations and banded vegetation	Heavily dependent of climatic conditions, but also on rock properties	When layered, different rock types often present different spectral properties (see below)	Banding similar to foliated metamorphic rocks, but typically longer and more regular
	Sandstone	Resistant to weathering, forming prominent landforms (hills, ridges, mesas, cliffs). Jointing well developed, medium- to low-density drainage system (good permeability)	May present good vegetation cover due to good porosity and permeability	Light-toned in VIS-NIR-SWIR imagery	Similar to limestones in arid regions, but lack their characteristic absorption at 2.35 μm (SWIR). Similar to quartzites, but these take place in metamorphic environments
	Shale	Easily eroded, forming low grounds and valleys. Gently rounded hills in humid climates. Generally impervious, leading to well-developed dense drainage systems. Jointing and bedding rarely prominent. May produce a thick soil cover in humid climates	Vegetation sparse or absent in semiarid climates. Vegetation bands may mark the lithology in humid regions, where shaley soils are used for agriculture	Light-toned in VIS-NIR-SWIR images, except in the 2.1–2.4 μm region, where clay minerals present absorption features	Similar to schists and phyllites (can differentiate based on the regional setting)
	Limestone and dolomite	Resistant to erosion in arid climates (forming ridges, hills). Prominent karst forms, particularly in humid regions (collapse structures, sinkholes, caverns, losing streams). Jointing well developed, but drainage density typically low. Soil typically light-coloured or reddish due to the solution residuals	Vegetation cover can be very dense in humid environments, and very sparse in dry environments.	Light-toned in VIS-NIR-SWIR images, except at longer SWIR wavelengths, where they may appear dark due to carbonate absorption at 2.35 μm. Iron-bearing weathering residuals may lead to absorption in the UV-blue region. SAR data can improve the identification under dense vegetation	Similar to sandstone if no clear karst features are observed. May be distinguished based on 2.35-μm absorption and on its absence around 9 μm in limestones. Limestone may be distinguished from dolomite in TIR images due to differences in thermal inertia
Igneous	General features	Absence of bedding and foliation (although large lava flows may give the impression of bedding). Massive, isotropic and homogeneous over large areas. Often well jointed, dendritic or angular drainage. Different shapes and dimensions, from regional-scale batholiths to dykes and sills	–	–	–
	Extrusive	Volcanic landforms (edifices, lava flows, cones, craters). Flows present rough surfaces and are discordant with the underlying rock. May be very susceptible to weathering. Lavas generally present high-density dendritic networks, which may be radial if associated with volcanic structures	Older extrusive rocks may present thicker soil and vegetation cover due to prolonged weathering	Light-toned on VIS-NIS-SWIR images, weathering, soil cover and vegetation may have significant influence in spectral response. Clay bands may be observed in the SWIR in altered flows	–
	Granite	More prone to weathering in humid climates. Spheroidal weathering with smooth, rounded shapes. Isolated outcrops through a thick weathered mantle. Large boulders. Steep, sharp,	–	Light-toned in the spectrum of reflected sunlight, but the spectral response may be altered by composition, degree of weathering and soil and vegetation cover	–

Table 3 (continued)

Rock type	Rock subtype	Landforms	Vegetation	Spectral response	Additional comments
		jagged forms in arid and semiarid regions. Low to medium drainage density, with angular patterns due to prominent jointing			
	Basalt	Highly susceptible to weathering (original landforms difficult to distinguish in highly weathered regions). Drainage networks may be almost absent at first due to high permeability. Fine dendritic networks develop on weathered plateau basalt due to low permeability. Columnar jointing may be present. Dark-coloured clayey soils develop as a result of weathering	Vegetation is sparse on younger flows, but weathered areas may support natural vegetation and agriculture	Dark in the VIS range, especially at the blue end. Medium tones in the NIR-SWIR ranges, with mottled appearance due to moisture variations. Soils are very dark in the SWIR range	Basalts may appear similar to acidic extrusive rocks, and may be differentiated on the basis of landforms, weathering and spectral properties
Metamorphic	General features	Marked by foliation and some stratification. Foliation is manifested in the shape of numerous short photo-lineations, typically parallel to each other. Rocks of regional metamorphism are typically deformed and fractured, thus controlling drainage and vegetation	Vegetation may be expected along fractures, even in semiarid climates	–	–
	Quartzite	Highly resistant to erosion, both in humid and arid climates. Renders prominent landscape features such as hills, ridges and scarps. Low- to medium-density drainage due to steep slopes, even if permeability is low. Rectangular and angular flow patterns	–	–	Appearance similar to sandstone, but quartzite takes place in metamorphic environments
	Marbles	Relatively resistant to erosion in dry climates. Form cliffs, hills and ridges. Low drainage density can be expected in humid regions due to karst phenomena. Joints are often well developed, much like in limestones	Similar to limestone	Similar to limestone	–

valuable information about the types of rocks that can be found underground and their properties. Electrical and magnetic surveys are frequently used in the process of siting boreholes, but the outcomes are seldom compiled in comprehensive databases. While there may be exceptions, the use of this kind of information is generally restricted to small-scale applications with an ad-hoc geophysical component (Omosuyi et al. 2013; Akinlalu et al. 2017; Helaly 2017; Bayewu et al. 2018).

Data integration and validation

Any attempt to map groundwater potential must take into consideration two crucial points: (1) perceptual bias on the part of the operator (i.e. making the map look like "what it should look like" based on personal belief) may have an overly strong bearing on the results; and (2) the outcomes of a groundwater potential map are virtually worthless without ground truth. In this context, both the way data are integrated and the validation procedure are essential to ensure representative outcomes.

Data integration procedures

Groundwater potential zoning is a classic example of a multicriteria decision problem (Ahmed et al. 2014), where the likelihood of attaining a target (finding groundwater) is contingent on a variety of factors—soil, lineaments, slope, geology, landforms, lithology, drainage. These sometimes contribute to this intent and sometimes offset each other, which makes the task more complex. The information needs to be integrated meaningfully so that, ultimately, every pixel in the map ends up with a reliable groundwater potential index.

In broad terms, there are two major approaches to data integration: expert decision systems and machine-learning methods. Expert decision systems are directly based on human judgement, and include techniques such as simple addition, multi-influence factor techniques or analytical hierarchy processes (Agarwal et al. 2013; Abrams et al. 2018). On the other hand, machine-learning methods comprise a large variety of approaches, including artificial neural network fitting, logistic regression, regression trees, random forest techniques and statistical tree algorithms (Duan et al. 2016; Chen et al. 2018). Generally speaking, machine-learning is less prone to procedural mistakes and perceptual bias, whereas expert methods provide the advantages of relying on a seasoned pair of eyes to discern features that may escape automatic detection. In practice, neither approach can be expected to render better results than the other.

Expert decision systems

Each information source provides a completely different set of variables. These may be either quantitative or qualitative, and not necessarily measurable in the same units. Hence, a crucial point in groundwater potential studies is data integration. For practical purposes, each pixel within each thematic map needs to be assigned a numerical score, or "weight", so that map algebra can be performed (Ibrahim-Bathis and Ahmed 2016; Govindaraj et al. 2017). This process necessarily relies on expert judgement to some extent, which means that a certain degree of subjectivity is always involved (Martín-Loeches et al. 2018).

The influence of each variable on groundwater potential presents two major components, namely, its comparative and intrinsic weights (Fashae et al. 2014; Das et al. 2017). The comparative weight of a variable represents how important it is in relation to the others, while its intrinsic weighting has to do with how the rating of a given variable is distributed "internally" (Ghodratabadi and Feizi 2015; Dinesan et al. 2015). For instance, under certain circumstances landforms may be deemed more important for groundwater potential than drainage density (Jasrotia et al. 2016), which means landforms will be assigned a greater comparative weight when putting both maps together with the rest. Then, landforms need to be classified into various types (inselbergs, pediments, floodplains), each one of which will receive a different score (intrinsic weighting).

The most rudimentary integration technique is simple additive weight, consisting of assigning an equal weight to each variable, assuming the intrinsic weights to be consistent in terms of its importance for groundwater potential. While conceptually straightforward, this approach may render good-quality results if the setting is appropriate., which is demonstrated by the work of Abrams et al. (2018) in Oman and the United Arab Emirates. In this case, expert methods (simple addition, analytical hierarchical processes) were observed to yield better results than machine-learning approaches (probabilistic frequency ratio). The authors attributed this to the limitations of the well dataset to predict groundwater potential in rugged terrain, as well as to the inability of the frequency ratio method to extrapolate groundwater potential beyond the spatial extent of known wells.

Multi-influence factor techniques (MIF) rank among the most popular methods to determine the weights of each variable (Magesh et al. 2012; Das et al. 2017; Thapa et al. 2017a, b; Nasir et al. 2018). The underlying principle behind MIF methods is that some of the variables involved may be interdependent, and that those which influence the others the most are those that also influence groundwater potential more strongly. Thus, each variable is compared individually against all others in order to establish a hierarchy—for instance, in crystalline terrains lineaments can be expected to exert a strong influence on the drainage network, but the opposite will not be true. The variable under consideration is assigned a value of 1 if it influences the other one significantly, of 0.5 if it does so in a minor way, and 0 if it does not or if both are unrelated. The comparative scores of the variable under consideration are added together. Then, its comparative weight is calculated as the percentage over the total score of all variables (Manikandan et al. 2014; Thapa et al. 2018). Finally, each variable is reclassed internally for the purpose of computing its intrinsic weights. The maximum intrinsic weight must coincide with the comparative weight of the variable, while the minimum may be zero or even negative.

Analytical hierarchy processes (AHP) are closely related to MIF methods (Saaty 2008). Expert-based pairwise combination remains similar, but the scores are normalized to smooth out the subjectivity component and tested for consistency. The final weightings for the thematic layers are the normalized values of the eigenvectors that are associated with the maximum eigenvalues of the ratio matrix (Mohammadi-Behzad et al. 2018). While the calculations are more complex than those involved in MIF, AHP is available in certain software packages, and is also frequently used in the groundwater potential literature (Agarwal et al. 2013; Shekhar and Pandey 2014; Aladejana et al. 2016; Mohammadi-Behzad et al. 2018). AHP is also versatile enough to be integrated with other approaches such as entropy analysis (Al Abadi et al. 2017).

Machine-learning methods

Machine learning is best described as a set of statistical approaches that focus on revealing hidden patterns in large datasets (Mitchell 1997). In the context of groundwater potential studies, machine-learning helps determine which variables are more closely associated with groundwater based on field evidence. Thus, the rationale behind machine-learning techniques is the opposite to that of manual methods. Based on ground truth (successful drilling spots, borehole yield, groundwater level), the computer examines the spatial relationships between all explanatory variables (geology, landforms, soil, etc.) to determine which ones are most significant (Odzemir 2011a, b; Naghibi et al. 2015). The results can then be used to develop a groundwater potential map.

Machine learning methods may be supervised or unsupervised (Hastie et al. 2009). Supervised methods consist in developing an algorithm that relates a series of potentially explanatory variables to a known output. On the other hand, unsupervised machine learning takes place when there are a set of explanatory variables but no known output (i.e. no ground-truth). In the first case, the goal is to predict an outcome, whereas in the second, the aim is to learn more about the internal dependencies among the explanatory variables (Kelleher et al. 2015). Typical examples of supervised approaches include support vector machines, statistical learners and classification trees, whereas unsupervised learning includes clustering and dimensionality reduction (Shalev-Shwartz and Ben-David 2014).

Supervised learning is particularly useful in the context of groundwater potential studies. Output-wise, supervised methods are split in two broad categories, namely regression and classification, the main difference being the type of results that can be expected (Hastie et al. 2009). Regression provides outcomes in terms of a continuous quantitative variable (borehole yield, spring flow, groundwater depth), whereas classification approaches are used to determine a series of bivariate or multivariate classes (presence vs absence of groundwater, presence vs absence of spring, low/medium/high groundwater potential). The use of machine-learning methods in the field of groundwater potential mapping is still relatively new. Tested approaches include weights of evidence (Lee et al. 2012; Al Abadi 2015; Madani and Niyazi 2015), probabilistic frequency ratio (Dadgar et al. 2017; Balamurugan et al. 2017; Jothibasu and Anbazhagan 2017; Abrams et al. 2018), logistic regression (Odzemir 2011a, b; Chen et al. 2018), functional tree models (Chen et al. 2018), evidential belief function models (Nampak et al. 2014; Rahmati and Melesse 2016; Mogaji and Lim 2018), or regression trees (Naghibi et al. 2017), among others.

Machine learning techniques are inherently complex, which means that predicting whether a method will perform better than another is too complicated a task for the human mind. Thus it is common practice to compare different methods and to either pick the best one or perform an ensemble of the results. The performance of machine-learning methods has been compared in the context of various studies—for instance, Naghibi et al. (2015) evaluated the performance of boosted regression tree, classification and regression tree, and random forest techniques to evaluate spring potential in the Koohrang watershed, Iran. All three models were validated satisfactorily by means of receiver operating characteristics curve methods. The boosted regression model rendered the best results, followed by classification and regression tree and random forest. Odzemir (2011a) carried out a similar exercise in the Sultan Montains, Turkey, where frequency ratio, weight of evidence and logistic regression models were tested. In this case, frequency ratio provided a better fit with observed data then the other two. Finally, Chen et al. (2018) compared ensemble weights of evidence with logistic regression and functional tree models to map spring potential in the Ningtiaota region, China, obtaining the better results with the latter.

Map validation

Al Saud (2010) provides a brief overview of about 20 groundwater potential studies carried out between the 1960s and 2008, including the authors' self-assessments. Unsatisfactory results were found in the earlier period, outcomes becoming increasingly more reliable from the 1980s. This can be partially explained by the increasing resolution of remote sensing information, as well as to a growing number of variables being taken into consideration. Indeed, earlier works were typically based on one or two potentially meaningful parameters (lineaments, landforms), whereas the modern literature on average relies on no less than six or seven (Fig. 1).

In practice, the only way to ensure that a groundwater potential map is actually representative is to validate it against field data. There are two approaches to validating a groundwater potential map, both of which are contingent on the quality and spatial distribution of borehole and/or spring data. The first one consists in checking the results against a sufficiently broad field dataset. Experience shows that the type of validation data will typically depend on what is available, rather than on the preferences of the operator. Thus, borehole success, pumping test or spring discharge data rank among the most sought-after validation sources (Agarwal et al. 2013; Gumma and Pavelic 2013; Agarwal and Garg 2016; Tahmassebipoor et al. 2016; Ahmed and Sajjad 2018). This is because these not only provide useful information as to the presence of groundwater, but also as of its suitability for different uses. In this context, validation procedures include comparison of the number of positive boreholes per potential zoning, well yield vs groundwater potential index, and receiver operating characteristic curves (Al Abadi 2015; Naghibi et al. 2015). In studies dealing with groundwater occurrence or storage potential, however, validating on groundwater depth/level may also be satisfactory (Kumar et al. 2014; Madani and Niyazi 2015; Nasir et al. 2018).

The second procedure is self-validation. Self-validation is achieved by using exhaustive borehole data in the process of developing the map (Diaz-Alcaide et al. 2017; Nsiah et al. 2018). Self-validated maps may include variables such as well yield, transmissivity, groundwater level or spring discharge, alongside remote sensing information and hydrogeomorphological cartography. By its own nature, self-validation can only be carried out in regions with a sufficiently well-developed knowledge base. Mixed validation approaches based on splitting the field database into “training”, “validation” and “test” datasets are often implemented in the context of machine-learning applications (Odzemir 2011a, b; Oh et al. 2011; Chen et al. 2018).

Discussion

A groundwater potential map serves the purpose of delineating those areas that may be more favourable for groundwater development within a given geographical setting. While developing a reliable groundwater potential map requires advanced notions of geology, hydrogeology and satellite science, the final outcomes are typically presented in visually appealing fashion, so that they can be interpreted by anybody (Bagyaraj et al. 2012). This has some inherent dangers, for the complexities and uncertainties of groundwater exploration are ultimately lost in a dimensionless colour scale ranging from “very low” to “very high”. As a result, groundwater potential maps have a natural tendency to replace reality in the eyes of stakeholders and decision-makers, which implies that care must be taken to ensure that end-users understand the pitfalls.

Attractive maps can be developed with relatively little data. Looking at the end product, however, there is no telling as to how comprehensive the mapping process or the datasets were. In this context, quality assurance is a major issue. Remarkably, however, a major drawback in groundwater potential studies is the absence of validation. Out of the 200-odd cases studies analysed in this research, over 70% did not present a robust validation mechanism. Of course, this cannot always be attributed to methodological flaw. The absence of validation is acceptable in preliminary studies. Take for instance those carried out in isolated regions, where there may be little or no hydrogeological knowledge prior to the development of the map. In such cases, groundwater potential maps are best interpreted as estimates pending on confirmation (Al Shaheeb et al. 2018; Mogaji and Lim 2018).

An important factor determining the reliability of a groundwater potential map is the quality and scale of the underlying datasets. Figure 1 provides an overview as to how various authors approached the issue of groundwater potential mapping in a wide variety of regions. As shown, the number of parameters involved in each study ranges from just four or five to over 10 or 12. Because of the inherent uncertainties of groundwater prospect, the availability of as much information as possible is generally desirable. The literature also shows that the resolution of the input data used in groundwater potential studies tends to be highly variable. More specifically, combining fine and coarse resolution information is common practice, as is the reclassification of explanatory variables (Manap et al. 2013, Bashe 2017, Dasho et al. 2017, Chaudhary and Kumar 2017, Jahan et al. 2018). This kind of simplification is often inevitable, even necessary in certain cases. However, it is only adequate if the map is to be used at the regional extent, as local inaccuracies can be expected to arise from mixing different scales. In such cases, groundwater potential maps should be interpreted as a tool to optimize the amount of field work involved, rather than as a low-cost substitute for local-scale surveys (Abdalla 2012; Mohammadi et al. 2014; Mandal et al. 2016). This is particularly relevant, for instance when siting boreholes for rural water supplies or humanitarian emergencies.

Furthermore, field datasets sometimes provide spatially biased information, with significant amounts of data in some regions and virtually none in others (Diaz-Alcaide et al. 2017). As voids are typically left for automated interpolation to fill, this may lead to spurious results. In other words, this suggests that a study with a large number of low-quality variables or very disperse information may render a less accurate picture of a given region than another one using fewer parameters with very high resolution.

Groundwater is context sensitive. A low-permeability formation may be considered an aquifer in a certain region because there is nothing else available, but may be disregarded in a neighbouring context where more permeable rocks occur. Moreover, flat areas with poorly developed drainage networks may be more prone to groundwater occurrence than hilly regions (Haghizadeh et al. 2017; Martín-Loeches et al. 2018). In other words, the explanatory variables and the likelihood of groundwater occurrence must be determined based on the specific features of each setting. This explains why there is no universal scale of groundwater potentiality. Attempts have been made to standardize scores at the national scale; take for instance the cases of Burkina Faso, Uganda and New Zealand (DEP 1993; MWE 2012; Tschritter et al. 2017). Such efforts make sense in national contexts because they allow managers to compare groundwater potential across more or less similar regions, but may become impractical at the continental or global scales due to the variability of geographical, geological and climatic contexts.

On a final note, there may be some margin to extend the number of variables involved in RS-based groundwater exploration. Since the vast majority of the literature deals with dry and tropical climates, the existing approaches are heavily geared towards these geographical domains. This is reasonable in view of the distribution of the world's population. However, from a methodological standpoint, it also means that the role of certain variables that could be relevant in colder settings such as snow-related factors, has seldom been discussed (Han and Nelson 2015).

Conclusions

This paper has provided an updated overview of groundwater potential methods based on a thorough review of the more recent literature. The large number of academic papers published in the last decade attests both to the practical value of the technique and to the need to improve our knowledge of groundwater resources in a rapidly changing world. Groundwater potential mapping is time- and cost-effective, and provides a practical way to integrate multiple data sources to delineate those areas which are more favourable for groundwater development. This represents a particularly important advantage in remote regions, where obtaining exhaustive field work may be impossible. However, groundwater potential maps cannot be interpreted as a low-cost substitute for field surveys, as there are many aspects of groundwater occurrence that are not easily captured on cartographic support.

Due to the widespread availability of RS/GIS technologies, as well as to the relatively small number of parameters involved, developing a groundwater potential map today is well within the reach of most hydrogeologists. Unfortunately, however, only a minority of the groundwater potential maps found in the literature have been adequately checked against ground truth. In this context, the main challenge ahead lies in developing high-quality maps that may be used to inform water policy. Because this should be preferably done in the context of validated outcomes, it is contended that academic groundwater potential studies should always be labelled either as "preliminary" or "validated", in order to prevent misinterpretations. Furthermore, it may often make sense to refer groundwater potential maps to the use for which they have been developed. This is because different uses (i.e. drinking, irrigation) present different water quantity and quality requirements.

From the methodological standpoint, the advent of machine-learning techniques represents an exciting development for the near future. In particular, the potential advantages of combining human experience with such approaches are enormous. In the authors' view, this can only result in more accurate mapping as these become increasingly widespread.

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