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By

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Integrated Management of Water Scarcity: From Conventional to Smart Approaches

Defended on September 2nd, 2022, in front of the jury composed of:

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Par

Tariq JUDEH

Gestion Intégrée De La Rareté De L'eau : Des Approches Conventionnelles Aux Approches Intelligentes

Soutenue le 2 Septembre 2022 devant le jury composé de

Isam SHAHROUR	Professeur, Université de Lille, France	Directeur
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Abstract

This thesis aims at establishing a smart management system to address the water scarcity in Palestine with emphasis on the assessment of water scarcity, protection of conventional water resources, adoption of rainwater harvesting (RWH), and use of dynamic smart water management. The thesis starts by investigating the state of the art and gaps of previous researches in addressing the water scarcity. Accordingly, a methodology is proposed to address these gaps with emphasis on the West Bank (Palestine). It includes (i) the assessment of water scarcity, (ii) the protection of conventional water resources using the GIS, water quality index and Machine Learning-based water quality prediction, (iii) the adoption of potential RWH for addressing the water scarcity, and (iv) the adoption of smart RWH system to promote the water security. Results indicate that seven out of the eleven West Bank governorates are suffering from extreme to acute water scarcity in 2020. Around 20% of the wells in the urban areas had experienced potability-related contamination. More than 95% of the potability-related contaminated samples are found in the Eocene Aquifer. Concerning groundwater nitrate contamination, Random Forest model successfully attained a maximum and average prediction accuracy of 91.70% and 88.54%, respectively. All water-contaminated samples were observed in areas with improper practices such as the use of cesspits, fertilizers, and pesticides. The smart RWH system showed a capability to cover 41% of the domestic water needs. The smart dual water system shows higher reliability in addressing the water demand compared to the smart RWH system solely. By adopting the dynamic management and a new supply agenda, the smart dual system showed a 100% capacity to address the water scarcity at all altitude levels in the study area. They also contributed to getting the best performance by using smaller storage tank size which could promote the city's socioeconomic development.

The knowledge-based framework and results presented in this thesis forms a step forward in the water engineering and sciences. However, this research shows some limitations including the dependency to downscaled global climate change models, and the lack of heavy metals characterization in the water quality aspects. Future research could focus on (i) considering a local climate change model to estimate the projected rainfall and water availability, and (ii) investigating the social acceptance for the adoption of the proposed smart system.

Keywords: Water scarcity, water management, smart water, machine learning, GIS, rainwater harvesting, water quality, climate change, Palestine

Résumé

Cette thèse porte sur le développement d'un système de gestion d'eau intelligent pour faire face à la pénurie d'eau en Palestine en combinant la rareté de l'eau, la protection des ressources en eau conventionnelles, la collecte des eaux de pluie (RWH) et l'utilisation d'une gestion d'eau dynamique et intelligente. Le premier chapitre présente l'état de l'art et les lacunes des recherches antérieures pour remédier à la pénurie d'eau. Ensuite, une méthodologie est proposée pour combler ces lacunes en mettant l'accent sur la Cisjordanie (Palestine). La méthodologie comprend (i) l'évaluation de la rareté de l'eau, (ii) la protection des ressources en eau conventionnelles à l'aide du SIG, de l'indice de qualité de l'eau et de la prévision de la qualité de l'eau basée sur l'apprentissage automatique, (iii) l'adoption de RWH potentiels pour remédier à la pénurie d'eau, et (iv) l'adoption d'un système RWH intelligent. Les résultats indiquent que sept des onze provinces de Cisjordanie souffrent d'une pénurie d'eau extrême à aiguë en 2020. Plus de 95 % des échantillons contaminés liés à la potabilité se trouvent dans l'aquifère de l'Éocène. En ce qui concerne la contamination par les nitrates des eaux souterraines, le modèle Random Forest a réussi à atteindre une précision de prédiction maximale et moyenne de 91,70 % et 88,54 %, respectivement. Les échantillons d'eau contaminés ont été détectés dans des zones où les pratiques étaient inappropriées, comme l'utilisation de fosses d'aisance, d'engrais et de pesticides. Le système RWH intelligent a montré une capacité à couvrir 41% des besoins domestiques en eau. Le système d'eau intelligent proposé montre une plus grande fiabilité pour répondre à la demande en eau par rapport au système RWH intelligent uniquement. En adoptant la gestion dynamique et un nouveau programme d'approvisionnement, le système intelligent a montré une capacité de 100% à faire face à la pénurie d'eau. Des meilleures performances ont été obtenues en utilisant des réservoirs de stockage de plus petite taille, ce qui pourrait favoriser le développement socio-économique de la ville.

Les résultats présentés dans cette thèse sont intéressant pour améliorer la gestion des ressources en eau. Cependant, nous sommes conscients des limites de cette recherche certaines, notamment la prise en compte d'une manière plus rigoureuse du changement climatique et la pollution des ressources en eau par métaux. La suite de cette étude pourra se concentrer sur (i) l'examen d'un modèle local de changement climatique pour estimer les précipitations et la disponibilité de l'eau, et (ii) l'étude de l'acceptation sociale de l'adoption du système intelligent proposé.

Mots-clés: Pénurie d'eau, gestion de l'eau, eau intelligente, apprentissage automatique, SIG, collecte de l'eau de pluie, qualité de l'eau, changement climatique, Palestine

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Abbreviations

Abbreviation	Definition
RWH	Rainwater Harvesting
RRWH	Rooftop Rainwater Harvesting
WASH	Water, Sanitation and Hygiene
MCM/y	Million Cubic Meters per Year
UN	United Nations
WHO	World Health Organization
SDBI	Supply Demand Balance Index
GIS	Geographic Information System
ML	Machine Learning
GNC	Groundwater Nitrate Contamination
IoT	Internet of Things
SDG	Sustainable Development Goals
IWMI	The International Water Management Institute
Q1	1st Quartile (25th Percentile)
Q3	3rd Quartile (27th Percentile)
WQI	Water Quality Index
WAWQI	Weighted Arithmetic Water Quality Index
AWAWQI	Adjusted Weighted Arithmetic Water Quality Index
KIM	Kriging Interpolation Method
OK	Ordinary Kriging
SK	Simple Kriging
UK	Universal Kriging
NH_4	Ammonium
DO	Dissolved Oxygen
BOD	Biochemical Oxygen Demand
NO_3	Nitrate
TN	Total Nitrogen
TP	Total Phosphorous
RFA	Random Forest Algorithm
ANN	Artificial Neural Network
CCFA	Canonical Correlation Forest Algorithm
SVM	Super Vector Machine Method
MSL	Mean Sea Level
l/c/d	Liter per Capita per Day
GWQI	Groundwater Quality Index
SVAT	Soil-Vegetation-Atmosphere Model
TWS	Total Water Supply
TWD	Total Water Demand
DWCR	Domestic Water Consumption Rate
RCCC-WBM	Research Center For Climate Change- Water Balance Model
HBV	Hydrologiska Byrans Vattenbalansavdelning Model
SWAT	Soil and Water Assessment Tool

POP_p	Projected Population
POPc	Current Population
WAAM	Weighted Arithmetic Average Method
SWARA	Step-Wise Assessment Ratio Analysis Method
PoGWQI	Groundwater Potability Index
PaGWQI	Groundwater Palatability Index
PoGWQS	Groundwater Potability Status
PaGWQS	Groundwater Palatability Status
PoGWQG	Groundwater Potability Grade
PaGWQG	Groundwater Palatability Grade
MRSA	Map Removal Sensitivity Approach
MAE	The Mean Absolute Error
EC	Electrical Conductivity
Na	Sodium
TC	Total Coliform
FC	Fecal Coliform
TDS	Total Dissolved Solids
Mg	Magnesium
Ca	Calcium
K	Potassium
HCO_3	Bicarbonate
Cl_2	Chlorine
Cl	Chloride
SO_4	Sulfate
CFU/100 mL	Colony-Forming Unit Per 100 Ml
NTU	Nephelometric Turbidity Unit
SSIP	Sample Size for Infinite Population
SS	Sample Size
MCL	Maximum Contaminant Level
PWA	Palestinian Water Authority
GCM	Global Climate Model
MoLG	Palestinian Ministry of Local Government
PMA	Palestinian Metrological Authority
R_e	Time-Based Reliability
R_v	Volumetric Reliability

Chapter 0. General Introduction

Main water challenges of arid and semi-arid areas

Given the increasing population growth and water demand, the sustainable management of water resources forms a necessity for most of the arid and semi-arid regions, especially in Palestine (Alawna and Shadeed, 2021; and Durán-Sánchez et al., 2018). Such management aims to satisfy the existing and future water demand and to address the water scarcity without causing the depletion and contamination to the water bodies (Durán-Sánchez et al., 2018). In the West Bank, Palestine, water scarcity is the main challenge that threaten the sustainable development (Alawna and Shadeed, 2021; and PWA. 2016). This scarcity has been deteriorated due to several factors including: the population growth and the associated increasing water demand, the water pollution, and the climate change impacts that imposed a terrific stress on the conventional water supplies (Judeh and Shahrour, 2021; and PWA, 2016). The existing political situation deepens the water scarcity since the Israeli Occupation controls the Palestinians' accessibility to their water resources (Judeh et al., 2017). Such control along with the Palestinians' dominant dependency to the conventional water resource (mainly to groundwater that contribute with more than 90% of the water supply) obstruct the alleviation of water scarcity through the adoption of sustainable management of water resources that relies on multi-sources of water supply (PWA, 2017). Thus, this research focuses on addressing the Palestinian water scarcity by the adoption of proper and sustainable water management practices. Such practices involve the monitoring and protection and of existing water resources, the adoption of alternative water resources (rainwater harvesting, RWH), and the adoption of smart water systems to improve the performance of the management of water resources.

Water scarcity

Water scarcity is a serious hazard that threaten the human life, and the agricultural, industrial, and urban development (Hasan et al., 2022; Chaudhary and Satheeshkumar, 2018; and Kahil et al., 2015). Scarcity can be seen in the physical in-availability of water resources, in the non-potability of available water due to the various contaminants reaching the different water bodies, or in the inaccessibility to water resources due to political, technical and institutional failure (Judeh and Shahrour, 2021). Such scarcity contrasting the recommendation of the World Health Organizations (WHO), and the United Nations (UN) Sustainable Development Goals-SDG 6 "ensure availability and sustainable management of water and sanitation for all" (UN, 2021). Scholars confirm the responsibility of such scarcity in the spread of infectious diseases (e.g., SARS, Ebola, and influenza). Such diseases could be eliminated by adopting the needed water, sanitation and hygiene (WASH) measures (Anser et al., 2020; Adams et al., 2019; and Zakar et al., 2012). Water scarcity is also linked to other diseases such as cholera, typhoid fever, salmonellosis, and dysentery (Anser et al., 2020; Adams et al., 2019; and Zakar et al., 2012). Agriculture and food security are also adversely affected by the water scarcity since it restricts the ability to address the increasing agricultural water demand (e.g. irrigated agriculture as well as livestock) (Shadeed et al., 2020; and Sullivan et al., 2003). Scarcity also impacts the food processing industries (Sullivan et al., 2003). Such deterioration in human health, agricultural and industrial development significantly threaten the sustainable urban development (Chaudhary and

Satheeshkumar, 2018; and Sullivan et al., 2003). As a result of the water scarcity, more than two billion people have insufficient access to water supply (Gonçalves et al., 2019). In the West Bank, the domestic water supply-demand gap was estimated at 58 million cubic meters per year (MCM/y) in 2018 (Judeh and Shahrour, 2021). In 2019, around 60% of Palestinians are suffering from high to very high domestic water poverty (Shadeed et al., 2019). On the other hand, about 61% of the West Bank governorates are characterized by high to very high agricultural water poverty (Shadeed et al., 2020). This in turn adversely impacted the water-food nexus in most of the Palestine governorates (Shadeed et al., 2020).

According to the UN' World Water Development Report, water scarcity is a major issue in today's world of 7.7 billion people. Such issue is expected to be more complicated by 2050 since the world population will increase by around 33% to reach around 10.2 billion. Most of the population growth is expected to occur in the developing countries (e.g. Palestine) (World Water Assessment Programme, 2018). By 2030, half of the world's population are expected to live in countries facing water scarcity status. This is expected to contribute to the displacement of 700 million people from the water-scare countries to the water-secured ones (Gonçalves et al., 2019). By 2050, around 90% of the world's population in the developing countries, especially in the arid and semi-arid areas will lack access to safe water supply (Gonçalves et al., 2019). Global water demand is expected to dramatically grow over the coming three decades among the domestic, agricultural, and industrial sectors. (World Water Assessment Programme, 2018). The global domestic water demand is expected to increase worldwide over the period 2020–2050, where the highest increase (300%) will be recorded in Africa and Asia (Wada et al., 2016). Global agricultural water demand is expected to increase by around 60% by 2050 (World Water Assessment Programme, 2018; and Wada et al., 2016). Considering the industry, global water demand is expected to increase by around 400% in 2050. Such growth will be spatially variated between 250% in Asia and 800% in Africa (World Water Assessment Programme, 2018; and Wada et al., 2016). In the West Bank, Palestine, population are expected to increase by around 75% between 2020 (around 2.7 million capita) and 2050 (around 4.7 million capita) (Courbage et al., 2016). This population growth is associated with significant growth in the domestic water needs from 110 MCM/year (for the current status) to 175 MCM/year (for the year 2050) (Judeh and Shahrour, 2021). Such dramatic increase in the water needs forms significant stresses on the limited conventional water resources (surface and groundwater) in Palestine (Judeh and Shahrour, 2021).

Climate change

Beside to the increasing water needs, climate change forms a major challenge to the sustainable management and mitigation of water scarcity (Stringer et al., 2021; Farsani et al., 2019; Gonçalves et al., 2019; and Abbaspour et al., 2009). The main driver of climate change is increasing greenhouse gas emissions from anthropogenic activities (Lu et al., 2019). As a result of the increase in the atmospheric concentration of greenhouse gas emissions, the global average surface temperature has risen by 0.6 °C to 0.8 °C over the past century (Lu et al., 2019). Such warming is 20-40% greater in the arid and semi-arid regions compared to the humid ones (MoFA Netherlands, 2018). Climate change has increased the incidents of extreme weather including, tropical storms, flash floods, droughts, and changes in precipitation (Bai et al., 2019; and Tegegne et al., 2017). In the arid to semi-arid areas, the water balance is usually negative since the average annual precipitation is generally close or even below the potential annual evaporation (Heyns, 2009). The high evaporation rate combined with unmanaged precipitation have led to a reduction in the levels of surface water resources (i.e., lakes and rivers) (Middleton and Sternberg, 2013). Yet, groundwater storage has continuously declined due to recharge and extraction imbalance (Heiß et al., 2020). In the Mediterranean region (including Palestine), Hochman et al., (2018) predicted changes in the length of seasons by the end of this century; the summer is expected to be longer by 49 %, while the winter season will be shortened by 56%. By 2100, global and regional climate models expected an increase in temperature between 2˚C to 2.7˚C in the region. On the other hand, annual precipitation is expected to experience a reduction ranging from 3% to 10% (Christensen et al., 2013). Subsequently, the water resources availability is expected to decrease by around 26% (Menzel et al., 2009). Other environmental changes might arise including the deficits in hydrological regimes, and the imbalances in natural production (Freij, 2021; and Christensen et al., 2013). Thus, implying the climate change impacts in the sustainable management of water resources in Palestine is of high importance (Durán-Sánchez et al., 2018).

Water pollution

Beside to the above mentioned reasons, the increased water scarcity could be attributed to several factors including: the water resources pollution, and the unaware use, allocation and management of the water resources (Shadeed et al., 2019; and Chitsaz and Azarnivand, 2017). According to the UN' World Water Development Report, the pollution of water resources is becoming worse, especially in the last few decades (World Water Assessment Programme, 2018). Such pollution is originated from point (from industry) and non-point (from agriculture and urban areas) sources (World Water Assessment Programme, 2018; and UNEP, 2016). Worldwide, around 730 million tons of sewage and other contaminating effluents are discharged into the water per year, where the industry is the main contributor (around 300 to 400 million tons per year) (World Water Assessment Programme, 2018). These loads affect most of the surface water quality (e.g. lakes and rivers), especially in Middle East (including Palestine) (Almasri et al., 2020; and UN, 2011). Moreover, many studies documented the deterioration of the groundwater resources quality worldwide (Chaudhary and Satheeshkumar, 2018; MacDonald et al., 2016; and Gleeson et al., 2012). Such deterioration is attributed to the low natural recharge, extensive use of pesticides in agricultural areas, heavy abstraction, and other anthropogenic activities (Adimalla, 2019). High levels of various minerals (e.g. Nitrate, NO_3) were found in the groundwater aquifers (Ayadi et al., 2018; El Alfy et al., 2015; and Krishnakumar et al., 2014). The increasing temperature of surface and groundwater resources has altered some biological and chemical processes and in turn impact the quality of water resources (Heiß et al., 2020). Subsequently, around 1.8 billion people drink a water contaminated by feces. Such contaminated water along with the poor hygiene and sanitation cause the death of around 1000 children each day (UN, 2018; UN, 2015a; UN, 2011). In the next few decades, water pollution is expected to intensify which form a threat to the world sustainable development (UNEP, 2016). In which, effluents from wastewater and industrial effluents are projected to significant increase due to the rapid urbanization (UNEP, 2016). Moreover, the increasing fertilizes-based agriculture is a significant source of nitrogen and phosphorus loading (UNEP, 2016). In 2050, the nitrogen and phosphorus effluents are projected to increase by around 180 % and 150 % respectively (UNEP, 2016). The list of water pollutants (with concentrations higher than the WHO standards) is increasing. These pollutants comprise the fragrances, pharmaceuticals, caffeine, hormones, personal care products, detergents, cleaning agents, and flame retardants (Sauve and Desrosiers, 2014). Such pollutants will be driven by the increasing population and economic growth and the lack of wastewater treatment facilities. Low and middle-income countries are the most vulnerable to these pollutants (Sauve and Desrosiers, 2014). In the West Bank, Palestine, around 25 MCM/y of untreated sewage is directly disposed in wadis and streams (UNEP, 2020). The Israeli settlers heavily contribute to the degradation of water resources and the environment in the West Bank, by the release of untreated wastewater into the natural streams and surrounding areas (ARIJ, 2015). Many Wadis in the region have become wastewater channels as in the case of Wadi Al Samin near Hebron, Wadi Al Zomer near Nablus, and Wadi Al Nar near Bethlehem (ARIJ, 2015). The discharged wastewater infiltrates into the soil and reaches the groundwater basins causing contamination of groundwater (Mahmoud et al., 2022; and Almasri et al., 2020). Moreover, the extensive use of fertilizers and pesticides cause the contamination of groundwater (mainly by NO_3) (Almasri et al., 2020).

Alternative water resources

Given the elevated stresses on surface and groundwater, adopting alternative water resources is of high significant to promote the water security (Karimidastenaei et al., 2022; Yu et al., 2022; and Judeh et al., 2021). Several alternative resources are adopted worldwide to support the conventional water resources (e.g. water desalination, RWH, and fog water collection) (Karimidastenaei et al., 2022; and Yu et al., 2022). However, the Israeli Occupation totally restricts the Palestinian access to their fresh and saline surface water (Judeh et al., 2017). Moreover, fog intensity in the West Bank is insufficient and highly temporally variated (PMA, 2018). Thus, RWH seems to be the most suitable supporter to the existing water supplies in the West Bank, where the long-term average annual rainfall is around 450 mm (Zabidi et al., 2020; and Shadeed et al., 2019).

Smart water

RWH systems consist of a collection catchment, conveyance, and storage tanks. It could be simply constructed and maintained. Harvested water contributes in reducing the burden on the surface and groundwater resources (Zabidi et al., 2020). However, the RWH yield is not secured at all times, since it is dependent to the rainfall volume and intensity, and to the system efficiency. In addition, the quality of RWH is not well secured (Judeh and Shahrour, 2021; and Zabidi et al., 2020). Thus, control plans for enhancing the systems efficiency and the harvested water quality are needed (Judeh and Shahrour, 2021; and Zabidi et al., 2020). Scholars proposed the adoption of smart systems (based on real-time and historical data) to address the limitations of engineering systems and to improve their performance (Petrolo et al., 2015; Castro et al., 2013; Kyriazis et al., 2013; and Stratigea, 2012). Such systems have been widely used in the water-related applications including; the monitoring of water leakage in urban networks (Mashhadi et al., 2021; and Farah and Shahrour, 2017), and water quality (Pasika and Gandla, 2020; Prasad et al., 2015; and Dong et al., 2015), and the promoting of water resources management (Ramos et al., 2020; Ntuli and Abu-Mahfouz, 2016; and Lee et al., 2015). The affordability of smart systems is flexible since they could be designed considering the economic status of the beneficiaries. The cost of the system ranges from the cheapest (e.g. full rely on crowdsourcing) to the most expensive (e.g. full rely on complex smart sensors). Concerning RWH, the use of smart systems is limited and lacks the integrity. The systems were designed considering a single-aspect upgrade on either water quantity (e.g. leak control) or water quality (e.g. pH control) (Ranjan et al., 2020; and Behzadian et al., 2018). Thus, there is a need to propose and dynamically manage a comprehensive smart RWH systems (considering quantity and quality control simultaneously). The effect of these systems to the mitigation of water scarcity is also needed to be investigated.

Scientific questions

The scientific question for this research is: could the integration of the conventional water resources protection, rainwater harvesting adoption, and dynamic smart water management contribute to addressing the water scarcity in Palestine?

To deal with this question, this research aims at establishing a smart management system to address the water scarcity in Palestine with emphasis on: the assessment of water scarcity, the protection of conventional water resources, the adoption of RWH, the implication of demographic and climate change effects, and the use of dynamic smart water management. Accordingly, literature review will be prepared to investigate the needed scientific contributions in this research in order to address the water scarcity and its drivers. Such contributions are unprecedentedly introduced at each phase of this research, including:

(i) Adopting the supply demand balance index (SDBI) to assess the current and future water scarcity in arid and semi-arid regions on light of the demographic and climate change impacts.
(ii) Proposing and adopting an adjusted water quality index (WQI) to perform an accurate, efficient, and informative groundwater potability and palatability assessment. Such assessment contributes in delineating the vulnerable areas for groundwater contamination.
(iii) Proposing a new approach combining Geographic Information System (GIS), statistical analysis and Machine Learning prediction models for the comprehensive management of the Groundwater Nitrate Contamination (GNC). Such approach along with the WQI are used to form a fundamental step in performing an efficient plan toward the protection of conventional water resources in the arid and semi-arid areas. They help in making the needed decisions and taking the required action for preserving the water quality in such areas.
(iv) Investigating the role of potential RWH in addressing the current and future water scarcity considering the demographic and climate changes.
(v) Proposing an innovative smart RWH system and a smart dual water supply system to secure the sufficiency and potability of the water supply and the reliability of the used systems.

After that, such contributions will be used as inputs in the research methodology that employed to develop and realize the research.

This thesis is presented in seven chapters:

Chapter 1 presents the state of the art concerning how previous researches addressed the water scarcity and its components. Accordingly, the chapter highlights the limitations/gaps of previous researches and introduces the contributions of this research to fill this gap.

Chapter 2 describes the methodology of this research. Based on the state of the art, the most suitable methods are picked, integrated and justified in order to introduce an integrated smart management of water scarcity in arid and semi-arid areas. Such methodology targets the West Bank (Palestine) and implies the assessment of water scarcity through the use of SDBI, the protection of conventional water resources using the WQI and the Machine Learning-based water quality prediction, the adoption of potential RWH for addressing the water scarcity, and the adoption of smart RWH system and smart dual water supply system to promote the water security in study area.

Chapter 3 presents the first issue entitled "Assessment of Current and Forecasted Water Scarcity in the Arid and Semi-Arid Areas". Such assessment is carried out considering the demographic and climate change effects. This application was targeted the West Bank as case study. The detailed review, methodology, results and discussion concerning the application are provided in the chapter.

Chapter 4 presents the second issue entitled "GIS-Based Spatiotemporal Mapping of the Groundwater Potability and Palatability Indices in Arid and Semi-Arid Areas". This application was targeted the West Bank as case study. The detailed review, methodology, results and discussion concerning the application are provided in the chapter.

Chapter 5 introduces the third issue in the thesis entitled "Use of GIS, Statistics and Machine Learning for Groundwater Quality Management: Application to Nitrate Contamination". On light of the Chapter 4 findings (northern parts of the West Bank is vulnerable for frequent water contamination events), this application was targeted the Eocene Aquifer (located to the north of the West Bank) as case study. Integrating the methods and outcomes of Chapters 4 and 5 contribute in formulating water resources protection plans and in taking the needed actions.

Chapter 6 presents the fourth issue in the thesis entitled "Rainwater Harvesting to Address Water Scarcity in Arid and Semi-Arid Areas: Application to Arid and Semi-Arid Areas". The West Bank is selected as a case study for this application. The potential ability of RWH to bridge the current and future water scarcity is conducted in light of the demographic and climate change effects. This helps in promoting more water-sustainable systems and plans.

Chapter 7 introduces the fifth issue in the thesis entitled: "Smart Rainwater Harvesting for Sustainable Potable Water Supply in Arid and Semi-Arid Areas". This application was targeted the Jenin City as a case study. It proposes a smart system (based on Internet of Things (IoT) and crowdsourcing) to unprecedentedly secure the potability of RWH. It also employs the dynamic management to imply the smart RWH system within the framework of the smart dual water supply system. Such system shows its high efficiency and reliability in addressing the domestic water scarcity in the selected study area.

Chapter 1. State of the Art

This chapter presents a state of the art about water scarcity management with focus on: (i) water scarcity assessment, (ii) protection of conventional water resources, and (iii) alternative and nonconventional water resources. It also discusses the role of Machine Learning and smart water systems in addressing the challenges of water scarcity management. Finally, it highlights the research gap and the contributions of this research to fill this gap.

1.1. Water scarcity management

The management of water scarcity is essential to ensure the optimum utilization of scarce water in terms of quality, quantity, and sustainability (Sheffield et al., 2018m; and Hering and Ingold, 2012). Such management contributes to mitigating the severity of water scarcity (Sheffield et al., 2018; and Hering and Ingold, 2012). The process of water scarcity management includes several phases including monitoring, controlling, and developing of water resources (Sheffield et al., 2018m; and Hering and Ingold, 2012).

Management of water scarcity has evolved over time. In the early civilizations, it was structure-based, representing a supply-oriented approach (Sheffield et al., 2018). In which, some studies focused on the quantity aspect of water scarcity management such as Sisay et al., (2017), Asati and Rathore (2012), Bhadra et al., (2010), and Ahmad and Simonovic (2000). Later, scholars gave particular interest in the quality of water and its impact on water scarcity like Gholami et al., (2020), Rabeiy (2018), Criollo et al., 2017, Zheng et al., (2017), and Wellen et al., (2015). As a response to the increasing water scarcity, special interest has been given to rainwater harvesting (RWH) and non-conventional water resources (Toosi et al., 2020; Zhang et al., 2019; and Sheffield et al., 2018).

Under the growing stress on water resources due to population growth, climate change, urbanization, and socioeconomic development, the smart water scarcity management has emerged (Barbieri et al., 2021; Patil et al., 2020; Nguyen et al., 2020; Chawla et al., 2020; and Hering and Ingold, 2012). At present, in the light of the digital revolution, there is an increasing interest in introducing new technologies and tools in water scarcity management such as smart systems, the internet of things (IoT), and Machine Learning (Li et al., 2020). For example, Zhou et al., (2018) developed a simulation-optimization model to estimate the optimal pumping rates of groundwater. The model was integrated with wireless sensors network to real-time monitor the quality of groundwater and facilitate decision-making. Pasika and Gandla (2020) developed a smart cost-effective water quality monitoring system using IoT. Farah and Shahrour (2017) presented a smart water leakage detection system based on hydraulic sensors and artificial neural networks (ANN).

To conclude, water scarcity management is a multidimensional issue that needs to be adopted considering all of its contributors (e.g. limited water availability, restricted water accessibility, water pollution, dependency to conventional water resources, climate change effects to the water resources, and the increasing water demand due to population growth) (Patil et al., 2020). However, such contributors differ spatially, and need to be identified prior the formulating the proper management plans (Patil et al., 2020). Considering the Palestinian case, there is a persistent need for adopting an efficient water scarcity management (by considering the water scarcity assessment, the protection of conventional water resources, the adoption of alternative and nonconventional water resources, and the adoption of smart water supply systems) in order to deal with the threaten challenges face the Palestinian water sector.

1.1.1. Water scarcity assessment

Given the dramatic increase in the population growth, the expansion agricultural and industrial activates, water scarcity becomes of serious concern (He et al., 2018; Liu et al., 2017; and Ercin, and Hoekstra, 2014). It threatens the human health, the water-food-energy-ecosystem nexus, and the sustainable development (He et al., 2018; Liu et al., 2017; and Ercin, and Hoekstra, 2014). Global statistics indicate that two billion people experience an extreme water scarcity conditions (UN, 2018). Studies show that more than half of the global population are expected to suffer from water scarcity by 2050 (UN, 2015a). Addressing water scarcity has been targeted as one of the main United Nation (UN) Sustainable Development Goals (mainly SDG 6) (UN, 2018; and UN, 2015a). Various definitions for water scarcity is introduced globally considering the water quantity, quality or both (Table 1.1).

Table 1.1. Water scarcity definitions

Definition	Reference
The adverse effect of extensive and unmanaged water utilization with respect to the water availability	(Kummu et al., 2016)
The ratio of sectoral freshwater utilization to the total available fresh water	(Van Vliet et al., 2017)
The volumetric shortage in freshwater availability	(CEO, 2014)
Water scarcity happens once the water demand exceeds the water availability during a certain period of the year (e.g. once deteriorated water quality limits its utilization).	(Wang et al., 2021)
The ratio of total fresh water withdrawn by all sectors to the water availability in a particular country or region	(Vanham et al., 2018)

One of the most convenient definitions for water scarcity is what stated by Taylor, (2009): “Water Scarcity is the insufficiency of available freshwater to address the needed water demand”.

Water scarcity assessment is stated as the core step for formulating an efficient strategy for addressing such scarcity (Jafari-Shalamzari and Zhang, 2018; and Liu et al., 2017). Various indices are used to evaluate water scarcity. Table 1.2 illustrates the different indices and their elements.

Table 1.2. Water scarcity indices

Index	Definition	Target		Reference
		Water quantity	Water quality	
Criticality ratio	The water use ratio to the total water availability	Yes	No	(Hussain et al., 2022; and Oki and Kanae, 2006)
Water poverty index	The arithmetic weighted average of five indicator (water availability,	Yes	Yes	(Shadeed et al., 2019; and Sullivan et al., 2003)

	accessibility, environment, use, and capacity)			
Falkenmark index	The per capita availability of water	Yes	No	(Nkiaka, 2022; and Falkenmark et al., 2009)
Integrated quantity–quality-environmental flow index	An index combining water quantity, water quality, and environmental flow requirement	Yes	Yes	(Liu et al., 2016)
The International Water Management Institute indicator (IWMII)	It considers the (i) ratio of the water supply to the total water availability and (ii) economic dimensions of water scarcity	Yes	No	(Liu et al., 2017)
Cumulative abstraction to demand ratio	The ratio of the cumulative daily water abstraction to the cumulative daily water demand	Yes	No	(Liu et al., 2017; and Hanasaki et al., 2008)

- **Criticality Ratio**

The criticality ratio index, is a commonly adopted indicator used for the assessment of water scarcity (Hussain et al., 2022; and Oki and Kanae, 2006). It compares the used amount of water to the total availability of renewable water resources. Water use is implying the water consumption and water withdrawals (Hussain et al., 2022; and Oki and Kanae, 2006). This index defines the water consumption as the water evaporation volumes from the different sources of water. In addition, water withdrawal implies the volumes of water that is withdrawn from these sources. However, the unilateral considering of water consumption or water withdrawal as a physical meaning of the water use could come up with unrealistic assessment of the water scarcity in this indicator (Hussain et al., 2022; and Oki and Kanae, 2006).

- **Water Poverty Index**

It introduces a relationship combining the physical availability of water resources, their abstraction possibility, and the welfare level of the targeted community (Sullivan et al., 2003). The index involves five indicators: water resources availability; water resources accessibility; people's capacity toward the efficient management of water resources; the use of water resources (domestic, agricultural, and industrial); water-related environmental integrity (e.g. effect to the ecosystem) (Shadeed et al., 2019). Such index is estimated using an arithmetic weighted average of the five indicators. Each indicator is standardized to a value ranges between 0 and 100. The resulting index lies also between 0 (representing the extreme water poverty conditions) and 100 (representing that there is no water poverty conditions) (Shadeed et al., 2019; and Sullivan et al., 2003). Despite the comprehensiveness of this index, its application is restricted by its complexity and its dependency to massive volume of data (Shadeed et al., 2019; and Sullivan et al., 2003).

- **The Falkenmark Index**

The Falkenmark index is a commonly used indicator for the characterization of water scarcity. It implies the ratio of the available water volume in a specific area per year to the number of people living in the area. Accordingly, four water scarcity classes are identified (Table 1.3) (Falkenmark et al., 2009).

Table 1.3. Falkenmark index classes

Class	Index value (m^3/capita/year)
No water stresses	> 1700
Water stresses	1000-1700
Water scarcity	500-1000
Absolute water scarcity	< 500

Despite its common application, the Falkenmark index considers only the water supply in its scarcity assessment (Wang et al., 2021). The index ignores the supply temporal variability and the inclusion of water demand. In which, the index thresholds don’t reveal the real spatial distribution of water demand among the areas where the index is adopted (Wang et al., 2021).

- **Integrated Water Quantity–Quality-Environment Flow Index**

This multi-dimensional and complex index integrates both quantity-based and quality-based indicators (Liu et al., 2016). The quantity-based index is estimated following the criticality ratio index while the quality-based indicator is estimated through the ratio of contaminated water to the total available water (Liu et al., 2016). The index has a threshold of 1.0, exceeding this threshold for the quantity-based indicator indicates an acute water scarcity (in water utilization). Moreover, breaking the threshold for the quality-based indicator indicates an extreme water contamination condition (Liu et al., 2016).

- **The IWMII Indicator**

A slightly complicated water scarcity index is developed by IWMII (Liu et al., 2017). Such index combines both the physical and economic dimensions of water scarcity. The index considers the ratio of water supply to the available and renewable freshwater resource. It also considers the country’s potential to upgrade water infrastructure and to enhance the efficiency of irrigational water use (Liu et al., 2017). However, the index is less commonly used comparing to other water scarcity indices. This could be attributed to its complexity and need for massive data that make it a time-consuming approach (Liu et al., 2017). Moreover, it has less intuitive interpretation with respect to other indices. Therefore, it is considered less attractive, informative, and understandable to the end-users and decision makers (Liu et al., 2017).

- **Cumulative Abstraction to Demand Ratio**

The Cumulative Abstraction to Demand Index is based on the findings of the global hydrological models (water abstraction and discharge from water resources in a daily basis) (Hanasaki et al., 2008). This index is estimated as the annual ratio of the cumulative daily water abstraction to the cumulative daily water demand (Hanasaki et al., 2008). However, various studies adopted this index on monthly scale (Liu et al., 2017; and Hanasaki et al., 2008). Therefore, it is considered a powerful approach for clarifying the climate change effect on water resources. The complex computational and modeling tasks along with the high demand for input data have restricted the adoption of this index for water scarcity assessment (Liu et al., 2017; and Hanasaki et al., 2008).

On light of the stated literature, the presented scarcity indices (criticality ratio, water poverty index, the falkenmark index, integrated water quantity–quality-environment flow index, the IWMII indicator, and cumulative abstraction to demand ratio) are complex (Hussain et al., 2022; Nkiaka, 2022; Liu et al., 2017; Liu et al., 2016 and Falkenmark et al., 2009). They require massive data that could be unavailable. Moreover, the dependency on great amount of data could produce unrealistic and uncertain results (Hussain et al., 2022; Nkiaka, 2022; Liu et al., 2017; Liu et al., 2016 and Falkenmark et al., 2009). To avoid such complexity and uncertainty, this research adopts a new index (introduced in 2017) called "supply demand balance index (SDBI)" for the water scarcity assessment (Huang and Yin, 2017). SDBI is a simple approach for the water scarcity assessment. It is estimated through the ratio of total water supply (TWS) to the total water demand (TWD) for a specific population in a specific area (Huang and Yin, 2017). SDBI is the only index that directly considers freshwater utilization and citizens' water needs. Its single value has the ability to characterizes the level of water scarcity on a scale ranging from "extreme" to "no" water shortage (Huang and Yin, 2017). It can efficiently consider the water quality issue by ignoring the contaminated water volume during the estimation of TWS. Thus, it is considered one of the easiest and most efficient tools for assessing the water scarcity, especially in urban areas (Huang and Yin, 2017).

1.1.2. Protection of conventional water resources

Protection of conventional water resources implies the preservation of both water quality and quantity, among the conventional water bodies (e.g. surface and groundwater) (Yang et al., 2022; and Almasri et al., 2020). Several physiochemical and biological pollutants threaten the quality of water resources and restrict their suitability for different uses (e.g. domestic and agricultural) (Mester et al., 2020; and Banda and Kumarasamy, 2020). Moreover, unmanaged and extensive use of water resources could lead to the decline of water levels and to the depletion of such resources (O'Neill et al., 2020). Protection of water resources have to be achieved relying on the outcomes of scientific-based approaches that then converted to plans, strategies and actions at the different levels (Lee et al., 2022; and Mester et al., 2020). Such approaches could recognize and monitor the water quality and quantity parameters among the water bodies, and compare them to standards (Pham et al., 2021; Mester et al., 2020; Ranjith et al., 2019; and Anayah and Almasri, 2009). This could be followed by performing a causal-effect relation for the water resources pollution and depletion (Lee et al., 2022; and Almasri et al., 2020). This contributes to taking the needed actions to manage, mitigate or even eliminate the risks of pollution and depletion of water resources (Almasri et al., 2020).

Various approaches are adopted for protecting the quality (e.g. pollution) and quantity (e.g. flow and levels) of water resources including; descriptive statistical assessment (Anayah and Almasri, 2009), water quality and quantity indices (Banda and Kumarasamy, 2020; Shadeed et al., 2020; Shadeed et al., 2019; Poonam et al., 2015; Li et al., 2014; and Ocampo-Duque et al., 2013), water quality and quantity mapping (Evans et al., 2020), and water quality and quantity modeling (Lee et al., 2022; Pham et al., 2021; and Ranjith et al., 2019).

- Descriptive statistical assessment

Descriptive statistical assessment is the simplest approach for assessing the water resources quality and quantity (Anayah and Almasri, 2009). Firstly, records for the threatening water quality parameters and for the water levels are obtained (e.g. from field and laboratory works, or water datasets) (Anayah and Almasri, 2009). Then, the statistical analysis employs the collected records to perform the descriptive assessment of water resources quality and quantity (Shadeed et al., 2019; and Anayah and Almasri, 2009). This approach enables the temporal analysis of water pollution and availability. Boxplots of the water records (e.g. minimum, 1st quartile (Q1), median, mean, 3rd quartile (Q3), maximum) are adopted to present the assessment results. However, this approach misses the spatial distribution/variability of water pollution and availability (Shadeed et al., 2019; and Anayah and Almasri, 2009). Moreover, it relies on a single parameter assessment by considering one of the water contaminants or one of the water availability determinates (e.g. water level) (Shadeed et al., 2019; and Anayah and Almasri, 2009). Therefore, it has a weak ability to construct the needed causal effect relationships for the water-related issues (Judeh et al., 2022; Shadeed et al., 2019; and Anayah and Almasri, 2009).

- Water quality and quantity indices

Water quality and quantity indices synthesize the water quality and quantity records into a precise, informative, and easily understood format (Singha et al., 2015). Each index has a single value that can describe the overall water quality/quantity conditions in a clearly communicated manner to all beneficiaries (e.g. decision makers, service providers, and end-users) (Al-Omran et al., 2015). Both indices help in performing the protection plans for the water bodies (Mester et al., 2020). Scholars adopted various water quantity/availability indices including: water vulnerability index and water poverty index (Shadeed et al., 2020; and Shadeed et al., 2019). Concerning the quality aspects, scholar adopted several water quality indices (WQI) for assessing the water resources quality including: the Canadian Council of Ministers of the Environment WQI (Neary et al., 2001), universal WQI (Boyacioglu, 2010; and Boyacioglu, 2007), the Horton model of WQI (Horton, 1965), Vaal WQI (Banda and Kumarasamy, 2020), Modified National Sanitation Foundation WQI (Poonam et al., 2015), fuzzy-based WQI (Ocampo-Duque et al., 2013), Bhargava’s WQI (Li et al., 2014), Scottish Research Development Department WQI (Banda and Kumarasamy, 2020), Martínez de Bascarón WQI (Banda and Kumarasamy, 2020), Liou’s WQI (Banda and Kumarasamy, 2020; and Liou et al., 2004), Oregon WQI (Cude, 2001; and Dunnette, 1979). However, such quality indices are rigorous to the input parameters (Mester et al., 2020; and Banda and Kumarasamy, 2020). In contrast, the weighted arithmetic water quality index (WAWQI) method has flexibility in the selection of parameters (Mester et al., 2020; and Banda and Kumarasamy, 2020). It characterizes the water quality status based on the most common pollutants in the study area (Mester et al., 2020; and Banda and Kumarasamy, 2020). However, the WAWQI weighting system for the input parameters has a high level of uncertainty which could lead to unrealistic outcomes (Mester et al., 2020; and Banda and Kumarasamy, 2020).

- Water quality and quantity mapping

Water quality and quantity mapping are the most adopted approach for the spatiotemporal analysis of water resources pollution and availability, respectively (Evans et al., 2020; Shadeed et al., 2019; and Anayah and Almasri, 2009). Water quality mapping mainly employs Geographic Information System (GIS) along with and statistical descriptive analysis and/or the WQI to carry out the contamination mapping. This approach enables the examination of the various factors that could affect the level of water contamination (e.g. soil type, water flow direction, conductivity, land use, and anthropogenic activities) (Anayah and Almasri, 2009).

Water quantity mapping could be achieved using various determinates such as water flow and water levels (Evans et al., 2020). Water level mapping enables the spatiotemporal visualization and quantification of water levels and volumes within the water resources (Evans et al., 2020). It is mainly estimated based on the interpolation of spatiotemporally distributed data (e.g. water level, and depth to water table). Such approach also enables the spatial estimation of water storage at a time steps (Evans et al., 2020). Various approaches are used for the spatiotemporal interpolation of water-related data, where Kriging Interpolation Method (KIM) is one of the most commonly used (Xiao et al., 2016). KIM enables the performing of uncertainty analysis for the resulted interpolated maps. (Xiao et al., 2016) adopted Ordinary Kriging (OK), Simple Kriging (SK) and Universal Kriging (UK) interpolation to predict the unknown depths to water table in an aquifer in Piedmont Plains, northwest China. It is found that interpolated water levels are matched to the actual water levels in almost all types of KIM interpolation (Figure 1.1). However, this mapping could only characterize the existing water quantity and quality status. In order to perform forecasting models for such status, mapping should be coupled with the Machine Learning approaches.

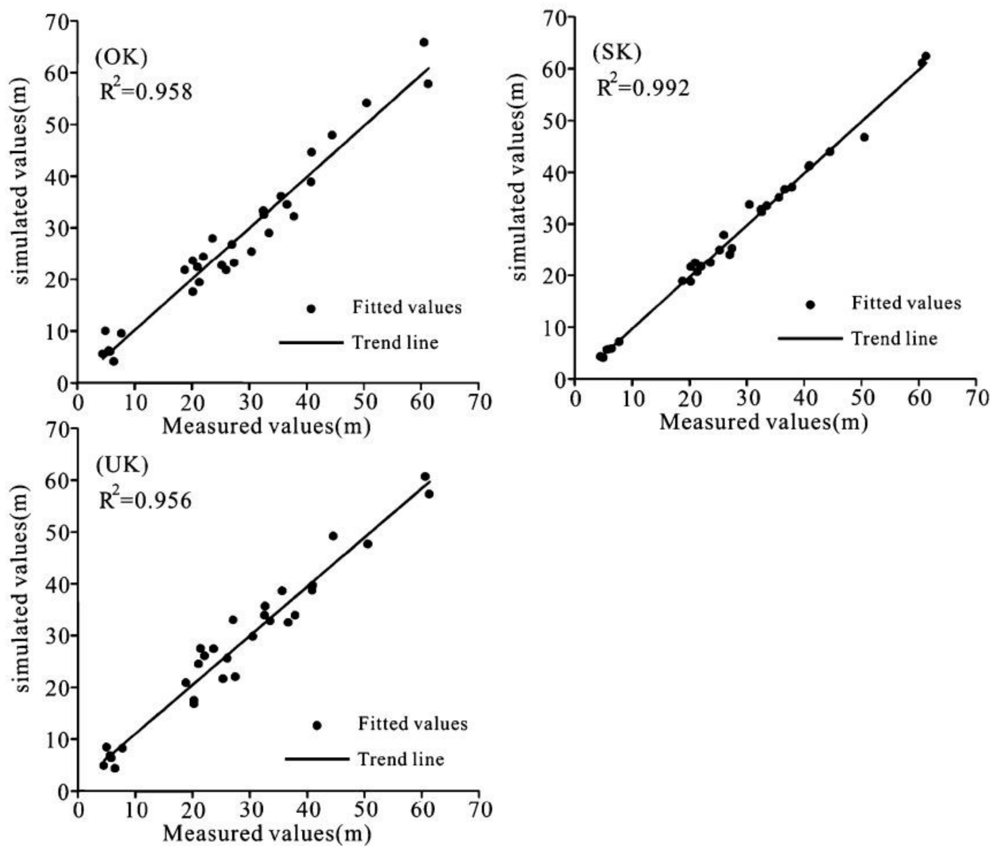


Figure 1.1. KIM-based interpolated vs. observed groundwater levels in an aquifer in piedmont plains, China (Xiao et al., 2016)

- Water quality and quantity modeling

Water quality and quantity models are robust tools that lead to the formulation of efficient plans for the protection of water resources (Raazia and Dar, 2022; Ejigu, 2021; and Medici et al., 2021). Water quality modeling implies mathematical/numerical simulations and representations of contaminants fate, transport, and degradation within the different water bodies (Ejigu, 2021). Such models involve three phases which are (i) model development, (ii) calibration, and (iii) validation (Ejigu, 2021). Scholars introduced and adopted various models for the water quality modeling such as TOMCAT, MT3D, SIMCAT, ECM catchment, MIKE-11, DRAINMOD, MONERIS, TOPCAT-NP, and QUAL2K (Table 1.4).

Table 1.4. Models used for water quality modeling

Model	Contaminants	Description	Reference
TOMCAT	Ammonium (NH_4), Dissolved Oxygen (DO), and Biochemical Oxygen Demand (BOD)	It considers the Monte Carlo analysis approach.	(Ranjith et al., 2019)
MT3D	Nitrate (NO_3), Chlorine (Cl_2), and salinity	It is a three-dimensional transport model.	(Yang et al., 2022)
SIMCAT	BOD, Cl, NH_4, DO, and NO_3	It considers deterministic, stochastic, and Monte Carlo approaches.	(Ejigu, 2021)
ECM catchment	Total Nitrogen (TN) and Total Phosphorous(TP)	It relies on data collection from different sources including: databases and questionnaires.	(Zhang et al., 2018a)
MIKE-11	NO_3, coliforms, DO, NH_4, TP, and BOD	It is a fully hydrodynamic approach.	(Thu Minh et al., 2022)
DRAINMOD	Salinity and TN	It considers the surface runoff, evapotranspiration, depth to water table, and drainage rates.	(Wilson et al., 2020)
MONERIS	TP, TN, and heavy metals	It is a semi-empirical, model that could be integrated to GIS for the run-off water quality modeling.	(Pastuszak et al., 2018)
TOPCAT-NP	TP, and TN	It adopted a subsurface flow and identical soil moisture equations	(Adams et al., 2020)
QUAL2K	DO, pH, BOD, Algae, TP, TN, and pathogens	It has no dynamic and stochastic characteristics	(Hoang et al., 2019)

Water quantity modeling requires mathematical simulation and representation of the water levels and flow through the surface and groundwater as a result of the hydrological cycle components (e.g. precipitation, runoff, evaporation, and transpiration) (Figure 1.2) (Raazia and Dar, 2022; Tao et al., 2022; and Medici et al., 2021). Several models have been used for the surface water flow modeling such as HEC-RAS (Costabile et al., 2020), QGIS (Lee et al., 2022), and HEC-HMS (Hamdan et al., 2021). Groundwater flow modeling are also widely used including MODFLOW (Behera et al., 2022), Parflow (Tran et al., 2021), and DFNWorks (Pham et al., 2021).

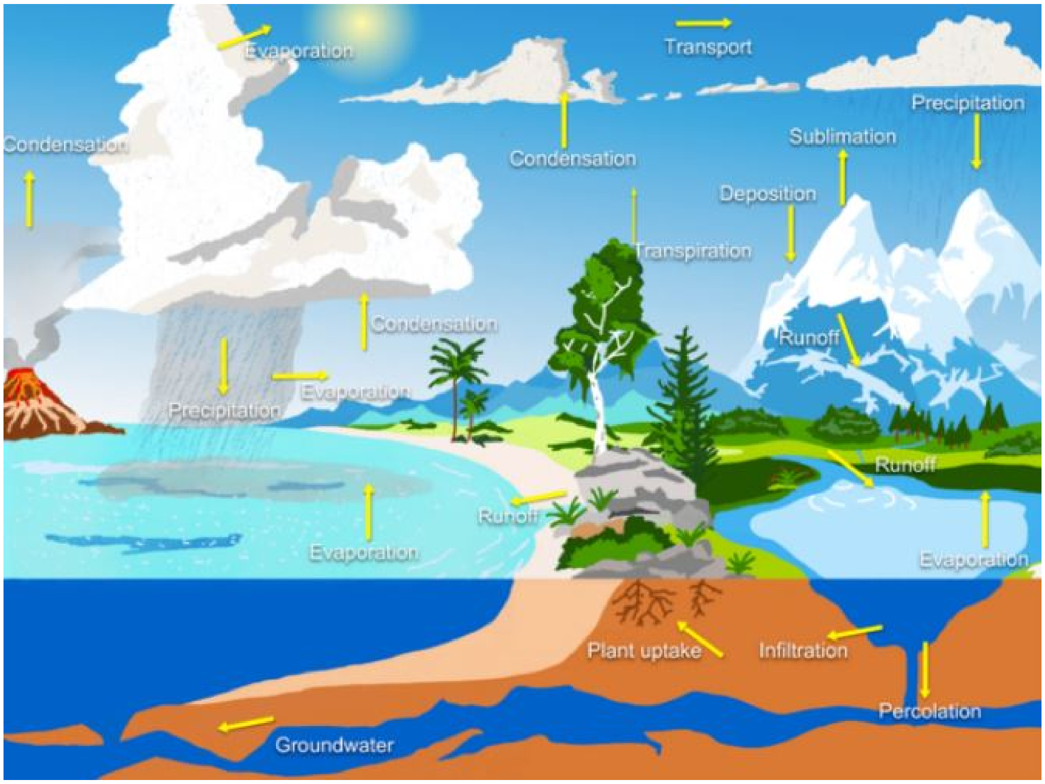


Figure 1.2. Hydrological cycle (Levizzani and Cattani, 2019)

However, water quality and quantity models require massive input data, and have a level of uncertainty due to the implying assumptions (Lee et al., 2022; Pham et al., 2021; and Ranjith et al., 2019).

1.1.3. Alternative and nonconventional water resources

The elevated stresses on the availability, accessibility and quality of the conventional water resources (e.g. surface and groundwater) urge the need to use alternative (e.g. RWH) and nonconventional (water desalination, and fog water collection) water resources (Karimidastenaei et al., 2022; and Yu et al., 2022). Such resources are employed to mitigate the increasing water scarcity, and to decrease the burden on the conventional water resources in different countries worldwide such as Gulf countries, Chile and Palestine (Charcosset, 2022; Karimidastenaei et al., 2022; Yu et al., 2022; Curto et al., 2021; and Zabidi et al., 2020).

Water desalination (removing of impurities and salts from saline water to produce fresh water) produces water that meet the global water quality standards (Charcosset, 2022; and Curto et al., 2021). It also reduces the pressure on freshwater resources. On the other hand, water desalination is very costly due to the need to construct and the operate the water desalination plants. The operation of the plants is high energy-consuming (Charcosset, 2022; and Curto et al., 2021). The energy cost accounts for around 50% of the total cost required for producing desalinated water

(Charcosset, 2022; and Curto et al., 2021). Desalination also has negative environmental impact since it could produce many chemicals including hydrochloric acid, carbon dioxide, and chlorine that could be dangerous in high concentrations (Charcosset, 2022; and Curto et al., 2021). Fog water collection (capturing and storing the water from wind-driven fogs) is cheap, easy to be installed and maintained, and consume limited or no energy. It produces water with good quality, especially in non-industrial areas (Karimidastenaei et al., 2022; and Yu et al., 2022). However, fog water collection requires very specific climatologic conditions where the fog is intensive. In addition, it could not be adopted as a solely source of water supply and it is unlikely to be adopted of national scale. In case that the end-users are not close to collection area, pipelines are needed to transport the water which could make the system uneconomic and hydraulically difficult (Karimidastenaei et al., 2022; and Yu et al., 2022). In the West Bank, access to the surface water (fresh and saline) is almost totally restricted by the Israeli occupation. Moreover, this low-income country could face serious difficulties in financing the construction and operation of the water desalination plants (Judeh et al., 2017). The fog collection is not common in the West Bank since the fog intensity is low (PMA, 2018). Therefore, and given the West Bank is characterized by a reasonable long-term average annual rainfall of about 450 mm, RWH (capturing and soring the rainwater, rather than allowing it to run off) considered a good supporter to the existing water supplies (Zabidi et al., 2020; and Shadeed et al., 2019).

1.2. Role of Machine Learning and smart water systems in the water scarcity management

According to sections 1.1.1., 1.1.2 and 1.1.3, the adopted methods for characterizing, managing and addressing the water scarcity have some limitations (e.g. complexity, uncertainty, and inefficiency). Thus, the following section will present the role of Machine Learning and smart water systems in addressing the limitations of these methods.

1.2.1. Machine learning

Machine Learning, a part of artificial intelligence, is an approach that uses computer algorithms (through the collected data and experience) to solve complex problems (Breiman, 2001; and Friedl et al., 1999). Machine Learning methods have powerful capability in predicting the water resources quantity and quality compared to the descriptive statistical assessment, water indices, water mapping and water modeling (Breiman, 2001; and Friedl et al., 1999). They are capable to detect pollution levels as well as the sources of pollution among the water bodies (Band et al., 2020; Uddameri et al., 2020; Canion et al., 2019; Knoll et al., 2019; Ransom et al., 2017; and Mair and El-Kadi, 2013). Scholars adopted several Machine Learning approaches (e.g. random forest algorithm (RFA), multiple linear regression, decision tree, support vector machine (SVM), boosted regression trees, logistic regression, cubist, and ANN) for the prediction of water resources contamination (Band et al., 2020; Uddameri et al., 2020; Canion et al., 2019; Knoll et al., 2019; Ransom et al., 2017; and Mair and El-Kadi, 2013). Concerning the water quantity, Machine Learning is widely used for the protection of water resources quantity (Xuanhui et al., 2018). It facilitates the monitoring of water levels, flow, and directions (Xuanhui et al., 2018; and

Emamgholizadeh et al., 2014). Examples of the artificial intelligence approaches that adopted for the monitoring of water levels are shown in Table 1.5.

Table 1.5. Artificial intelligence models for water level/flow monitoring

Methods	Target	Reference
RFA	To predict the variation in water level	(Valipour et al., 2013)
ANN	to come up with accurate predictions without increasing the needed computational time	(Emamgholizadeh et al., 2014)
Canonical Correlation Forest Algorithm (CCFA)	Addressing the data-scarcity and performing an efficient water level prediction model	(Xuanhui et al., 2018)
SVM	to overcome the variation in groundwater level prediction	(Yoon et al., 2011)

Machine learning methods are highly recommended for massive spatiotemporal data (Band et al., 2020). The accuracy of such models is dependent on the quality of input data and the complexity of related phenomena (Band et al., 2020). Thus, performing a benchmarking analysis is important to identify the most suitable Machine Learning method (Band et al., 2020). This contributes to reducing the complexity of Machine Learning methods by decreasing the number of input parameters (Band et al., 2020). It also contributes to enhancing the accuracy for the prediction models (Band et al., 2020).

1.2.2. Smart water supply systems

The smart water system employs the IoT-based sensors and crowdsourcing across for gathering the water-related data. This contributes to performing a real-time monitoring and control among the several water grid components (Ntuli and Abu-Mahfouz, 2016). Scholars adopted certain architecture for the smart water systems (Shahrour and Xie, 2021; and Li et al., 2020). It involves six layers: physical layer, monitoring layer, data transfer layer, data processing layer, control layer, and smart services layers (Figure 1.3) (Shahrour and Xie, 2021; and Luciani et al., 2018).

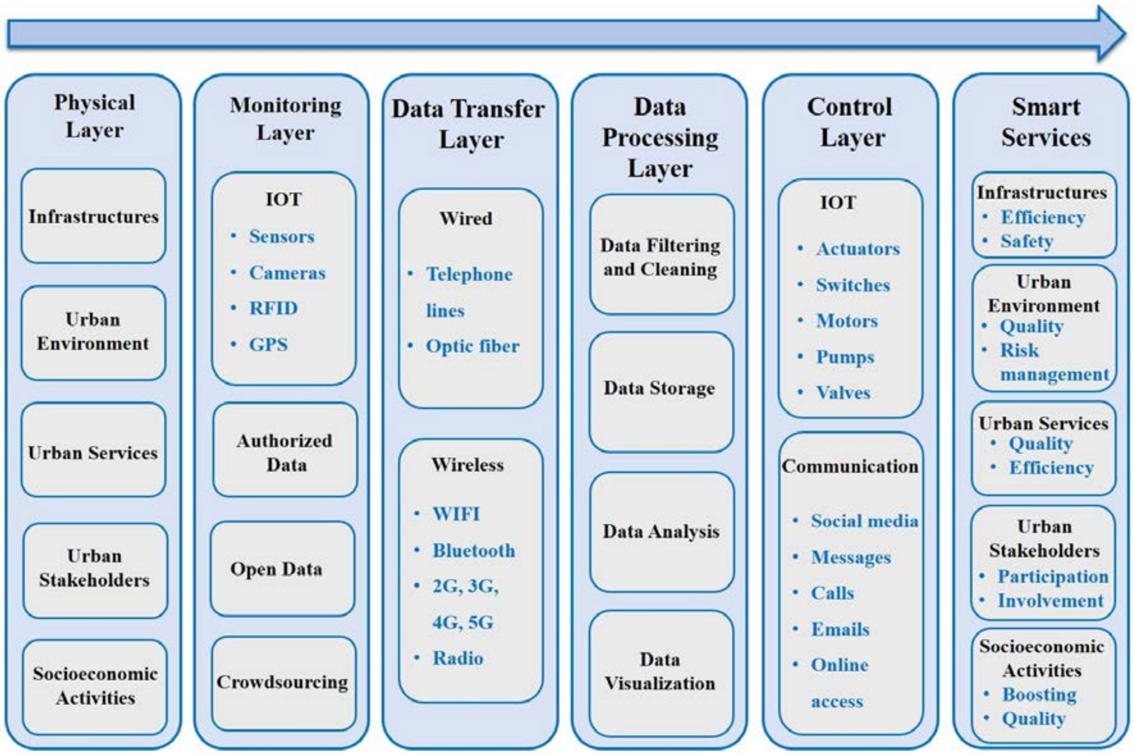


Figure 1.3. Architecture of Smart systems

Smart systems have been adopted to monitor and address the water related-challenges (Li et al., 2020). They efficiently contribute to monitoring the surface water flow (Fell et al., 2019) and quality (Budiarti et al., 2019; and Yan et al., 2017), the groundwater levels (Akbari and Alizadeh-Noughani, 2019), the groundwater quality (Jha, 2020), and the performance of the water desalination plants (Alshehri et al., 2021). In addition, they are used for optimizing the performance of the municipal water distribution networks (Table 1.6). To do so, several smart sensors and devices are installed within the distribution networks (Table 1.7) (Li et al., 2020; and Helmbrecht et al., 2017).

Table 1.6. Smart interventions and their roles in water distribution networks

Intervention	Clarification	Reference
Optimizing water supply and minimizing water leak	Performing a real-time monitoring for water flow and water levels among the components of the water distribution network can assist in optimizing the water supply volumes and in detecting, localizing, reducing, and eliminating the water leak.	(Li et al., 2020)
Securing drinking water quality	Smart real-time monitoring for the probable water contaminants (e.g. free chlorine, coliforms, pH, and turbidity) assists in mitigating and addressing such contaminations.	(Di Nardo et al., 2013)

Promoting the system life cycle	Monitoring the status and performance of system' components (e.g. pipelines, pumps, valves, and storage tank) can contribute to performing the needed maintenance or replacement of the system components. This will promote the life of the system.	(Schilean and Giurca, 2018; and Romano and Kapelan, 2014)
Minimizing energy loss	Monitoring and reducing the water leak volumes as well as the water volumes to be treated, pumped, and transported can contribute to minimizing the system energy demand.	(Helmbrecht et al., 2017; and Ton and Smith, 2012)
Optimizing pressure supply	Real-time monitoring of the water pressure can help in detecting any pressure deficit in the water distribution network.	(McKenna and Keane, 2016)

Table 1.7. Smart sensors/devices in the water distribution networks

Smart sensor/device	Function	Addressed challenges
Smart water flow sensors	Monitoring the water flow	Extensive water utilization, Pipe burst, and water leakage
Smart water quality sensor	Ensuring the potability of water	Water contamination, and network deterioration
Smart water pressure sensor	Monitoring the water pressure	Pressure instability, and energy loss
Smart pumps	Assessing pump performance and efficiency	Pressure unbalance, and energy loss
Smart valves	Multi-direction operation	Water leakage, and pipe burst

Concerning RWH, smart technologies are adopted to address the challenges of the conventional roof RWH systems (Ranjan et al., 2020; and Behzadian et al., 2018). Such systems have several shortcomings including: (i) the un-potability of the harvested water (Dao et al., 2021; Palermo et al., 2020; and Rostad et al., 2016), (ii) the uncontrolled filling and emptying process of the RWH storage tanks, and (iii) the inability of water leakage detection (Behzadian et al., 2018). Smart IoT-based sensors are adopted to monitor the RWH level in the storage tank (Behzadian et al., 2018). This contributes to securing a reliable non-potable water supply, and in detecting water leak (Behzadian et al., 2018). Moreover, smart IoT-based water quality sensors are used to monitor the harvested water quality (based on pH values) (Ranjan et al., 2020).

However, smart interventions to address the RWH-related challenges (e.g. water pollution, shortage, and leak) are separately adopted. Thus, introducing a comprehensive smart RWH system (on light of the smart system architecture shown in Figure 1.3) is needed to address the RWH-related challenges and overcome the water scarcity.

1.3. Research gaps, objectives and contributions

According to the literature review, the elements of water scarcity management are fragmentally used. The adopted management systems lack the reasonable transition from the assessment of water scarcity, the prevention of deepen the scarcity, and reaching to the mitigation/elimination of such scarcity. The adopted indices (criticality ratio, water poverty index, the falkenmark index, integrated water quantity–quality-environment flow index, the IWMII indicator, and cumulative abstraction to demand ratio) for the water scarcity assessment don't simultaneously consider the water availability, quality and citizens' water needs. In addition, they don't consider the climate and demographic impacts. The adopted methods for the protection of the water resources have several limitations including their complexity, uncertainty, dependency to massive input data, the inability to perform clear causal effect relationships, and the inability to predict the levels of water pollution along with their sources (Evans et al., 2020; Shadeed et al., 2019; and Anayah and Almasri, 2009). The RWH adoption for supporting the conventional water resources lacks the consideration of climate change impacts. Moreover, RWH role in mitigating/eliminating the water scarcity is missed. Finally, scholars don't introduce any smart RWH system to simultaneously address the limitations of conventional RWH system (e.g. system reliability, water leaks and pollution).

These research gaps constitute the ore of this research with emphasis on the following question: could the integration of the conventional water resources protection, rainwater harvesting adoption, and dynamic smart water management contribute to addressing the water scarcity in Palestine?

To deal with this question, this research aims at establishing a smart management system to address the water scarcity in Palestine with emphasis on: the assessment of water scarcity, the protection of conventional water resources, the adoption of RWH, the implication of demographic and climate change effects, and the use of dynamic smart water management (Figure 1.4).

Accordingly, this research aims at achieving the following contributions:

(i) Adopting the supply demand balance index (SDBI) to assess the current and future water scarcity in arid and semi-arid regions on light of the demographic and climate change impacts.

(ii) Proposing and adopting an adjusted water quality index (WQI) to perform an accurate, efficient, and informative groundwater potability and palatability assessment. Such assessment contributes to delineating the vulnerable areas for groundwater contamination.

(iii) Proposing a new approach combining Geographic Information System (GIS), statistical analysis and Machine Learning prediction models for the comprehensive management of the Groundwater Nitrate Contamination (GNC). Such approach along with the WQI are used to form a fundamental step in performing an efficient plan toward the protection of conventional water resources in the arid and semi-arid areas. They help in making the needed decisions and taking the required action for controlling the deepen of water scarcity.

(iv) Investigating the role of potential RWH in addressing the current and future water scarcity considering the demographic and climate changes.

(v) Proposing an innovative smart RWH system and a smart dual water supply system to secure the sufficiency and potability of the water supply and the reliability of the used systems. This will be followed by investigating the role of smart systems in mitigating the water scarcity level.

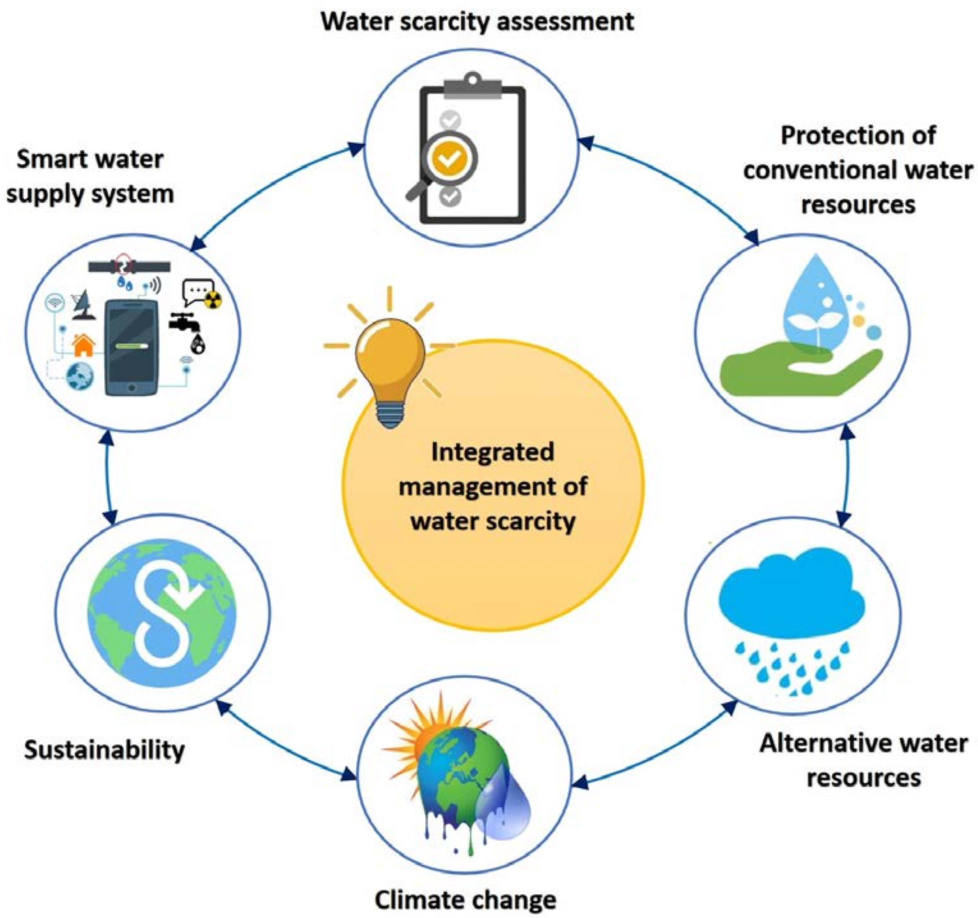


Figure 1.4. Research outline

1.4. Conclusion

This chapter presented the state of the art about the water scarcity in Palestine with a focus on the smart management of such scarcity. It combined the water scarcity assessment, the protection of the water resources, and the adoption of smart RWH system.

This next chapter will present the methodology adapted for the smart management of the water scarcity. Then, vulnerable case studies that form a good example of the arid and semi-arid areas with limited water availability will be picked and characterized. After that, applications of the different scientific contributions will be presented in order to achieve the research objectives. Finally, some recommendations will be presented.

Chapter 2. Research Methodology

2.1. Introduction

This chapter presents the research methodology of this research. It has been designed to answer the research question "*could the integration of conventional water resources protection, rainwater harvesting adoption, and dynamic smart water contribute to addressing water scarcity in Palestine considering the demographic, political and climate change challenges?*" and to achieve the research objective "*establishing a smart management system to address the water scarcity in Palestine with emphasis on: the assessment of water scarcity, the protection of conventional water resources, the adoption of RWH, the implication of demographic and climate change effects, and the use of dynamic smart water management*".

Since the research is carried out considering the Palestinian water context, this chapter starts by presenting the features (e.g. geographical setting and demographic composition) and the water-related challenges of the selected case study (West Bank, Palestine). Then, the materials and methods are presented with emphasis on the options to deal with each research question (at each phase), the selection and justification of the most suitable options, and the contribution of this research at the several phases.

2.2. Study area

This research concerns the West Bank (Palestine), which is an arid and semi-arid area with water scarcity. It is also governed by a specific political status that directly affects the water security.

2.2.1. Geographical extent and main characteristics

The West Bank, Palestine, is the landlocked area located to the West of Jordan (Figure 2.1). It covers 11 governorates with 5860 km^2 and around 3.12 million inhabitants (PCBS, 2020a).

The maximum (1022 m above mean sea level, MSL) and minimum (410 m below MSL) ground surface elevation are located in Hebron and Jericho governorates, respectively (UNEP, 2003). The land-use map shows three main classes: rough grazing, agricultural areas, and built-up areas (urban and rural), which account for 63%, 32%, and 5% of the study area, respectively (Shadeed et al., 2019). Soil textures range from clay (47%), clay loam (31%), loamy (9%), sandy loam (8%) to bare rock (5%) (Shadeed et al., 2019). The West Bank is characterized by a Mediterranean climate with a high seasonal deviation (Shadeed et al., 2020). The average rainfall is about 450 mm/year (Shadeed et al., 2020). Approximately 80% of the West Bank ranges from arid to semi-arid, while the rest (20%) is classified as sub-humid (Shadeed et al., 2019). Thus, the West Bank is internationally classified as an arid to the semi-arid region (Judeh et al., 2021).

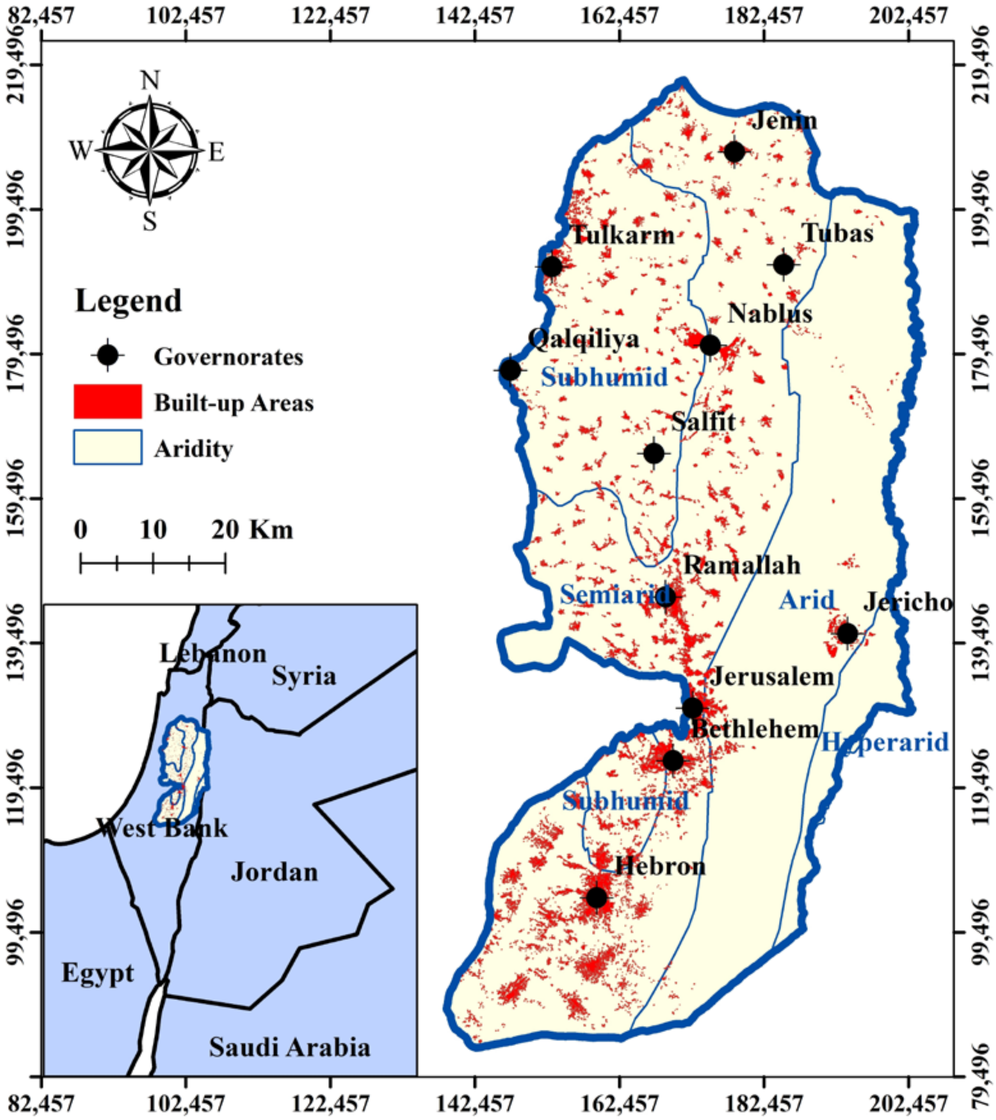


Figure 2.1. The geographical setting of the West Bank

2.2.2. Water challenges in Palestine

The scarcity of water is a feature of the Palestinians' life (PWA, 2016). The average daily water consumption per capita in the country is well below the internationally recommended rate by the World Health Organization (WHO) of 100 liters per capita per day (l/c/d) (Human Rights Council, 2021). The gap between supply and demand for domestic use in the West Bank was estimated at 58 million cubic meters per year (MCM/y) in 2018. About one-third of the Palestinian water supply is lost by leakage due to the poor and deteriorated condition of water supply grids linking the West Bank's communities (Human Rights Council, 2021). This could be attributed to the obstructions to maintenance and upgrades by the Israeli Occupation (Human Rights Council, 2021).

In 1995, the Oslo II Agreement has put 80% of the shared water resources under the control of the Israeli Occupation. The Interim Agreement was intended for five years; however, it is still the main agreement regulating shared water resources. Oslo Accord and Oslo II Agreement divided the West Bank into three parts: Areas A, B, and C. Area A is under the Palestinian Authority civil and security control. It accounts for less than 18% of the West Bank area. Area B is under Palestinian civil control and joint Israeli Occupation and Palestinian security control. It represents 21% of the West Bank. Area C represents 61% of the total area of the West Bank, includes the most fertile agricultural areas in the West Bank and the majority of water resources, and is under complete Israeli Occupation control (PWA, 2017; and UN, 2015b).

The Israeli Occupation has limited the access of Palestinians to their water resources and restricted the Palestinian's ability to improve the water availability (Judeh et al., 2017). It has imposed many restrictions on access to water resources, building new water installations (such as deep groundwater wells and dams in Area C, construction of wastewater treatment plants and desalination plants), and maintenance of existing ones (Human Rights Council, 2021; and Judeh et al., 2017). As a result, Palestinians lack appropriate water infrastructure; suffer from irregular water supply, and are at high risk of water scarcity (PWA, 2013).

The main water source in Palestine is the groundwater. It represents more than 90% of the water supply in the West Bank and Gaza strip (Almasri et al., 2020). The quality of the groundwater has deteriorated (mainly polluted by Nitrate, NO_3) during the past decades especially in the coastal aquifer in Gaza strip, where water is not safe for domestic use, which threatened the public health of many Palestinians (PWA, 2017; and PWA, 2011). Consequently, assessing the existing and forecasted Palestinian water challenges is the core of this research. Such assessment is carried out based on the literature review (e.g. papers, books, and reports) with a focus on the following issues (Figure 2.2):

(i) Water resources availability

(ii) Water resources accessibility

(iii) Water resources quality

(iv) Population growth and the increasing water demand

(v) Climate change

These issues and their associated social, economic, and environmental consequences are discussed in the following sections.

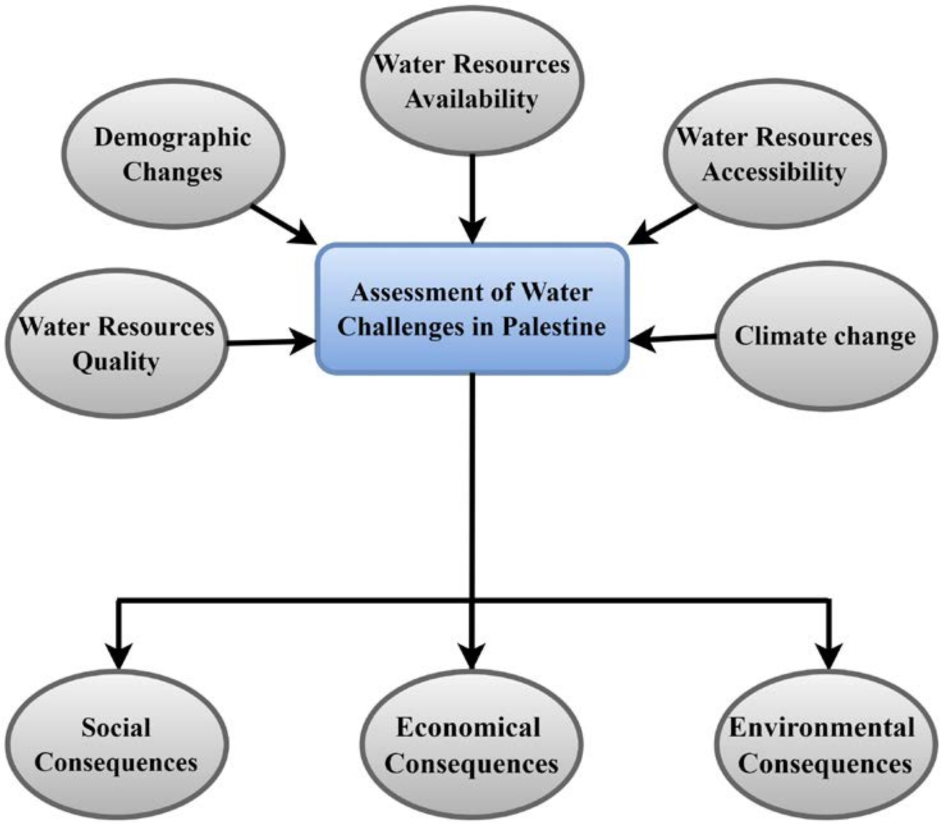


Figure 2.2. Assessment of water challenges in Palestine

2.2.2.1. Water resources availability and accessibility

The main water resources in Palestine are: (i) surface water represented by The Jordan river and wadis, (ii) groundwater aquifers including the eastern basin, western basin, north-eastern basin, and coastal aquifer, (iii) non-conventional water resources (e.g. desalinated water), and (iv) rainfall.

- *Surface water*

The surface water resources include the Jordan River and ephemeral wadis (Judeh et al, 2017). The Jordan river is the major surface water resource in the region, that shared among Palestine, Jordan, Syria, Lebanon, and the Israeli Occupation (PWA, 2013). The river originates from the Hasbani in the south of Lebanon, and the Banias and the Dan at Jabl el-Shaykh (Mount Hermon). It flows from Jabl el-Shaykh in the north (2200 m above MSL) into Lake Tiberius, continues to join with the Yarmouk River at the Triangle in the south, and discharges into the Dead Sea, which is the lowest land-based elevation on Earth (425 m below MSL) (PWA, 2013). The Israeli Occupation has the biggest share of the river's water (Human Rights Council, 2021), while the Palestinian have been deprived of their rights to the utilization of the Jordan River's water by the Israeli Occupation (Isaac and Sabbah, 2017). The water input from the Lower Jordan River into the Dead Sea has dramatically decreased over years from approximately 1400 MCM/y to 30 MCM/y (PWA, 2013). This is mainly due to the diversion of water from the Jordan River to the

National Israeli Water Carrier (more than 500 MCM/y) and the construction of dams upstream, in addition to natural factors. The reduced water discharge into the Dead Sea over the past century has led to a major decline in the water level of the Dead Sea of around 1 meter/year, consequently, the surface area has shrunk by almost the half (UNEP, 2020)

Another important potential source of the water in Palestine is Wadis related to runoff water flows during the rainy season. Wadis are classified based on the direction of flow into the eastern wadis towards the Dead Sea and the western wadis towards the Mediterranean. The floodwater long-term average annual flow in wadis is about 165 MCM/y in the West Bank (PWA, 2017; and PWA, 2011). In Gaza Strip, Wadi Gaza is the main wadi and it is located in the east. Except for periods of heavy rainfall, the wadi is mostly dry because the Israeli Occupation traps the natural flow that feeds the wadi for its irrigation purposes (UNEP, 2020).

- *Groundwater*

The main water source in Palestine is groundwater. Over 90% of the freshwater supply in the country comes from aquifers (UN, 2016). Four major aquifers exist in Palestine; three in the West Bank and One in Gaza Strip (Figure 2.3). The largest basin in the West Bank is the Western Basin with an annual yield that varies from 318 to 430 MCM/y (PWA, 2013). The Palestinian utilization of this basin according to Oslo Acord is limited to 22 MCM/y, while the Israeli Occupation heavily exploited this basin at a very high rate of 340 to 430 MCM/y (PWA, 2017; and PWA, 2011). The second basin in the West Bank is the Northeastern Basin. It has an annual yield of about 135 to187 MCM/y. The Palestinian utilization of this basin is around 42 MCM/y, while Israeli Occupation exploitation is about 103 MCM/y (Mizyed, 2018). The Third basin is the Eastern Basin. It is divided into three sub-aquifers: Jordan Valley, Northeastern Tip, and Mountainous Heights. The annual yield of this basin is about 125 to 197 MCM/y. The allocation of this basin is 42 MCM/y for the Palestinians and 103 MCM/y for the Israelis (Mizyed, 2018). Gaza Coastal Aquifer represents the only source of water in the strip. The water-bearing strata thickness ranges between 120 to 150 m in the west and along the coast and a few meters in the eastern region. The annual average recharge rate of the coastal aquifer is about 55 to 60 MCM/y (PWA, 2017; and PWA, 2011).

Figure 2.3. Groundwater flow, divides and aquifers in the West Bank and Gaza Strip

More than 25 years after Oslo II Accord entered into force, the Israeli Occupation is still controlling over 80% of the shared groundwater resources in Palestine. This interim agreement was intended to five years. However, it remains the key agreement regulating the water use in Palestine (Human Rights Council, 2021). Table 2.1 shows the water allocation and utilization according to Article 40 of the Oslo Acord (Mizyed, 2018; and PWA, 2013).

Table 2.1. Groundwater allocation (utilization) according to Oslo Agreement

Division	**Allocation (utilization in 2011) in MCM/y**			
	Western aquifer	Northeastern aquifer	Eastern aquifer	Total
Israeli Occupation	340 (411)	103 (103)	40 (150)	483 (664)
Palestinian utilization	22 (25)	42 (20)	54 (42)	118 (87)
Additional quantity for Palestinian development	0	0	78	78

There are 383 groundwater wells in the West Bank (Figure 2.4). 119 wells are not in service and require rehabilitation and others have dried up (PWA, 2013). The Israeli Occupation restrictions limit the rehabilitation and the maintenance of the Palestinian wells and drilling new deep wells (Human Rights Council, 2021; and Judeh et al., 2017). The Israeli Occupation owns 39 wells in the West Bank. The estimated average annual groundwater pumping of these wells is about 54 MCM/y. Inside the Green Line, the Israeli Occupation has not less than 500 wells most of which are tapping the Western Basin, with a total annual abstraction rate greater than the recharge rates.

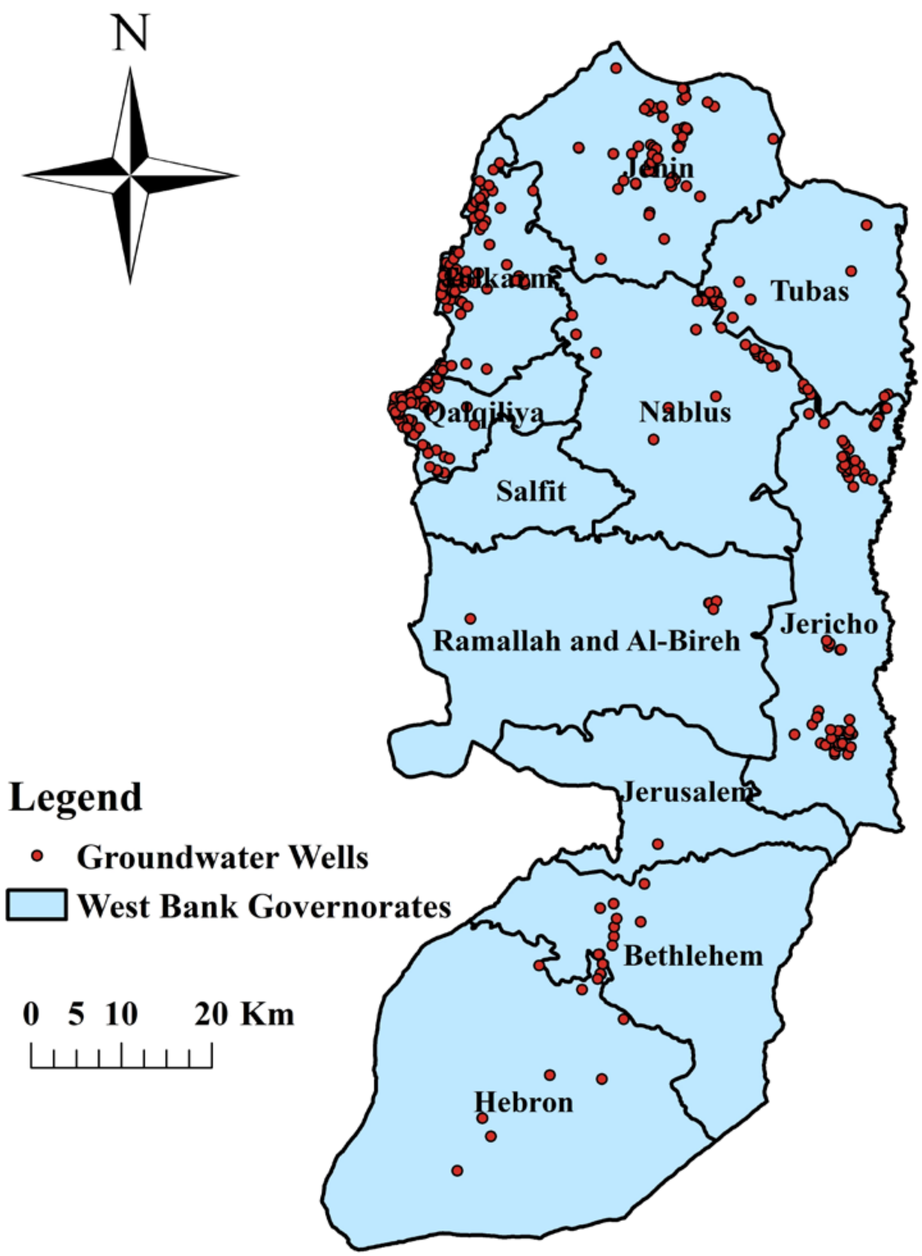


Figure 2.4. Spatial distribution of the groundwater wells in the West Bank

Many pumping wells in the West Bank and Gaza Strip showed a clear decline in the level of groundwater mostly in the south of the West Bank and northern and southern parts of Gaza Strip (Figure 2.5) (PWA, 2018; and PWA, 2011). Groundwater level depends on various factors such as the meteorological conditions and the recharge and abstraction rates. In the case of the West Bank, the decline is mainly attributed to droughts and the intensive exploitation of groundwater by the Israeli Occupation (MoFA Netherlands, 2018), while in Gaza strip the intensive local pumping is the major reason behind serious declines in water levels (Al-Najjar et al., 2021).

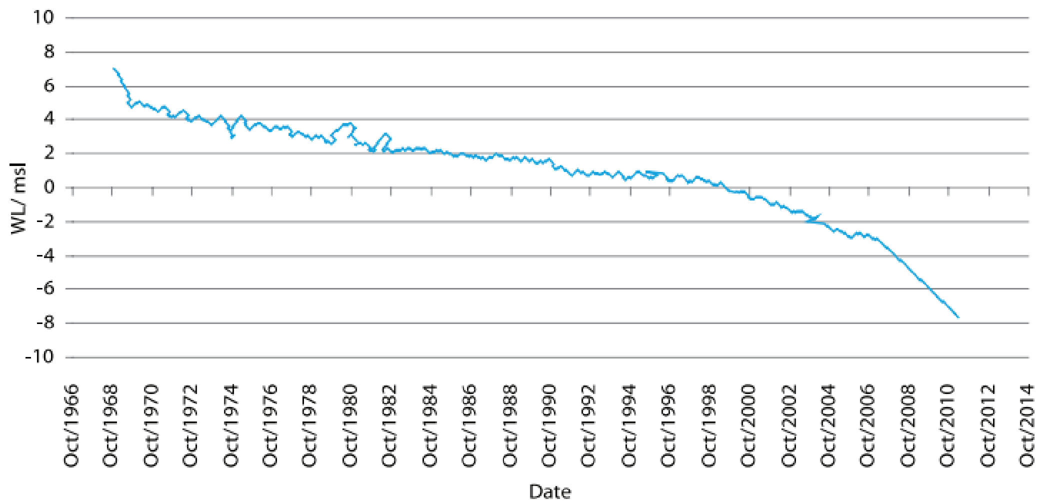


Figure 2.5. Decline of groundwater level in the Well L/57 located in Gaza Strip between 1966 and 2014

Springs discharge is another form of groundwater abstraction from aquifer systems in the West Bank. Approximately 300 springs exist in the West Bank, the majority of the springs are small and have a discharge rate below 0.1 liter/second (PWA, 2013). These springs have a long-term annual discharge of about 54 MCM/y. In recent years, the total annual average discharge has dropped to about half of the long-term annual average mainly due to droughts (UNEP, 2020). The Dead Sea springs are under the control of the Israeli Occupation, the overall yearly discharge of these springs reaches 110 MCM/y (PWA, 2017; and PWA, 2011).

- *Non-conventional water resources*

Desalinated water is an example of the non-conventional water resource adopted in Gaza Strip (PWA, 2013). Desalination has become the main source of domestic water in the strip since (i) the intensive local pumping has caused serious deterioration of the Coastal Aquifer and (ii) the intrusion of saltwater from the Mediterranean Sea has amplified the situation leading to water salinity. A total of 286 desalination plants exist in Gaza (European Investment Bank, 2019). In the West Bank, most of the brackish water desalination plants are small-scale commercial projects (PWA, 2013). The desalination process is very expensive and energy-intensive. The acute shortage in electricity and other energy types in the country has limited the ability of desalination plants to obtain their capacity and caused others to stop operating (Human Rights Council, 2021).

Due to the incapacity of existing water resources (conventional and nonconventional) to address the water shortage status in Palestine, Palestinian Government is obliged to purchase water from water companies belong to the Israeli Occupation (e.g. Mekorot) (Judeh et al., 2017). In 2018, the Palestinian government purchased 85.7 MCM, of which 73.7 MCM were supplied to communities in the West Bank while the rest were supplied to Gaza strip communities (PCBS, 2021a). Most of this Purchased water has been extracted from the West Bank's Mountain aquifers (WASH Custer-State of Palestine, 2021).

- *Rainfall*

The long-term average annual rainfall in the West Bank and Gaza strip is about 454 mm and 356 mm, respectively (PWA, 2013). The mean annual rainfall in the country has an extreme spatial distribution due to the location of Palestine in a transitional climatic zone between the arid, semi-arid and Mediterranean zones (MoFA Netherlands, 2018). The mean annual rainfall in the West Bank varies from 700 mm in the west to less than 160 mm in the arid eastern part (Figure 2.6). In Gaza strip, the coastal climate is dominant, the mean annual rainfall decreases from about 520 mm in the north to 220 mm in the south (PWA, 2017; and PWA, 2011).

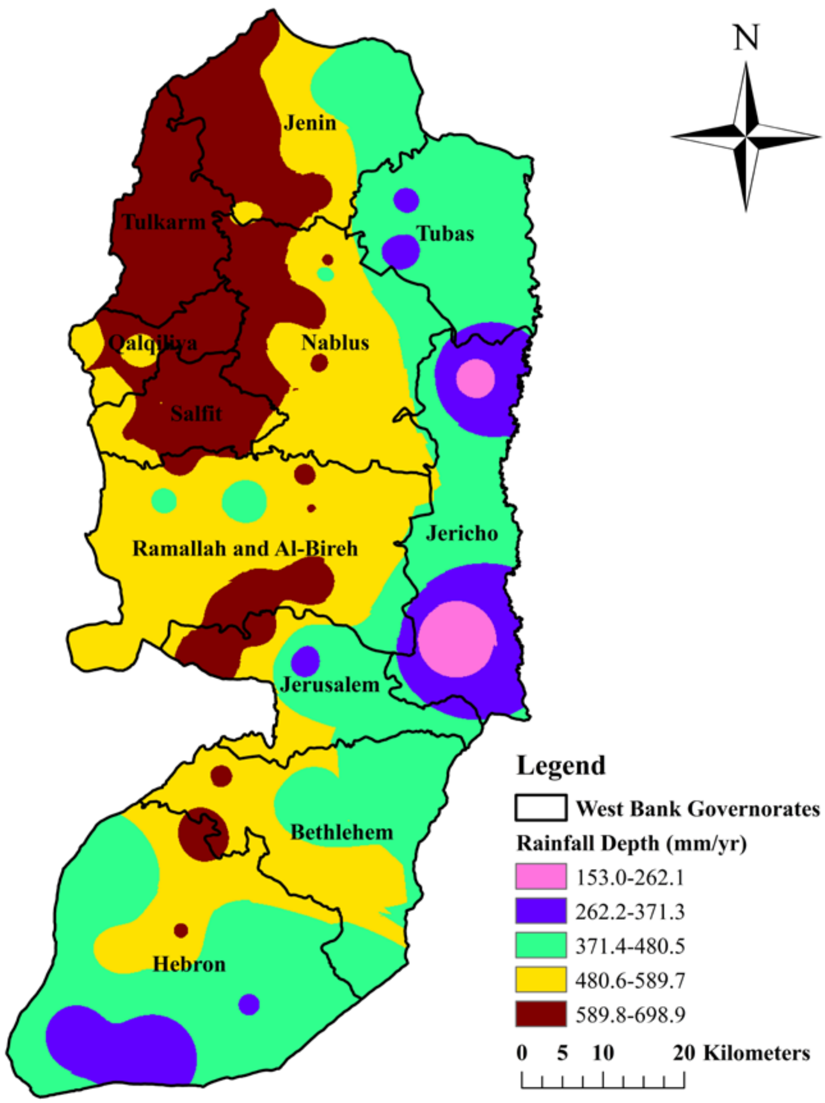


Figure 2.6. Long-term average annual rainfall in the West Bank

The uncertainty of surface and groundwater supply (mainly due to political aspects) in Palestine makes rainwater harvesting (RWH) an urgent and sustainable option to address the existing domestic water supply–demand gap (Shadeed et al., 2019). Despite that, the exiting RWH plans and projects need to be optimized to promote the water security in Palestine (Shadeed et al., 2019).

The harvesting of rainwater for agricultural and domestic use is an ancient practice in Palestine. It dates back to 4000 years ago (Shadeed and Lange, 2010). Different harvesting methods are used in the West Bank including cisterns, dams such as the Al' Auja dam which has a storage capacity of 700,000 m^3, and agricultural ponds like those in Jordan Valley and Marj Ibn A'mer (PWA, 2017; and PWA, 2011). However, the harvesting of the surface runoff water in wadis is not developed enough in Palestine because of the required high investments and the Israeli Occupation restrictions. However, many communities in the West Bank rely on the RWH. Water harvesting is performed using a very common and traditional technique based on the rooftop runoff harvesting (UNEP, 2020). To maximize the benefit of these randomized individual practices, more efforts should be done by the government and local authorities especially in the northwestern part of the West Bank because it has very high suitability for domestic RWH as illustrated in Figure 2.7 (Shadeed et al., 2019).

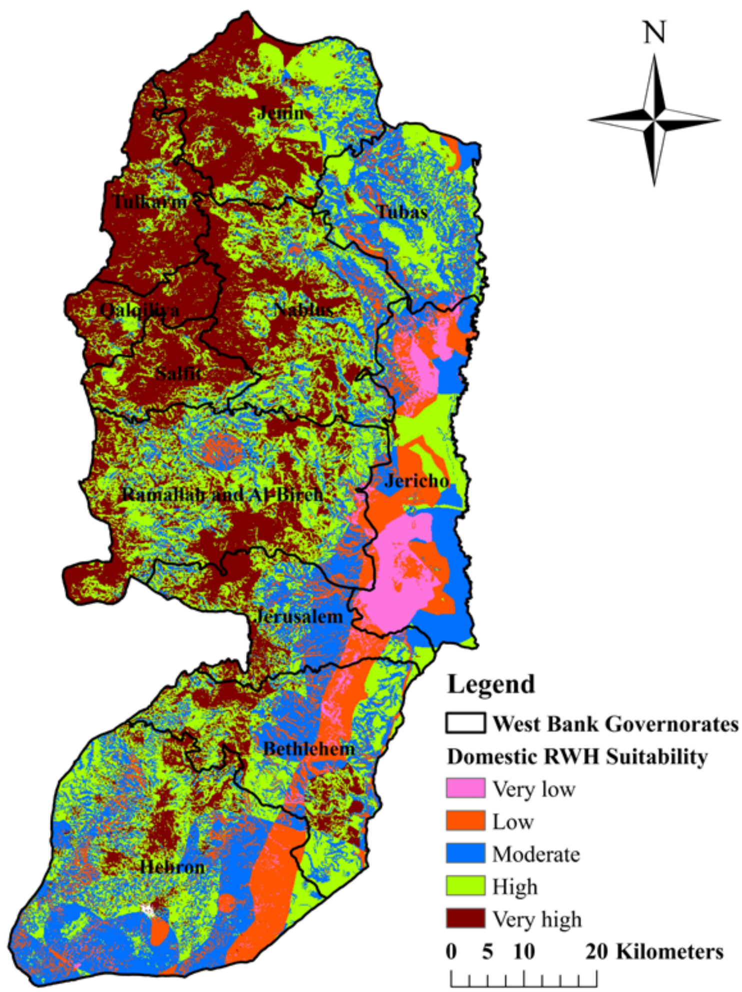


Figure 2.7. RWH suitability map for domestic uses in the West Bank

On light of the water shortage conditions that threaten the Palestinian water sector, there is an urge need to (i) spatiotemporally assess the severity of water scarcity based on scientific-based approaches, (ii) optimize the sustainable use of the conventional water resources (rain, surface, and groundwater), (iii) adopt alternative water supply options, (iv) adopt a comprehensive water resources management plans.

2.2.2.2. Water resources quality

Water scarcity in Palestine is driven by both water quantity and water quality (Almasri et al., 2020). The declining of the water resources quality is a consequence of human activities such as unmanaged agricultural practices as well as natural phenomena such as droughts (Jebreen et al., 2018). Although these influences are usually coupled, this section will focus on the human influence, and the latter will be discussed in the next section.

The discharge of untreated wastewater into the environment is a major source of water resources contamination in Palestine (Almasri et al., 2020). About 25 MCM/y of untreated sewage is disposed of directly in wadis and streams in the West Bank due to lack of wastewater infrastructure and wastewater treatment plants (UNEP, 2020). Many Wadis in the region have become wastewater channels as in the case of Wadi Al Samin near Hebron, Wadi Al Zomer near Nablus, and Wadi Al Nar near Bethlehem. The Israeli settlers also contribute to the degradation of water resources and the environment in the West Bank, by the release of untreated wastewater into the natural streams and surrounding areas (ARIJ, 2015). The discharged wastewater infiltrates into the soil and reaches the groundwater basins causing contamination of groundwater (Mahmoud et al., 2022; and Almasri et al., 2020).

The quality of the groundwater in the West Bank is still acceptable. However, high levels of NO_3 and Chloride (Cl) have been found in some areas (PWA, 2013). In Tulkarm and Qalqiliya, elevated levels of NO_3 above the WHO limits have been identified in some wells (Figure 2.8) due to infiltration of wastewater and pesticides from poor agricultural practices (PWA, 2013; and WHO, 2011). In the Jordan Valley area, most wells have high concentrations of Cl that exceed the WHO guidelines, while the NO_3 concentration is acceptable (PWA, 2017; and PWA, 2016).

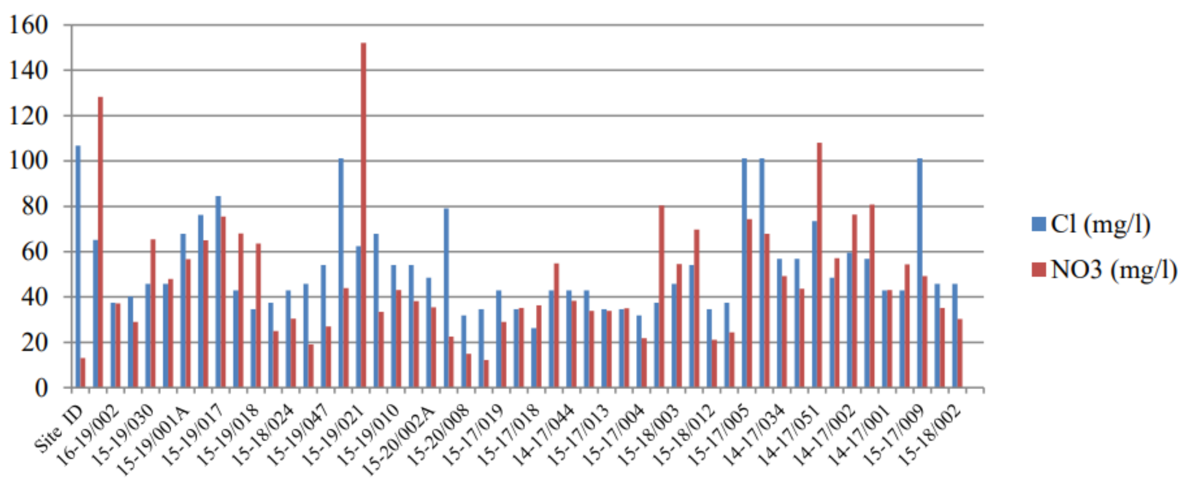


Figure 2.8. Average annual concentrations of NO_3 and Cl in groundwater wells in Tulkarm and Qalqiliya

Worse water quality status is found in Gaza Strip where the groundwater is undrinkable (UNEP, 2020). Poor agricultural practices such as intensive use of agricultural pesticides combined with the infiltration of wastewater into the Coastal Aquifer have increased the concentration of NO_3 (UNEP, 2020). The levels of NO_3 exceed 300 mg/L in residential areas (served by cesspits) and decrease to 50 mg/L in non-residential areas (ARIJ, 2015). The recommended concentration of NO_3 by the WHO is below 50 mg/L (WHO, 2011). The excessive local pumping of the groundwater from the Coastal Aquifer has increased the level of salinity and Cl beyond the WHO guidelines (Efron et al., 2019). This could be referred to the infiltration of seawater and brine from the Mediterranean and deeper layers as a consequence of this practice (Efron et al., 2019). The concentration of Cl varies from 100 to more than 2000 mg/l (Figure 2.9). Subsequently, more than 97% of the water pumped from the Coastal Aquifer is not suitable for human consumption (Efron et al., 2019).

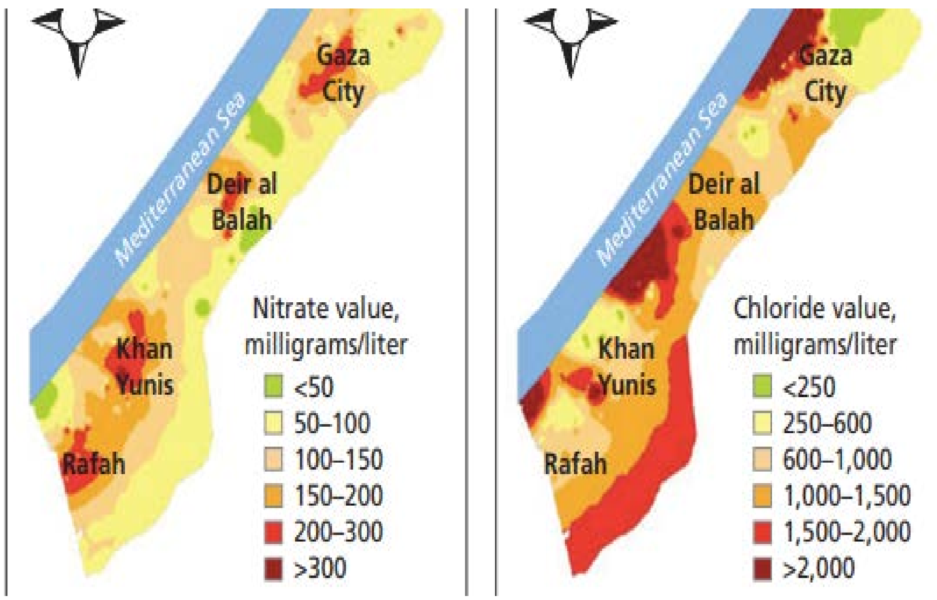


Figure 2.9. Spatial distribution of NO_3 and Cl amongst Gaza Coastal Aquifer

On light of the deteriorated water quality in the West Bank and Gaza Strip, protection plans are required for the protection of the water resources.

2.2.2.3. Effect of climate change and demographic growth on water resources

Palestine is located in the Middle East region in a transitional climatic zone (Al-Najjar et al., 2020; MoFA Netherlands, 2018; and Ighbareyeh et al., 2015). Its climate is characterized by cool wet winters and hot dry summers, locally modified by altitude and latitude (MoFA Netherlands, 2018). Based on the De Martonne index of aridity, the country is classified into different zones: arid to hyper-arid in the eastern and southern parts, semi-arid to sub-humid in the western part, and semi coastal area (Richard and Issac, 2012). All of these fluctuations in addition to the unstable political situation have made the country extremely vulnerable to climate change (Ighbareyeh et al., 2015).

The climate changes are evident in Palestine (Al-Najjar et al., 2020; MoFA Netherlands, 2018; and Ighbareyeh et al., 2015). It can be seen through the rising in annual average temperature, the reduction in rainfall, and the increase in droughts (Al-Najjar et al., 2020; MoFA Netherlands, 2018; and Ighbareyeh et al., 2015). The mean annual temperature of the country has shown a clear increasing trend during the period 1843-2013 (Hasan et al., 2022). The probability of very hot summer days has increased (Al-Najjar et al., 2020; MoFA Netherlands, 2018; and Ighbareyeh et al., 2015). The average annual rainfall of the West Bank and Gaza Strip has shown a decreasing trend during the period 2001-2011. A similar trend was observed at Jerusalem station for the rainy season from 1964 to 2012 (Richard and Issac, 2012). The increase in the incidence of drought occurrence is also evident. The droughts events have increased in the country by over 80% during the past decade as illustrated in Figure 2.10 (Al-Najjar et al., 2020). The increase in the incidence of drought occurrence is attributed to the reduction in precipitation and rise in evaporation as a result of temperature increase (Al-Najjar et al., 2021).

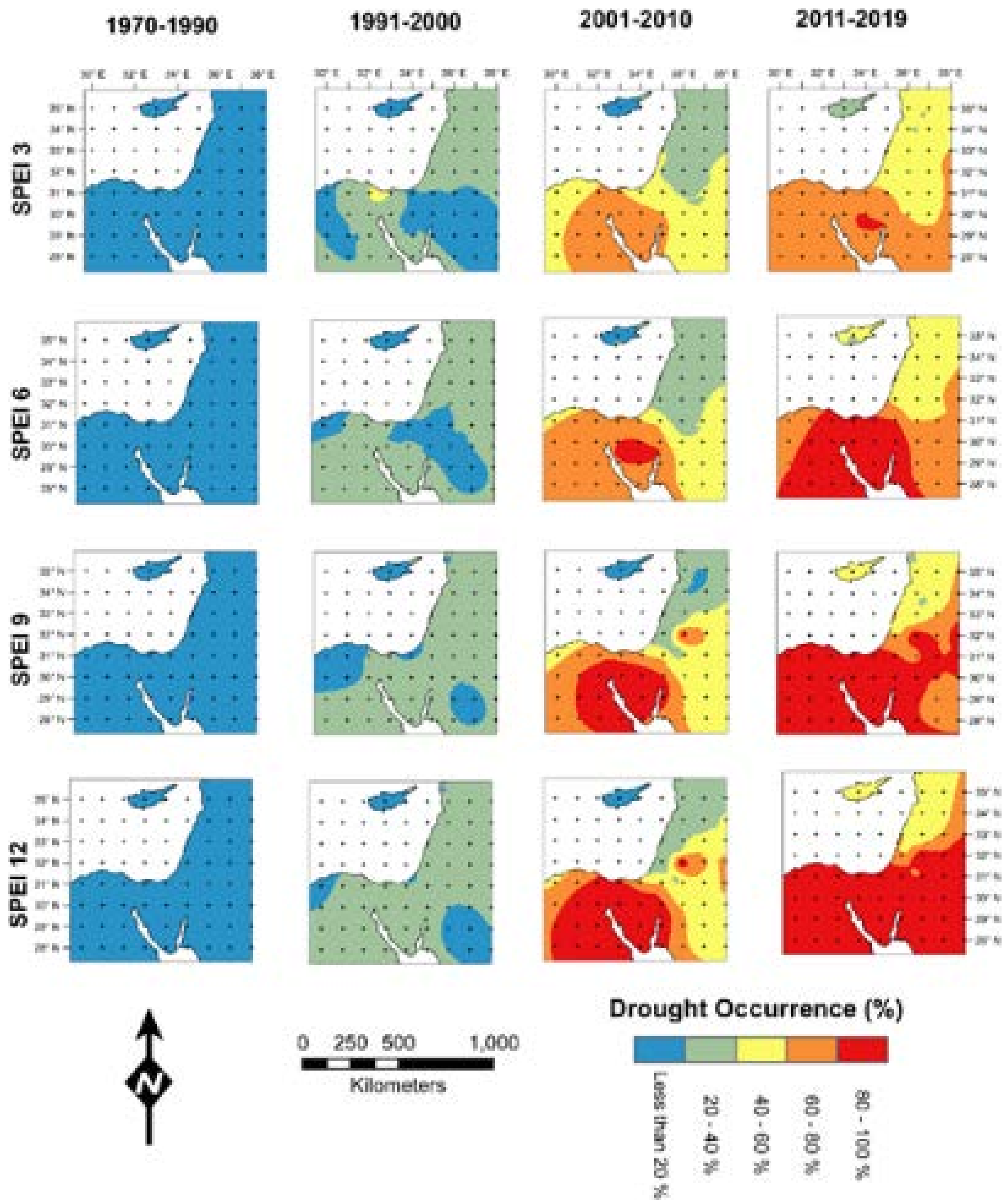


Figure 2.10. Drought occurrence in the MENA

Due to the temperature rising, evaporation will increase and water needs will grow. The aridity and desertification are expected to increase (Mizyed, 2018). The reduction in the precipitation amounts and changes in its patterns will affect the availability of the water resources (e.g. reduce groundwater recharge) (Mizyed, 2018). Mizyed (2018) used hydrological modeling to quantify the impact of changes in precipitation and temperature on the natural recharge of the groundwater. The simulation was based on different scenarios: (a) rise in monthly average temperature by 2˚C to 3˚C, (b) decrease in annual precipitation by 3%, 6%, 10%, and 15%. All scenarios are based on Christensen et al., (2013) predictions in the Mediterranean region. Table 2.2 shows the relative changes in the natural recharge of the three main aquifers in the West Bank under different climate change scenarios. A spatial variation in the impact of climate change on the natural recharge could be observed: a reduction by 10 % in the annual precipitation will reduce the natural recharge by 14% to 24%, with the highest reduction in the Eastern Aquifer recharge which is located in the drier area (Mizyed, 2018). The effect of the temperature increase is also recognized, but less significant than the rainfall reduction.

Table 2.2. Relative changes in recharge under different climate change scenarios for the West Bank aquifers

Aquifer	**Annual Precipitation (mm)**	**Scenario**				
		3˚C temperature increase	3% Precipitation reduction	6% Precipitation reduction	10% Precipitation reduction	15% Precipitation reduction
North eastern	546	9.1%	6.8%	13.9%	22.9%	39.7%
Western	564	8.4%	2.4%	7.5%	14.0%	28.2%
Eastern	327	13.2%	6.8%	14.4%	24.4%	51.0%
Total	440	9.8%	4.5%	10.7%	18.7%	36.7%

Al-Najjar (2021) modeled the impact of the climate change on the groundwater level in the Coastal Aquifer in Gaza Strip. The study first forecasted the climate parameters during the next 20 years; the average annual rainfall is predicted to decrease by 5.2%, the temperature is expected to rise by about 1 °C, and the relative humidity is most likely to decrease by 8%. Simultaneously, the sunshine hours and potential evaporation will increase by about 5 hours and 111 mm, respectively. The abstraction rate of the groundwater is predicted to be doubled by 2040. Then, the researchers analyzed the combined effect of the climate change and the over-pumping on the groundwater storage. The result of the simulation is presented in Figure 2.11. It shows a drop in the groundwater levels between 1.13 and 28 m in 2040.

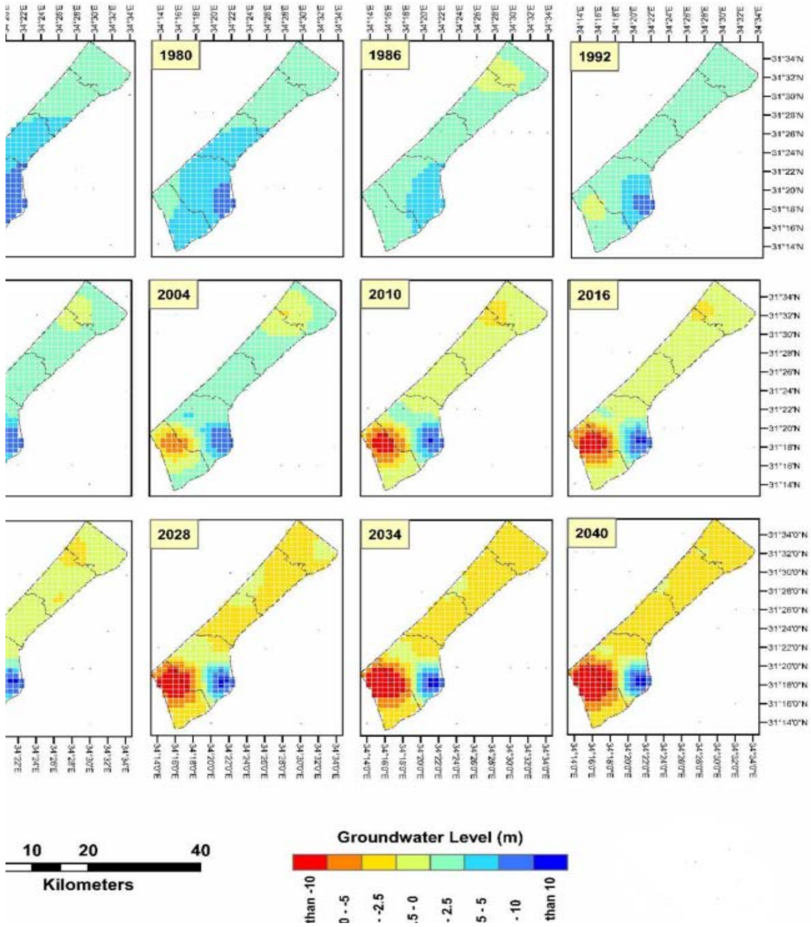


Figure 2.11. Spatiotemporal impact of climate change and over-pumping on the groundwater level of the Gaza Coastal Aquifer between 1974 and 2040

The quality of the water resources is also jeopardized by the climate change (UNDP, 2010). The levels of salinity of the groundwater will increase due to the reduction in the precipitation which will reduce the recharge of the groundwater (Smithers et al., 2016; and UNDP, 2010). The case of the Coastal Aquifer is very critical as it has high permeability and a shallow water table. Under the projected rise of the sea level by 0.1 to 0.4 m by 2100, the intrusion of the seawater into the aquifer will increase, which will raise the salinity of the Coastal Aquifer.

Abd-Elhamid et al., (2015) simulated the current and future intrusion of seawater into the Gaza Coastal Aquifer. They showed a severe seawater intrusion into the aquifer which makes the groundwater non-drinkable. The future seawater intrusion was simulated under different scenarios. An extra intrusion of 250 m in the coastal aquifer is predicted under a reduction of 0.5 m in the water table because of over-abstraction. While a 100 cm rise in the sea level will result in about 500 m of additional seawater intrusion. Yet, the combined effect of over-pumping and rise in sea level is expected to increase the intrusion by about 1 km into the aquifer.

The climate change will exacerbate the water stress with a deterioration of the water quality, reduction in the water supply, and increase in the domestic and agricultural water demand (Al-Najjar et al., 2021; Mizyed, 2018; and Abd-Elhamid et al., 2015). The stability of the country and the socio-economic conditions will be negatively affected by the climate change. Thus, there is a need for adaptation strategies to the climate change (Iglesias et al., 2011).

2.3. Materials and methods

The research framework adopted in this research consists of four phases (Figure 2.12). The first phase targets the assessment of the current and future water scarcity in the West Bank. The second one concerns the protection of the quality of the water resources. The third one assesses the potential capacity of RWH to address the water scarcity. The last phase proposes a smart RWH system and smart dual water supply system to promote the domestic water security. This chapter briefly discusses the four phases. The detailed description will be presented in the application chapters.

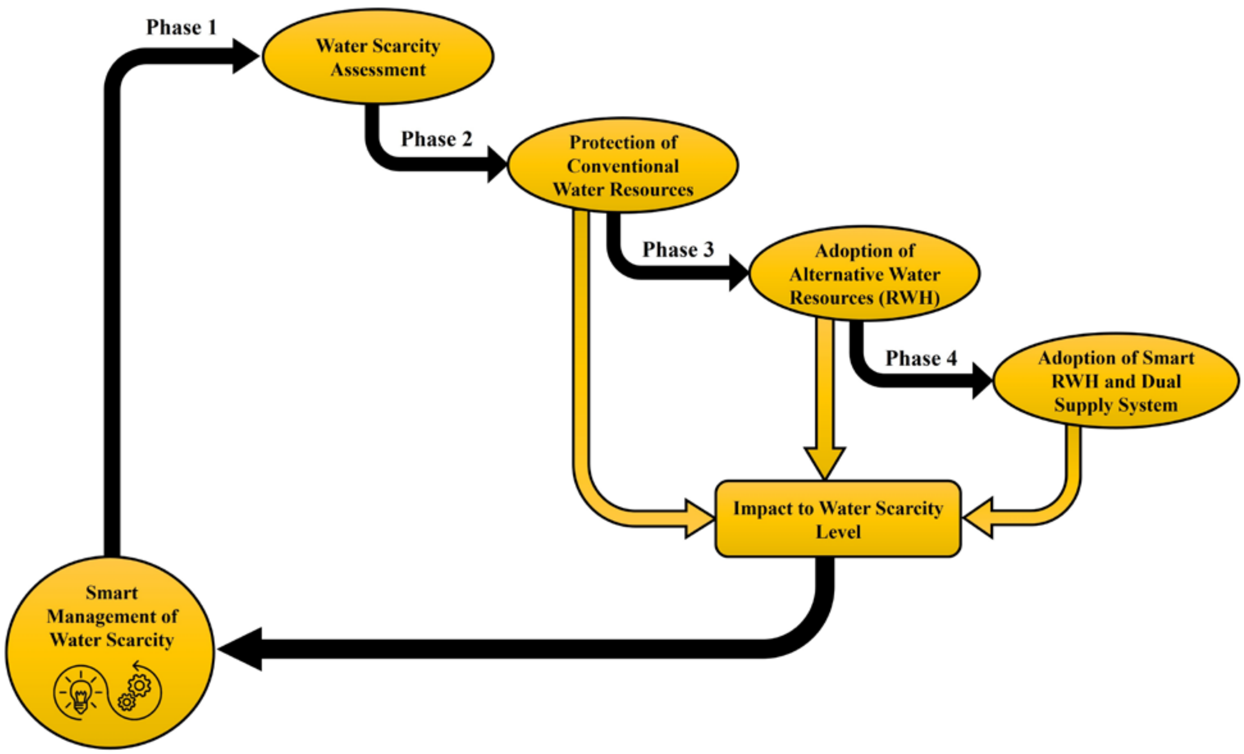


Figure 2.12. Overall research methodology

2.3.1. Assessment of the water scarcity

This section presents the methodology used for assessing the water scarcity in the West Bank (Figure 2.13). According to literature review, scholars adopted several methods for water scarcity assessment including criticality ratio, water poverty index, the falkenmark index, integrated water quantity–quality-environment flow index, the International Water Management Institute Indicator (IWMII), and cumulative abstraction to demand ratio (Hussain et al., 2022; Nkiaka, 2022; Liu et al., 2017; Liu et al., 2016; and Falkenmark et al., 2009). The used indices are complex. They require massive input data, and could come up with misleading uncertain results (Hussain et al., 2022; Nkiaka, 2022; Liu et al., 2017; Liu et al., 2016; and Falkenmark et al., 2009).

To overcome these limitations, this research adopts the supply demand balance index (SDBI) to assess the existing domestic water scarcity. This index is simple and have a single value resulted from dividing the water supply to the water demand (Huang and Yin, 2017). The value can assess the water scarcity level on a scale ranging from “extreme” to “no” water shortage. It can simultaneously consider freshwater utilization, water quality, and citizens’ water needs. The SDBI simplicity enables to consider the climate change and demographic effects on the future water scarcity (Huang and Yin, 2017). This research investigates the climate change effects on the water resources availability till 2050 as well as the impact of the population growth on the domestic water demand. The SDBI, Geographic Information System (GIS), climate change and demographic growth models are integrated to assess the future water scarcity. The detailed methodology for the assessment of existing and projected water scarcity in the West Bank is presented in Section 3.2.

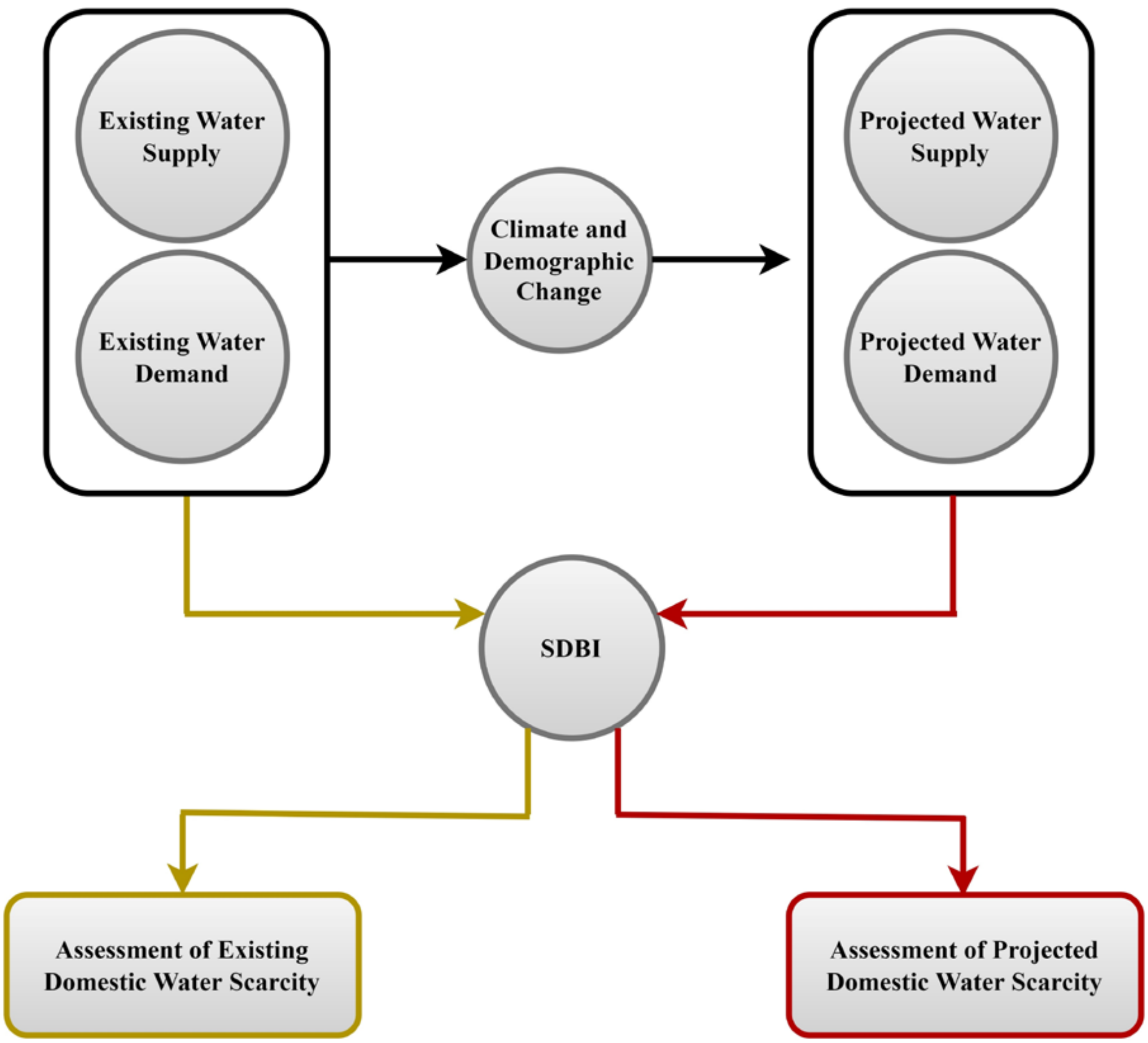


Figure 2.13. Assessment of existing and projected water scarcity

2.3.2. Protection of the conventional water resources

According to the state of art, scholars adopted several methods for protecting the groundwater quality including the descriptive statistical assessment (Judeh et al., 2022; and Anayah and Almasri, 2009), the water quality indices (WQI) (Banda and Kumarasamy, 2020; Shadeed et al., 2020; Shadeed et al., 2019; Poonam et al., 2015; Li et al., 2014; and Ocampo-Duque et al., 2013), the water quality mapping (Judeh et al., 2021), and the water quality modeling (Pham et al., 2021; and Ranjith et al., 2019). These methods have several limitations: complexity (e.g. water quality modeling), uncertainty (e.g. WQI and water quality mapping), dependency on massive input data (e.g. water quality modeling), and the inability to predict the levels of water pollution along with their sources (e.g. all listed methods) (Shadeed et al., 2019; and Anayah and Almasri, 2009).

To address these limitations, this research proposes to combine four methods (Figure 2.14). The first method adjusts and employs a new GIS-based Groundwater Quality Index (GWQI) for the groundwater potability and palatability assessment and mapping. This adjusted index contributes in addressing the complexity and uncertainty of previously-used indices. It contributes in properly identifying the hotspots for groundwater contamination and the most threatening contaminants. The second method uses a GIS-based descriptive statistical assessment for constructing a causal-effect relation for groundwater contamination with a focus on the resulted hotspot in the first method (Judeh et al., 2022). Such relation helps in investigating the main sources and factors affecting the groundwater contamination including: (i) well depth, (ii) well use, (iii) anthropogenic on-ground activities, (iv) soil type, (v) land use, (vi) groundwater flow, (vii) aquifer conductivity, and (viii) watersheds. The third method employs such factors and sources for realizing a Machine Learning-based Random Forest model (RFA) for predicting the groundwater contamination (Judeh et al., 2022). The adoption of RFA will contribute in addressing the prediction limitations/incapability of the other methods used for water quality protection. The fourth method employs climate change model (Soil-Vegetation-Atmosphere Model, SVAT) for assessing the change in groundwater storage till 2050 (Menzel et al., 2009).

The integration of the four methods helps in providing a sustainable plan for the groundwater protection through:

(i) The allocation of hotspots for groundwater pollution, and the identification of the most threatening sources for such contamination. Instructions and recommendation for protecting such spots is presented (with focus on the man-made activities).

(ii) The forecasting of groundwater storage changes till 2050 based on climate change scenarios. Adopting alternative water resources is introduced accordingly. This will decrease the burden on groundwater and will preserve its level (from declining or even depletion).

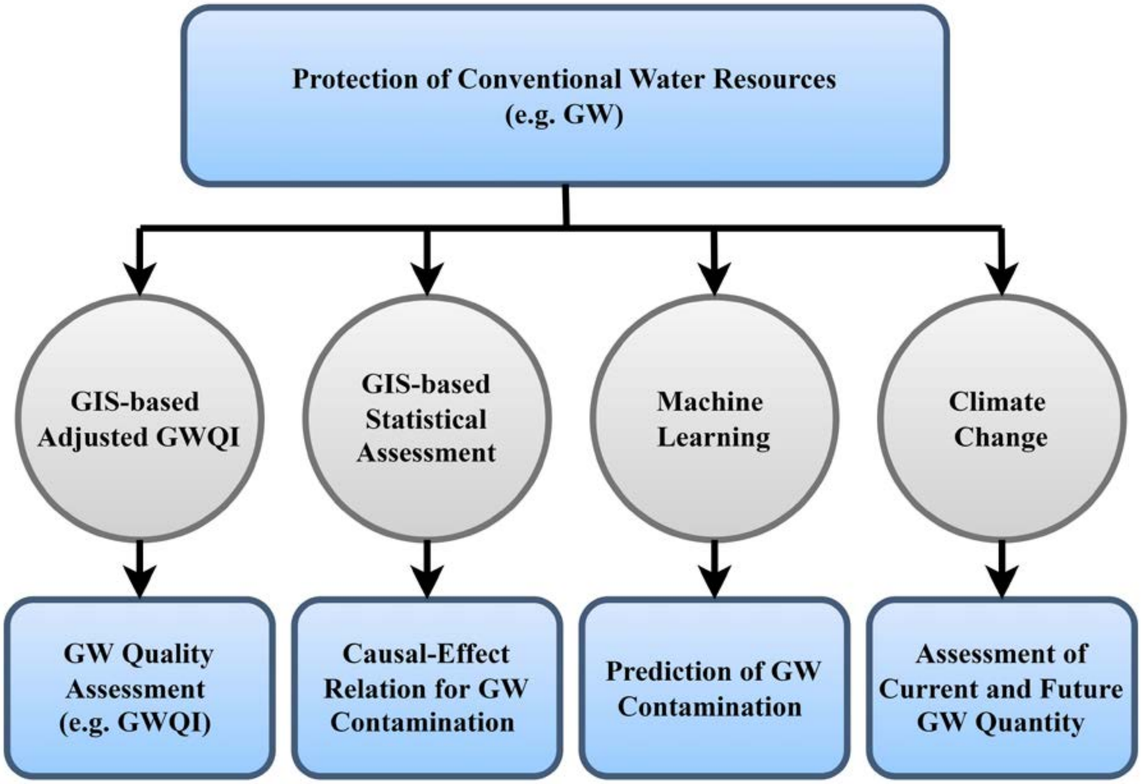


Figure 2.14. Protection of conventional water resources

2.3.3. Adoption of alternative water resources

This section presents the methodology used for investigating the role of alternative water resources in addressing the water scarcity in West Bank (Figure 2.15). Previous researches focused on the estimation of the potential water volumes that the alternative water resources can produce. The effect of these volumes to the water scarcity level was not investigated. This research employs the GIS and Gould and Nissen-Petersen’s equation to estimate the potential RWH volumes in the current status. After that, climate change impact on the rainfall is investigated. Finally, the current and future RWH volumes are implied within the SDBI. This contributes to investigate the role of the harvested water in alleviating the water scarcity.

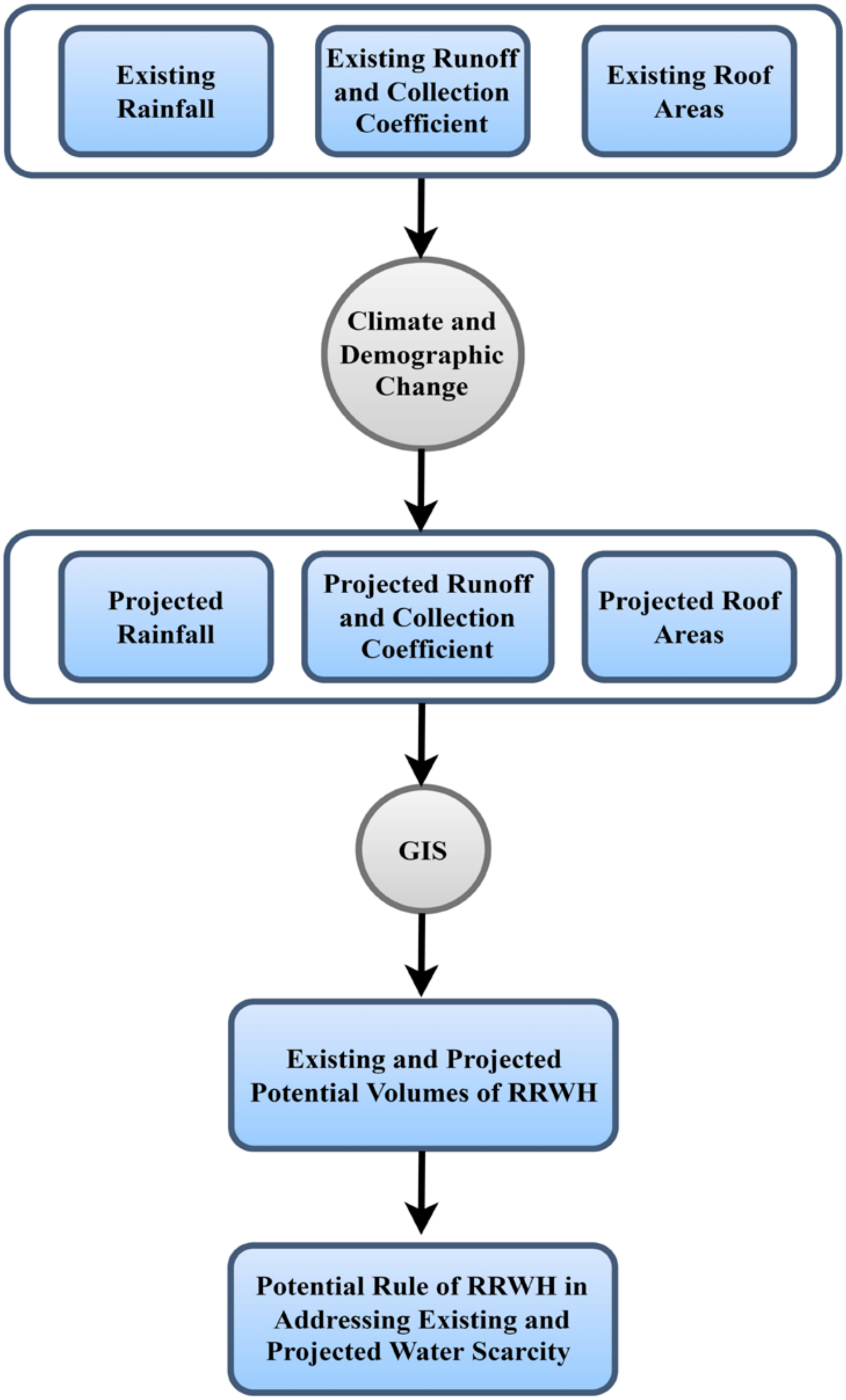


Figure 2.15. Investigating the role of potential RWH in addressing the current and future domestic water scarcity

2.3.4. Smart RWH and dual water supply system

The conventional RWH systems have several limitations. They don't control the filling and emptying process of the storage tanks. Moreover, the water leakage throughout the system is not controlled (Behzadian et al., 2018). To overcome these limitations, this research proposes a smart RWH system (Figure 2.16), which employs smart sensors and crowdsourcing to monitor and control the harvested water' potability, level, and leak. The dynamic management is adopted to optimize the size of the storage tank. The smart RWH system is integrated with the municipal water supply. The smart dual water supply system is designed considering the sharing of water at a neighborhood level. A reliability analysis for assessing the system' performance is performed. Finally, the role of the system in addressing the water scarcity in the West Bank is investigated.

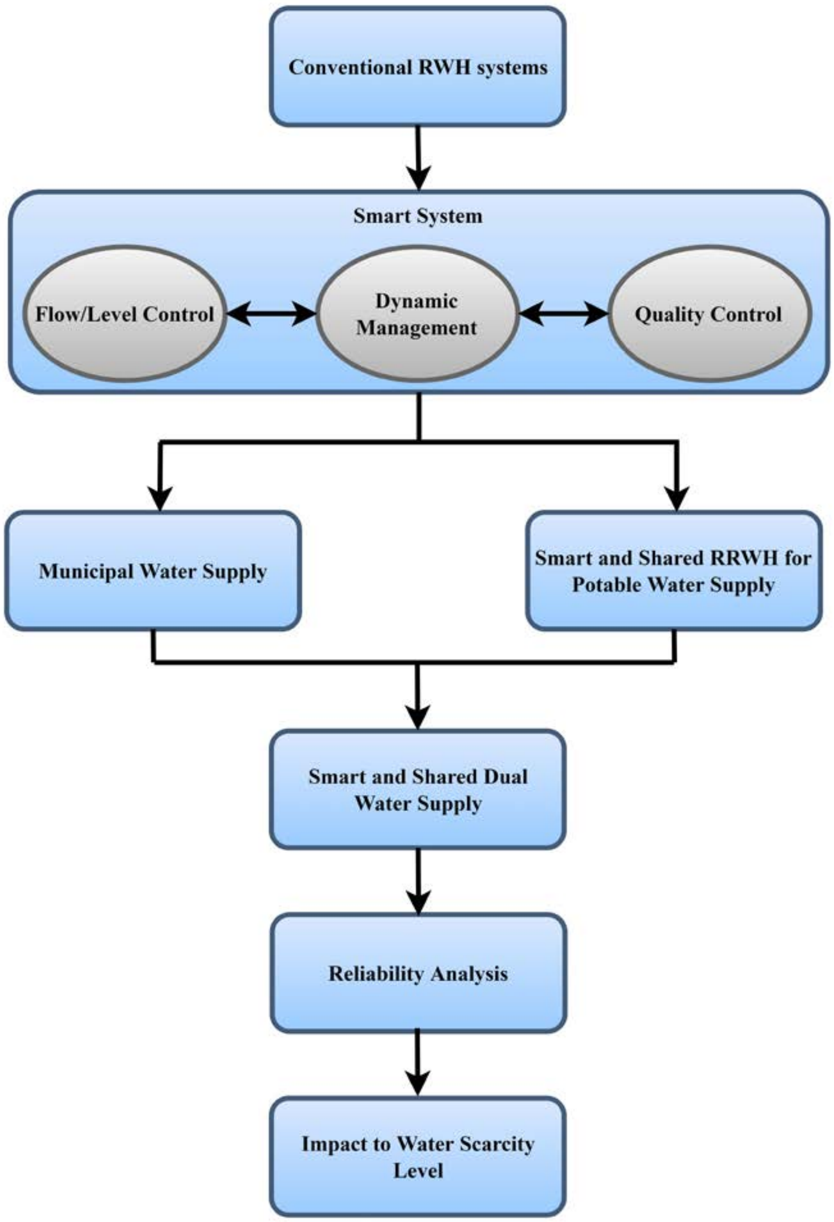


Figure 2.16. Methodological framework for smart RWH and smart dual water supply systems

2.4. Conclusion

This chapter presented an innovative framework for the smart management of the water scarcity. It combines the smart technology and Machine Learning for the assessment, preservation, mitigation and reduction of the water scarcity. The framework considers the water scarcity main causes: limited water availability, restricted water accessibility, water pollution, increase in the water demand, and the climate change.

The proposed framework is applied to the West Bank. The use of GIS and SDBI for the assessment water scarcity will be presented in Chapter 3. The use of GIS, statistics, and the new adjusted GWQI for the protection of the conventional water resources will be presented in chapters 4 and 5. The adoption of the Gould and Nissen-Petersen's equation and GIS to assesses the potential capacity of RWH in addressing water scarcity will be discussed in chapter 6. The use of the smart systems to address the water security will be described in. chapter 7.

Chapter 3. Assessment of Current and Forecasted Water Scarcity in the Arid and Semi-Arid Areas

3.1. Introduction

This chapter aims at assessing the domestic water scarcity in arid and semi-arid areas with emphasis on the West Bank in Palestine. Domestic water scarcity is defined as the inability of available freshwater to satisfy the needed domestic water demand (Taylor, 2009). According to the World Health Organization (WHO), water scarcity adversely affects the water consumption and hygiene (Howard and Bartram, 2003). Areas suffering from water scarcity are classified as risky to human health (Howard and Bartram, 2003). Water scarcity increases the spread of infectious diseases (e.g. Influenza, Ebola, and SARS) (Anser et al., 2020; Adams et al., 2019; and Zakar et al., 2012). The United Nation (UN) Sustainable Development Goal (SDG-6.4) expressed the necessity of decreasing the number of people affected by domestic water scarcity (UN, 2021). Domestic water scarcity is of increasing concern, especially in arid and semi-arid areas (Shadeed et al., 2019). This could be attributed to the increasing water demand and the vulnerability of water resources under climate change (Shadeed et al., 2019; The Arab Water Council, 2009; and Menzel et al., 2009). In the West Bank, the domestic water supply-demand gap reached 40% of the water demand in 2018 (PCBS, 2021b).

Assessing the water scarcity constitutes a vital step in addressing water scarcity challenges (Jafari-Shalamzari and Zhang, 2018; and Liu et al., 2017). Various indices are used to evaluate the domestic water scarcity. The Falkenmark index uses the per capita water availability as an indicator of water scarcity (Falkenmark et al., 2009; and Falkenmark et al., 1989). (Damkjaer and Taylor, 2017; and Oki and Kanae, 2006) proposed to use the criticality ratio index to estimate water scarcity. (Shadeed et al., 2019; Jafari-Shalamzari and Zhang, 2018; and Liu et al., 2018) used water poverty for water scarcity assessment. This indicator considers the average of the following elements: water availability, accessibility, capacity, use, and environment. According to (Huang and Yin, 2017), the supply demand balance index (SDBI) is the only index that directly considers both water availability and citizens' water needs. It provides a simple way of assessing the domestic water scarcity by estimating the ratio of the water supply to the water demand. It has a single value that characterizes the water scarcity level on a scale ranging from “extreme” to “no” water shortage (Huang and Yin, 2017).

Climate change influences the availability of water resources (Urama and Ozor, 2010). The projected water demand is affected by the demographic changes (Johannsen et al., 2016). Consequently, assessing the domestic water scarcity could be viewed as a dynamic process (Johannsen et al., 2016). However, the literature review shows that the assessment of the domestic water scarcity through SDBI does not properly consider the climate change.

The contribution of this chapter could be summarized by the use of the SDBI to assess the current and projected domestic water scarcity in the West Bank. It is organized as follows. First, it presents the research methodology for the estimation of SDBI. It describes the case study with emphasis on data collection, and finally, it discusses the resulted scarcity levels in the West Bank, Palestine.

3.2. Materials and methods

3.2.1. Methodology

The methodology adopted in this research is illustrated in Figure 3.1. It includes three phases. It starts by identifying and quantifying the total water supply (TWS) in million cubic meters per year (MCM/y), the total water demand (TWD) in MCM/y. The second phase estimates the effect of climate change and population growth to the TWS and TWD (till 2050), respectively. The last phase employs the SDBI (by implying the current and projected TWS and TWD) to assess the current and projected domestic water scarcity in the study area.

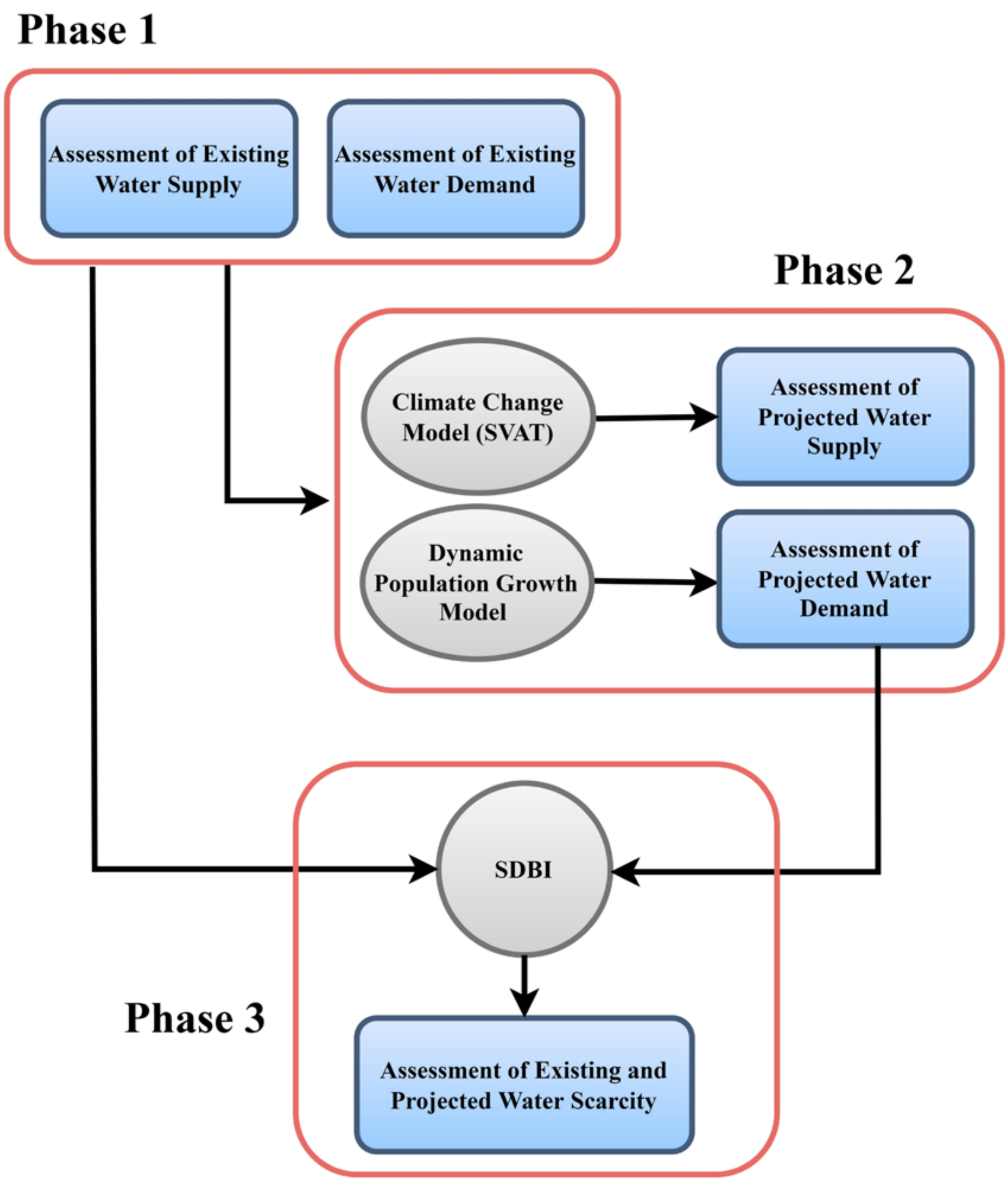


Figure 3.1. Research methodology

3.2.1.1. Assessment of TWS and TWD

The assessment of domestic water scarcity starts by identifying and quantifying the sources of water supply (e.g. surface water, groundwater, desalination and etc.). Accordingly, the current TWS is estimated. The domestic water consumption rate (DWCR) is specified considering the recommendation of WHO (Howard and Bartram, 2003). Such rates, along with the population statistics, are used to estimate the TWD.

$$\mathrm{TWD_i} = \frac{\mathrm{DWCR} * \mathrm{POP_i} * 365}{1000} \qquad \text{(Equ. 3.1)}$$

Where,

TWD_i is the TWD for the i^{th} year in (MCM/y)

POP_i is the population for the i^{th} year in (capita)

3.2.1.2. Impacts of climate and demographic change to TWS and TWD

Scholars adopted various models to characterize the effect of climate change to water resources availability. Such models include (i) Water Balance Model developed by the Research Center for Climate Change (RCCC-WBM) (Qiao et al., 2021), (ii) Hydrologiska Byrans Vattenbalansavdelning model (HBV) (Versini et al., 2016), (iii) Soil and Water Assessment Tool (SWAT) (Emami and Koch, 2019), and (iv) Soil-Vegetation-Atmosphere Model (SVAT) (Menzel et al., 2009). According to (Petropoulos et al., 2009), the SVAT has the following strengths compared to the other models: (i) consideration of fine time-step analysis which goes in line with the time-steps of the physical processes simulations, (ii) flexibility of the input parameters and their time-steps records, and (iii) consideration of the under-ground layer (e.g. soil layer), on-ground layer (e.g. vegetation layer), and over-ground layer (atmospheric layer) (Petropoulos et al., 2009). This model was used for the determination of TWS in MCM/y in 2050 (Menzel et al., 2009). The model has a resolution of 18 x 18 km^2 and involves rainfall, climatic, vegetation, landscape and soil parameters as inputs. Rainfall parameters include the rainfall depth, patterns and spatial distribution. Climatic and vegetation parameters involve the solar radiation and the leaf area index, respectively. Landscape parameters imply the elevation, slope and land-use, while the soil parameters include soil type, texture and field capacity (Menzel et al., 2009).

The schematic overview of the SVAT model is shown in Figure 3.2. First, the model considers the different inputs. Then, characterizing the infiltration, percolation, interception, transpiration, and runoff is carried out. Finally, the vertical and horizontal water flow is estimated at the different time steps (Menzel et al., 2009).

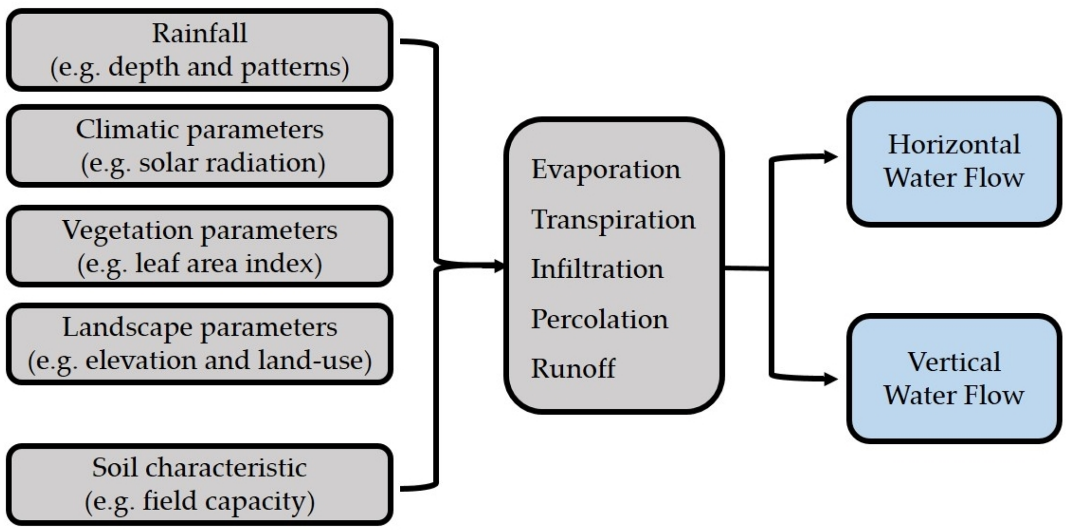


Figure 3.2. Schematic overview of the adopted SVAT model

Projected population (POP_p) and DWCR in 2050 are employed to quantify the projected TWD for the year 2050.

3.2.1.3. Assessment of the domestic water scarcity

Current and projected TWS and TWD are used to estimate the SDBI for 2020 and 2050 (Huang and Yin, 2017). This index is used for the assessment of domestic water scarcity. In addition, SDBI could be used at the regional and national levels (Huang and Yin, 2017). It is estimated by the ratio between TWS and TWD:

$$SDBI_i = \frac{TWS_i}{TWD_i} \qquad \text{(Equ. 3.2).}$$

Where,
$SDBI_i$: supply demand balance index for the i^{th} year
TWS_i: total water supply for the i^{th} year in (MCM/y)
TWD_i: total water demand for the i^{th} year in (MCM/y)

According to (Huang and Yin, 2017), five domestic water scarcity levels are identified, as summarized in Table 3.1.

Table 3.1. Domestic water scarcity values and the associated levels (Huang and Yin, 2017)

SDBI level	SDBI value
Extreme water scarcity	(0,0.3)
Acute water scarcity	[0.3,0.6]
Moderate water scarcity	(0.6,0.9)
Slight water scarcity	[0.9,1)
No water scarcity	≥1

3.2.2. Data collection and application

The proposed methodology is applied to the West Bank, Palestine. Data are collected from different sources. The historical and current population statistics are collected from the Palestinian Central Bureau of Statistics (PCBS) (PCBS, 2021c). WHO recommended a DWCR of about 100 liters per capita per day (l/c/d) (Howard and Bartram, 2003). Accordingly, Equ. 3.1 is used for the estimation of historical and current TWD for the whole West Bank. Figure 3.3 shows the increasing trend in population and TWD. Population increases from 1.78 million capita to 3.05 million capita, and TWD increases from 65.2 MCM/y to 111.4 MCM/y between 1997 and 2020.

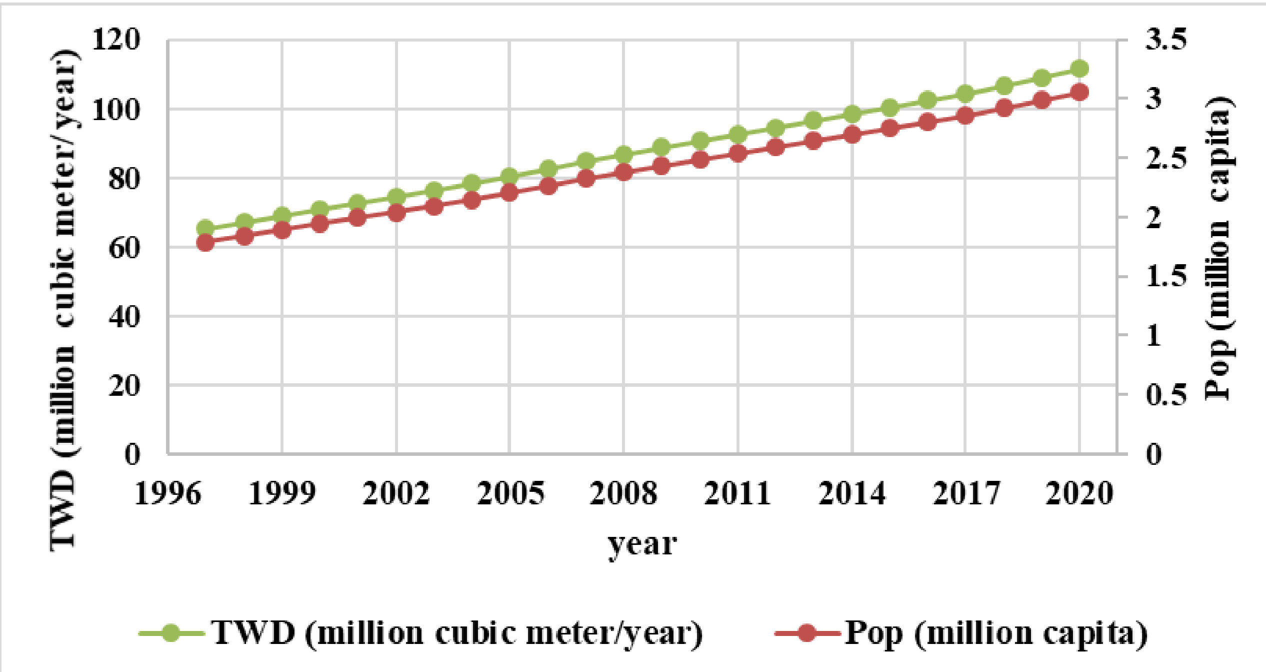


Figure 3.3. Historical and current statistics of population and TWD in the whole West Bank between 1997 and 2020

POP_p (in 2050) is estimated using a dynamic population projection model (Courbage et al., 2016); which considers several determinants such as age, sex, fertility, international migration trends, and mortality rates.

Equ. 3.1 is used for the determination of the TWD in 2020 and 2050 on a governorate scale. Table 3.2 summarizes the results for the eleven West Bank governorates. TWD in 2020 varies between 1.9 MCM/y (Jericho) and 27.8 MCM/y (Hebron), with an average value of 9.9 MCM/y. In 2050, the TWD is expected to vary between 3.2 MCM/y (Jericho) and 50.9 MCM/y (Hebron), with an average value of 15.7 MCM/y, which is about 58% higher than that in 2020.

Table 3.2. Current and projected population (POP_c and POP_p) and TWD

Governorate	POP_c	POP_p	TWD 2020 (MCM/y)	TWD 2050 (MCM/y)
Jenin	332050	481000	12.1	17.6
Tubas	64507	133000	2.4	4.9
Tulkarm	195341	227000	7.1	8.3
Nablus	407754	532000	14.9	19.4
Qalqilya	119042	174000	4.3	6.4
Salfit	80225	101000	2.9	3.7
Ramallah & Al-Bireh	347818	602000	12.7	22.0
Jerusalem	461666	642000	16.9	23.4
Jericho	52355	89000	1.9	3.2
Bethlehem	229884	354000	8.4	12.9
Hebron	762541	1394000	27.8	50.9

By characterizing the probable sources of water in the West Bank, it is found that water desalination and surface water have no contribution to the TWS (PCBS, 2021a; and PCBS, 2020b). Groundwater (through the pumping wells and the springs) is the only adopted source of water to supply citizens by their needs. Therefore, TWS is quantified through the estimation of the supplied (by services providers) groundwater volumes in the study area. Such volumes are gained from PCBS database (PCBS, 2021b). The variation in TWS in the West Bank governorates in 2020 is illustrated in Table 3.3. The lowest TWS is recorded in Ramallah & Al-Bireh with around 1.1 MCM/y, while the highest TWS is in Nablus (8.5 MCM/y).

Table 3.3. TWS in the different West Bank governorates in 2020

Governorate	TWS in 2020 (MCM/y)
Jenin	3.7
Tubas	2.7
Tulkarm	6.6
Nablus	8.5
Qalqilya	5.2
Salfit	1.5
Ramallah & Al-Bireh	1.1
Jerusalem	1.4
Jericho	2.9
Bethlehem	2.0
Hebron	6.6

The rate of change in TWS between 2020 and 2050 are estimated using the downscaled SVAT model developed by GLOWA (Menzel et al., 2009). The GIS-based Raster Calculator is then used to estimate the values of TWS in 2050. However, downscaled SVAT model involves uncertainties (Gunkel and Lange, 2012; and Menzel et al., 2009). To mitigate this shortcoming, available data at the highest spatial and temporal resolution were used (Gunkel and Lange, 2012; and Menzel et al., 2009). Calibration of SVAT model was carried out using historical and current TWS records (in 2015 and 2020, respectively) (PCBS, 2021b). Due to limited data availability, this calibration is conducted for Jenin governorate. Actual TWS in 2015 (3.63 MCM/y) is used to predict the TWS in 2020 (using SVAT) for Jenin governorate. It is found that the predicted TWS in 2020 equals around 3.68 MCM/y. Such prediction is significantly close to the actual TWS in 2020 which equal to 3.70 MCM/y (with a relative error of about 0.005) (PCBS, 2021b). This slight relative error provides a considerable level of confidence by the used model.

Figure 3.4 illustrates the distribution of current and projected TWS in the West Bank. It indicates that all the governorates, except Jenin and Nablus, will experience in 2050 a decrease in TWS compared to 2020. This maximum decrease could reach 26% (in the Northern part of the West Bank).

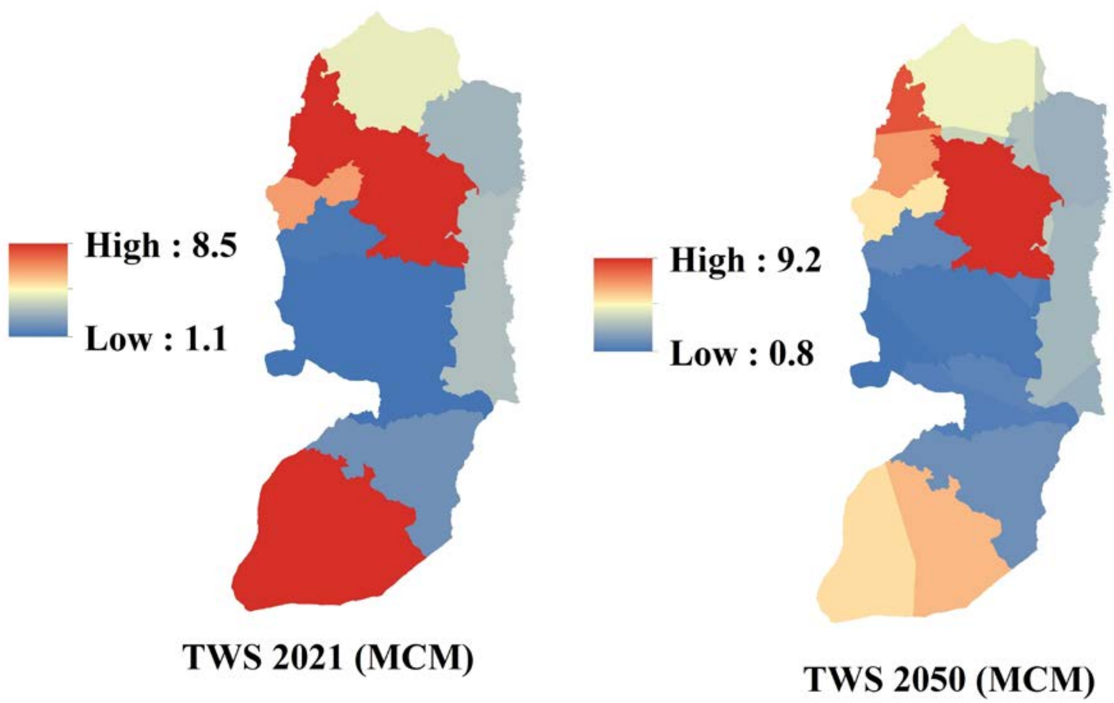


Figure 3.4. Variation in TWS considering climate change

3.3. Results and discussion

This section presents and discusses the SDBI values and the domestic water scarcity levels in the West Bank governorates for the years 2020 and 2050 (Table 3.4). In 2020, the status "no water shortage" is observed in Jericho, Qalqilya, and Tubas, with a SDBI of about 1.5, 1.2, and 1.1, respectively. A slight water shortage is observed in Tulkarm, while the rest of the West Bank governorates experienced an extreme to acute water shortage. Results of the current water scarcity in the West Bank are compatible with the results of other scholars (Jabari et al., 2020; and Shadeed et al., 2019). All governorates (except for Tubas, Ramallah & Al-Bireh, and Jerusalem) have water scarcity/poverty categories, which are similar to the findings of (Shadeed et al., 2019). Compared to (Jabari et al., 2020), compatible water scarcity/security categories exist in all governorates except Tulkarm and Jericho. The gap in characterizing the water status in some governorates could be attributed to the approaches and indicators adopted by scholars. For example, (Shadeed et al.,

2019) adopted the weighted arithmetic average method (WAAM) by considering the water availability, accessibility, capacity, use, and environment for assessing the water status, while (Jabari et al., 2020) used the same method but in considering other indicators such as water resources, water services, and water governance. Adopting WAAM with flexible input indicators to characterize the water scarcity/poverty was discussed by (Goodarzi et al., 2021; Koirala et al., 2020; and De Sousa Cordão et al., 2020), who confirmed that the change in the input indicators could affect the estimation of the water poverty/scarcity status (Goodarzi et al., 2021; Koirala et al., 2020; and De Sousa Cordão et al., 2020).

In 2050, lower SDBI values are expected to be recorded comparing to the year 2020. All governorates have water scarcity levels that range from extreme, acute, to moderate scarcity. This indicates that the water scarcity challenges will be severest in the future. Therefore, sustainable management of water scarcity must be adopted through the consideration of the climate and demographic impacts. This will contribute to addressing the future water challenges.

Table 3.4. SDBI values and water scarcity levels in the West Bank governorates in 2020 and 2050

Governorate	SDBI value		Domestic water scarcity level	
	2020	2050	2020	2050
Jenin	0.29	0.17	Extreme	Extreme
Tubas	1.14	0.50	No Shortage	Acute
Tulkarm	0.92	0.61	Slight	Moderate
Nablus	0.57	0.33	Acute	Acute
Qalqilya	1.20	0.62	No Shortage	Moderate
Salfit	0.50	0.31	Acute	Acute
Ramallah & Al-Bireh	0.08	0.04	Extreme	Extreme
Jerusalem	0.08	0.04	Extreme	Extreme
Jericho	1.53	0.74	No Shortage	Moderate
Bethlehem	0.24	0.10	Extreme	Extreme
Hebron	0.24	0.08	Extreme	Extreme

3.4. Conclusion

This chapter presented a new methodology for assessing the domestic water scarcity in arid and semi-arid areas. First, the current total water supply (TWS) and total water demand (TWD) are estimated. Then, the effects of the climate change and the population growth on the TWS and TWD are investigated in 2050. Finally, the SDBI is used to assess the current and projected domestic water scarcity in the West Bank.

Results showed that seven out of the eleven West Bank governorates are suffering from extreme to acute water scarcity in 2020. Due to the climate and demographic change impact, one more governorate is expected to suffer from extreme to acute scarcity level by 2050.

This research helps decision-makers to properly evaluate the current and projected water scarcity challenges in the West Bank and to establish proper water management strategies to address the water scarcity.

Chapter 4. GIS-Based Spatiotemporal Mapping of the Groundwater Potability and Palatability Indices in Arid and Semi-Arid Areas

4.1. Introduction

This chapter aims at assessing the quality of the groundwater resources to establish efficient water protection plans and address the water scarcity in the West Bank. Groundwater forms a major source of potable water for many countries in the world (Masindi and Foteinis, 2020; and Almasri et al., 2020). It has been naturally purified by the infiltration process. Therefore, it is usually of excellent quality and requires no more than slight monitoring and treatment (Li et al., 2021; Mays and Scheibe, 2018; and Singha et al., 2015). Unluckily, excellent quality is no longer assured due to human activities (Li et al., 2021; Ortega et al., 2020; Ahmad et al., 2020; and Lee and Murphy, 2020). Indeed, urban (e.g., use of cesspits for wastewater disposal), agricultural (e.g., intensive use of fertilizers and pesticides), and industrial (e.g., unmanaged solid waste disposal) activities increase the soluble contaminants reaching groundwater (Khan et al., 2021; Abul Hasan et al., 2021; Kumar et al., 2020; Peixoto, 2020; Estrada et al., 2020; Alaizari et al., 2018; Baalousha, 2017). Scholars have confirmed the increasing health risk associated with groundwater contamination (Karunanidhi et al., 2021; and Kadam et al., 2021), which could cause different diseases (e.g., hepatitis, dysentery, poisoning, blue baby syndrome, and cancers) and lead to death (Khan et al., 2021; Abul Hasan et al., 2021; Peixoto, 2020; Kubicz et al., 2020; Khaiwal et al., 2019; and Raza et al., 2017).

The assessment of the groundwater quality is necessary for evaluating its suitability for human usage. Traditionally, researchers adopted the single parameter assessment to characterize the groundwater quality (El Baba et al., 2020). They compared the parameter' concentration to the drinking water standards (El Baba et al., 2020). This traditional approach does not consider the multi-contaminant effect on drinking water (El Baba et al., 2020). Thus, researchers embraced the groundwater quality index (GWQI) as a strategic tool for characterizing groundwater quality (Kayemah et al., 2021; Kumari, 2020; and Al Aboodi et al., 2018). It considers physical, chemical, and biological water characteristics according to drinking water standards. GWQI identifies the groundwater quality using a single score (Kayemah et al., 2021; Kumari, 2020; and Al Aboodi et al., 2018). The score can be transformed into excellent, good, satisfactory, poor, and undrinkable water. Decision–makers and end-users could easily understand this approach (Kayemah et al., 2021; Kumari, 2020; and Al Aboodi et al., 2018). The GWQI is applied in many countries such as Mexico (Salcedo et al., 2016), Portugal (Stigter et al., 2006), Hungary (Mester et al., 2020), India (Selvaganapathi et al., 2017) Malaysia (Roslan et al., 2007), Algeria (Bouderbala, 2017), Egypt (Abdelaziz et al., 2020), and United Arab Emirates (Kayemah et al., 2021).

Various methods were used to develop the water quality index (WQI) for the groundwater resources such as the Horton model of WQI (Horton, 1965), Modified National Sanitation Foundation WQI (Poonam et al., 2015), Scottish Research Development Department WQI (Banda and Kumarasamy, 2020), Oregon WQI (Cude, 2001; and Dunnette, 1979), Martínez de Bascarón WQI (Banda and Kumarasamy, 2020), Bhargava's WQI (Li et al., 2014), Canadian Council of

Ministers of the Environment WQI (Neary et al., 2001), Liou's WQI (Banda and Kumarasamy, 2020; and Liou et al., 2004), fuzzy-based WQI (Ocampo-Duque et al., 2013), Vaal WQI (Banda and Kumarasamy, 2020) and universal WQI (Boyacioglu, 2010; and Boyacioglu, 2007). The weighted arithmetic water quality index (WAWQI) method has flexibility in the input parameters (Mester et al., 2020; and Banda and Kumarasamy, 2020). It estimates the GWQI considering the most common contaminants (Tyagi et al., 2013).

As stated by Aleem et al., (2018), the combination of GWQI and spatial analysis has proved to be a robust tool for assessing the groundwater quality (Alexakis, 2021; and Aleem et al., 2018). The geographic information system (GIS) enables the use of various interpolation methods for GWQI spatial analysis, such as proximity interpolation, inverse distance weighted interpolation, and the kriging interpolation method (KIM) (Li et al., 2019; and Lodwick et al., 1990). Compared to other interpolation methods, the KIM method employs statistical approaches to eliminate the spatial trends in data. It also characterizes the spatial data autocorrelation by defining the optimal experimental variogram model (Li et al., 2019; and Lodwick et al., 1990).

In the West Bank, the groundwater quality has deteriorated due to the weak sewer infrastructure, unmanaged human practices, and weak quality monitoring systems (Almasri et al., 2020; and Anayah and Almasri, 2009). Various studies confirmed the groundwater contamination using descriptive and statistical methods (Daghara et al., 2019; Aish, 2013; and Anayah and Almasri, 2009). However, such methods are less comprehensive than the GWQI in assessing the groundwater contamination (Tyagi et al., 2013). GWQI considers the combined influence of contaminants which in turn provides decision-makers with informative results (Tyagi et al., 2013).

This chapter presents an adjusted WAWQI method to develop the groundwater potability (PoGWQI) and palatability (PaGWQI) indices in the West Bank. The GWQI method is used for the first time to assess the groundwater quality in the West Bank. The chapter discusses an unparalleled adjustment of the WAWQI method for developing the GWQI method. The adjusted method combines experts' opinions, step-wise assessment ratio analysis method (SWARA), and the conventional WAWQI method. The proposed approach can help decision-makers to develop strategies for protecting water resources.

4.2. Materials and methods

4.2.1. Methodology

Figure 4.1 shows the methodology adopted in this research. It includes four phases: development of PoGWQI and PaGWQI, mapping of water quality indices, performing a sensitivity analysis, and constructing causal-effect analysis for understanding and prioritizing the factors affecting PoGWQI and PaGWQI.

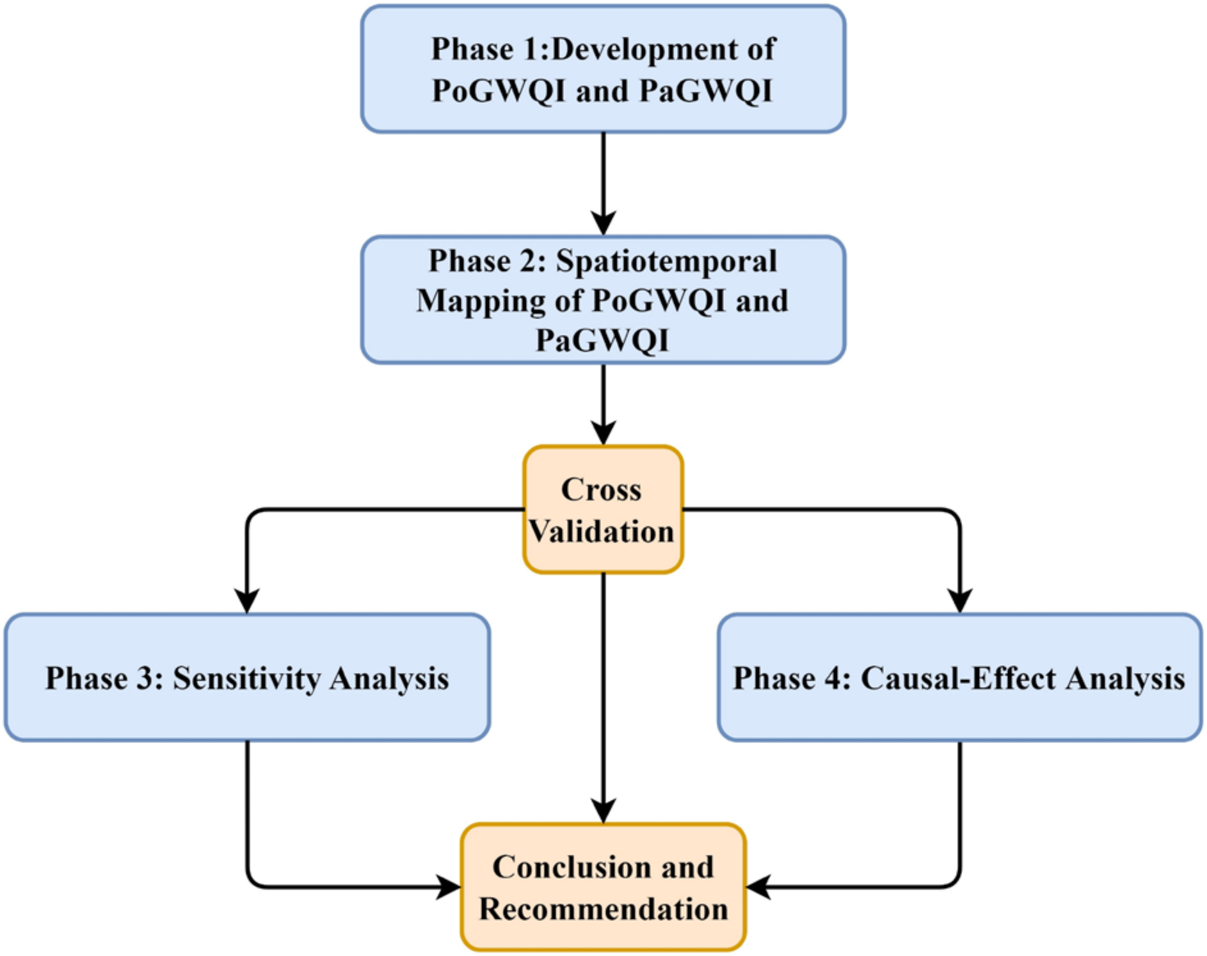


Figure 4.1. Overall methodological framework

4.2.1.1. Development of potability and palatability groundwater quality indexes (PoGWQI and PaGWQI)

This section proposes a new approach for developing PoGWQI and PaGWQI (Figure 4.2). It relies on the conventional WAWQI method for developing both indices. This method has no restriction in selecting the water quality parameters included in the calculation (Balan et al., 2012; and Rao and Manjula, 2010). It is based on the selection of the most widespread parameters that threaten water quality. The conventional WAWQI can be used according to the following steps (Oni, 2016; and WHO, 2011).

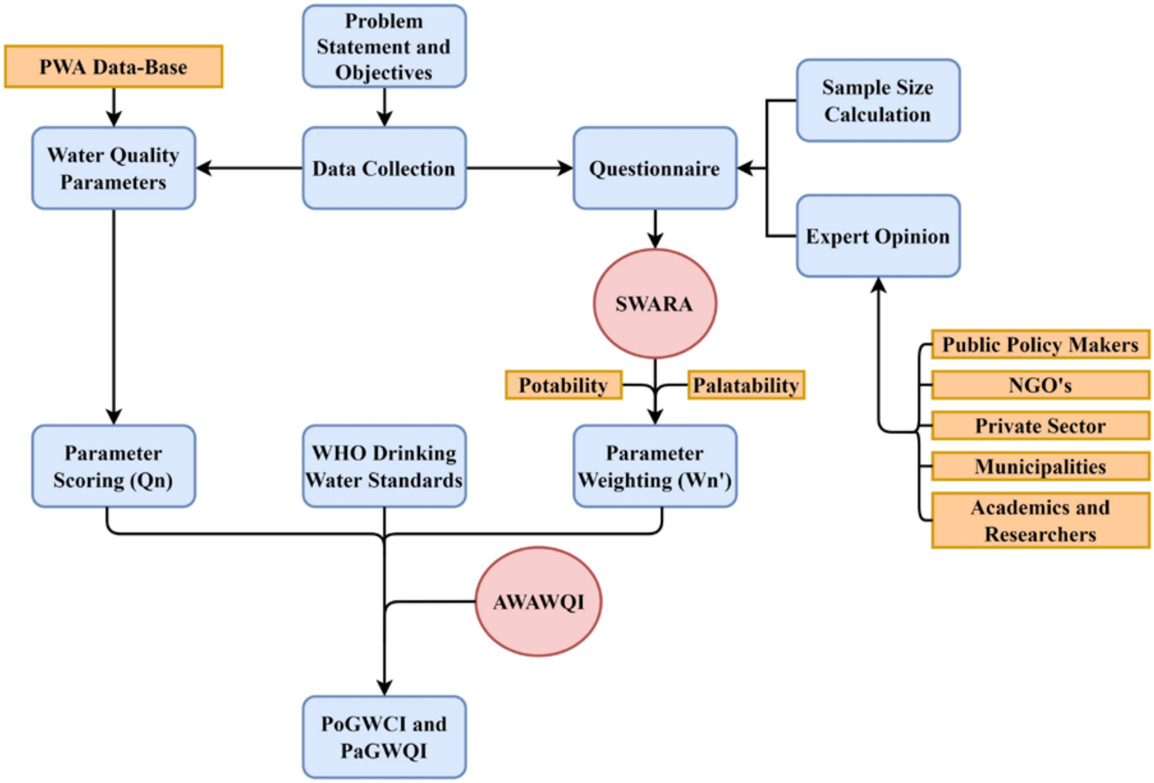


Figure 4.2. Development of potability and palatability groundwater quality indexes (PoGWQI and PaGWQI)

The first step concerns selecting the quality parameters for water potability and palatability. The second step consists of estimating the quality scores (Q_n) for the water quality parameters using the following expression:

$$Q_n = 100 \left(\frac{Vn - Vi}{Vs - Vi}\right) \qquad \text{(Equ. 4.1)}$$

where, V_n is the measured amount of the nth parameter in the analyzed water, V_i is the ideal amount nth parameter in pure water, and V_s is the standard permissible amount for the nth parameter according to the World Health Organization (WHO) (PWA, 2020; WHO, 2011; and Keršulien et al., 2010).

The third step corresponds to estimating the weights (W_n) for water quality parameters using the following formulas:

$$K = \frac{1}{\sum(1/Vs)} \qquad \text{(Equ. 4.1)}$$

$$Wn = \frac{K}{Vs} \qquad \text{(Equ. 4.2)}$$

where k, is the proportionality constant.

The last concerns estimating PoGWQI and PaGWQI using the WQI formula:

$$WQI = \frac{\sum Qn\, Wn}{\sum Wn} \quad \text{(Equ. 4.3)}$$

The conventional WAWQI' weighting system uses the standard permissible parameter (V_s) to assign the importance of the water quality parameters. Since this method does not consider the impact of the water quality parameters on human health and water acceptability, it could lead to inaccurate quality indices. In some cases, WQI could show excellent water potability, while some of the water quality parameters that significantly affect water potability exceed the WHO standards. Alternatively, this research proposes the use of adjusted WAWQI (AWAWQI) method that considers experts' opinions to develop a comprehensive weighting system for the water quality parameters. The new system assigns the permeameters' weights considering the effect of quality parameters on the water potability and palatability. A close-ended questionnaire is used to assess the importance of quality parameters concerning water potability and palatability. Experts assess each parameter using the Likert scale (1, Not important, and 5, Extremely important). The questionnaire was addressed to water experts in the selected case study. The SWARA method was used to determine the weights of quality parameters ($W_n{}'$) using the following formulas (Tyagi et al., 2013):

$$sj = \sum_{j}^{n} \frac{Aj}{n} \quad \text{(Equ. 4.4)}$$

$$kj = \begin{cases} 1, & j = 1 \\ sj + 1, & j > 1 \end{cases} \quad \text{(Equ. 4.5)}$$

$$qj = \begin{cases} 1, & j = 1 \\ \dfrac{qj - 1}{kj}, & j > 1 \end{cases} \quad \text{(Equ. 4.6)}$$

$$Wn' = \frac{qj}{\sum_{k=1}^{n} qj} \quad \text{(Equ. 4.7)}$$

where Aj is the Likert scale score given by expert i

n is the total number of experts.

sj, kj and qj are intermediary parameters used in the method.

Accordingly, the AWAWQI was used to develop PoGWQI and PaGWQI in this research:

$$Adjusted\ WQI = \frac{\sum Qn\, Wn'}{\sum Wn'} \quad \text{(Equ. 4.8)}$$

Five potability and palatability groundwater quality statuses (PoGWQS and PaGWQS) and grades (PoGWQG and PaGWQG) were identified according to Brown et al., (1970). Except for grade "E", all grades were considered potable and palatable but with gradual quality (Table 4.1).

Table 4.1. Identification of potability and palatability groundwater quality statuses (PoGWQSs, PaGWQSs), and grades (PoGWQGs, and PaGWQGs) (Brown et al., 1970)

PoGWQI/PaGWQI	PoGWQS	PaGWQS	PoGWQG/PaGWQG
≤25	Excellent	Excellent	A
25.01–50	Good	Good	B
50.01–75	Satisfactory	Satisfactory	C
75.01–100	Poor	Poor	D
>100	Undrinkable	Unpalatable	E

The proposed weighting system considers the degree of severity of each water quality parameter on health in the local context. However, the proposed method could be combined with other methods for water quality assessment.

The proposed method is convenient for spatial water quality mapping. It could be used by decision-makers to scan the water quality at a large scale and to develop strategies for water resource protection.

4.2.1.2. Potability groundwater quality index (PoGWQI) and palatability groundwater quality index (PaGWQI) mapping

Qn values were imported into Arc GIS and then were interpolated using the KIM method, which KIM is highly recommended. In this method, the input data are biased and spatially correlated (Li et al., 2019). The KIM method relies on statistics and spatial autocorrelation. Therefore, it is widely used in soil science, geology, and groundwater contamination research (Lodwick et al., 1990). GIS-based raster calculator was used to processing the interpolated Qn and Wn′ values to develop spatiotemporal PoGWQI and PaGWQI mapping.

Water quality data from unconsidered groundwater wells are used to perform cross-validation for the resulted PoGWQI and PaGWQI maps. Such validation examines the ability and accuracy of KIM in predicting groundwater quality.

4.2.1.3. Mapping sensitivity analysis

Sensitivity of PoGWQI and PaGWQI toward the input quality parameters is performed using the map removal sensitivity approach (MRSA) (Lam et al., 2020; Guio-Blanco et al., 2018; and Kursa, 2014). The mean absolute error (MAE) in PoGWQI and PaGWQI was calculated by removing each of their input quality parameters separately.

4.2.1.4. Causal-effect analysis

Causal-effect descriptive analysis was used to understand how PoGWQI and PaGWQI changed within the different classes of influencing factors (land-use, soil texture, aquifer, well' depths, and rainfall). Then, the relative importance of each influencing factor was estimated using the random forest (RFA) and factor importance analysis. RFA is widely applied in life science for classifying the importance of influencing factors (Kursa, 2014). It can characterize features' importance at all multivariate interactions included in algorithm (Almasri et al., 2020).

4.2.2. Application to the West Bank

According to various research works, the relevant water quality parameters in the West Bank concern turbidity, chloride (Cl), pH, electrical conductivity (EC), nitrate (NO_3), hardness, sodium (Na), total coliform (TC), fecal coliform (FC), total dissolved solids (TDS), magnesium (Mg), calcium (Ca), potassium (K), bicarbonate (HCO_3), and sulfate (SO_4) (El Baba et al., 2020; Daghara et al., 2019; and Aish, 2013). Due to a lack of data, this research will focus on nine parameters, including pH, HCO_3, Cl, SO_4, NO_3, TDS, FC, hardness, and turbidity. Data was collected from the Palestinian Water Authority (PWA) database (PWA, 2020). Collected records are distributed among 79 domestic wells in the West Bank over the period 2001–2016. Quality parameters were divided into two groups according to WHO guidelines and experts' opinions (Tyagi et al., 2013). The first group included parameters affecting water potability, such as FC and NO_3. The second one concerned water palatability such as pH, HCO_3, Cl, SO_4, Hardness, TDS, and Turbidity.

V_n, V_i, and V_s of the selected water quality parameters are illustrated in Table 4.2 (PWA, 2020; WHO, 2011; and Keršulien et al., 2010).

Table 4.2. V_n, V_i, and V_s values of water quality parameters (PWA, 2020; WHO, 2011; and Keršulien et al., 2010)

Water Quality Parameter	**V_n (Range)**	**V_i**	**V_s**	**Unit**
Fecal Coliform (FC)	0–120	0	10	CFU/100 ml
Nitrate (NO_3)	0–128	0	50	mg/L as NO_3
Chloride (Cl)	12–2573	0	250	mg/L
Total Dissolved Solids (TDS)	33–5288	0	600	mg/L
Turbidity	0–13	0	5	NTU
pH	6.8–8.6	7	6.5–8.5	-
Sulfate (SO_4)	0–600	0	250	mg/L
Hardness	168–1110	0	500	mg/L
Bicarbonate (HCO_3)	76–431	0	120	mg/L

A close-ended questionnaire was addressed to 42 water-related bodies in the West Bank. These bodies are defined as the targeted population (*Pop*) (Table 4.3). Accordingly, the sample size for infinite population (*SSIP*) and the required sample size (*SS*) were calculated according to the Cochran formula (Cochran, 1965).

$$SSIP = \frac{Z^2 p(1-p)}{e^2} \quad \text{(Equ. 4.9)}$$

$$SS = \frac{SSIP}{1 + (\frac{SSIP-1}{Pop})} \quad \text{(Equ. 4.10)}$$

Where, Z value (given 95% confidence interval), population proportion (p) and margin of error (e) were equal to 1.96, 0.5 and 0.1 respectively. Accordingly, a *SSIP* of 96 and a *SS* of 29 were recorded. However, this questionnaire was filled out by 41 water experts from 30 water-related institutions to ensure more accuracy.

Table 4.3. Targeted water-related bodies for the groundwater quality survey

Group	Total No. of Water-Related Institutions (Pop)	No. of Surveyed Institutions	No. of Respondents
Policymakers and related public bodies	7	6	13
Municipalities (in cities)	11	6	6
Non-governmental organizations (NGOs)	5	4	4
Private sector	10	5	5
Universities and water Institutes	9	9	13

Accordingly, and by employing SWARA, two weighting systems were developed concerning water potability and palatability (Table 4.4).

Table 4.4. Groundwater potability and palatability weighting systems in the West Bank

Parameter	Potability W_n'	Palatability W_n'
FC	55.1	-
NO_3	44.9	-
Cl	-	19.0
TDS	-	17.1
Turbidity	-	15.6
pH	-	14.0
SO_4	-	12.8
Hardness	-	11.5
HCO_3	-	10.0

AWAWQI treats the scores and weights illustrated in Tables 4.3 and 4.4 to develop PoGWQI and PaGWQI in the West Bank.

4.3. Results

4.3.1. Groundwater potability and palatability in the West Bank

Figure 4.3 illustrates the distribution of PoGWQGs and PaGWQGs in the West Bank. It shows that 49%, 33%, 13%, and 3% of the tested samples among all wells had A, B, C, and D-PoGWQGs, respectively. Around 2% of the tested samples were found to be unsafe for drinking (E-PoGWQG). The undrinkable samples were found in 4 wells (5.1% of all wells) in the West Bank (Figure 4.4).

Those wells are located in the northern and middle of the West Bank and have different rates of unpotable samples. Figure 4.4 shows that 67% of the samples taken from Well #1 were unpotable. Well #2, Well #3, and Well #4 have 13%, 11%, and 10% probability of providing unpotable water.

On the other hand, none of the West Bank wells had A-PaGWQG; 28%, 64%, and 3% of the tested samples had B, C, and D-PaGWQGs, respectively (Figure 4.3); 5% of unpalatable samples were recorded in two wells in the Eastern part of the study area. However, all samples (100% probability) taken from both wells were found to be unpalatable.

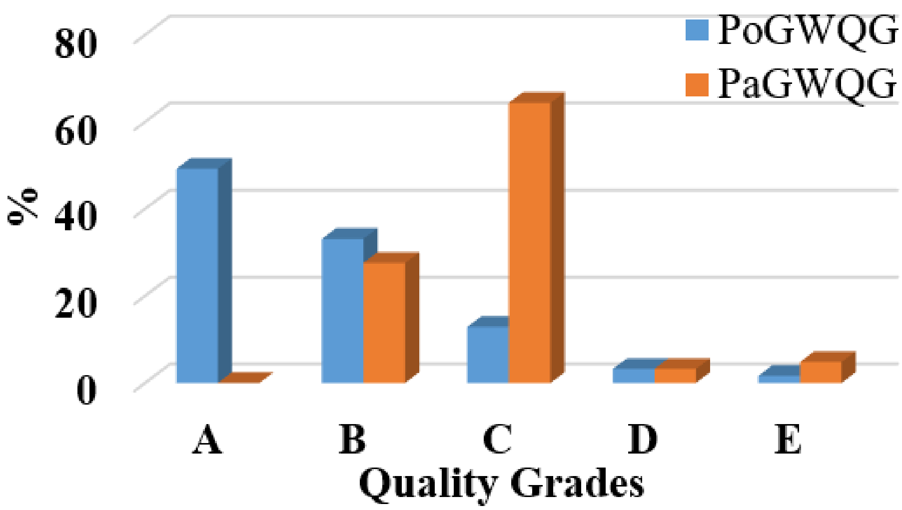


Figure 4.3. PoGWQGs and PaGWQGs in the West Bank

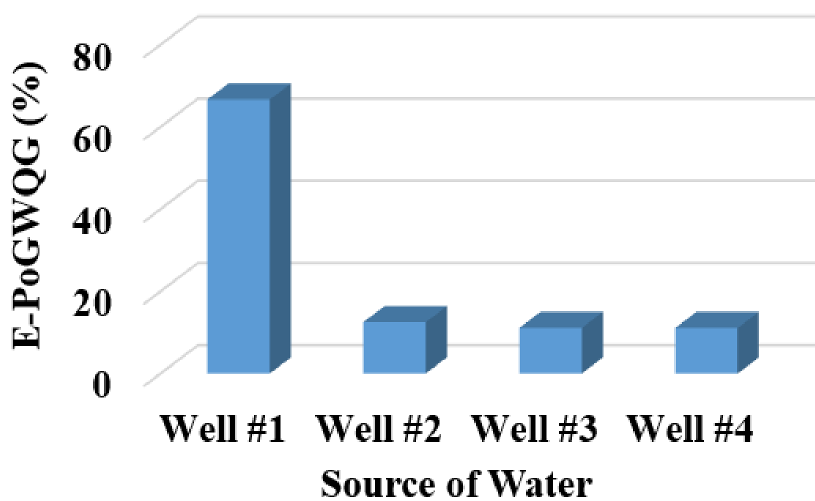


Figure 4.4. Un-potability rate over four contaminated groundwater wells in the West Bank

4.3.2. Spatiotemporal mapping of PoGWQI and PaGWQI

GIS and KIM were used to establish a spatiotemporal mapping for both PoGWQI and PaGWQI. Cross-validation for the PoGWQI and PaGWQI mapping was conducted. Table 4.5 shows the validation results for two groundwater sources (wells) located in the middle and northern parts of the West Bank during the period 2001–2016. It is found that 14 out of the 17 PoGWQGs were correctly predicted (82.4% prediction accuracy). On the other hand, only one PaGWQG was incorrectly predicted (94.1% prediction accuracy). Figure 4.5 shows the PoGWQI and PaGWQI maps over the period 2001–2016. During the years 2001, 2007, 2010, 2011, 2015, and 2016, PoGWQG ranged from A, B to C. In 2003, 2004, 2009, and 2012, D and E grades appeared in the far north of the West Bank. Only in 2005 did the middle part of the West Bank experience groundwater potability contamination. This spatiotemporal variation in PoGWQI refers to the flash biological groundwater contamination (mainly due to FC). Such flash contamination could be caused by a direct seepage of the wastewater (mainly from cesspits) to shallow groundwater wells. On the other hand, the southern part of the West Bank was free of groundwater potability contamination.

Figure 4.5 indicates that PaGWQI had a more consistent trend. The eastern part of the West Bank was characterized by permanent unpalatable groundwater. PaGWQG ranges from D to E. Moreover, grade D frequently appeared (in 6 non-successive years) in the far south of the study area. This stability of PaGWQI could be related to the permanent high salinity near the Dead Sea (the Eastern part of the study area). The middle, eastern and northern parts provide almost palatable water.

Table 4.5. Cross-validation results for PoGWQGs and PaGWQGs among two groundwater wells in the West Bank

Groundwater Source	Year	Actual PoGWQG	Interpolated PoGWQG	Actual PaGWQG	Interpolated PaGWQG
Source #1	2003	A	A	B	B
Source #1	2004	A	A	C	C
Source #1	2005	A	C	B	B
Source #1	2007	A	A	B	B
Source #1	2009	A	A	C	C
Source #1	2010	A	A	C	C
Source #1	2011	A	A	B	B
Source #1	2012	A	B	B	B
Source #2	2001	C	C	C	C
Source #2	2003	C	C	C	C
Source #2	2004	C	C	C	C
Source #2	2005	C	C	C	C
Source #2	2007	B	B	C	C
Source #2	2010	D	C	C	C
Source #2	2011	C	C	C	C

Source #2	2012	C	C	C	B
Source #2	2016	C	C	C	C

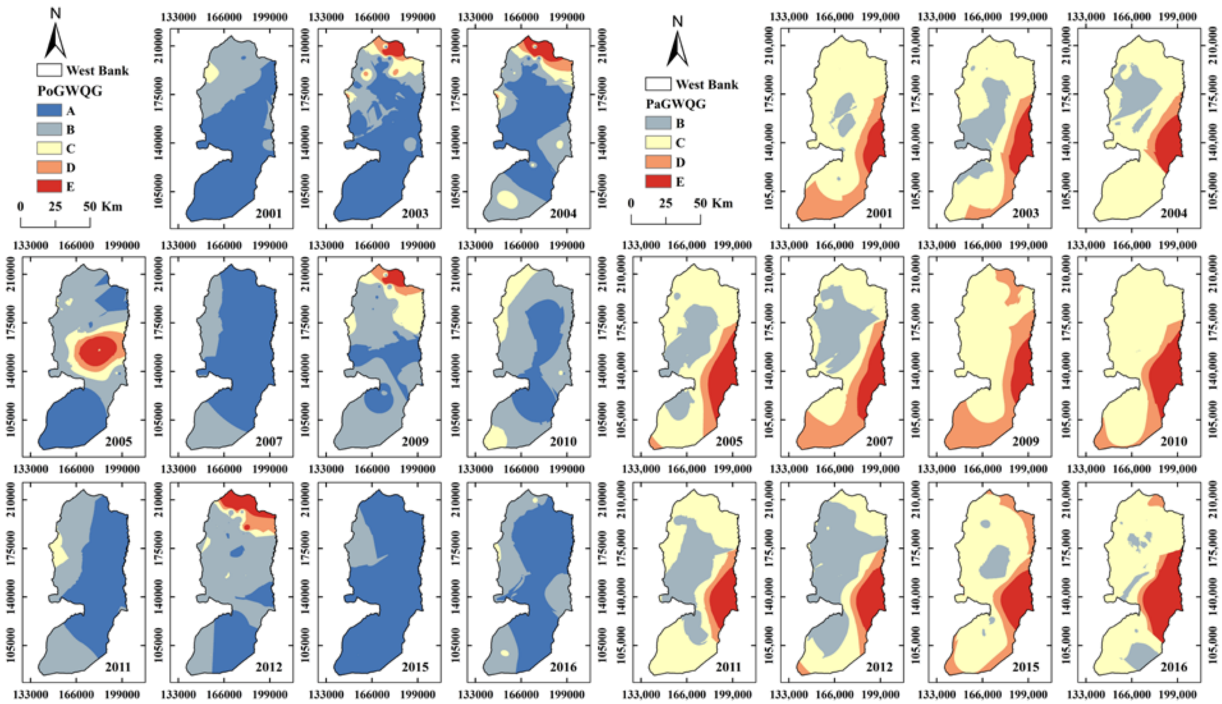


Figure 4.5. Spatiotemporal mapping of PoGWQI and PaGWQI in the West Bank between 2001 and 2016

Figure 4.6 indicates that Jerusalem and Bethlehem governorates had the best potable water with almost 100% A-PoGWQG. It is also found that PoGWQGs range from A to D in Hebron, Qalqiliya, and Tulkarm governorates. Jenin governorate recorded the worst water potability with an E-PoGWQG of about 9%. This was followed by Tubas and Ramallah and Al Bireh, with an E-PoGWQG of about 5% and 3%, respectively. This could be related to the use of cesspits for wastewater disposal. It could also be referred to as the intensive use of agrochemicals.

Except for Jericho (with 100% E-PaGWQG), all governorates had zero E-PaGWQG. Generally, the palatability grades from B to D. The unpalatable water in Jericho could be caused by the saltwater intrusion from the Dead Sea. In this area, the TDS increased up to around 5300 mg/L.

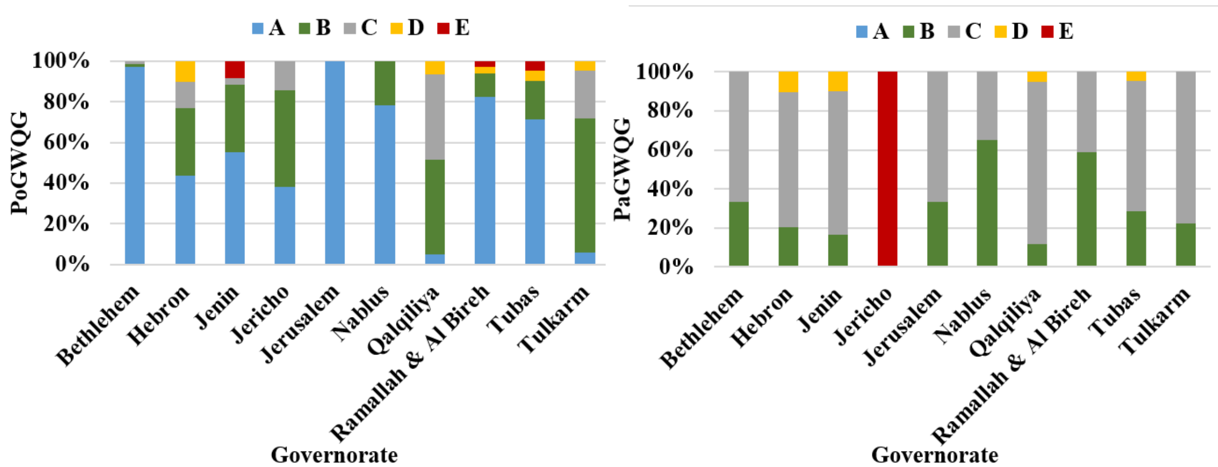


Figure 4.6. PoGWQGs and PaGWQGs cross the West Bank governorates

4.3.3. Analysis of indices' sensitivity

The sensitivity of indices stems from the scores (values) and weights of their input parameters. Figure 4.7 indicates that PoGWQI was highly sensitive to the NO_3 concentrations with a MAE of 23–37 units. FC also had a significant influence on PoGWQI with a MAE between 19–30 units.

Results show that HCO_3 was the most influencing parameter in estimating PaGWQI. This result contrasted with the experts' opinion, who considered HCO_3 as the lowest influencing parameter. This high importance of HCO_3 could be related to its high concentration. TDS and Cl follow it with MAE between 7–18 and 6–16 units, respectively.

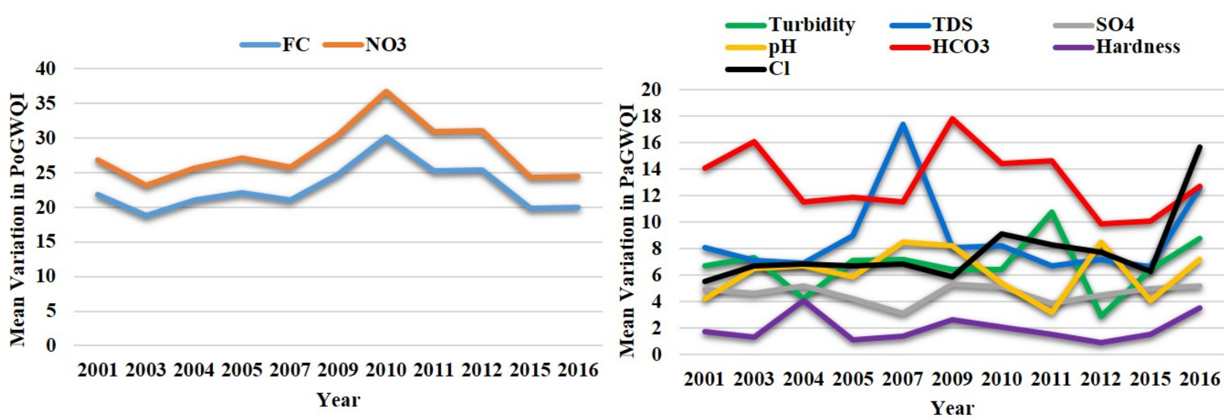


Figure 4.7. Sensitivity analysis of PoGWQI and PaGWQI

4.4. Discussion

This section presents an analysis of the influence of various factors on PoGWQI and PaGWQI (e.g., land-use, soil texture, aquifer types, well depths, and the long-term average rainfall). Figure 4.8 indicates that urban areas have the worst water potability status (with 20% of E-PoGWQG) compared to the other land-use classes. This result could be attributed to the poor sewage network in this area. Around 54% of the urban areas are unserved by the sewer network (PCBS, 2021d). Most citizens rely on cesspits for wastewater disposal (PCBS, 2021d). Such cesspits cause a significant wastewater seepage to the groundwater aquifers, leading to high FC and NO_3 concentrations. Agricultural areas have around 1% of E-PoGWQG. Agrochemical applications could be the main reason for groundwater contamination (Alexakis, 2020). Farmers extensively use agrochemicals to enhance their food production and to maximize their profits (Almasri et al., 2020). The best water potability was recorded under rough grazing. PoGWQGs under this land-use class ranged from A (80%), B (18%) to C (2%). Residential, agricultural, and industrial human-made activities are limited in this land-use class. The worst PaGWQGs status was observed in agricultural areas (with around 13% of E-PaGWQG). This result is due to the intensive use of agrochemical with significant SO_4 and TDS concentrations.

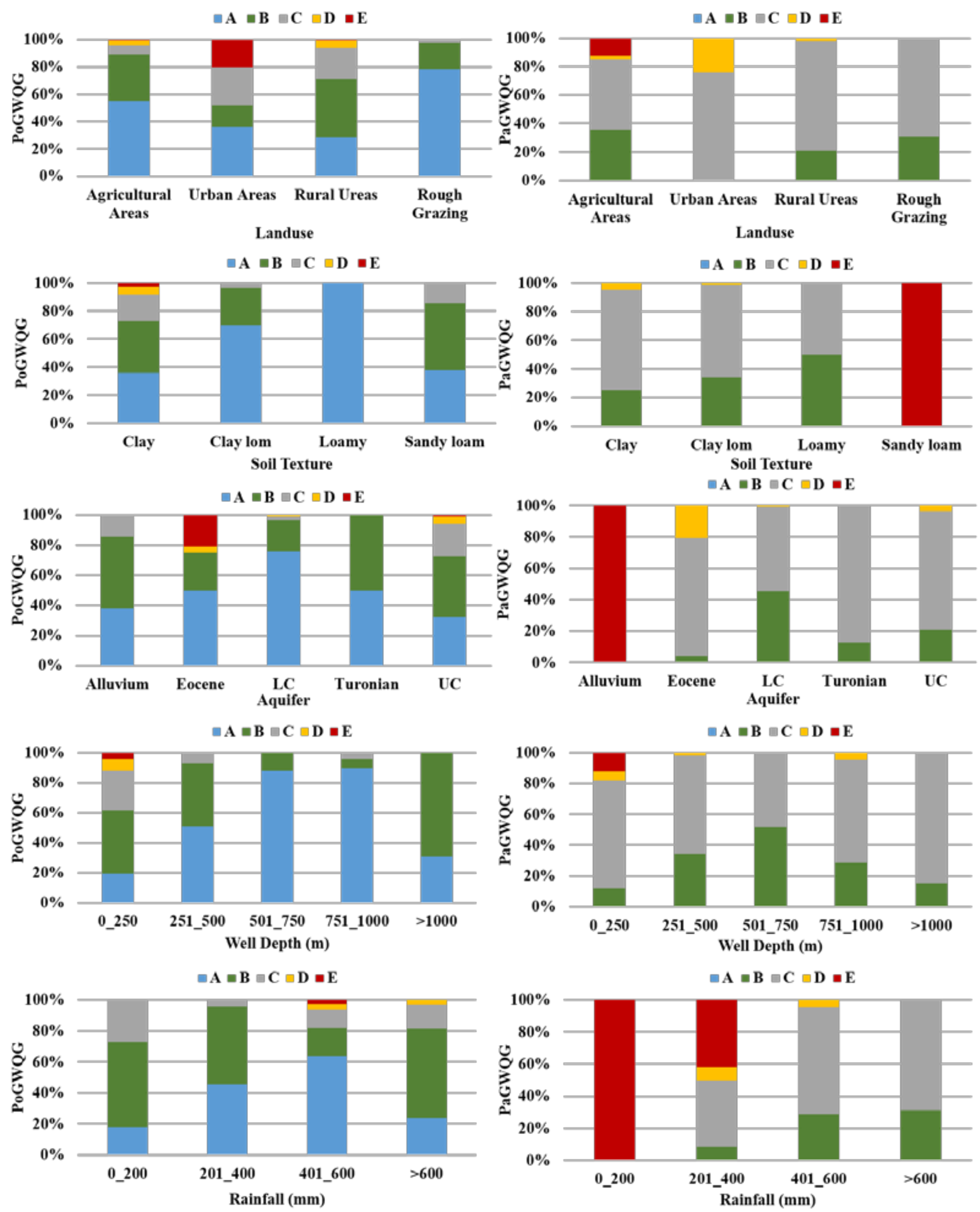


Figure 4.8. Factors affecting PoGWQI and PaGWQI in the West Bank

Despite the fact that clay soil has the highest water holding capacity and the lowest infiltration rate compared to other soil textures, it recorded the worst PoGWQGs. However, clay soil is the dominant soil texture in the West Bank, and it has a significant intersection with the residential and agricultural areas (Onwuka and Ezugwu, 2019). By contrast, groundwater wells under sandy loam were extremely unpalatable (with E-PaGWQG of 100%). This soil texture is distributed in the Eastern part of the West Bank with direct intrusion from the Dead Sea. Consequently, the saltwater infiltrates easily to over-pumped wells (Abd-Elhamid et al., 2015).

Figure 4.8 shows that almost all the unpotable water samples were found in the Eocene Aquifer (20% with E-PoGWQG). Moreover, the Alluvium Aquifer was dominated by unpalatable water (100% with E-PaGWQG). This contamination could be related to the unconfined character of the aquifers. Indeed, unconfined aquifers are vulnerable to contamination due to their direct connection with the ground surface (Anayah and Almasri, 2009). Other aquifers were almost free of water contamination.

All E-PoGWQG and E-PaGWQG samples were found in shallow wells (Below 250 m). Deeper wells were more potable and palatable. This observation indicates that well depth and groundwater contamination were negatively proportional. Various research works confirmed and discussed this negative outcome (Anayah and Almasri, 2009). On-ground contaminants are easily infiltrated and leached to the shallow wells, whereas deep wells are more protected (Almasri et al., 2020). Infiltrated contaminated water follows mixing processes through its way to deep wells. Moreover, both microorganisms and soil particles degrade and filtrate contaminants before leaching into the deep wells (Almasri et al., 2020).

Wells with D and E-PoGWQGs were located in areas with high average annual long-term rainfall (above 400 mm). A relatively high recharge rate characterizes those areas. Therefore, contaminants are infiltrating and leaching groundwater more easily (Almasri et al., 2020). Moreover, high rainfall could cause contaminants' wet deposition (e.g., NO_3) that reaches the ground surface and leaches to groundwater (Almasri et al., 2020). By contrast, unpalatable groundwater was found under rainfall-poor areas (mainly below 200 mm). However, those areas were located in the West Bank's eastern coastal and directly affected by the Dead Sea salinity.

The relative importance of the different factors affecting PoGWQI and PaGWQI was estimated using RFA (Figure 4.9). Results showed that factors' relative importance concerning PoGWQI deviated more compared to PaGWQI. Wells' depths and land-use had the main influence on PoGWQI with a relative importance of about 35% and 22%, respectively. This result reflects the high vulnerability of shallow wells to NO_3 and FC contamination (specifically in urban areas). Both contaminants can directly reach shallow wells through wastewater seepage from cesspits.

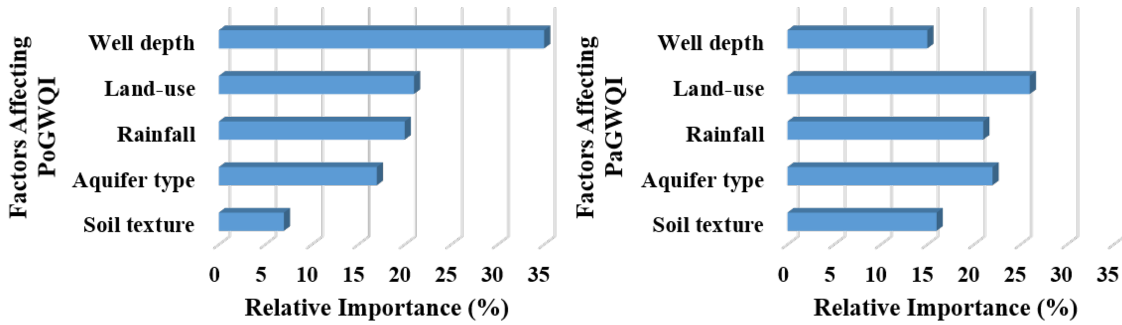


Figure 4.9. Relative importance analysis for the main factors affecting PoGWQI and PaGWQI

On the other hand, all factors have a close relative influence (15–25%) on PaGWQI estimation. This influence could be referred to as the multi-causes for the high values in PaGWQI input parameters. These unaccepted values in some of the input parameters, such as (pH, TDS, and HCO_3) are caused by human activities (associated with land use), aquifer, or soil characteristics (e.g., mineralized formations).

4.5. Conclusion

An adjusted weighted arithmetic water quality index method was used to assess the groundwater quality in the West Bank. This enhances the conventional WAWQIM method by considering the experts' opinions through a close-ended questionnaire and SWARA method. AWAWQI, GIS, and KIM were combined for the first time for the spatiotemporal mapping of PoGWQI and PaGWQI. This combination enabled an in-depth analysis of the groundwater contamination, its causes, and potential consequences. Results showed that (i) around 5% of the wells in the West Bank had experienced potability-related contamination, (ii) deep wells had better PoGWQI and PaGWQI than shallow ones, (iii) water contamination was observed in areas with improper practices such as the use of cesspits, fertilizers, and pesticides. The protection of water resources in these areas requires urgent intervention to reduce (i) wastewater infiltration by installing sanitation systems, septic tanks, and sealed cesspits, and (ii) the use of chemicals and pesticides in areas impacting the groundwater resources.

The proposed method is helpful for decision-makers. It allows conducting a large-scale scan of the water quality to develop efficient water resources protection plans and to manage the water scarcity. The proposed method could be combined with other water-quality control methods to control the water quality.

Chapter 5. Use of GIS, Statistics and Machine Learning for Groundwater Quality Management: Application to Nitrate Contamination

5.1. Introduction

Groundwater nitrate contamination (GNC) is a common problem that threatens the drinkability of the groundwater (Mas-Pla and Menció, 2019). The severity of the GNC depends on the importance of the groundwater as a main source for uses among which, the domestic use is the most challenging (PWA, 2017; Almasri and Ghabayen, 2008; Khayat et al., 2006; Almasri and Kaluarachchi, 2004; and Schröder et al., 2004). GNC severity depends on the Nitrate (NO_3) concentration with reference to the maximum contaminant level (MCL). According to the World Health Organization (WHO), the MCL is equal to 50 mg/l (WHO, 2003). The use of water beyond the MCL for drinking has been linked to methemoglobinemia and cancers (Almasri et al., 2020; and Comly, 1987).

Groundwater quality management has become of great importance in all groundwater-dependent countries (UN, 2011). Given the widespread and riskiness of the GNC, it is considered as a fundamental aspect for the water resources protection (UN, 2011) particularly in areas with vulnerable groundwater quality (Mas-Pla and Menció, 2019). An efficient management of GNC requires GNC assessment and prediction (Knoll et al., 2019; Anayah and Almasri, 2009; and Hajhamad and Almasri, 2009).

Different approaches were proposed to assess the GNC: descriptive statistical assessment (Anayah and Almasri, 2009), GIS-based groundwater NO_3 mapping (Ducci, 2018), lumped-parameter models (Hajhamad and Almasri, 2009), Geodetector-Based Frequency Ratio (Shrestha and Luo, 2018), Optimized-DRASTIC Methods (Shrestha and Luo, 2018), parametric IPNOA (Rizeei et al., 2018), data-driven logistic regression models (Rizeei et al., 2018), water quality index (WQI) (Barkat et al., 2021), and groundwater potability index (Judeh et al., 2021). Groundwater quality strategies should rely on robust and accurate models for the prediction of groundwater contamination (Knoll et al., 2019). The Machine Learning methods have been successfully used as predictive tools for the GNC (Breiman, 2001; and Friedl et al., 1999). Researchers adopted an algorithm to obtain an average of multiple predictions to decrease the bias and to improve the prediction accuracy (Breiman, 2001; and Friedl et al., 1999). Logistic regression, random forest (RFA), decision tree, multiple linear regression, boosted regression trees, support vector machine (SVM), cubist, and Bayesian artificial neural network (ANN) are commonly used as predictive models for the GNC (Band et al., 2020; Uddameri et al., 2020; Canion et al., 2019; Knoll et al., 2019; Ransom et al., 2017; and Mair and El-Kadi, 2013). The prediction capability, efficiency and accuracy of Machine Learning methods are dependent on the complexity of the case under consideration and quality of the available data. Therefore, it is important to conduct benchmarking analysis to select the best Machine Learning method (Band et al., 2020). A comprehensive integration of spatiotemporal assessment and spatiotemporal prediction of GNC is still missing. This research will combine the GIS-based geospatial analysis and the descriptive statistical analysis for the development of spatiotemporal GNC assessment. Results will be used as input for building the Machine Learning GNC prediction model.

Spatiotemporal data is the core input of GNC assessment and prediction models (Anayah and Almasri, 2009). Given its ability in processing, analyzing, interpolating and visualizing spatiotemporal data, Geographic Information System (GIS) has a key role in the spatial assessment and prediction of groundwater quality (Maqsoom et al., 2020). It is widely adopted in the United States (Schilling and Wolter, 2007), Germany (Rodda et al., 1999), Iran (Sheikhy Narany et al., 2014) and China (Maqsoom et al., 2020).

Palestinians are facing two main water challenges: the low groundwater availability and the deterioration of its quality (El Baba et al., 2020; and UNDP, 2013). A recent field study of the GNC in Palestine showed that the NO_3 concentration in 91% of the groundwater samples exceeded the MCL (Qrenawi and Shomar, 2020). However, many aquifers in Palestine that are still not well characterized for recent occurrences of NO_3.

This chapter proposes an approach that combines GIS, statistical analysis and Machine Learning prediction models for the comprehensive management of the GNC. The application of this approach in the Eocene Aquifer, Palestine constitutes a vital issue because this aquifer accounts for 95% of the water supply in this area (PWA, 2017).

5.2. Materials and methods

5.2.1. Methodology

In order to outline the comprehensive management of GNC, this section introduces an unparalleled methodology. It consists of three phases: data collection and preparation, GIS-based GNC assessment, and Machine Learning-based GNC prediction (Figure 5.1).

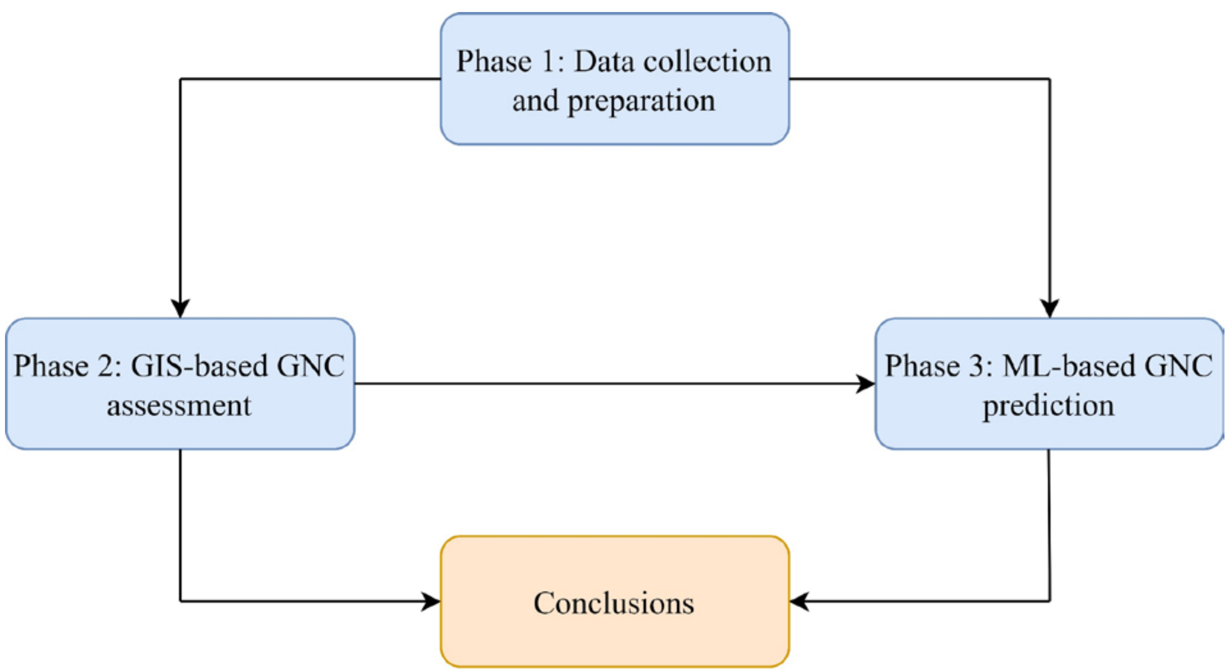


Figure 5.1. Methodological framework

5.2.1.1. *Data collection*

This phase involves the collection of spatiotemporal NO_3 records for the groundwater wells in the study area. It also involves a gathering of spatial information concerning well uses, well depths, soil types, land uses, surrounding anthropogenic activities, and watersheds.

5.2.1.2. *GIS-based GNC assessment*

GIS and statistical descriptive analysis treat the collected records to carry out a geo-statistical assessment of GNC. GIS has the powerful of considering the spatial variations concerning GNC and considering the factors causing such variations. Statistical descriptive analysis enables the frequency detection of any abnormal event (e.g. NO_3 above MCL). Boxplots of the NO_3 concentration (e.g. minimum, 1st quartile (Q1), median, mean, 3rd quartile (Q3), maximum) were used to present the assessment results. Factors affecting GNC are specified through the examination of various factors such as land use, soil type, watershed, groundwater flow direction, well use, well depth and etc.

Kriging Interpolation Method (KIM) employs assessment results (e.g. spatiotemporal mean GNC records) to develop GIS-based spatiotemporal GNC maps. KIM has the powerful of considering both spatial autocorrelation and statistical models (Judeh et al., 2021; and Lodwick et al., 1990). It is highly effective in cases where quality records are biased and spatially correlated (Li et al., 2019). Therefore, researchers confirm its suitability for groundwater contamination and hydrogeology researches (Lodwick et al., 1990).

5.2.1.3. *Machine Learning-based GNC prediction*

This research employs RFA for predicting the probability to exceed the globally stated NO_3 MCL thresholds. RFA is selected among other Machine Learning methods due to its ability and collectivity in integrating multiple decision tree algorithms (Rodriguez-Galiano et al., 2014). It has the ability to generate repeated predictions of the same phenomenon (Rodriguez-Galiano et al., 2014). Furthermore, it can quantify the relative importance of the input influencing factors (Breiman, 2001).

RFA model is built through the online platform Kaggle. GNC distribution and its influencing factors resulting from GNC assessment are used as inputs for RFA prediction model. These factors include both natural and man-made ones. Accordingly, a CSV file includes both assessment results (influencing factors) and the NO_3 records from the different groundwater wells is executed using Kaggle platform. After that, data analysis, visualization and prediction were coded on the platform using Python Script. The coded prediction model is trained using randomly picked 80% of the database. The remaining 20% are used to test the prediction accuracy.

5.2.2. Study area

The Eocene Aquifer is an unconfined aquifer located in the northern part of the West Bank, Palestine. It has a total surface area of 430 km^2 covering areas from Jenin, Nablus and Tubas governorates (Figure 5.2) (Khader et al., 2013; and SUSMAQ, 2004). It serves 36 communities with a total population of about 225,000 capita (PCBS, 2020c). The groundwater flows from the south to the north and northeast (Tubeileh et al., 2006). Rainfall plays a major role in recharging the aquifer. The annual rainfall varies between 400 mm and 600 mm and mainly occurs in winter

(Shadeed et al., 2019; and Shadeed, 2013). The West Bank climate is classified as hot and dry during the summer and cool and wet in winter (Shadeed et al., 2020).

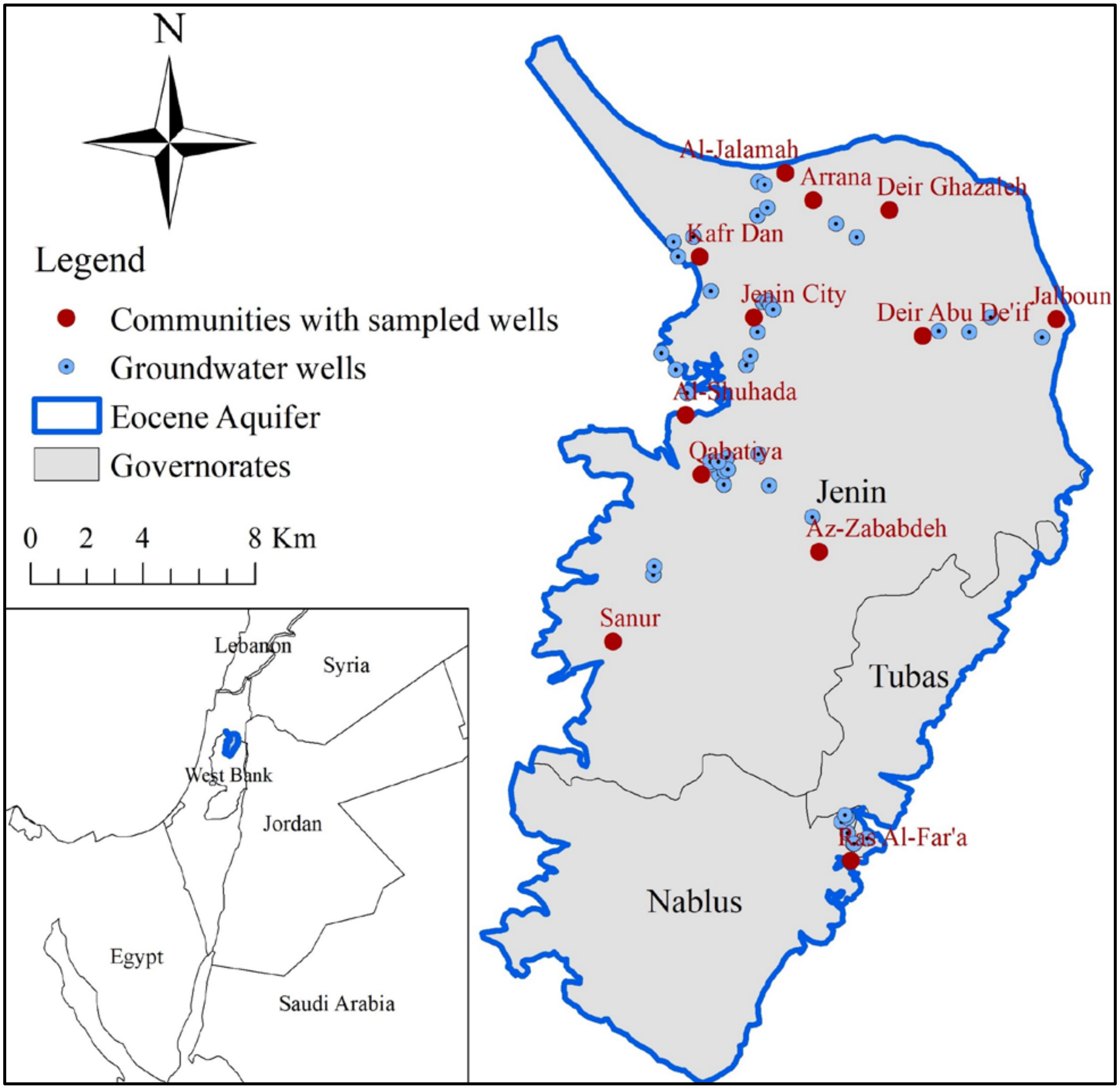


Figure 5.2. The geographic setting of the Eocene Aquifer

The study area is characterized by intensive agricultural activities with an extensive use of agrochemicals (Almasri et al., 2020). It includes about 17,000 hectares of irrigable areas including 6,500 hectares of irrigated area (Nofal, 2019). The aquifer was exploited by 129 wells including 54 active ones (45 for agricultural and nine for domestic uses) (Nofal, 2019). 43 out of the 54 active wells are distributed among 12 communities. Table 5.1 summarizes the statistical descriptive parameters of the groundwater NO_3 in the 12 communities. Arrana, Jenin city and Ras Al-Far'a (54% of the population) have mean and median NO_3 concentrations exceeding the MCL.

Furthermore, seven out of the 12 communities (82% of the population) use groundwater wells that have a maximum NO_3 concentration exceeding the MCL.

Table 5.1. Descriptive statistics of the NO_3 concentrations (mg/l) in different communities in the Eocene Aquifer (period 1982 - 2019)

Communities	**Population in 2019**	**No. of samples**	**Mean**	**Median**	**Min**	**Max**
Al-Jalamah	2,343	41	48	50	11	64
Arrana	2,498	8	57	59	32	71
Al-Shuhada	2,375	4	4	4	2	5
Az-Zababdeh	4,402	7	19	19	10	28
Deir Abu De'if	7,278	8	11	11	1	22
Deir Ghazaleh	1,166	39	45	46	7	80
Jalboun	2,906	8	9	6	2	25
Jenin city	51,557	150	70	53	0	216
Kafr Dan	6,809	63	47	45	6	85
Qabatiya	25,247	84	39	19	0	192
Ras Al-Far'a	1,323	103	66	58	6	256
Sanur	5,202	7	12	11	8	19

The ground surface elevation in the study area ranges from 100 m above mean sea level (MSL) in the north to 925 MSL in the south. The geologic cross section for the aquifer shows the following formations; limestone, dolomite and marl of Cenomanian to Turonian age, chalk and chert of Senonian age, chalk, limestone and chert of Eocene age and alluvium of Pleistocene to Recent age. However, the Eocene Aquifer overlies the Upper Cenomanian-Turnoian Aquifer, with a transition zone of chalk and chert that varies in thickness between 20 to 480 m (SUSMAQ, 2004) (Figure 5.3).

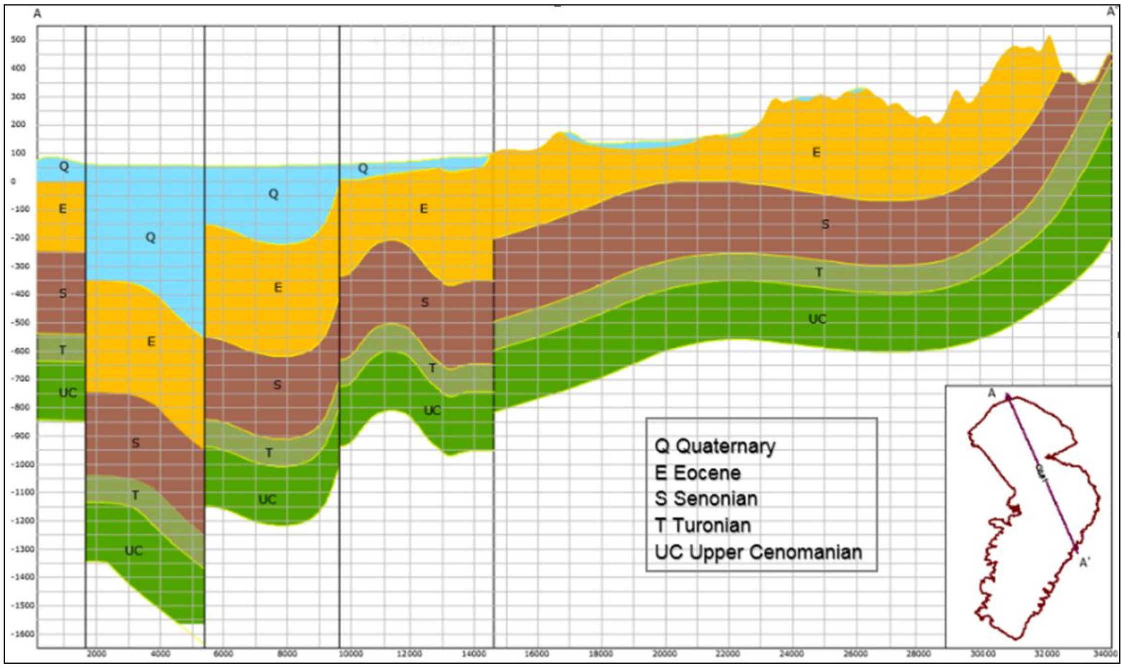


Figure 5.3. Geologic cross section of the Eocene Aquifer

5.2.3. Data collection and application to the Eocene Aquifer

Two datasets are used in this research: (i) Palestinian Water Authority (PWA) dataset for 27 wells over the period 1982-2012 (PWA, 2020) and (ii) field dataset for 24 wells which were sampled during the period 2017-2019. Eight mutual wells have recorded in the datasets which have both historical (1982-2012) and recent (2017-2019) NO_3 concentration values. However, the two datasets were combined into a one composite GIS- based data, which includes data for 43 wells. It includes the following indicators: well depths, coordinates of spatial location (X, Y), type (use), on-ground activities, NO_3 concentration and sampling date. The collected data was manipulated under the GIS environment where wells were spatially joined by communities, watersheds, soil types and land use shapefiles.

Accordingly, GNC assessment and mapping in the study area is conducted. Considering RFA model, four levels of NO_3 contamination are identified (Table 5.2). Levels are selected considering both: WHO guidelines, and the natural breaks of the continuous NO_3 records in the database (WHO, 2003).

Table 5.2. Levels of GNC used in Machine Learning methods

NO_3 Level (mg/l)	Description
<25	Not contaminated by NO_3
25-50	Reasonable NO_3 concentration
50-100	Contaminated by NO_3
>100	Extremely contaminated by NO_3

5.3. Results and Discussion

5.3.1. Assessment of GNC

5.3.1.1. Spatiotemporal Nitrate distribution across the aquifer

Figure 5.4 shows the key statistics of the annual NO_3 concentrations for the period 1982-2019. It is noticed that the mean values are mostly above the MCL. Median values are always below the mean and close to the MCL. This observation indicates that approximately 50% of the NO_3 concentrations are above the MCL. The maximum values of the annual NO_3 concentrations are always higher than the MCL, approaching its up-limit value of 256 mg/l in 2012. Such concentrations clearly reflect the high groundwater contamination through the mean, median, 75th percentile and maximum NO_3 concentrations. However, Figure 5.4 considers only the temporal GNC and neglects the spatial variation.

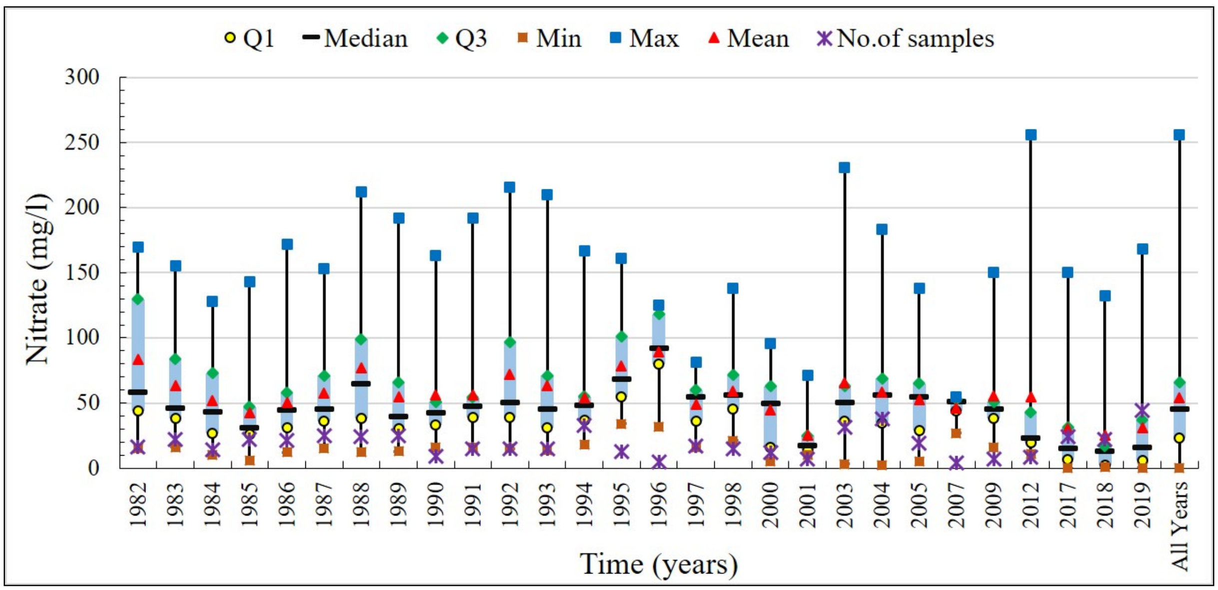


Figure 5.4. Annual NO_3 concentration statistics in the Eocene Aquifer (Period 1982-2019)

Figure 5.5 shows the spatiotemporal distribution of GNC in the Eocene Aquifer between 1982 and 2019. A significant increase in the GNC is noticed in the southern part of the aquifer. This is due to the intensive application of agrochemicals in this part, which provides citizens in the study area by the needed fruits and vegetables. On the other hand, the middle part shows a decreasing GNC trend. This is due to the construction and rehabilitation of sewer network in Jenin city and its suburbs.

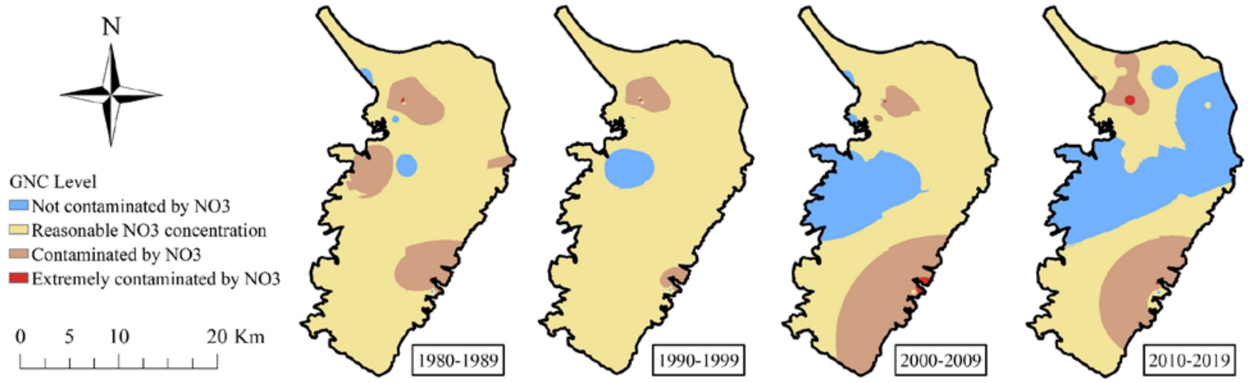


Figure 5.5. Spatiotemporal distribution of GNC in the Eocene Aquifer between 1982 and 2019

5.3.1.2. Influence of the soil type

The soil map of the Eocene Aquifer area contains five types of soil: Terra Rossa, Mediterranean Brown Forest, Alluvial, Colluvial-Alluvial and Brown Alluvial covering 48, 16, 14, 13 and 7% of the study area, respectively (Nofal, 2019). Figure 5.6 illustrates the minimum, 25th percentile, mean, median, 75th percentile and maximum NO_3 concentrations for the different soil types. It indicates that the mean NO_3 concentrations in the groundwater under all soil types are equal or exceed the MCL. Since the different soil types in the study area have a similar permeabilities, they have nearly the same mean, median and 75th percentile groundwater NO_3 concentrations. This result indicates a low influence of the soil type on the groundwater NO_3 concentration.

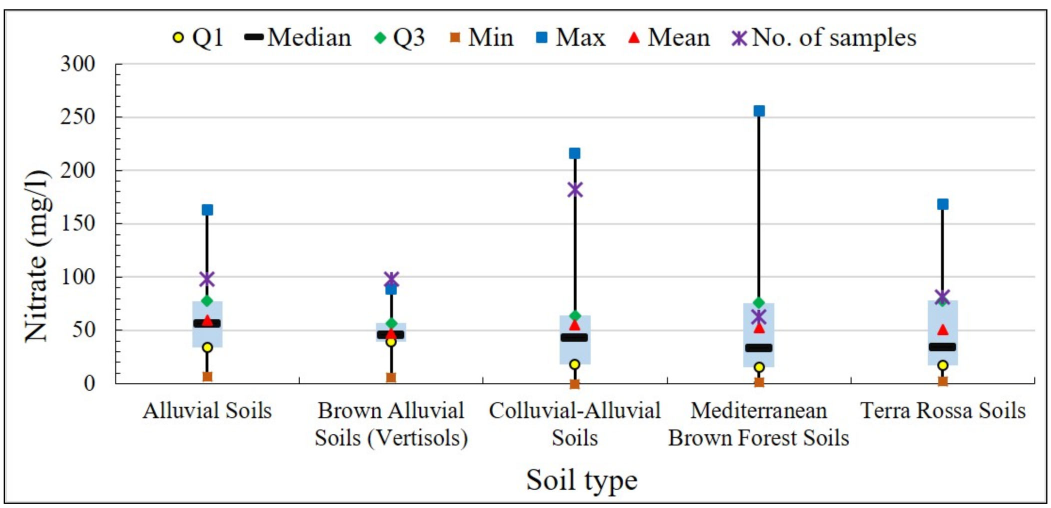


Figure 5.6. Influence of soil type on NO_3 concentration (period 1982-2019)

5.3.1.3. Influence of the land use

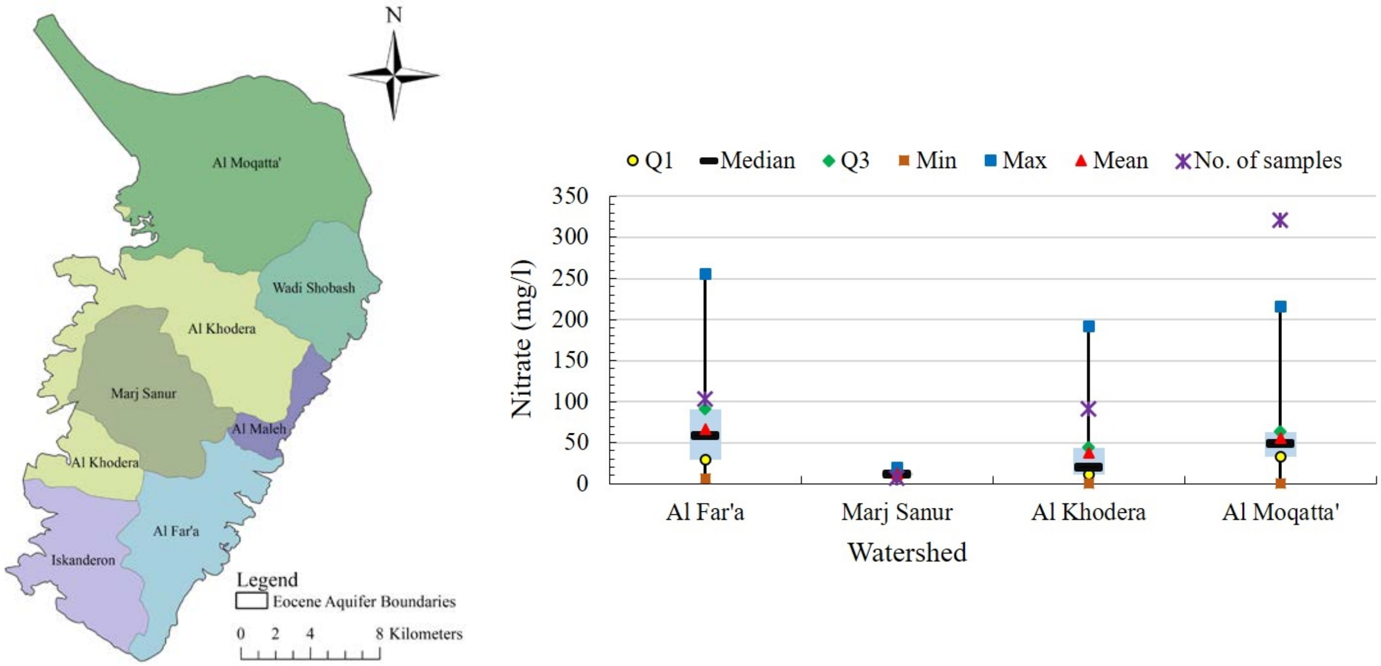
Table 5.3 summarizes the key statistics of NO_3 concentrations for the different land use classes. It shows that the groundwater under the discontinuous urban areas has the highest mean NO_3 concentration with a value of 85 mg/l. This can be attributed to the extensive use of cesspits for wastewater disposal. Furthermore, fertilizers are used in the green spaces distributed among this land use class. The second highest mean NO_3 concentration is observed in the groundwater under the irrigated cultivation with a value of 55 mg/l. This area is subjected to an extensive use of agrochemicals. The lowest mean value occurred under the olive groves as expected since olive trees are usually planted in the mountainous areas where either the depth to groundwater is high or contaminants are being washed away with surface runoff. Except for olive groves, all the maximum NO_3 concentrations exceed the MCL. The overall maximum NO_3 concentration is located in the groundwater under the discontinuous urban areas with a value of 256 mg/l.

Table 5.3. Influence of land use on NO_3 concentrations (period 1982-2019)

Land use	Number of Samples	Concentration (mg/l)			
		Mean	Median	Min	Max
Continuous Urban Areas	42	37	34	5	95
Discontinuous Urban Areas	148	85	78	0	256
Drip Irrigated Arable	59	49	45	19	85
Forest	11	24	24	0	53
Green Houses	5	41	50	16	54
Irrigated Complex Cultivation	73	55	43	6	169
Non Irrigated Arable Land	13	34	28	10	56
Non Irrigated Complex Cultivation	126	43	47	1	89
Olive Groves	45	15	16	1	42

5.3.1.4. Influence of watersheds

The Eocene Aquifer area overlaps seven different watersheds: Al-Moqatta', Al-Khodera, Marj Sanur, Iskanderon, Al-Far'a, Wadi Shobash and Al-Maleh (Figure 5.7a). The first four watersheds drain into the west to the Mediterranean Sea; while the others drain into the east to the Jordan River. Actually, the available NO_3 concentration data were only distributed among four watersheds; Al-Far'a, Marj Sanur, Al-Khodera and Al-Moqatta'. Figure 5.7b illustrates the minimum, 25^{th} percentile, mean, median, 75^{th} percentile and maximum NO_3 concentrations for the different watersheds for the period 1982-2019. Marj Sanur watershed was excluded from the discussion as it has unrepresentative number of NO_3 concentration readings (7 readings). The groundwater wells located in Al-Far'a watershed has mean and median NO_3 concentrations that exceed the MCL. It also has the highest maximum and 75^{th} percentile values compared to other watersheds. This is due to the intensive use of agrochemicals in the watershed as it is considered as ‘the food basket’ for the northern part of the West Bank and the most dominated watershed by agriculture in the West Bank (Almasri et al., 2020). Mean and median NO_3 concentrations are approximately equal to MCL at Al-Moqatta' watershed while the lowest concentrations were recorded at Al-Khodera watershed.



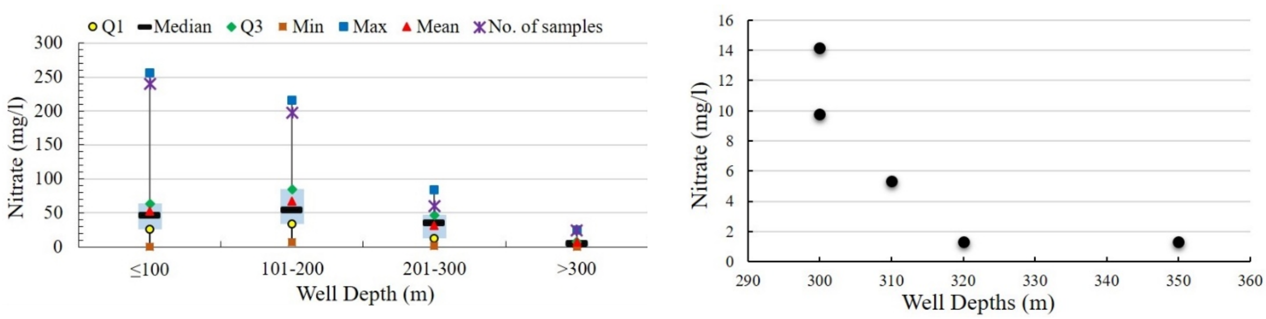
(**a**) Watershed locations (**b**) GNC in the watersheds (2019)

Figure 5.7. Influence of watersheds and their locations on the NO_3 concentration (period 1982 - 2019)

5.3.1.5. Influence of well depth

Generally, there is an inverse relationship between well depths and NO_3 concentration (Anayah and Almasri, 2009; Tesoriero and Voss, 1997; Hallberg, 1989; and Freeze et al., 1979). Figure 5.8a shows the variation of the statistical parameters with the well depth. It clearly indicates high NO_3 concentrations in the first 100 m of the aquifer. After that, NO_3 concentration significantly decreases with depth and becomes insignificant below 300 m. This NO_3 profile could be attributed to the following factors: denitrification in groundwater, groundwater movement and the associated NO_3 transport and mixing.

The NO_3 concentration is also influenced by other factors such as land use, groundwater recharge and fertilization practices. To reduce the influence of these factors, analysis was conducted on samples from five adjacent wells (distributed among an area of 2.37 km^2) in Qabatiya. Figure 5.8b illustrates the variation of concentrations with depth for these samples. It clearly shows that the NO_3 concentration decreases with the increase in depth.

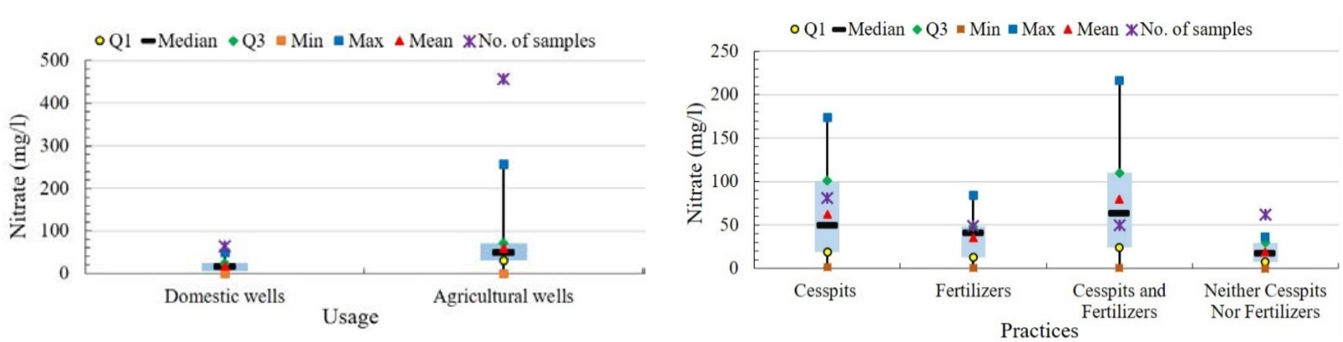


(**a**) for all groundwater wells (1982-2019) (**b**) for five adjacent groundwater wells (2017-2019)

Figure 5.8. Influence of well depth on the NO_3 concentration

5.3.1.6. Influence of the wells use and the anthropogenic practices

The groundwater wells are used for domestic and agricultural activities. Figure 5.9a shows that the agricultural wells have higher median (49 mg/l), mean (59 mg/l), 75th percentile (71 mg/l) and maximum (256 mg/l) values as compared to the domestic wells. The domestic wells have NO_3 concentrations in the range of 0 to 49 mg/l with a median, mean and 75th percentile that equal 16, 18 and 25 mg/l, respectively. The intensive use of agrochemicals in agriculture and cesspits for wastewater disposal are the main source of on-ground nitrogen loading in the study area (Canion et al., 2019). Collected data was used to investigate the influence of these factors on GNC. Practices in the proximity of the sampled wells were classified into four categories: extensive presence of cesspits, extensive application of fertilizers, extensive use of cesspits and fertilizers, and neither cesspits nor fertilizers. Figure 5.9b illustrates the statistics of NO_3 concentrations for the four practices. It shows that the highest concentrations are located in the category "extensive use of cesspits and fertilizers", followed by the category "extensive use of cesspits" and then the category "extensive use of fertilizers".



(**a**) Well use (1982-2019) (**b**) Anthropogenic practices (2019)

Figure 5.9. Influence of well use and anthropogenic practices on the NO_3 concentration

5.3.2. Machine Learning-based GNC prediction model

GNC Assessment outcomes are integrated with the Machine Learning-based GNC prediction model. They provided the prediction model by the GNC distribution as well as by the main factors influencing this distribution. Such information is used as an input for the development of the prediction model. Generally, assessment results indicated that except soil type, all factors (well depth, well use, land use, watershed, and fertilization and wastewater disposal practices) can be used as inputs for the Machine Learning prediction model. RFA model was built considering these factors and executed 10 times. Table 5.4 shows that the obtained accuracy scores range between 83.3% and 91.7% with an average value of 88.5%.

Table 5.4. Prediction accuracy for RFA model over 10 execution trials

Trial	1	2	3	4	5	6	7	8	9	10	Mean
Accuracy (%)	89.6	91.7	91.7	83.3	85.4	87.5	89.6	91.6	83.3	91.7	88.5

Table 5.5 shows the RFA confusion matrix for the best trial (accuracy = 91.7). It indicates two types of errors: safe error (error of predicting worse than contamination situation) and risk error (error of predicting less than contamination level). The safe error equals 2.08%, while the risk error equals 6.22%. Figure 5.10 shows the distribution of wells with correct, safe error and risk error prediction. It is noticed that the false predicted wells are not spatially correlated. They are distributed amongst the northern, middle and southern parts of the study area. Table 5.6 illustrates that both errors in the false predicted wells are occurred on the margins of the thresholds between two successive contamination levels. Actual and predicted GNC in wells 1 and 2 are close to the threshold of 25 mg/l. Moreover, actual and predicted values are around the threshold of 50 mg/l in wells 3 and 4. This reflects the low severity of the prediction model errors.

Table 5.5. Confusion matrix for the RFA prediction model (trial 10, Table 5.4)

	Contamination Level	Predicted contamination level			
		Not contaminated by NO_3 (%)	Reasonable NO_3 concentration (%)	Contaminated by NO_3 (%)	Extremely contaminated by NO_3 (%)
Actual contamination level	Not contaminated by NO_3 (%)	27.08	2.08	0	0
	Reasonable NO_3 concentration (%)	2.08	50	0	0
	Contaminated by NO_3 (%)	0	4.14	8.37	0
	Extremely contaminated by NO_3 (%)	0	0	0	6.25

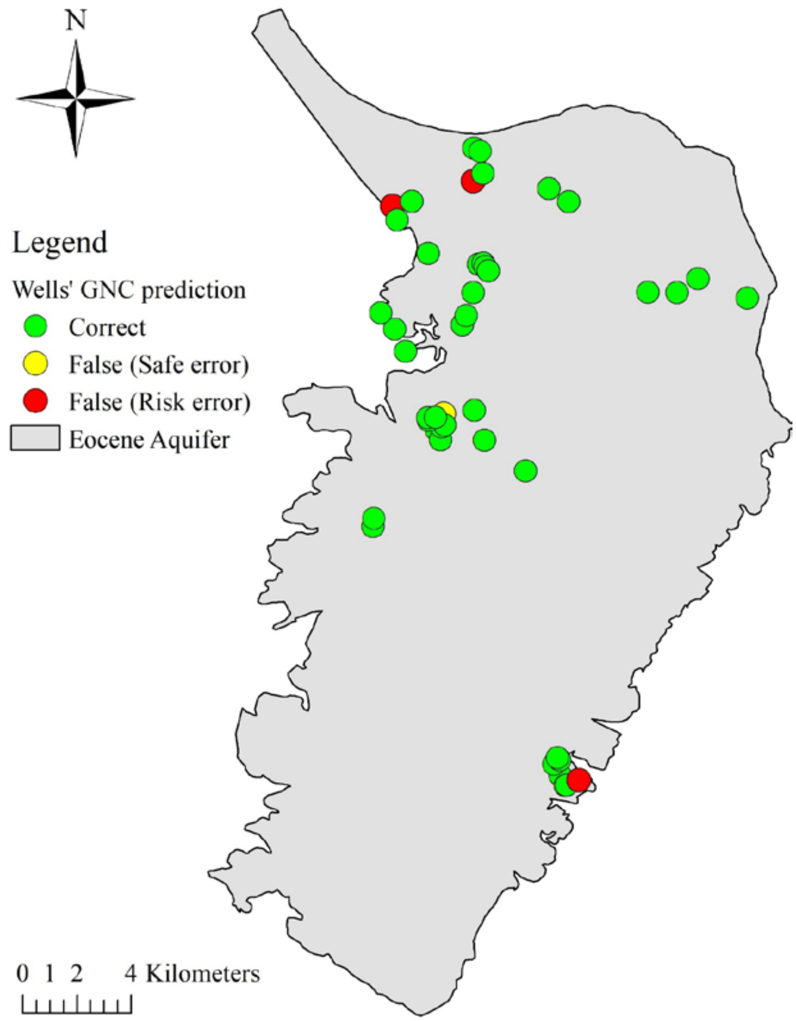


Figure 5.10. Distribution of correct and false predicted wells concerning GNC

Table 5.6. Types of prediction errors for the false predicted wells

Well	Actual NO_3 concentration (mg/l) (level)	Threshold (mg/l)	Predicted NO_3 concentration (mg/l) (level)	Prediction error type
Well #1	23 (Not contaminated)	25	28 (Reasonable concentration)	Safe error
Well #2	27 (Reasonable concentration)	25	21 (Not contaminated)	Risk error
Well #3	54 (Contaminated)	50	47 (Reasonable concentration)	Risk error
Well #4	52 (Contaminated)	50	46 (Reasonable concentration)	Risk error

Table 5.7 shows the relative importance of the input factors used in the RFA prediction model. It is obvious that the well depth (with 41% relative importance) is the most influencing factor, followed by anthropogenic-related factors. This reflects the high vulnerability of shallow groundwater wells to GNC. It also highlights the severity of uncontrolled man-made practices (land use, and fertilization and wastewater disposal method) upon the GNC. On the other hand, watershed and well use have the lowest influence with relative influence of 14% and 7% respectively.

There is a difficulty in controlling the depths of existing and new wells due to political restrictions. Therefore, management options should be directed toward the anthropogenic-related factors. In which, the control of intensive use of fertilizers and cesspits are the most important ones. Decision makers are advised to embrace the land use planning as a strategic tool for mitigating GNC in the study area. Protection zones for groundwater wells have to be delineated and sources of GNC have to be prohibited in those zones.

Table 5.7. Importance of input factors used in the RFA prediction model

Factors	**Well depth**	**Land use**	**Anthropogenic activities**	**Watershed**	**Well use**
Relative importance (%)	41	20	18	14	7

5.4. Conclusion

This chapter presented a new approach that combines GIS, statistics and Machine Learning to assess and predict GNC in the Eocene Aquifer, Palestine. The integration of GIS and statistical analysis led to a comprehensive spatiotemporal assessment of GNC. This assessment provided the RFA model by the input factors. Assessment indicated serious NO_3 contaminations of the Aquifer. GIS maps indicated an increasing GNC trends in the southern part of the study area. Results showed the necessity to use five factors (well depth, well use, land use, watershed, and fertilization and wastewater disposal practices) in the RFA predictive model of the GNC. RFA model successfully attained a maximum and average prediction accuracy of 91.70% and 88.54%, respectively.

Decisions makers could use the approach presented in this chapter to establish a knowledge-based approach for the sustainable management of the groundwater quality in Palestine. Collaboration is crucial between different stakeholders to establish groundwater monitoring programs to support the sustainable use of the groundwater through the control of agrochemicals and cesspits.

Chapter 6. Rainwater Harvesting to Address Water Scarcity in Arid and Semi-Arid Areas

6.1. Introduction

This chapter aims to analyze the capacity of rooftops rainwater harvesting (RWH) in addressing the domestic water scarcity in arid and semi-arid areas. RWH is commonly adopted to support the insufficient conventional water resources (Abu-Zreig et al., 2019). It is widely used in Pakistan (Abbas et al., 2021), Kenya (Mundia, 2021), East Africa (Bernard and Joyfred, 2020), Ghana (Boakye and John-Jackson, 2015), Afghanistan (Rahimi and Murakami, 2017), Zambia (Malambo and Huang, 2016), Sri Lanka (Sendanayake, 2016), Bangladesh (Biswas and Mandal, 2014), Iran (Sheikh, 2020), Egypt (Gado and El-Agha, 2020), and Jordan (Abu-Zreig et al., 2019; and Abdulla and Al-Shareef, 2009). RWH efficiency depends on many factors, including rainfall volume, patterns and distribution, catchment area, and catchment type (Gebreyess and Woldeamanuel, 2019; and Ffolliott et al., 2014).

A sustainable water resources management should consider the climate change and demographic growth (Menzel et al., 2009). This chapter contributes to this objective through (i) investigating the ability of the potential RWH in addressing the current domestic water scarcity, (ii) analyzing the role of RWH in addressing the future water scarcity relate to the demographic and climate changes. The chapter is organized as follows. First, it presents the research methodology, including the estimation of the potential RWH. Then, it describes its application on a case study. Finally, it discusses the role of the RWH in addressing the domestic water scarcity in the West Bank, Palestine.

6.2. Materials and methods

6.2.1. Methodology

The methodology adopted in this research is illustrated in Figure 6.1. Geographic Information System (GIS) is used to map the rainfall and rooftops spatial distribution in 2020. A Global Climate Model (GCM) (called European Centre Hamburg Model, Version 4) estimates the spatial rainfall distribution in 2050 (Menzel et al., 2009). This model is downscaled up to 18 x 18 km^2 resolution using a Regional Climate Model (Mesoscale Model, Version 5). These models were developed and validated by GLOWA (Menzel et al., 2009). The projected (2050) rooftops distribution is estimated assuming a linear relationship with the population growth in the study area.

Gould and Nissen-Petersen's equation along with GIS employ the current and projected rainfall and rooftops to estimate the potential RWH (Gould and Nissen-Petersen, 1999). In addition, this equation considers the RWH collection efficiency and runoff rate (Gould and Nissen-Petersen, 1999). An average runoff and collection efficiency coefficient (C) of about 0.9 is suggested by several scholars (See equ. 6.1) (Alawna and Shadeed, 2021; Farreny et al., 2011; and Abdulla and Al-Shareef, 2009).

$$\mathrm{RWH_i} = \sum_{i=1}^{n} C * RF_{ij} * A_{ij} \qquad \text{(Equ. 6.1)}$$

Where,

RWH_i: potential RWH volume for the i^{th} year in (m^3/year)

RF_{ij}: average rainfall for the j^{th} rooftop in the i^{th} year in (m/year)

A_{ij}: area of the j^{th} rooftop in the i^{th} year in (m^2/year)

n: number of rooftops

The current and projected RWH is integrated with the total water supply (TWS) (calculated in chapter 3) in the years 2020 and 2050, respectively. Then, current and projected supply demand balance index (SDBI) and the associated water scarcity levels (presented in chapter 3) are re-estimated by considering RWH.

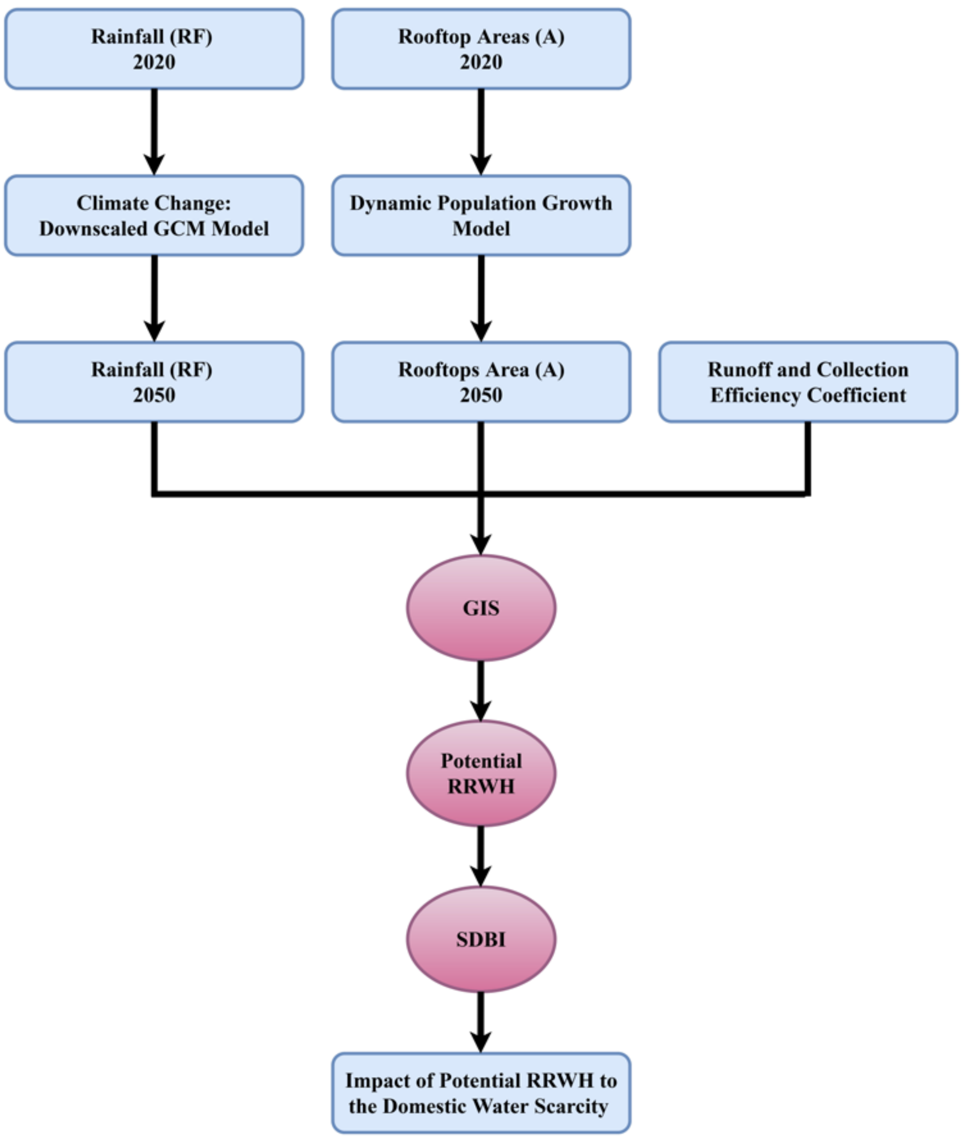


Figure 6.1. Research methodology

6.2.2. Data collection and application

The proposed methodology is applied to the West Bank, Palestine which is located to the west of the Dead Sea (detailed description of the study area is previously presented in Section 2.2). Data are collected from different sources. The building rooftops shapefile in 2020 is obtained from the Ministry of Local Government (MoLG) (MoLG, 2021). The projected rooftop areas in 2050 are estimated, assuming a linear relation with the population growth (this population growth is estimated in Chapter 3). Table 6.1 summarizes the current and projected rooftop areas for the eleven West Bank governorates. The authors are aware of the limitation of this assumption, which could be improved in the future.

Table 6.1. Current and projected POP and rooftop areas

Governorate	POP_c	POP_p	Rooftops area 2020 (km^2)	Rooftops density (m^2/capita)	Rooftops area 2050 (km^2)
Jenin	332050	481000	10.5	31.7	15.3
Tubas	64507	133000	1.7	26.5	3.5
Tulkarm	195341	227000	6.0	30.8	7.0
Nablus	407754	532000	11.5	28.3	15.1
Qalqilya	119042	174000	3.3	27.8	4.8
Salfit	80225	101000	2.7	33.4	3.4
Ramallah & Al-Bireh	347818	602000	11.7	33.7	20.3
Jerusalem	461666	642000	4.9	10.7	6.8
Jericho	52355	89000	2.2	42.4	3.8
Bethlehem	229884	354000	7.3	31.6	11.2
Hebron	762541	1394000	21.8	28.7	39.9

Current rainfall for the West Bank are obtained from the Palestinian Metrological Authority (PMA) (PMA, 2018). PMA has 75 spatially distributed rainfall stations in the West Bank governorates (Figure 6.2). Table 6.2 summarizes the number of rainfall satiations per km^2 (for each governorate). It is noticed that the station resolution (density) ranges from 0.1 (in Hebron and Jerusalem) to 0.8 (in Salfit) station per km^2.

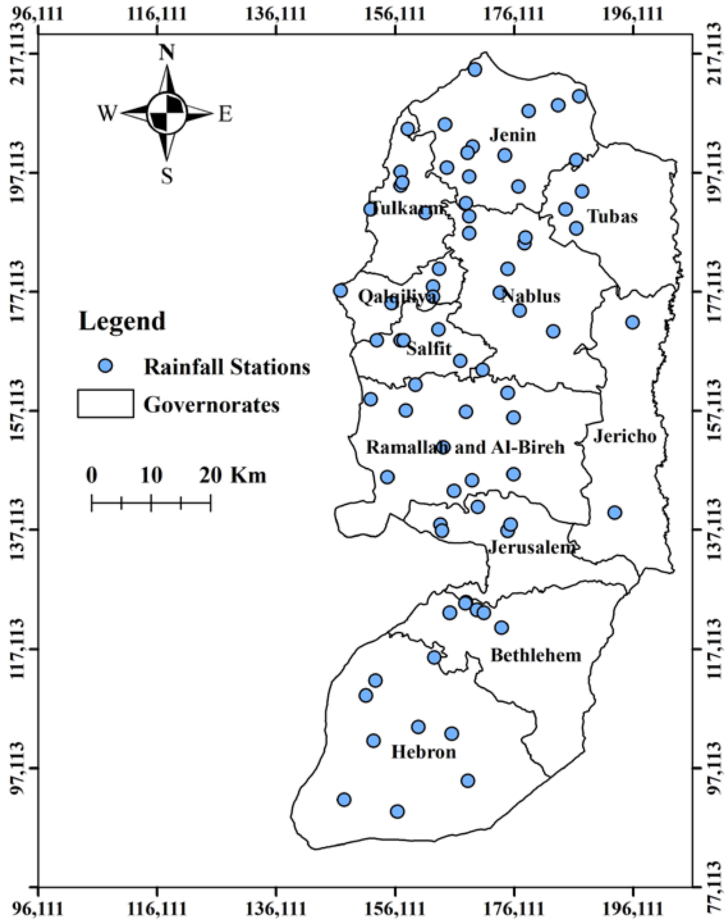


Figure 6.2. Distribution of rainfall stations in the West Bank

Table 6.2. Density of rainfall measurements in the West Bank

Governorate	No. of rainfall stations	Urban area (km²)	Rainfall stations density (station/km²)
Jenin	13	23.3	0.6
Tubas	3	5.1	0.6
Tulkarm	6	21.4	0.3
Nablus	9	27.6	0.3
Qalqilya	5	6.8	0.7
Salfit	5	6.7	0.8
Ramallah & Al-Bireh	11	38.7	0.3
Jerusalem	5	37.3	0.1
Jericho	3	10.2	0.3
Bethlehem	6	27.0	0.2
Hebron	9	77.2	0.1

Figure 6.3 shows a GIS-based spatial interpolation for average annual rainfall from the spatially distributed rainfall stations. This interpolation is realized at a scale of 100*100 m^2. It is indicated that the average annual rainfall (in 2020) ranges from 166 mm/year (in the eastern part) to 662 mm/year (in the middle part), with a mean value of 520 mm/year. Table 6.3 provides the average annual rainfall for the different West Bank governorates in 2020. However, the used rainfall data could form a source of uncertainty in the rainfall-dependent models (e.g. climate change models for rainfall and water availability) (Fraga et al., 2019; and Muñoz et al., 2014). Scholars confirm the sensitivity of rainfall-dependent models to rainfall uncertainty (Fraga et al., 2019; and Muñoz et al., 2014). The highest sensitivity occurs in the rainy periods (e.g. October to March). In dry periods with few rainfall amount, the rainfall-dependent models are less sensitive to rainfall uncertainties (Fraga et al., 2019; and Muñoz et al., 2014). Such uncertainty could be addressed by performing a cross validation for the rainfall records using different approaches (Fraga et al., 2019; and Muñoz et al., 2014).

Table 6.3. Average annual rainfall for the different West Bank governorates in 2020

Governorate	Average annual rainfall in 2020 (mm/year)
Jenin	498
Tubas	402
Tulkarm	630
Nablus	574
Qalqilya	662
Salfit	656
Ramallah & Al-Bireh	579
Jerusalem	537
Jericho	166
Bethlehem	518
Hebron	487

The rate of change in rainfall between 2020 and 2050 are estimated using the downscaled GCM models developed by GLOWA (Menzel et al., 2009). The GIS-based Raster Calculator is then used to estimate the values of rainfall in 2050. Figure 6.3 illustrates the distribution of rainfall in the West Bank. It indicates that all the governorates, except Jenin and Nablus, will experience in 2050 a decrease in rainfall volumes (up to 15%) comparing to the year 2020.

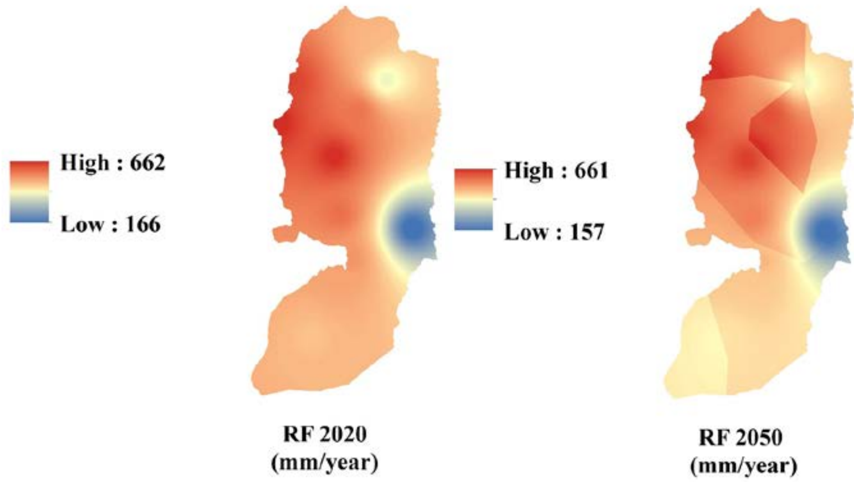


Figure 6.3. Variation in rainfall considering climate change

6.3. Results and discussion

6.3.1. RWH for the mitigation of existing domestic water scarcity

This section discusses the use of RWH as an efficient option for addressing the domestic water scarcity challenge in the West Bank. In 2020, the potential RWH in the West Bank can provide approximately 40 million cubic meters/year (MCM/y), which accounts for 95% of the water supply (42 MCM/y).

Table 6.4 summarizes the impact of adopting RWH on the increase in TWS. Jericho has the lowest increase (11%), followed by Tubas, Qalqilya, Tulkarm, and Nablus. The highest increase (577%) is observed in Ramallah and Al-Bireh. These results indicate the importance of RWH in addressing the water scarcity challenges.

Table 6.4. Contribution of RWH to TWS (in 2020)

Governorate	Increase in TWS after adopting RWH (%)
Jenin	133
Tubas	23
Tulkarm	52
Nablus	70
Qalqilya	38
Salfit	108
Ramallah & Al-Bireh	577
Jerusalem	169
Jericho	11
Bethlehem	170
Hebron	145

Considering the political and technical water supply challenges in the West Bank (Judeh et al., 2017), RWH presents a valuable alternative to address these challenges. Table 6.5 shows that

RWH can cover around 54% of the total water semand (TWD) in Salfit and between 40 and 48% in Nablus, Bethlehem, Qalqilya, Ramallah, and Al-Bireh, and Tulkarm governorates.

Table 6.5. Contribution of RWH to TWD in 2020

Governorate	The ratio of RWH to TWD (%)
Jenin	39
Tubas	26
Tulkarm	48
Nablus	40
Qalqilya	45
Salfit	54
Ramallah & Al-Bireh	48
Jerusalem	14
Jericho	17
Bethlehem	40
Hebron	34

Figure 6.4 shows the impact of the RWH on the domestic water scarcity level in Tulkarm and Jerusalem in 2020. The highest effect is observed in Tulkarm. Exploiting around 16% of the roofs for RWH could drop the scarcity level to "no water shortage". The rest roof areas could support other purposes such as agricultural and industrial uses. The extra RWH can also support water shortages in other governorates.

Figure 6.4 shows that the RWH has low efficiency in addressing the domestic water scarcity in Jerusalem: Jerusalem faces an "extreme water shortage" after fully adopting RWH in 2020. This low performance of the RWH is due to the low ratio of rooftops to the population, which is around 10.7 m^2/citizen, to be compared to values in the rest of the West Bank governorates, which varies between 26.5 and 42.4 m^2/citizen.

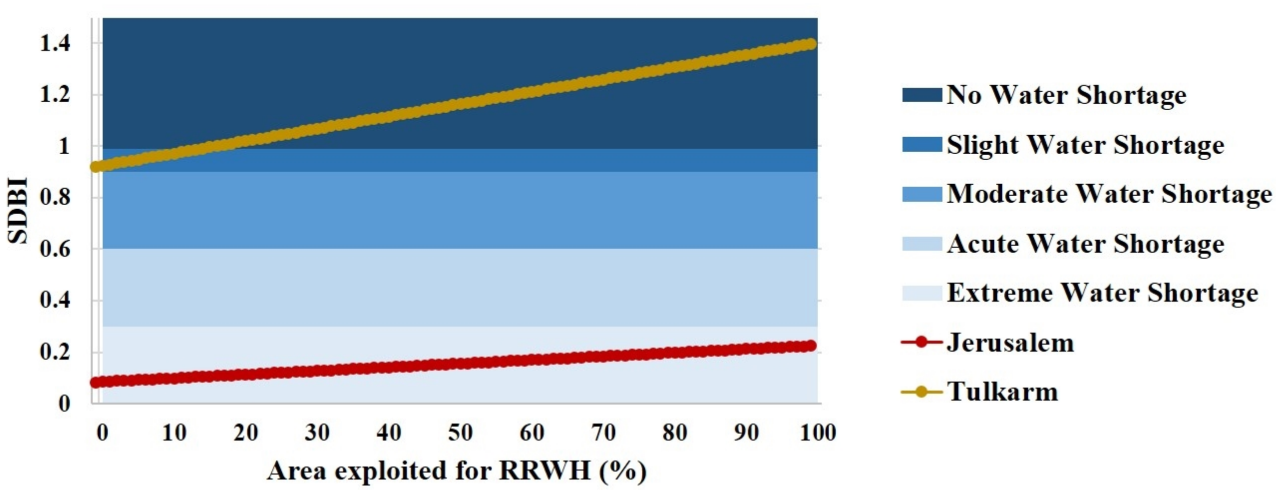


Figure 6.4. Impact of the RWH on the domestic water scarcity in Jerusalem and Tulkarm governorates (in 2020)

Tables 6.6 summarizes the impact of using four rooftops rates in the RWH (25%, 50%, 75%, and 100%) on domestic water scarcity. It shows that full or partial use of the RWH will cover the TWS in Tubas, Qalqilya, and Jericho. However, the status of 'No shortage" in Slafit requires a full adoption of the RWH. The latter is not sufficient to afford the TWS in Ramallah & Al-Bireh, and Hebron. This result argues for a national water strategy that shares the RWH capacities.

Table 6.6. Impact of RWH on the domestic water scarcity level in 2020

Governorate	**RWH adoption rate**			
	25%	**50%**	**75%**	**100%**
Jenin	Acute	Acute	Moderate	Moderate
Tubas	No shortage	No shortage	No shortage	No shortage
Nablus	Moderate	Moderate	Moderate	Slight
Qalqilya	No shortage	No shortage	No shortage	No shortage
Salfit	Moderate	Moderate	Slight	No shortage
Ramallah & Al-Bireh	Extreme	Acute	Acute	Acute
Jericho	No shortage	No shortage	No shortage	No shortage
Bethlehem	Acute	Acute	Acute	Moderate
Hebron	Acute	Acute	Acute	Acute

Results confirm the findings of Alawna and Shadeed, (2021) and Shadeed et al., (2019) concerning the potential of RWH in the different West Bank governorates. However, Shadeed et al., (2019) focused only on the optimal allocation of the RWH in the West Bank, while Alawna and Shadeed, (2021) focused on estimating potential RWH volume. Other scholars treated separately the allocation and the estimation of potential RWH (Ranaee et al., 2021; Hashim and Sayl, 2021; and Alwan et al., 2020;). This research contributed to the analysis of the capacity of the potential RWH to cover water scarcity by quantifying the influence of RWH on the current and future domestic water scarcity.

6.3.2. RWH efficiency at different urban scales

This section discusses the RWH efficiency at different urban scales (city, village, and camp), emphasizing the Jenin governorate in 2020. Figure 6.5 shows that the full adoption of RWH in Jenin City can change the water scarcity status from "acute water shortage" to "no water shortage". Furthermore, this full adoption can change the water scarcity status in (i) Jenin Camp from "acute water shortage" to "moderate water shortage" and (ii) in villages from "extreme water shortage" to "acute water shortage". These results indicate that the lowest RWH efficiency concerns the Jenin camp. The variation of the efficiency of the potential RWH is related to the ratio of the rooftops to the population. This ratio equals 16 m^2/citizen in the camp compared to 29 m^2/citizen and 48 m^2/citizen in the villages and the city, respectively.

Exploiting 65% of the rooftops is enough to cover the TWD in Jenin city. Therefore, full roof exploitation in this city could help mitigate or even eliminate the domestic water scarcity in the camp and villages.

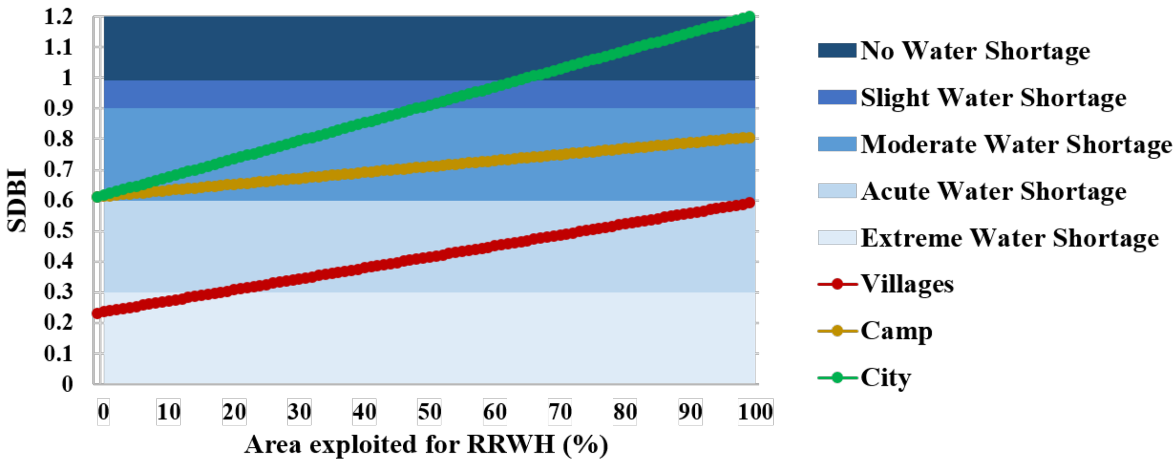


Figure 6.5. Impact of the RWH on domestic water scarcity for the different urban scales of Jenin governorate

6.3.3. Projected capacity of RWH to address the domestic water scarcity in 2050

This section discusses the capacity of the adoption of RWH to address the projected domestic water scarcity in 2050. The projected RWH is expected to provide around 59 MCM/y in 2050, which is 1.5 times the projected municipal water supply. Table 6.7 summarizes the influence of the RWH on both TWS and TWD. Full adoption of the RWH is expected to increase the values of TWS from 20% (in Jericho) to 1038% (in Ramallah and Al-Bireh). This full adoption can satisfy half of the needed TWD in Salfit, and between 13 and 48% in other West Bank governorates.

Table 6.7. Contribution of RWH to TWS and TWD in 2050

Governorate	Increase in TWS after adopting RWH (%)	The ratio of RWH to TWD (%)
Jenin	177	41
Tubas	49	25
Tulkarm	60	48
Nablus	89	42
Qalqilya	57	43
Salfit	141	51
Ramallah & Al-Bireh	1038	46
Jerusalem	250	13
Jericho	20	17
Bethlehem	285	36
Hebron	296	30

Table 6.8 summarizes the impact of projected RWH on water scarcity in the West Bank in 2050. Tulkarm and Qalqilya could reach “no water shortage” status. A “slight water shortage” could be reached in Jericho and Nablus by exploiting 50% and 100% of the roofs, respectively. Salfit, Tubas, and Jenin are expected to reach a (moderate water shortage) status by exploiting

50%, 50%, and 100% of their roofs. In other governorates, full adoption of the RWH will not be enough to cover the domestic water needs. A full RWH adoption efficiently addresses the domestic water scarcity challenges in Ramallah and Al-Bireh, Bethlehem and, Hebron. For these governorates, the domestic water scarcity will be improved from “extreme water shortage” to “acute water shortage”. The best improvement from “extreme water shortage” to “moderate water shortage” is expected in Jenin. Likewise, a reasonable improvement from “moderate water shortage” to “no water shortage” is expected in Tulkarm and Qalqilya.

Table 6.8. Impact of RWH on the domestic water scarcity level in 2050

Governorate	RWH adoption rate				
	0%	**25%**	**50%**	**75%**	**100%**
Jenin	Extreme	Acute	Acute	Acute	Moderate
Tubas	Acute	Acute	Moderate	Moderate	Moderate
Tulkarm	Moderate	Slight	No shortage	No shortage	No shortage
Nablus	Acute	Acute	Moderate	Moderate	Slight
Qalqilya	Moderate	Moderate	Slight	No shortage	No shortage
Salfit	Acute	Acute	Moderate	Moderate	Moderate
Ramallah & Al-Bireh	Extreme	Extreme	Extreme	Acute	Acute
Jerusalem	Extreme	Extreme	Extreme	Extreme	Extreme
Jericho	Moderate	Moderate	Slight	Slight	Slight
Bethlehem	Extreme	Extreme	Acute	Acute	Acute
Hebron	Extreme	Extreme	Extreme	Acute	Acute

6.4. Conclusion

This chapter presented an analysis of the capacity of the rainwater harvesting in addressing the domestic water scarcity in arid and semi-arid areas. Results show that the RWH can address the current domestic water scarcity in the majority of the West Bank governorates. A national policy to share the potential RWH capacity will increase the efficiency of the RWH by a share of the excess water harvesting among the West Bank governorates. An estimation of the potential RWRH capacity in 2050 shows that it could cover about 1.5 times the conventional water supply. However, this research is subjected to the following limitations: (i) lack of accurate rooftops projection model in 2050, (ii) absence of detailed information about the roof types (e.g., concrete, clay-tiles, steel, etc.), which affect the RWH efficiency, and (iii) the absence of local climate change models for predicting future rainfall and water resources availability. This research attempted to overcome these limitations by considering (i) a proportional relationship between the projected population and rooftops, (ii) an average runoff coefficient and collection efficiency of 0.9 as suggested in the literature. This research could be improved in the future by considering (i) a local rooftop model, (ii) a local climate change model to estimate the projected rainfall and water availability, and (iii) monitoring the water demand, water supply, rainfall intensity, and the rooftops water harvesting.

Chapter 7. Smart Rainwater Harvesting for Sustainable Potable Water Supply in Arid and Semi-Arid Areas

7.1. Introduction

This chapter presents a smart rainwater harvesting (RWH) system to address the water scarcity in arid and semi-arid areas, which face severe environmental challenges (Patrão et al., 2020), particularly a decrease in freshwater, population growth and water resources contamination (Preeti and Rahman, 2021; Jaren and Mondal, 2021; Villar-Navascués and Fragkou, 2021; Ayt-Ougougdal et al., 2020; and Chourabi et al., 2012). The conventional water supply systems have limited capacity to meet the water demand. For example, in the West Bank, conventional systems can provide only 60% of the domestic water demand (PCBS, 2021b).

Several authors presented the advantages of using RWH in arid and semi-arid areas (Preeti and Rahman, 2021; Ranaee et al., 2021; Judeh and Shahrour, 2021; and Tamagnone et al., 2020). Conventional rooftop RWH systems include a collection catchment, conveyance and storage tanks (Abdulla et al., 2021). These systems have several strengths, including (i) independency, (ii) proximity of RWH storage tanks to users, (iii) ease of construction and maintenance, (iv) flood mitigation, and (v) reduction of pressure on water resources (Abbas et al., 2021; and Słyś and Stec, 2020). However, these conventional systems have some limitations (Dao et al., 2021), particularly a lack of control of the quality of the harvested water (Dao et al., 2021). As a result, the RWH is considered an undrinkable source of water (Palermo et al., 2020; and Rostad et al., 2016). In addition, the conventional systems don't monitor (i) the filling and emptying process of the storage tanks as well as (ii) the water leakage (Behzadian et al., 2018). These processes are governed considering different factors: rainfall volume and intensity, tank storage capacity, and water demand (Behzadian et al., 2018).

Scholars proposed the use of the smart technology to enhance the engineering systems' efficiency and overcome their limitations (Petrolo et al., 2015; Castro et al., 2013; Kyriazis et al., 2013; and Stratigea, 2012). The smart technology uses real-time and historical data to improve the performance and resilience of urban systems (Petrolo et al., 2015; Castro et al., 2013; Kyriazis et al., 2013; and Stratigea, 2012). They are used in different fields such as health (Zhao et al., 2021; and Carminati et al., 2021), transportation, mobility (Bin Hariz et al., 2021; and Anagnostopoulos, 2021), indoor risk management (Wehbe and Shahrour, 2021), energy (Martins et al., 2021), and environment (Vishnu et al., 2021). They are also used to enhance the water supply (Mudumbe and Abu-Mahfouz, 2015; and Savić et al., 2014), monitor urban water networks (Rasekh et al., 2016; and Wu et al., 2015), detect water leakage (Mashhadi et al., 2021; and Farah and Shahrour, 2017), monitor water quality (Pasika and Gandla, 2020; Prasad et al., 2015; and Dong et al., 2015), and enhance the water resources management (Ramos et al., 2020; Ntuli and Abu-Mahfouz, 2016; Lee et al., 2015; and Robles et al., 2014).

Scholars used the smart technology to address the shortcomings of the conventional RWH systems at the household level (Ranjan et al., 2020; and Behzadian et al., 2018) with a focus on a single-aspect upgrade (Ranjan et al., 2020; and Behzadian et al., 2018) on either water quantity or water quality. Behzadian et al., (2018) discussed the use of Internet of Things (IoT-based sensors) to control the water level in the RWH tanks. This use secures sufficient spare in the tank to receive the runoff following storm events. It has been found that adopting the water-level monitoring in RWH tanks can pointedly mitigate urban flooding and secure non-potable water supply (Behzadian et al., 2018). Ranjan et al., (2020) discussed using an IoT-based water quality sensor to control the harvested water quality. The sensor helps diverting the harvested water (based on its pH value) into two storage tanks: potable and non-potable tanks. Harvested water in the tanks is then directed to appropriate uses (e.g. drinking and irrigation). However, the use of pH to control the harvested water potability is controversial. The World Health Organization (WHO) stated the vulnerability of RWH to physical (e.g. Turbidity), chemical (e.g. Nitrate, Lead, and Zinc), and biological contamination (e.g. Coliform) (Frichot et al., 2021; and WHO, 2011). The type of contamination depends on different factors including (i) the RWH surrounding activities (e.g. urban, industrial, and agricultural activities) and (ii) roofs, pipes, and storage tanks materials (Frichot et al., 2021; and WHO, 2011).

Considering the challenges of the water harvesting and the limitations of the conventional water harvesting system, this chapter proposes an innovative smart water harvesting system that combines (i) water tank sharing at the neighborhood level, (ii) a dual water supply system, and (iii) a comprehensive smart monitoring of the water quality, water level and the water leakage in the system. Moreover, the chapter investigates the ability of the proposed system in addressing the domestic water scarcity.

7.2. Materials and methods

7.2.1. Methodology

The methodology adopted in this research involves four phases, as shown in Figure 7.1. The first phase targets the characterization of the potential causes of RWH contamination and insufficiency. Phase two employs the characterization outputs to design the smart RWH/dual system architecture. Phase three aims at performing a reliability analysis of the smart system performance. The last phase aims at investigating the impact of proposed system to the alleviation of water scarcity conditions.

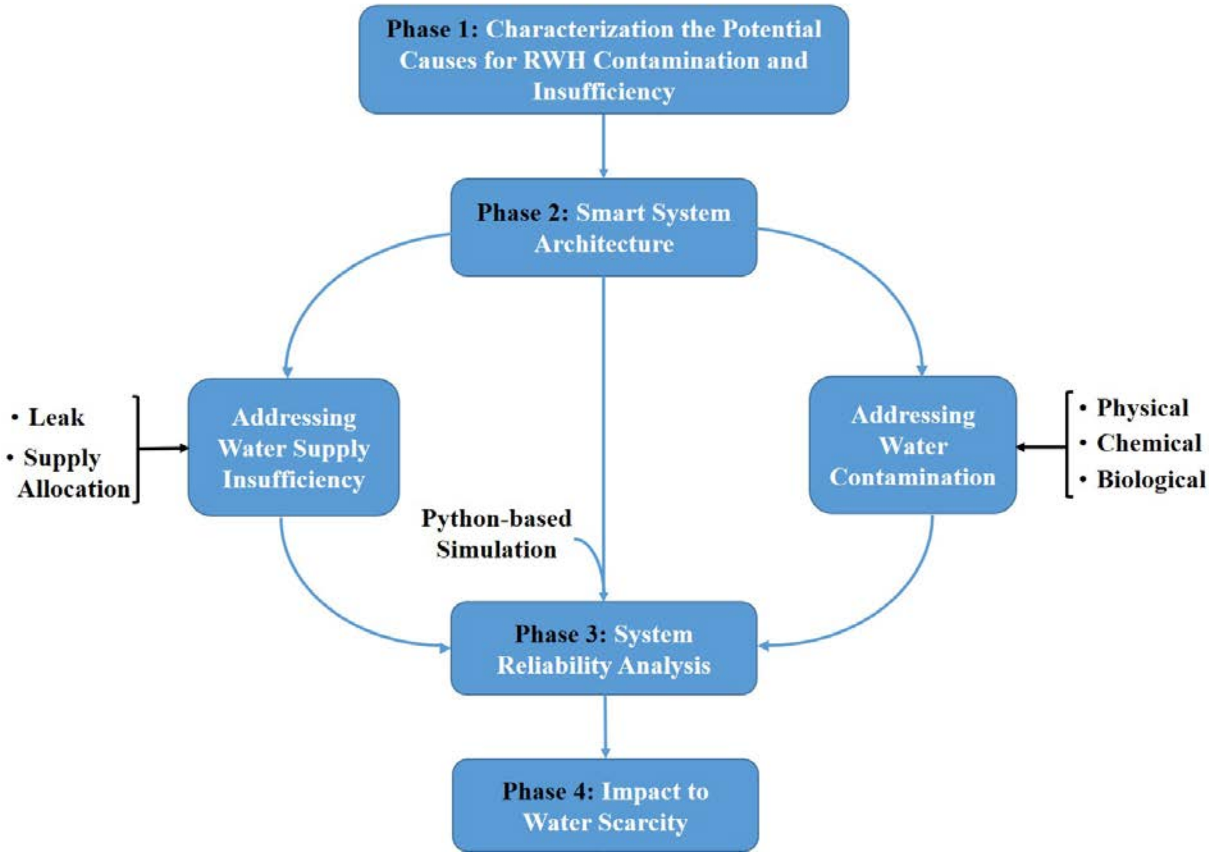


Figure 7.1. Research methodology

7.2.1.1. Sources for RWH contamination and inefficiency

Although RWH is less vulnerable to contamination than surface and groundwater resources, it could be exposed to contamination sources (Wu et al., 2016; and Mosley, 2005). The first source is the atmosphere, as the rain droplets could absorb the air contaminants such as Nitrite, Carbon Dioxide, and Sulfate (Osayemwenre and Osibote, 2021). It could also acquire heavy metals due to industrial emissions (e.g. Lead, Zinc, Copper, and Cadmium) (Chubaka et al., 2018). The second source is the rooftop materials (Osayemwenre and Osibote, 2021) (e.g. lead-based roofs) which are classified as a hotspot for various toxins (Abbasi and Abbasi, 2011). The third source is the wastes (e.g., fecal material and leaves) originated by the creatures (e.g. birds) and trees and settled on the roofs (Abbasi and Abbasi, 2011). These sources could cause physical, chemical, and biological contamination of the RWH (Alim et al., 2020; and Vilane and Simiso, 2018). The type of RWH contamination differs spatially (Vilane and Simiso, 2018; and Tamimi, 2016). It depends on the surrounding activities that pollute the roofs and air (Vilane and Simiso, 2018; and Tamimi, 2016). Monitoring and implementing treatment units for these contaminations are complex, costly, and time-consuming (Ighalo and Adeniyi, 2020; and Hasan et al., 2019). Thus, characterizing the probable contaminants and their sources is a core step in constructing an efficient and financially feasible quality monitoring system. This research characterizes the RWH contamination by considering: (i) the spatial sampling of the RWH from different locations, (ii) the laboratory analysis of the collected samples, and (iii) the literature review (Figure 7.2).

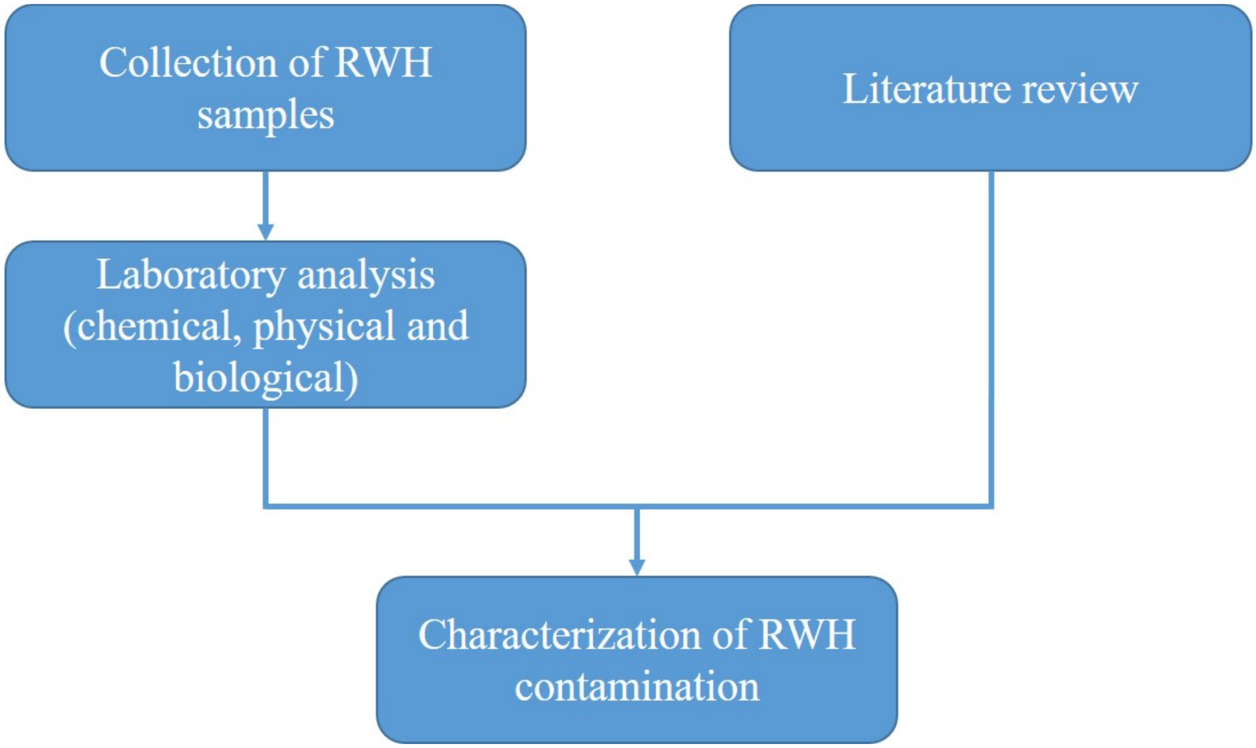


Figure 7.2. Characterization of RWH contamination

The inefficiency of RWH systems in providing a reasonable water supply volume could be attributed to un-controllable and controllable factors (Das, 2019; and Abu-Zreig et al., 2019). The uncontrollable factors include the rainfall volumes and patterns and the roof area (Judeh and Shahrour, 2021). The controllable ones imply the proper sizing of the RWH storage tank, the leak in the RWH system, the efficiency of the RWH system components (e.g. pumps and valves), and the roof type (Judeh and Shahrour, 2021; Das, 2019; and Abu-Zreig et al., 2019). Therefore, controlling and monitoring these controllable components is the key to an efficient RWH system.

7.2.1.2. Smart RWH system architecture

The smart RWH system is used to ensure (i) early detection of water contamination and water leak, (ii) the control of water contamination and water leak, (iii) satisfying the needed domestic water demand, and (iv) the wise and sustainable use of available water resources/supply. In addition, the system ensures (i) data collection, (ii) interaction with users, and (iii) the control of the smart system' equipment such as valves and pumps.

The architecture of the smart RWH system involves six layers, as illustrated in Figure 7.3. The physical layer includes the physical components of the water harvesting system, the municipal water supply, and the users. The monitoring layer includes sensors used to monitor the water quality, water flow, and the water level in the water tank. The data transfer layer uses wireless technology for data transmission from the monitoring system to the server. The data processing layer operates data cleaning, storage, analysis, and visualization. The control layer includes actuators that control the water flow, such as pumps and valves. Finally, the smart services include the detection of water contamination or water leak and the optimal tank filling.

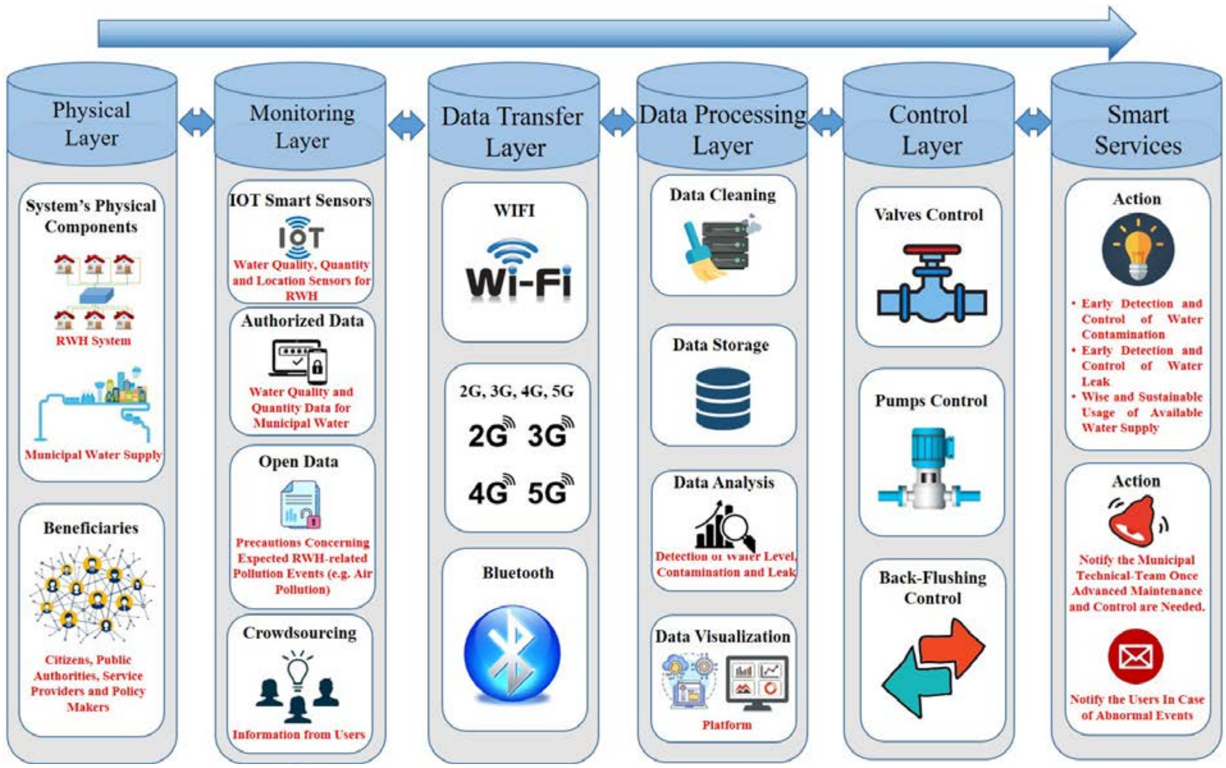


Figure 7.3. Architecture of the smart RWH system

- The Physical layer

The water supply, leak, and contamination are influenced by the building's distribution, citizens' density, and the water distribution systems (Rojek and Studzinski, 2019; and Mizuki et al., 2012). Therefore, the smart water supply system is designed to consider the physical components (Figure 7.4), which could be organized in three groups. The first involves the building roofs, gutters, shared RWH tank, household water tank, RWH distribution network (from roofs to shared RWH tank and from shared RWH tank to household water tanks), valves, overflow pipe, pump, backflow preventer, municipal water supply, and control panel. The second group involves the inlet filter, first flush diverter, RWH tank screen, over-flow pipe screen, treatment unit, discharge pipe, and flushing unit. The third group concerns the users, public authorities, service providers, and policymakers.

The building roofs are considered the catchment area for receiving the falling rainfall droplets. Such droplets are transported through the gutters (channels located around the edge of a sloping roof) to the RWH distribution network. The latter is used to transport the rainwater from the roofs to the shared RWH tank. Valves are used to control the water supply. Pumps transport the harvested rainwater from the shared tank to the household water tank installed on the top of the house. The house tank is also connected to the municipal water system. Backflow preventers are installed to protect the pump.

An inlet filter is installed to catch the large debris and prevent them from entering the pipe of the RWH distribution network. A first flush diverter is used to capture and divert the contaminated harvested water during the first rain because different substances and deposits could contaminate it on the roof. However, this diverter forms the second defense line since it captures the contaminants not captured by the inlet filter. The RWH tank screen is located at the entry point of the RWH storage tank. It has two main roles: filtering the harvested water before reaching the storage tank and preventing the pests and mosquitos from entering the tank. The overflow pipe screen (filter) is installed at the end of the overflow pipe. It prevents pets and mosquitos from entering the RWH system. A treatment unit is added to convert the non-potable into potable water. This unit will be based on the characterization of the probable RWH contamination in the study area. A discharge pipe is installed to discharge the non-potable water away from the distribution network and prevent it from reaching the household water tank. Finally, a flushing unit is added for cleaning, disinfecting, and flushing the RWH system.

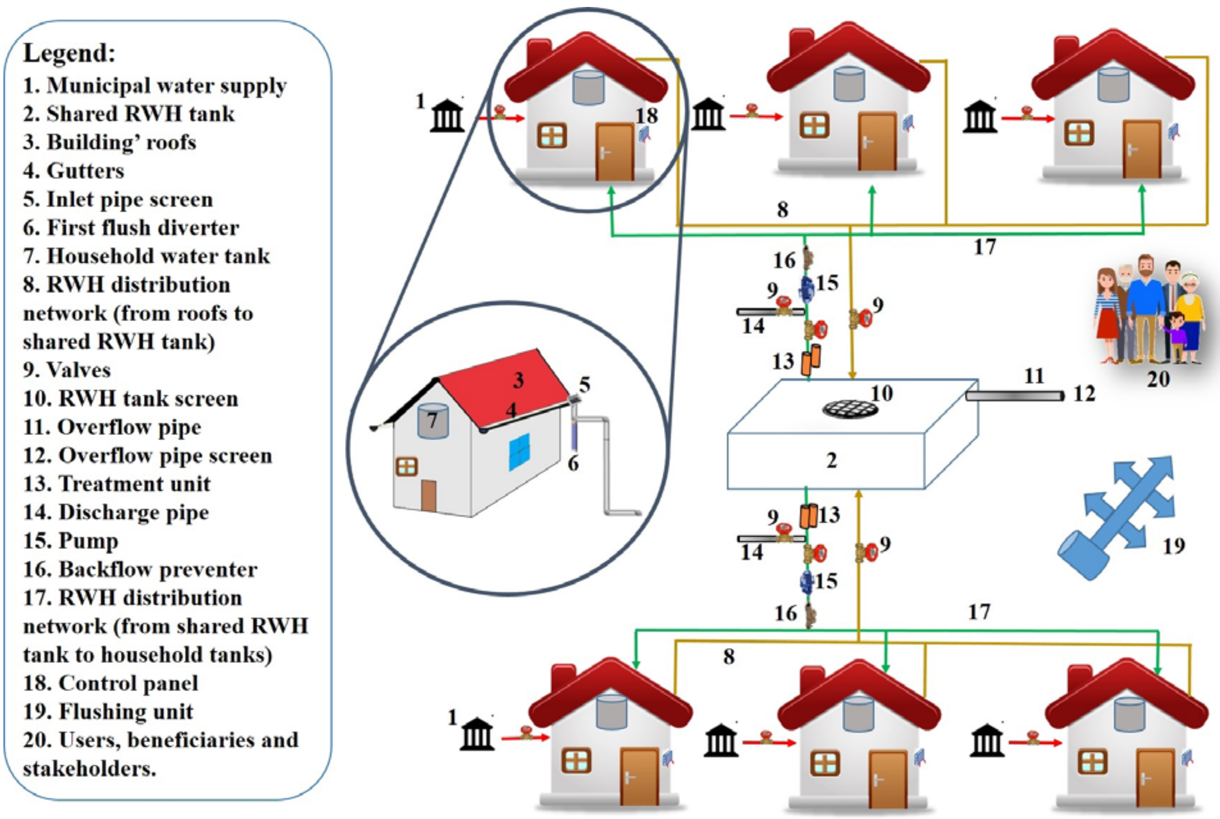


Figure 7.4. Physical components of the smart RWH system

- The Monitoring and data transfer layer

This layer ensures data collection using the following sensors: (i) smart water flow meter to monitor the water flow in the distribution network, (ii) water level sensor to monitor the water level in the shared RWH tank and the household's tanks, (iii) smart water quality device to monitor the water quality in the RWH system and (iv) leak detection sensor: these sensors can detect the indoor water leak for the different household equipment. In addition, sensors can perform a real-time collection and transmission of data to the RWH server (Figure 7.5).

The system also collects the water supply agenda from the water provider, the weather and air quality forecasting from the relevant authorities, and information from users about the water quality or shortage in the RWH service (Shahrour and Xie, 2021; and Guo et al., 2015).

Data transfer is carried out using wireless networks (e.g., WIFI, Bluetooth, and 4G). Wireless networks transmit the collected data from the IoT sensors to the server, where data are processed and analyzed.

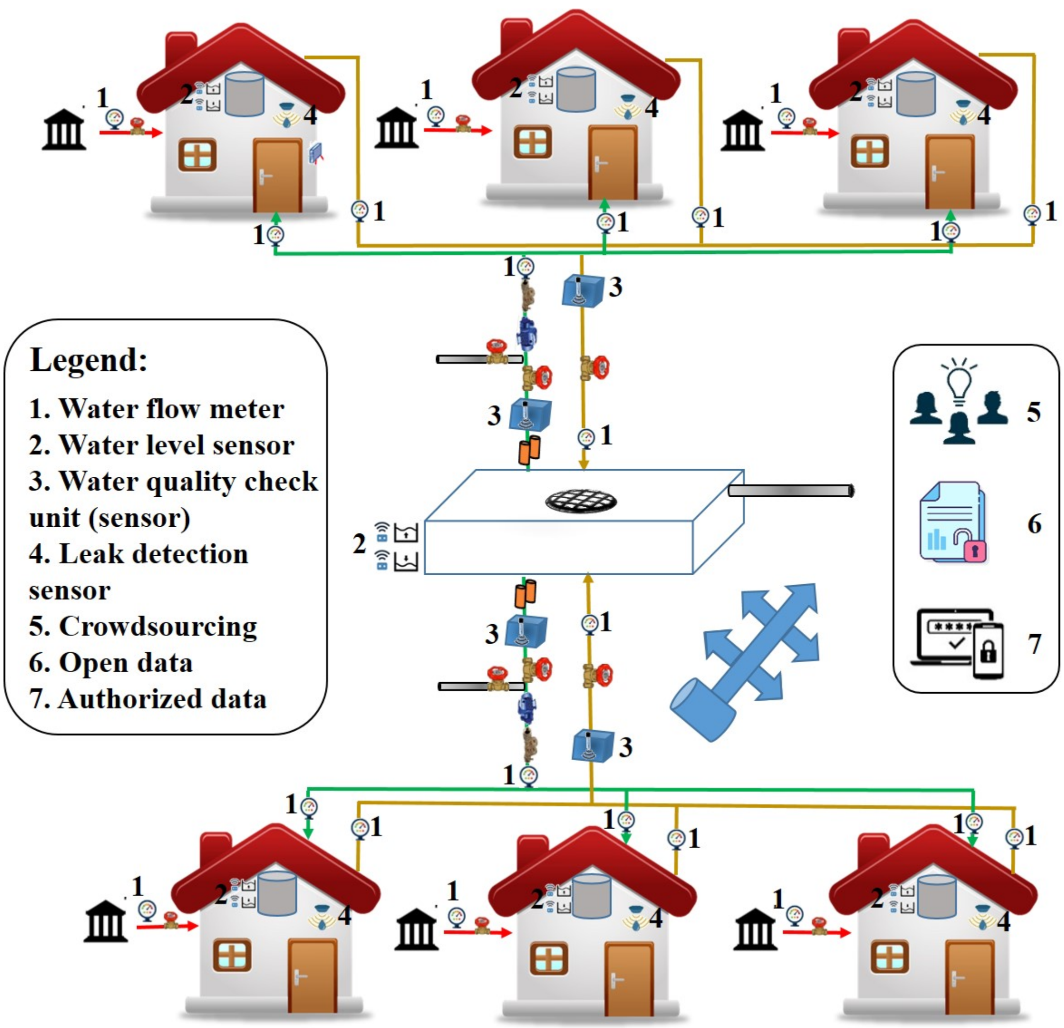


Figure 7.5. Monitoring components of the smart RWH system

- Data processing layer

The data processing layer operates the following tasks: data cleaning, data storage, analysis, and visualization. Data cleaning is the process of guaranteeing data correctness, consistency, and usability (Hu, 2021; and Love et al., 2021). It involves detecting and removing/replacing/correcting inaccurate records from the database (Wehbe and Shahrour, 2021). The smart systems' actions depend highly on the input data (Northcutt et al., 2021). Therefore, cleaning collecting data could significantly help the smart systems avoid inappropriate actions. Data storage implies the containment and integration of collected data in a specific location (database) (Liu et al., 2022). The access, calling, and manipulation of stored data should be secured (e.g., using XQuery) (Robie, 2007). Data analysis converts the collected, cleaned, and stored data into helpful information (Elhoseny et al., 2018; and Tang et al., 2015), which is then used to conduct suitable actions (Elhoseny et al., 2018; and Tang et al., 2015). In this research, data is statistically analyzed. Water quality records are statistically compared to the drinking water standards stated by WHO (WHO, 2011). Statistics concerning water flow, volumes, and levels in the RWH system are analyzed and compared. This analysis helps detect a water leak and allocate water resources to users. Data visualization is the graphical representation of the analyzed data (Da Silva Lopes et al., 2020; and Ji et al., 2019). It forms an effective way of communication, especially where the input data is big data (e.g. temporal, spatial, and spatiotemporal data) (Elhoseny et al., 2018).

Data cleaning, storage, analysis, and visualization are connected to the smart platform. The platform receives real-time data from the water level sensors, water flow meters, and leak detection sensors. It can then detect the water leak in; (i) RWH system, (ii) municipal water system, (iii) indoor household equipment, and (iv) indoor water network. The platform also receives water quality records concerning the treated RWH from the water quality check unit. These real-time records will be available for the users on the platform.

- Control layer and the provided smart services

Following data analysis, the smart system operates control actions of pumps and valves. For example, pumps will be automatically shut down in case of water contamination to avoid a non-potable water supply. Valves will be used to discharge the contaminated water through the discharge pipes. Moreover, back-flushing will be automatically operated to clean and disinfect the RWH system from the contaminants. In case of detecting the water leak, pumps and valves will be temporally turned off to minimize water losses.

The smart system provides several services, including (i) the early detection of water contamination, (ii) the early detection of the water leak, (iii) the smart control and elimination of water contamination to secure potable water supply, (iv) the optimal use of available water resources (e.g., RWH and municipal water supply), (v) incidents notification to users.

7.2.1.3. Smart system reliability analysis

The smart water systems' reliability aims to assess the efficiency and capability of the system to supply the water demand (Karim et al., 2021; and Fulton, 2018). Scholars introduced two indices for the estimation of the systems reliability: (i) time-based reliability (R_e), which designates the ratio of days with a fully met water demand in one year, (ii) and the volumetric reliability (R_v), which denotes the ratio of the annual supplied water to the annual volume of water demand (Preeti and Rahman, 2021; Zhang et al., 2018b; Ursino and Grisi, 2017; and; Basinger et al., 2010).

This research is based on a simulation-based R_e and R_v dataset obtained using a python code on the Kaggle platform. The simulation is carried out in three steps. The first step consists of estimating the daily water demand (D_t) and the daily captured volume of RWH at the roofs (S_t). The second step targets the quantification of the daily volume of rainwater in the RWH tank (V_t), the daily overflow from the RWH tank (O_t), and the daily shortage in covering the needed water demand (X_t). Finally, the last step targets the estimation of both R_e and R_v.

First step: Estimation of D_t and S_t

The daily per capita water consumption rate (DWCR) is identified in view of the WHO recommendation (WHO, 2011). Such rates, along with the residents' statistics, are employed to estimate D_t.

$$\mathrm{Dt} = \frac{\mathrm{DWCRt} * \mathrm{POP}}{1000} \qquad \text{(Equ. 7.1)}$$

Where,

D_t: the water demand in the t^{th} day (m^3/day)

DWCR: the daily per capita water consumption rate in liter/capita/day (l/c/d)

POP: the resident's statistics (capita)

S_t is estimated using Gould and Nissen-Petersen's equation (Gould and Nissen-Petersen, 1999):

$$\mathrm{S_t} = \sum_{j=1}^{n} \mathrm{RFt} * \mathrm{Aj} * \mathrm{RCj} \qquad \text{(Equ. 7.2)}$$

Where,

S_t: the potential daily RWH volume for the shared system in the t^{th} day (m^3/day)

RF_t: daily rainfall for the t^{th} day (m/day)

A_j: area for the j^{th} rooftop (m^2)

RC: runoff and collection efficiency coefficient for the j^{th} rooftop (Judeh and Shahrour, 2021)

t: the day (1 to 365)

j: the building number

n: total number of buildings

- Second step: Estimation of V_t, O_t, and X_t

The estimation of V_t, O_t, and X_t is conducted using the following formulas (Fulton, 2018):

$$O_t = Max(0, V_{t-1} + S_t - D_t - C) \qquad \text{(Equ. 7.3)}$$

$$V_t = \sum_{t=1}^{365} Max(0, V_{t-1} + S_t - D_t - O_t) \qquad \text{(Equ. 7.4)}$$

$$X_t = Min(0, V_{t-1} + S_t - D_t) \qquad \text{(Equ. 7.5)}$$

Where:

O_t: daily overflow from the RWH tank (m^3)

V_t: daily water volume in the RWH tank in the current day

V_{t-1}: daily water volume in the RWH tank in the previous day
S_t: daily captured volume of rainwater at the roof (m^3)
D_t: daily water demand (m^3)
C: tank size/capacity (m^3)
X_t: daily shortage in covering the needed water demand (m^3)
t: day (1 to 365)

- Third step: Estimation of R_e and R_v

R_e and R_v are estimated using the following formulas (Preeti and Rahman, 2021; Zhang et al., 2018b; Ursino and Grisi, 2017; and Basinger et al., 2010):

$$R_e = \frac{N-U}{N} * 100 \qquad \text{(Equ. 7.6)}$$

$$R_v = \frac{AWS}{AWD} * 100 \qquad \text{(Equ. 7.7)}$$

Where:
N: total days in a year (365 days)

U: number of days with water shortage each year ($X_t>0$) (in days)

AWS: annual water supply from the system (in m^3)

AWD: annual water demand (in m^3)

7.2.1.4. Smart system impact to the water scarcity

Following Equ. 3.2 and Table 3.1, the domestic water scarcity level in the study area is estimated. Such level is characterized before and after the adoption of the smart system.

7.2.2. Data collection and application

The application of the proposed methodology is carried out in a small neighborhood in Jenin city, which is located in the North of the West Bank, Palestine (Figure 7.6). Table 7.1 summarizes the characteristics of the six buildings in the neighborhood.

Figure 7.6. BIM representation for the case study

Table 7.1. Characteristics off the buildings in the case study

Parameter	Building number					
	Building 1	Building 2	Building 3	Building 4	Building 5	Building 6
roof area (m^2)	125.6	188.3	160.9	134.6	208.9	148.6
roof material	bricks	concrete	concrete	bricks	concrete	bricks
RC	0.85	0.9	0.9	0.85	0.9	0.85
resident number	7	6	4	8	4	5

However, the water supply continuity is vulnerable and ranges between 2-3 days/week (Jenin Municipality, 2019). Each of the high-altitude, moderate-altitude, and low-altitude locations in the study area are separately supplied (7 days every 3 weeks). Therefore, supply volumes vary considering the altitude of the community and the season (Table 7.2). DWCR of about 100 l/c/d is specified for the study area according to WHO and Palestinian Water Authority (PWA) recommendations (PWA, 2017; and Howard and Bartram, 2003).

Table 7.2. Municipal supply capacity at the neighborhood level

Altitude	Supply rate (m^3/day of supply/neighborhood)*	
	Dry season (May to Oct)	Rainy season (Nov to Apr)
high-altitude,	7	15
moderate-altitude,	10	25
low-altitude	22	35

* neighborhood is adjacent houses in the study area (mainly 5-15 houses)

The community receives an average annual rainfall of around 590 mm/year, while the maximum annual daily rainfall is about 62.3 mm/day (PMA, 2018). Therefore, the number of rainy days (with rainfall depth of more than 1 mm/day) is around 50 days (PMA, 2018). The temporal distribution of the daily rainfall in the study area is shown in Figure 7.7. It is noticed that most of the rainfall falls between October and April.

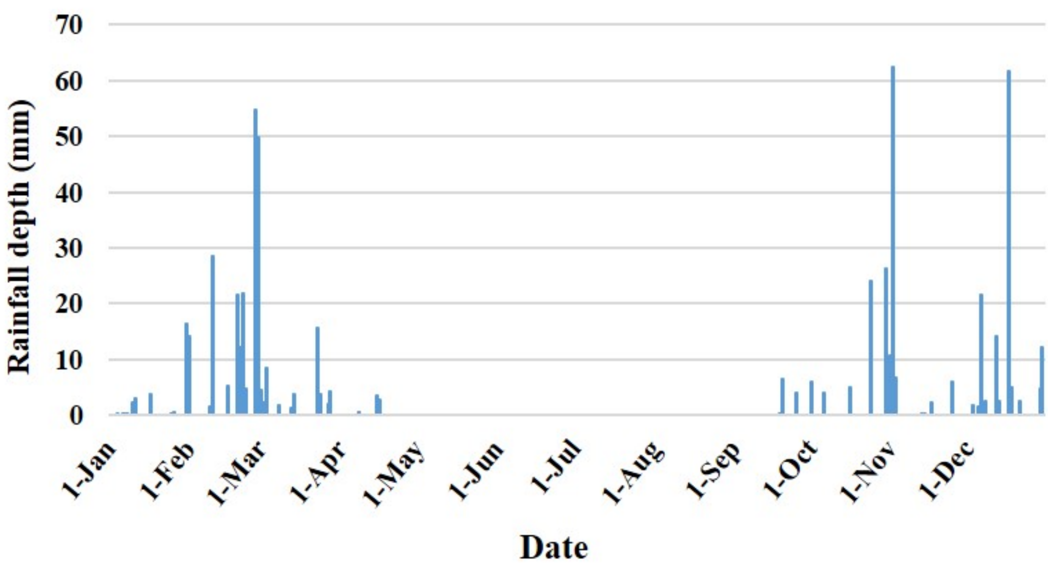


Figure 7.7. Temporal distribution of the daily rainfall in the study area

A spatially distributed RWH samples are collected from 35 residential units in Jenin city (Figure 7.8). The sampling process is carried out between October and December 2021. RWH samples are analyzed at the laboratory for various physiochemical and biological water quality parameters, including pH, Turbidity, Alkalinity, Total Dissolved Solids (TDS), FC, and Residual Chlorine. The sampling and analysis processes are carried out considering the regulations and procedures stated by the WHO (WHO, 2011). Analysis results are then compared to the WHO drinking water standards (WHO, 2011).

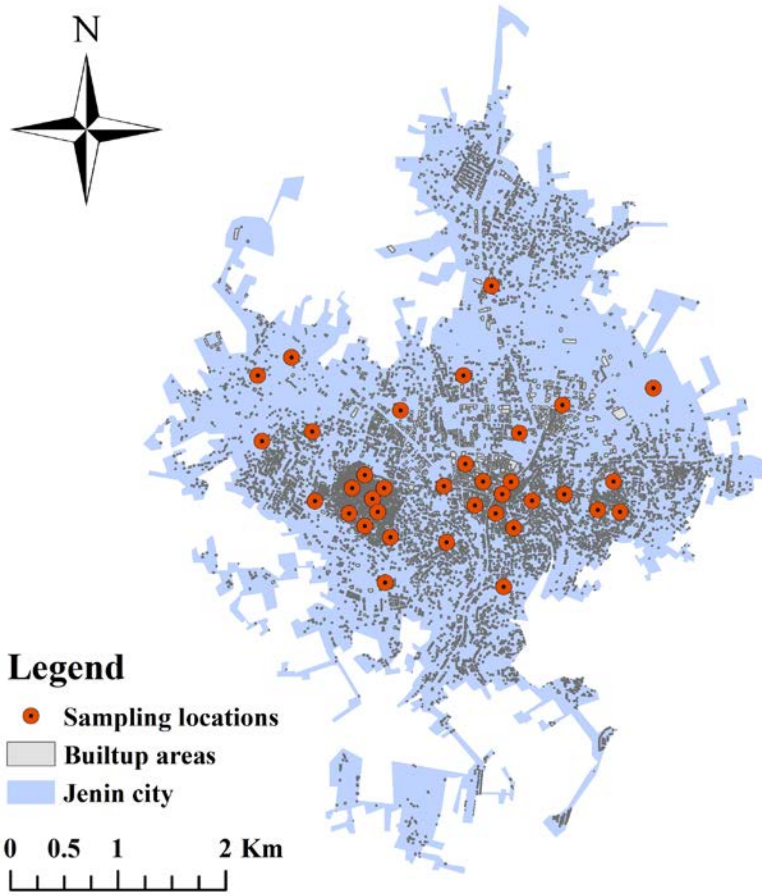


Figure 7.8. RWH sampling locations

7.3. Results and discussion

7.3.1. Smart RWH quality assessment and control

This section assesses the probable physiochemical and biological contamination in the collected RWH samples (Table 7.3). Accordingly, it proposes the most suitable and feasible smart quality control options. Table 7.3 shows that pH, Alkalinity, and TDS are within the acceptable limits of the WHO standards for all the samples. In contrast, 20% of the samples exceed the thresholds of the WHO turbidity standards. Measured turbidity could reach 29 nephelometric turbidity units (NTU), about six times higher than the maximum allowable limit (5 NTU). This could be related to the absence of screens and filters in the practiced RWH systems in the study area (Mahmoud et al., 2018). High turbidity protects the organisms (e.g. bacteria and pathogens) in the drinking water (Muoio et al., 2020; Alenazi et al., 2020; and Soros et al., 2019). In which disinfecting the water (e.g. through chlorination) becomes less efficient. Thus, consuming such water could cause nausea and headaches to users (Muoio et al., 2020; Alenazi et al., 2020; and Soros et al., 2019).

Around 49% of the samples recorded FC levels higher than the WHO standards. The maximum presence of FC in the sampled water reaches 545 CFU/100 ml (around 55 times the maximum allowable limit by WHO). This could be attributed to the extensive use of cesspits for wastewater disposal (Judeh et al., 2021). Leaching from these cesspits could contaminate the underground RWH tank (Al-Batsh and Al-Khatib, 2019; Mahmoud et al., 2018; and Daoud et al., 2011). Birds, animals, and other creatures' fecal waste (on the roof or next to the storage tank) form a main source of FC in the harvested rainwater (Al-Batsh and Al-Khatib, 2019; Mahmoud et al., 2018; and Daoud et al., 2011). Elevated numbers of FC in drinking water are linked the infection by the stomach and intestinal diseases such as diarrhea and nausea (Xu et al., 2022; and Wang and Deng, 2019). The severity of such health problems might be higher and could be life-threatening for people suffering from immune deficiencies (Xu et al., 2022; and Wang and Deng, 2019).

51% of the samples recorded a residual chlorine concentration lower than the minimum recommended concentration. Securing the minimum recommended chlorine concentration in drinking water is important (Goyal and Patel, 2015; and Helbling et al., 2009) to eliminate bacteria's harmful effects and prevent water recontamination during the storage phase (Goyal and Patel, 2015; and Helbling et al., 2009). On the other hand, around 6% of the samples exceed the maximum allowable residual chlorine concentration. High residual chlorine concentrations can react to form hypochlorous acid and hypochlorites (Kali et al., 2021; and Hrudey et al., 2015). Therefore, consuming water with high chlorine concentrations could cause human health problems such as diarrhea, vomiting, stomachaches, poisoning, and bladder cancer (Kali et al., 2021; Pickering et al., 2019; Hrudey et al., 2015; and Källén and Robert, 2000). In addition, high chlorine levels affect the water palatability since it becomes of unpleasant taste and odor (Crider et al., 2018; and Wang et al., 2018).

Results of the physiochemical and biological assessment are compatible with what was found by other scholars for the southern (Al-Batsh and Al-Khatib, 2019; Celik et al., 2017; and Al-Salaymeh et al., 2011), Middle (Mahmoud et al., 2018), and northern (Daoud et al., 2011) parts of the West Bank.

Table 7.3. Physiochemical and biological analysis of RWH samples

Parameter	Min	Mean	Median	Max	WHO standards	Number of contaminated samples (%)
pH	6.92	7.32	7.31	7.75	6.5-8.5	0 (0%)
Turbidity (NTU)	0.18	3.37	0.95	28.50	≤ 5.00	7 (20%)
Alkalinity (mg/L $CaCO_3$)	65.00	169.74	145.00	325.00	≤ 400.00	0 (0%)
TDS (mg/L)	72.00	185.49	175.00	302.00	≤ 600.00	0 (0%)
FC (CFU/100 ml)	0.00	92.23	9.00	545.00	≤ 10.00	17 (48.6%)
Residual Chlorine (mg/L)	0.00	0.27	0.17	2.10	0.2-0.8	20 (57.1%)

Figure 7.9 indicates the negative relationship between residual chlorine and FC among the 35 samples. Such a relationship goes in line with other researchers' findings (Yousefi et al., 2018; Zafarzadeh et al., 2014; and Farooq et al., 2008). It is found that 16 out of the 17 contaminated samples by FC are also out of the stated limits of residual chlorine. They almost fall below the minimum threshold of residual chlorine (0.2 mg/l). So, controlling the levels of residual chlorine in RWH will relatively secure the control of FC as well.

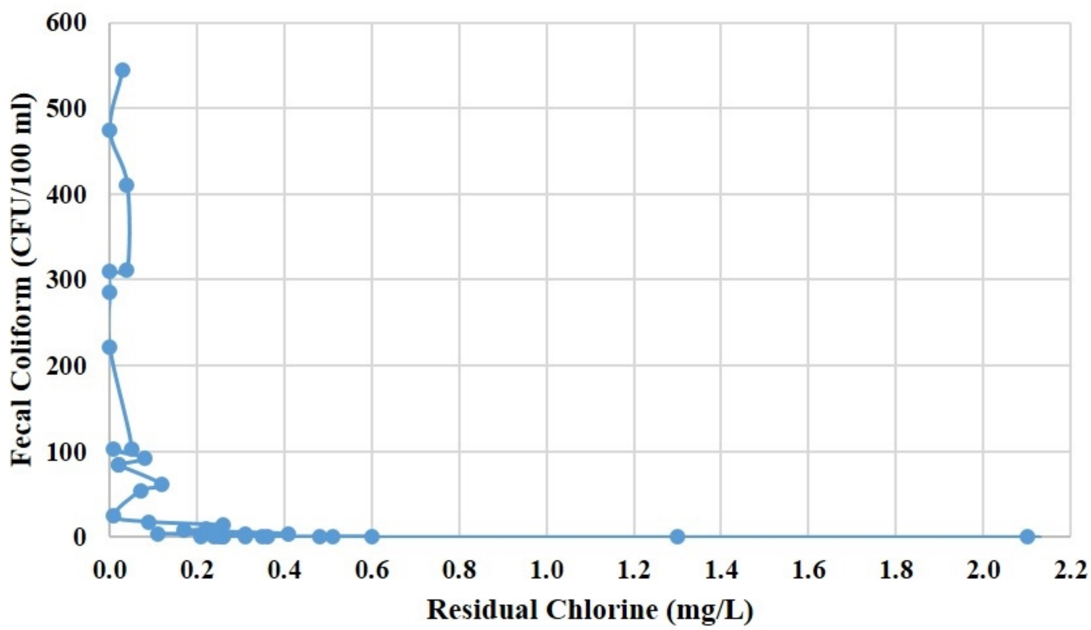


Figure 7.9. Residual chlorine VS. FC among the RWH samples

The physiochemical and biological analysis shows that the control of the RWH turbidity is the first defense line for securing RWH potability in the study area. Such control could be performed by installing the inlet pipe screen, first flush diverter, filter, and overflow pipe screen. The smart monitoring of turbidity could be conducted by assessing the performance of such a defense line. This could be achieved by using (i) smart turbidity sensors and/or (ii) conventional turbidity meters and crowdsourcing.

Controlling the FC and residual chlorine levels is the most important part of the RWH quality control. According to WHO, RWH requires 2 mg/l of chlorine to be disinfected (to inactive the organisms, including FC) (WHO, 2011; and Howard and Bartram, 2003). Thus, WHO recommended an optimal chlorination rate of about 2.5 mg/l to ensure the disinfection of existing FC (WHO, 2011; and Howard and Bartram, 2003). Such disinfection maintains a residual chlorine concentration of a round 0.5 mg/l in the harvested water. This will secure the re-disinfection of future FC contamination during the storage and pumping phases (WHO, 2011; and Howard and Bartram, 2003). Thus, the use and calibration of the chlorination unit are of high importance in the smart RWH system. In addition, residual chlorine sensors/meters are noticeably cheaper than other water quality sensors (including FC sensors/meters) (WHO, 2011; and Howard and Bartram, 2003). So, this research proposes the use of these feasible sensors to control FC and residual chlorine levels through the RWH system in the study area.

7.3.2. Smart RWH/dual system reliability

This section discusses the reliability of the smart RWH system in supplying the residents with their potable water needs. The potential annual RWH volume at the roofs is around 507 m^3. However, the actual annual RWH volume that could be stored and utilized depends on different factors, including the system quality (e.g., percent of the leak) and the size of the RWH storage tank. Figure 7.10 shows the effect of RWH tank size on the annual RWH and overflow volumes. It is found that the annual storage of the RWH increases with the tank size to attain a maximum of about 500 m^3 for a tank size of 112 m^3. This size guarantees no overflow from the tank.

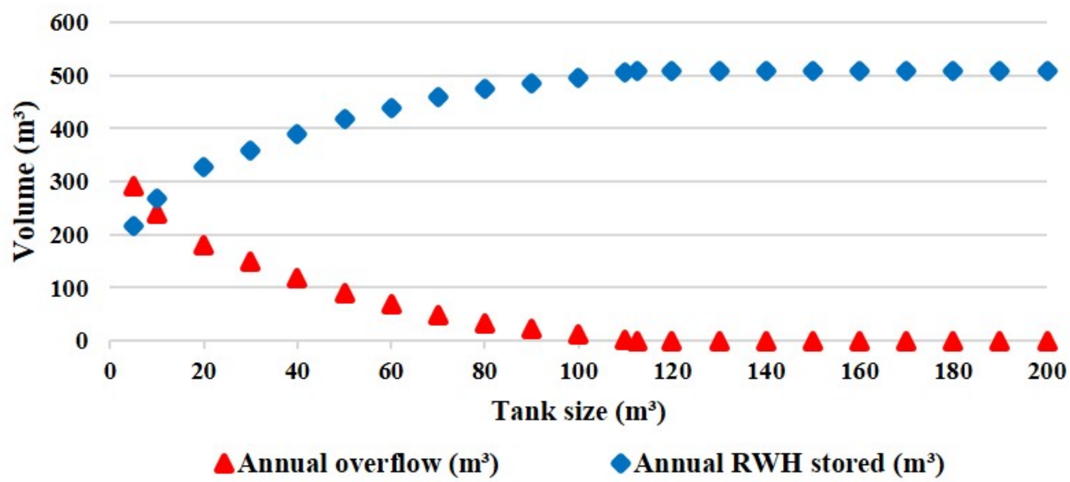


Figure 7.10. Effect of tank size to the annual utilized RWH volumes and the annual overflow

According to Equation 7.1, the annual water demand for the study area is around 1240 m^3/year. The lowest shortage (59%) in water supply could be reached by using the optimal tank size (112.5 m^3). However, using lower sizes is associated with a higher shortage rate. For instance, the tank of 5 m^3 size has 83% shortage in providing the needed water demand (Figure 7.11).

Figure 7.12 displays the influence of the tank size on R_e and R_v of the smart RWH system. R_e is around 12.6% for the 5 m^3 tank. Such a rate covers the water demand for 46 days. The maximum R_e (37.5%) is recorded for the 112.5 m^3 tank, which means that the residents' water demand is covered for 137 days. Concerning R_v, the maximum recorded rate is 41%. This implies providing the residents with an average daily supply of (41 l/c/d).

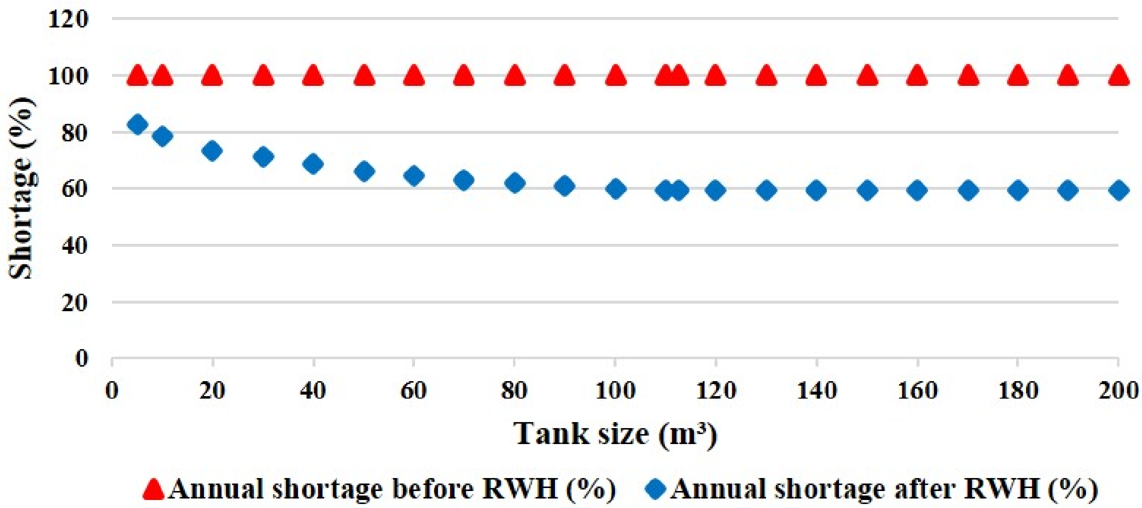


Figure 7.11. Effect of tank size to the annual shortage through the smart RWH system

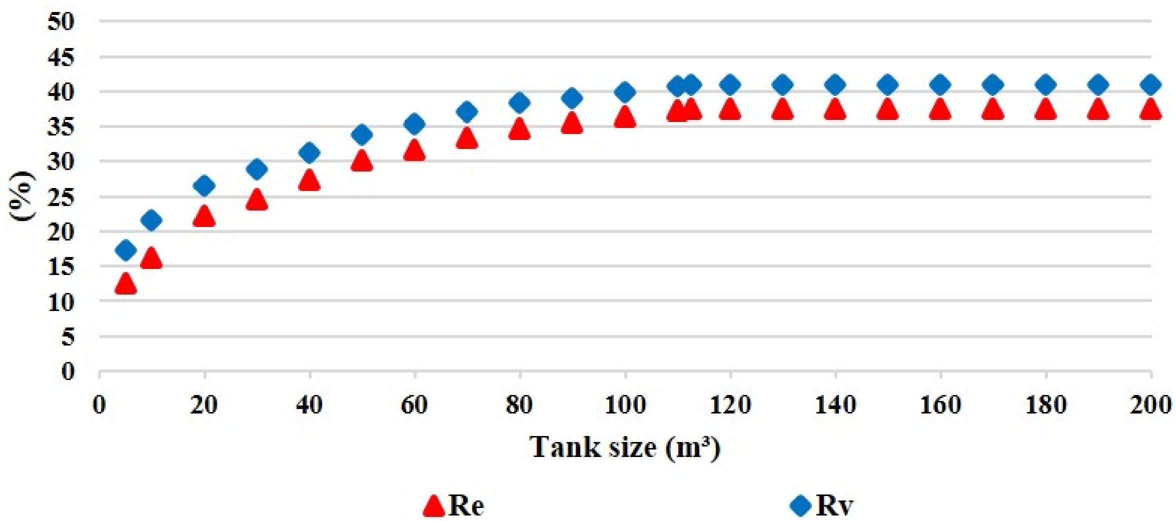
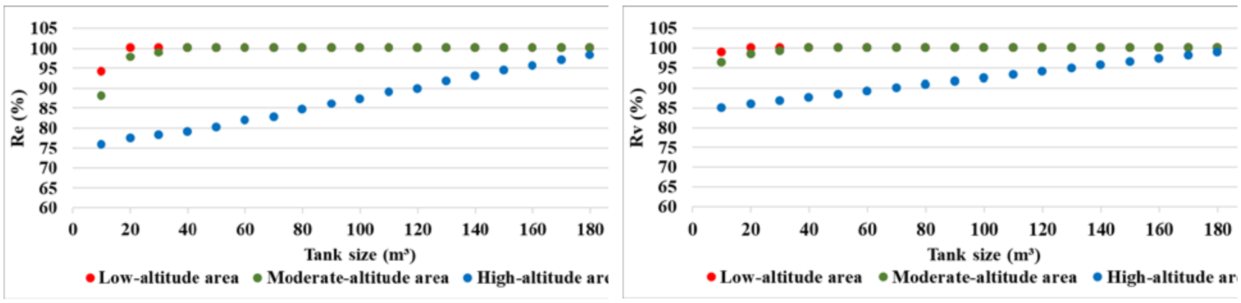


Figure 7.12. Effect of tank size to the Re and Rv through the smart RWH system

To overcome the water shortage with the RWH system, it is necessary to use the dual water system that combines RWH and municipal water supply (Kang and Lansey, 2012). Various researchers discussed the concept and performance of the dual supply system (Burszta-Adamiak and Spychalski, 2021; Rasoulkhani et al., 2019; Cole et al., 2018; Nguyen and Han, 2014; and Kang and Lansey, 2012). Scholars agreed on adopting two independent distribution networks; centralized and decentralized (Burszta-Adamiak and Spychalski, 2021; Rasoulkhani et al., 2019; Cole et al., 2018; Nguyen and Han, 2014; and Kang and Lansey, 2012). This section discusses the dynamic management of the proposed dual water supply system. Such management considers the various spatial levels in the study area (e.g. high-altitude, moderate-altitude, and low-altitude locations).

Figure 7.13 shows the effect of the tank size on R_e and R_v for the smart dual water supply system in light of the existing municipal water supply agenda. Both reliability indices hit 100% for the low-altitude (using tank sizes of 20 m^3) and moderate-altitude locations (using tank sizes of 40 m^3). This implies fully addressing water scarcity (0% of water shortage). Concerning high-altitude locations, R_e ranges between 76% (for 10 m^3 tank) and 98% (for 190 m^3 tank). In addition, R_v ranges between 85% (for 10 m^3 tank) and 99% (for 190 m^3 tank).

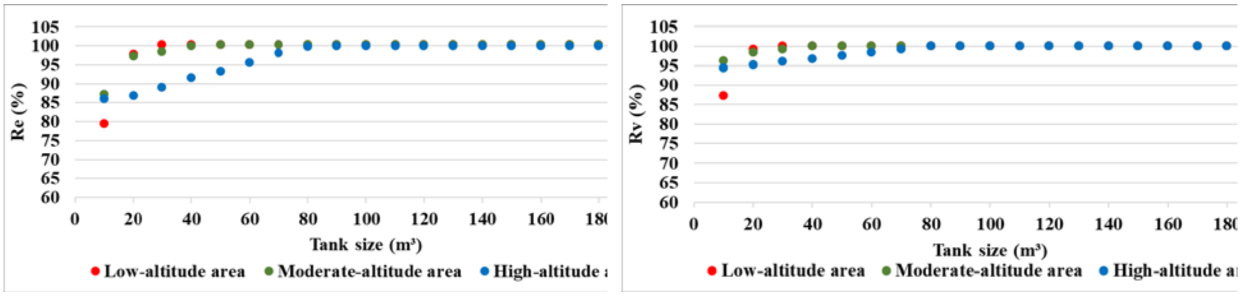


(**a**) (**b**)

Figure 7.13. Impact of tank size on: (a) Re; (b) Rv of the dual supply system considering the existing municipal water supply agenda

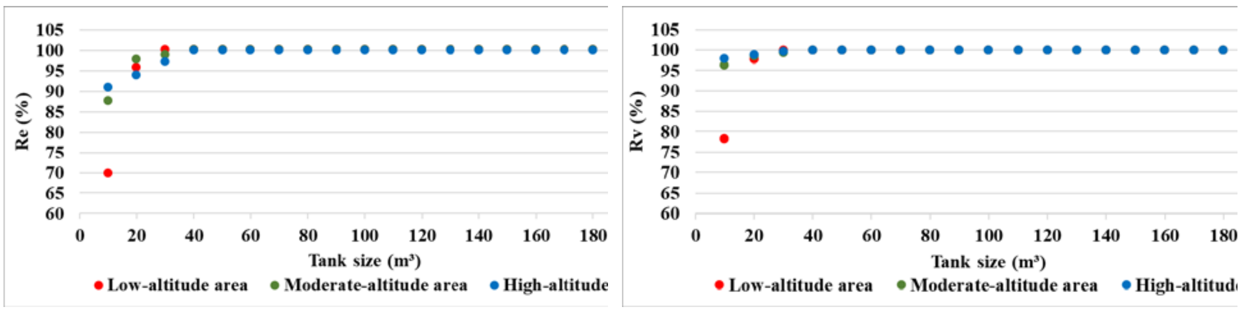
Such results urge the need to propose and examine other municipal water supply agendas in order to achieve 100% reliability for all altitude levels. Thus, two agendas are introduced: (i) agenda A (9, 7, 5 days of water supply per 3 weeks for high-altitude, moderate-altitude, and low-altitude locations, respectively), and agenda B (10, 7, 4 days of water supply per 3 weeks for high-altitude, moderate-altitude, and low-altitude locations, respectively).

Figure 7.14 shows that agenda A could assist in reaching the full reliability (both R_e and R_v) at all altitude levels in the study area. This could be realized by utilizing tank sizes of 30, 40, and 80 m^3 for the low-altitude, moderate-altitude, and high-altitude regions, respectively. On the other hand, it is found that agenda B achieves the same reliability records (100%) by utilizing smaller tank sizes. Tank sizes of 30 m^3 could be used in low-altitude areas, and 40 m^3 could be in moderate-altitude and high-altitude areas (Figure 7.15). Such reliabilities contribute to addressing the acute water scarcity in Jenin City (Table 7.4). Table 7.4. shows that under Agenda B, a “slight water scarcity” could be reached by using a 20 m^3 tank size for all altitudes. Moreover, a “no water scarcity” could be reached by using a 30, 40, and 40 m^3 tank size for the low-altitude, moderate-altitude, and high-altitude regions, respectively. These results indicate the efficiency of the dual water system in fully addressing the water scarcity in the study area compared to the smart RWH system solely. It also shows the need for rescheduling the existing municipal water supply agenda.



(a) (b)

Figure 7.14. Impact of tank size on: (a) Re; (b) Rv of the dual supply system considering agenda A



(a) (b)

Figure 7.15. Impact of tank size on: (a) Re; (b) Rv of the dual supply system considering agenda B

Table 7.4. Impact of tank size on the domestic water scarcity levels of the dual supply system considering agenda B

Tank size	Domestic water scarcity level		
	Low-altitude	**Moderate-altitude**	**High-altitude**
10	Moderate	Slight	Slight
20	Slight	Slight	Slight
30	No scarcity	Slight	Slight
40	No scarcity	No scarcity	No scarcity
50	No scarcity	No scarcity	No scarcity

7.4. Conclusion

This chapter introduced and assessed the reliability of a smart RWH dual water supply system to address the potable water shortage in the arid and semi-arid areas. Results indicated the need for implying a crowdsourcing-based, automated-based treatment and check units in the smart system to control the water turbidity, fecal coliform, and residual chlorine in the harvested rainwater in Jenin city. The smart RWH system showed a capability to cover 41% of the domestic water needs.

Results indicated the efficiency and reliability of the dual water system in addressing the water demand compared to the smart RWH system solely. The dynamic management of the system (including the storage) enables hitting the best reliability by using smaller storage tank size. This could have a significant positive effect on the city's socioeconomic development. Results also showed a need for rescheduling the existing municipal water supply agenda. By adopting the dynamic management and a new supply agenda, the smart dual system showed a capacity to address the water scarcity at all altitude levels in the study area.

Future research could focus on (i) the cost-benefit analysis for the smart RWH system and (ii) the social acceptance investigation for the adoption of the proposed system.

General Conclusion and Perspectives

Water scarcity is found as a serious hazard that threaten the human life, and the agricultural, industrial, and urban development. The management of this hazard is a complex issue due to its multi-contributors: limited water availability, restricted water accessibility, water pollution, increase in the water demand, and the climate change. To address this complexity, this thesis presented an innovative framework for an effective management of the water scarcity. It combined water resources monitoring, data analysis using statistics and Machine Learning, and use of the smart technology. The proposed framework was applied to the West Bank in Palestine, which is considered as an arid to semi-arid area with vulnerable water resources. It consists of four phases. The first phase employed the supply demand balance index (SDBI) to assess the current water scarcity in the West Bank. The consideration of the impact of the climate change and demographic growth constituted an added value to the research. They enable the assessment of future water scarcity. The second phase targeted the protection of the quality of the water resources. An adjusted weighted arithmetic water quality index method (AWAWQI) and Machine Learning were used to assess, predict and preserve the water quality in the West Bank. The index facilitated conducting a large-scale scan of the water quality. It enabled an in-depth analysis of the groundwater contamination, its causes, and potential consequences. The proposed AWAWQI helped in addressing the limitations of the previously adopted weighted arithmetic water quality indices (e.g. uncertain results due to the unrealistic weighting system). Machine Learning (Random Forest) is adopted to predict the groundwater nitrate contamination (GNC) at this most vulnerable aquifer in the study area. Random Forest is an added value to the framework since it has the ability to generate repeated predictions of GNC. It helped in quantifying the relative importance of the input influencing factors. GIS-based spatiotemporal maps indicated an increasing GNC trends in the southern part of the Eocene Aquifer. The third phase combined the GIS, and Gould and Nissen-Petersen's equation to investigate the potential capacity of the rainwater harvesting (RWH) in addressing the water scarcity. The use of GIS enabled the spatiotemporal analysis of input data. The conventional RWH systems showed several limitations: unsecured quality, weak performance, and the water leakage. To overcome these limitations, the last phase proposed a smart RWH system and smart dual water supply system to promote the domestic water security.

Results indicated that seven out of the eleven West Bank governorates are suffering from extreme to acute water scarcity in 2020. One more governorate is expected to suffer from extreme to acute scarcity level by 2050. However, scarcity assessment results are dependent to the adopted downscaled global climate change models, which considers the main limitation of scarcity assessment phase. Around 20% of the wells in the urban areas had experienced potability-related contamination, with high concerns in the shallow wells. More than 95% of the potability-related contaminated samples are found in the Eocene Aquifer (located in the northern part of the West Bank). However, dropping the consideration of heavy metals (due to lack of data) is the main limitation of this resulted indices. Random Forest model successfully attained a maximum and average GNC prediction accuracy of 91.70% and 88.54%, respectively. All water-contaminated samples were observed in areas with improper practices such as the use of cesspits, fertilizers, and pesticides. The protection of water resources in these areas requires urgent intervention to reduce

(i) the wastewater infiltration by installing sanitation systems, septic tanks, and sealed cesspits, and (ii) the use of chemicals and pesticides in areas impacting the groundwater resources.

Results also showed that the RWH can address the current and future domestic water scarcity in the majority of the West Bank governorates. A national policy to share the potential RWH capacity will increase the efficiency of the RWH by a share of the excess water harvesting among the West Bank governorates. The smart RWH/dual system showed its capacity to secure the harvested water potability by implying a crowdsourcing-based, automated-based treatment and check units in the system. These units enabled the control the water turbidity, fecal coliform, and residual chlorine in the harvested rainwater. Results indicated the efficiency and reliability of the smart dual water system in addressing the water demand compared to the smart RWH system solely. By adopting the dynamic management and a new supply agenda, the smart dual system showed a capacity to address the water scarcity at all altitude levels in the study area. They also contributed to getting the best performance by using smaller storage tank size which could promote the city's socioeconomic development.

The knowledge-based framework presented in this thesis forms a step forward in the management of water scarcity in arid and semi-arid areas. It proposed an efficient scarcity-mitigation solutions based on recent approaches. The framework novelty stems from its ability to integrate the technical (e.g. via rainwater water simulations), sustainable (e.g. via climate change and demographic growth models), and technological (e.g. via Machine Learning and smart systems) solutions towards the sustainable mitigation of water scarcity challenges. The framework showed its ability to support the water security in conflict areas with restricted water accessibility. This would support the steadfastness of the suffering communities in their land, which in turn contribute to addressing the water-related migration as stated by the United Nations (UN, 2021; and UN, 2018).

Future research could focus on (i) considering a local climate change model to estimate the projected rainfall and water availability, and (ii) investigating the social acceptance for the adoption of the proposed smart system.

References

1. Abbas, S.; Mahmood, M.; Yaseen, M. Assessing the Potential for Rooftop Rainwater Harvesting and Its Physio and Socioeconomic Impacts, Rawal Watershed, Islamabad, Pakistan. *Environ. Dev. Sustain*. **2021**, *10*, pp.1-22. https://doi.org/10.1007/s10668-021-01422-z.
2. Abbasi, T.; Abbasi, S. A. Sources of Pollution in Rooftop Rainwater Harvesting Systems and Their Control. *Critical Reviews in Environmental Science and Technology* **2011**, *41*, pp.2097–2167. https://doi.org/10.1080/10643389.2010.497438.
3. Abbaspour, K.C.; Faramarzi, M.; Ghasemi, S.S.; Yang, H. Assessing the impact of climate change on water resources in Iran. *Water resources research* **2009**, *45* (10). https://doi.org/10.1029/2008WR007615.
4. Abdelaziz, S.; Gad, M.; Tahan, A. Groundwater Quality Index Based on PCA: Wadi El-Natrun, Egypt. *J. Afr. Earth Sci.* **2020**, *172* (103964). Doi:10.1016/j.jafrearsci.2020.103964.
5. Abd-Elhamid, H.; Javadi, A.; Qahman, K. Impact of Over-Pumping and Sea Level Rise on Seawater Intrusion in Gaza Aquifer (Palestine). *J. Water Clim. Chang.* **2015**, *6*, pp.891–902, doi:10.2166/wcc.2015.055.
6. Abdulla, F. A.; Al-Shareef, A. W. Roof Rainwater Harvesting Systems for Household Water Supply in Jordan. *Desalination* **2009**, *243* (1), pp.195–207, https://doi.org/https://doi.org/10.1016/j.desal.2008.05.013.
7. Abdulla, F.; Abdulla, C.; Eslamian, S. *Concept and Technology of Rainwater Harvesting: Handbook of Water Harvesting and Conservation.*; John Wiley & Sons Ltd: New Jersey, United States, 2021; pp 1–16.
8. Abul Hasan, M.; Ahmad, S.; Mohammed, T. Groundwater Contamination by Hazardous Wastes. *Arab. J. Sci. Eng.* **2021**, *46*, pp.4191–4212. doi:10.1007/s13369-021-05452-7.
9. Abu-Zreig, M.; Ababneh, F.; Abdullah, F. Assessment of Rooftop Rainwater Harvesting in Northern Jordan. *Phys. Chem. Earth* **2019**, *114* (1), pp.1-10. https://doi.org/10.1016/j.pce.2019.08.002.
10. Adams, E. A.; Stoler, J.; Adams, Y. Water Insecurity and Urban Poverty in the Global South: Implications for Health and Human Biology. *Am. J. Hum. Biol.* **2019**, *32* (1), pp.1-12. https://doi.org/https://doi.org/10.1002/ajhb.23368.
11. Adams, R.; Quinn, P.; Barber, N.; Burke, S. Identifying Flow Pathways for Phosphorus Transport Using Observed Event Forensics and the CRAFT (Catchment Runoff Attenuation Flux Tool). *Water* **2020**, *12* (1081). https://doi.org/10.3390/w12041081.
12. Adimalla, N. Groundwater quality for drinking and irrigation purposes and potential health risks assessment: a case study from semi-arid region of South India. *Exposure and health* **2019**, *11* (2), pp.109-123. https://doi.org/10.1007/s12403-018-0288-8.
13. Ahmad, N.; Sultana, R.; Yoshida, M.; Salahuddin, M. Groundwater Contamination Issues in Chiniot Area, Punjab, Pakistan. *IJESD* **2020**, *11*, pp.123–127. doi:10.18178/ijesd.2020.11.3.1237.
14. Ahmad, S.; Simonovic, S.P. System dynamics modeling of reservoir operations for flood management. *Journal of computing in civil engineering* **2000**, *14* (3), pp.190-198. https://doi.org/10.1061/(ASCE)0887-3801(2000)14:3(190).
15. Aish, A. Drinking Water Quality Assessment of the Middle Governorate in the Gaza Strip, Palestine. *Water Resour. Ind.* **2013**, *4*, pp.13–20. doi:10.1016/j.wri.2013.09.004.

16. Akbari, M.; Alizadeh-Noughani, M. Assessing early warning for desertification hazard based on E-SMART indicators in arid regions of northeastern Iran. *Journal of Arid Environments*. **2019**, *174* (104086). DOI: 10.1016/j.jaridenv.2019.104086.
17. Al Aboodi, A.; Abbas, S.; Ibrahim, H. Spatial Distribution of Groundwater Quality Index in Safwan-Zubair Area. *J. Eng. Appl. Sci.* **2018**, *13*, pp.6091–6098. doi:10.3923/jeasci.2018.6091.6098.
18. Alaizari, H.; Achaouch, A.; Fadli, M.; Al-Kadse, F. Analytical Groundwater Contamination by Heavy Metals. *Appl. J. Environ. Eng. Sci.* **2018**, *4*, pp.299–308. doi:10.48422/IMIST.PRSM/ajees-v4i3.11254.
19. Alawna, S.; Shadeed, S. Rooftop Rainwater Harvesting to Alleviate Domestic Water Shortage in the West Bank, Palestine. *An-Najah Univ. J. Res. (N. Sc.)* **2021**, *35* (1), pp.83-108.
20. Al-Batsh, N.; Al-Khatib, I. A.; Ghannam, S.; Anayah, F.; Jodeh, S.; Hanbali, G.; Khalaf, B.; van der Valk, M. Assessment of Rainwater Harvesting Systems in Poor Rural Communities: A Case Study from Yatta Area, Palestine. *Water* **2019**, *11* (3). https://doi.org/10.3390/w11030585.
21. Aleem, M.; Shun, C.J.; Li, C.; Aslam, A.M.; Yang, W.; Nawaz, M.I.; Ahmed, W.S.; Buttar, N.A. Evaluation of Groundwater Quality in the Vicinity of Khurrianwala Industrial Zone, Pakistan. *Water* **2018**, *10* (1321). doi:10.3390/w10101321.
22. Alenazi, M.; Hashim, K. S.; Hassan, A. A.; Muradov, M.; Kot, P.; Abdulhadi, B. Turbidity Removal Using Natural Coagulants Derived from the Seeds of Strychnos Potatorum: Statistical and Experimental Approach. *{IOP} Conference Series: Materials Science and Engineering* **2020**, *888* (1). https://doi.org/10.1088/1757-899x/888/1/012064.
23. Alexakis, D.E. Meta-Evaluation of Water Quality Indices. Application into Groundwater Resources. *Water* **2020**, *12* (1890). doi:10.3390/w12071890.
24. Alexakis, D.E. Water Quality Indices: Current and Future Trends in Evaluating Contamination of Groundwater Resources. *Water* **2021**, *13* (401), doi:10.3390/w13040401.
25. Alim, M. A.; Rahman, A.; Tao, Z.; Samali, B.; Khan, M. M.; Shirin, S. Suitability of Roof Harvested Rainwater for Potential Potable Water Production: A Scoping Review. *Journal of Cleaner Production* **2020**, *248* (119226). https://doi.org/https://doi.org/10.1016/j.jclepro.2019.119226.
26. Almasri, M. N.; Ghabayen, S. M. Analysis of Nitrate Contamination of Gaza Coastal Aquifer, Palestine. *Journal of Hydrologic Engineering* **2008**, *13* (3). https://doi.org/10.1061/(ASCE)1084-0699(2008)13:3(132).
27. Almasri, M. N.; Judeh, T. G.; Shadeed, S. M. Identification of the Nitrogen Sources in the Eocene Aquifer Area (Palestine). *Water* **2020**, *12* (4). https://doi.org/10.3390/w12041121.
28. Almasri, M. N.; Kaluarachchi, J. J. Assessment and Management of Long-Term Nitrate Pollution of Ground Water in Agriculture-Dominated Watersheds. *Journal of Hydrology* **2004**, *295* (1–4). https://doi.org/10.1016/j.jhydrol.2004.03.013.
29. Al-Najjar, H.; Ceribasi, G.; Dogan, E.; Abualtayef, M.; Qahman, K.; Shaqfa, A. Stochastic time-series models for drought assessment in the Gaza Strip (Palestine). *Journal of Water and Climate Change* **2020**, *11* (S1), pp.85–114. https://doi.org/10.2166/wcc.2020.330.
30. Al-Najjar, H.; Ceribasi, G.; Dogan, E.; Qahman, K.; Abualtayef, M.; Ceyhunlu, A.I. Statistical modeling of spatial and temporal vulnerability of groundwater level in the Gaza Strip (Palestine). *H2Open Journal* **2021**, *4* (1), pp.352-365. https://doi.org/10.2166/h2oj.2021.120.

31. Al-Omran, A.; Al-Barakah, F.; Altuquq, A.; Aly, A.; Nadeem, M. Drinking water quality assessment and water quality index of Riyadh, Saudi Arabia. *Water Quality Research Journal* **2015**, *50* (3), pp.287–296. https://doi.org/10.2166/wqrjc.2015.039.
32. Al-Salaymeh, A.; Al-Khatib, I. A.; Arafat, H. A. Towards Sustainable Water Quality: Management of Rainwater Harvesting Cisterns in Southern Palestine. *Water Resources Management* **2011**, *25* (6), pp.1721–1736. https://doi.org/10.1007/s11269-010-9771-0.
33. Alshehri, M.; Bhardwaj, A.; Kumar, M.; Mishra, S.; Gyani, J. Cloud and IoT based Smart Architecture for Desalination Water Treatment. *Environmental Research* **2021**, *195*. DOI: 10.1016/j.envres.2021.110812.
34. Alwan, I. A.; Aziz, N. A.; Hamoodi, M. N. Potential Water Harvesting Sites Identification Using Spatial Multi-Criteria Evaluation in Maysan Province, Iraq. *ISPRS Int. J. Geo-Inf.* **2020**, *9* (4), pp.1-17. https://doi.org/10.3390/ijgi9040235.
35. Anagnostopoulos, T. A Predictive Vehicle Ride Sharing Recommendation System for Smart Cities Commuting. *Smart Cities* **2021**, *4* (1), pp.177–191. https://doi.org/10.3390/smartcities4010010.
36. Anayah, F.M.; Almasri, M.N. Trends and Occurrences of Nitrate in the Groundwater of the West Bank, Palestine. *Appl. Geogr.* **2009**, *29*, pp.588–601. doi:10.1016/j.apgeog.2009.01.004.
37. Anser, M. K.; Islam, T.; Khan, M. A.; Zaman, K.; Nassani, A. A.; Askar, S. E.; Abro, M. M. Q.; Kabbani, A. Identifying the Potential Causes, Consequences, and Prevention of Communicable Diseases (Including COVID-19). *BioMed Res. Int.* **2020**, *2020* (8894006), pp.1-13, https://doi.org/10.1155/2020/8894006.
38. Applied Research Institute Jerusalem (ARIJ). *State of the Environment in the State of Palestine;* ARIJ: Jerusalem, Palestine, 2015; Pp. 1-23.
39. Asati, S.R.; Rathore, S.S. Comparative study of stream flow prediction models. *International Journal of Life Sciences Biotechnology and Pharma Research* **2012**, *1* (2), pp.139-151.
40. Ayadi, Y.; Mokadem, N.; Besser, H.; Redhaounia, B.; Khelif, F.; Harabi, S.; Nasri, T.; Hamed Y. Statistical and geochemical assessment of groundwater quality in Teboursouk area (Northwestern Tunisian Atlas). *Environ Earth Sci* **2018**, *77*, 349. https://doi. org/10.1007/s12665-018-7523-2.
41. Ayt Ougougdal, H.; Yacoubi Khebiza, M.; Messouli, M.; Lachir, A. Assessment of Future Water Demand and Supply under IPCC Climate Change and Socio-Economic Scenarios, Using a Combination of Models in Ourika Watershed, High Atlas, Morocco. *Water* **2020**, *12* (6). https://doi.org/10.3390/w12061751.
42. Baalousha, H. Vulnerability, Probability and Groundwater Contamination Risk. *Environ. Earth Sci*. **2017**, *76* (384). *doi:*10.1007/s12665-017-6634-5.
43. Bai, Y.; Ochuodho, T.O.; Yang, J. Impact of land use and climate change on water-related ecosystem services in Kentucky, USA. *Ecological Indicators* **2019**, *102,* pp.51-64. https://doi.org/10.1016/j.ecolind.2019.01.079.
44. Balan, I.; Shivakumar, M.; Kumar, P. An Assessment of Ground Water Quality Using Water Quality Index in Chennai Tamil Nadu, India. *Chron. Young Sci.* **2012**, *3,* pp.146–150, doi:10.4103/2229-5186.98688.
45. Band, S. S.; Janizadeh, S.; Pal, S. C.; Chowdhuri, I.; Siabi, Z.; Norouzi, A.; Melesse, A. M.; Shokri, M.; Mosavi, A. Comparative Analysis of Artificial Intelligence Models for Accurate Estimation of Groundwater Nitrate Concentration. *Sensors (Switzerland)* **2020**, *20* (20), pp.1–23. https://doi.org/10.3390/s20205763.

46. Banda, T.; Kumarasamy, M. A Review of the Existing Water Quality Indices (WQIs). *Pollut. Res.* **2020**, *39*, pp.489–514.
47. Barbieri, M.; Barberio, M.D.; Banzato, F.; Billi, A.; Boschetti, T.; Franchini, S.; Gori, F.; Petitta, M. Climate change and its effect on groundwater quality. *Environmental Geochemistry and Health* **2021**, *10*, pp.1-12. https://doi.org/10.1007/s10653-021-01140-5.
48. Barkat, A.; Bouaicha, F.; Bouteraa, O.; Mester, T.; Ata, B.; Balla, D.; Rahal, Z.; Szabó, G. Assessment of Complex Terminal Groundwater Aquifer for Different Use of Oued Souf Valley (Algeria) Using Multivariate Statistical Methods, Geostatistical Modeling, and Water Quality Index. *Water* **2021**, *13* (11). https://doi.org/10.3390/w13111609.
49. Basinger, M.; Montalto, F.; Lall, U. A Rainwater Harvesting System Reliability Model Based on Nonparametric Stochastic Rainfall Generator. *Journal of Hydrology* **2010**, *392* (3), pp.105–118. https://doi.org/https://doi.org/10.1016/j.jhydrol.2010.07.039.
50. Behera, A.K.; Pradhan, R.M.; Kumar, S.; Chakrapani, G.J.; Kumar, P. Assessment of Groundwater Flow Dynamics Using MODFLOW in Shallow Aquifer System of Mahanadi Delta (East Coast), India. *Water* **2022**, *14* (611). https://doi.org/10.3390/w14040611.
51. Behzadian, K.; Kapelan, Z.; Mousavi, J.; Alani, A. Can Smart Rainwater Harvesting Schemes Result in the Improved Performance of Integrated Urban Water Systems? *Environmental Science and Pollution Research* **2018**, *25*. https://doi.org/10.1007/s11356-017-0546-5.
52. Bernard, B.; Joyfred, A. Contribution of Rainfall on Rooftop Rainwater Harvesting and Saving on the Slopes of Mt. Elgon, East Africa. *The Sci. World J.* **2020**, *2020* (7196342), pp.1–11. https://doi.org/10.1155/2020/7196342.
53. Bhadra, A.; Bandyopadhyay, A.; Singh, R.; Raghuwanshi, N.S. Rainfall-runoff modeling: comparison of two approaches with different data requirements. *Water Resources Management* **2010**, *24* (1), pp.37-62. https://doi.org/10.1007/s11269-009-9436-z.
54. Bin Hariz, M.; Said, D.; Mouftah, H. T. A Dynamic Mobility Traffic Model Based on Two Modes of Transport in Smart Cities. *Smart Cities* **2021**, *4* (1), pp.253–270. https://doi.org/10.3390/smartcities4010016.
55. Biswas, B.; Mandal, B. Construction and Evaluation of Rainwater Harvesting System for Domestic Use in a Remote and Rural Area of Khulna, Bangladesh. *Int. Sch. Res. Notices* **2014**, *2014* (751952), pp.1-6, https://doi.org/10.1155/2014/751952.
56. Boakye, E.; John-Jackson, N. Quantifying Rooftop Rainwater Harvest Potential: Case of Takoradi Polytechnic in Takoradi, Ghana. *IJSR* **2015**, *5*, pp.6–391. https://doi.org/10.21275/v5i6.NOV164223.
57. Bouderbala, A. Assessment of Water Quality Index for the Groundwater in the Upper Cheliff Plain, Algeria. *J. Geol. Soc. India* **2017**, *90*, pp.347–356. doi:10.1007/s12594-017-0723-7.
58. Boyacioglu, H. Development of a Water Quality Index Based on a European Classification Scheme. *Water SA* **2007**, *33*, pp.101–106. doi:10.4314/wsa.v33i1.47882.
59. Boyacioglu, H. Utilization of the Water Quality Index Method as a Classification Tool. *Environ. Monit. Assess.* **2010**, *167*, pp.115–124. doi:10.1007/s10661-009-1035-1.
60. Breiman, L. Random Forests. *Machine Learning* **2001**, *45* (1). https://doi.org/10.1023/A:1010933404324.
61. Brown, R.M.; McClelland, N.I.; Deininger, R.A.; Tozer, R.G. A Water Quality Index: Do We Dare? *Water Sewage Works* **1970**, *117*, pp.339–343.

62. Budiarti, R.; Sukaridhoto, S.; Hariadi, M.; Purnomo, M. Big Data Technologies using SVM (Case Study: Surface Water Classification on Regional Water Utility Company in Surabaya). *International Conference on Computer Science, Information Technology, and Electrical Engineering (ICOMITEE)* **2019**, pp.94-101. doi: 10.1109/ICOMITEE.2019.8920823.
63. Burszta-Adamiak, E.; Spychalski, P. Water Savings and Reduction of Costs through the Use of a Dual Water Supply System in a Sports Facility. *Sustainable Cities and Society* **2021**, *66* (102620). https://doi.org/https://doi.org/10.1016/j.scs.2020.102620.
64. Canion, A.; McCloud, L.; Dobberfuhl, D. Predictive Modeling of Elevated Groundwater Nitrate in a Karstic Spring-Contributing Area Using Random Forests and Regression-Kriging. *Environmental Earth Sciences* **2019**, *78* (9). https://doi.org/10.1007/s12665-019-8277-1.
65. Carminati, M.; Sinha, G. R.; Mohdiwale, S.; Ullo, S. L. Miniaturized Pervasive Sensors for Indoor Health Monitoring in Smart Cities. *Smart Cities* **2021**, *4* (1), pp.146–155. https://doi.org/10.3390/smartcities4010008.
66. Castro, M.; Jara, A. J.; Skarmeta, A. F. G. Smart Lighting Solutions for Smart Cities. *27th International Conference on Advanced Information Networking and Applications Workshops* **2013**, pp.1374–1379. https://doi.org/10.1109/WAINA.2013.254.
67. Celik, I.; Tamimi, L. M. A.; Al-Khatib, I. A.; Apul, D. S. Management of Rainwater Harvesting and Its Impact on the Health of People in the Middle East: Case Study from Yatta Town, Palestine. *Environmental Monitoring and Assessment* **2017**, *189* (6). https://doi.org/10.1007/s10661-017-5970-y.
68. CEO. *Water Mandate Driving Harmonization of Water-Related Terminology*; CEO: Oakland, USA, 2014; Pp. 1-16.
69. Charcosset, C. Classical and Recent Developments of Membrane Processes for Desalination and Natural Water Treatment. *Membranes* **2022**, *12* (267). https://doi.org/10.3390/membranes12030267.
70. Chaudhary, V.; Satheeshkumar, S. Assessment of groundwater quality for drinking and irrigation purposes in arid areas of Rajasthan, India. *Applied Water Science* **2018**, *8* (8), pp.1-17. https://doi.org/10.1007/s13201-018-0865-9.
71. Chawla, I.; Karthikeyan, L.; Mishra, A.K. A review of remote sensing applications for water security: Quantity, quality, and extremes. *Journal of Hydrology* **2020**, *585*. https://doi.org/10.1016/j.jhydrol.2020.124826.
72. Chitsaz, N.; Azarnivand, A. Water scarcity management in arid regions based on an extended multiple criteria technique. *Water Resources Management* **2017**, *31* (1), pp.233-250. https://doi.org/10.1007/s11269-016-1521-5.
73. Chourabi, H.; Nam, T.; Walker, S.; Gil-Garcia, J. R.; Mellouli, S.; Nahon, K.; Pardo, T. A.; Scholl, H. J. Understanding Smart Cities: An Integrative Framework. *45th Hawaii International Conference on System Sciences* **2012**, pp.2289–2297. https://doi.org/10.1109/HICSS.2012.615.
74. Christensen, J.; Kanikicharla, K.; et al. Climate phenomena and their relevance for future regional climate change. In *Climate change 2013 the physical science basis: Working group I contribution to the fifth assessment report of the intergovernmental panel on climate change*, Cambridge University: Cambridge, England, 2013; pp. 1217-1308.
75. Chubaka, C. E.; Whiley, H.; Edwards, J. W.; Ross, K. E. Lead, Zinc, Copper, and Cadmium Content of Water from South Australian Rainwater Tanks. *International journal of environmental research and public health* **2018**, *15* (7). https://doi.org/10.3390/ijerph15071551.

76. Cochran, W.G. Sampling Techniques 2. *Biometr. Z.* **1965**, *7* (203), doi:10.1002/bimj.19650070312.
77. Cole, J.; Sharvelle, S.; Fourness, D.; Grigg, N.; Roesner, L.; Haukaas, J. Centralized and Decentralized Strategies for Dual Water Supply: Case Study. *Journal of Water Resources Planning and Management* **2018**, *144* (5017017). https://doi.org/10.1061/(ASCE)WR.1943-5452.0000856**.**
78. Comly, H. H. Cyanosis in Infants Caused by Nitrates in Well Water. *JAMA: The Journal of the American Medical Association* **1987**, *257* (20). https://doi.org/10.1001/jama.1987.03390200128027.
79. Costabile, P.; Costanzo, C.; Ferraro, D.; Macchione, F.; Petaccia, G. Performances of the New HEC-RAS Version 5 for 2-D Hydrodynamic-Based Rainfall-Runoff Simulations at Basin Scale: Comparison with a State-of-the Art Model. *Water* **2020**, *12* (2326). https://doi.org/10.3390/w12092326.
80. Courbage, Y.; Hamad, B. A.; Zagha, A. *Palestine 2030 - Demographic Change: Opportunities for Development*; UNFBA: Ramallah, Palestine, 2016; Pp. 1-275.
81. Crider, Y.; Sultana, S.; Unicomb, L.; Davis, J.; Luby, S. P.; Pickering, A. J. Can You Taste It? Taste Detection and Acceptability Thresholds for Chlorine Residual in Drinking Water in Dhaka, Bangladesh. *Science of The Total Environment* **2018**, *613–614*, pp.840–846. https://doi.org/https://doi.org/10.1016/j.scitotenv.2017.09.135.
82. Criollo, R.; Velasco, V.; Nardi, A.; De Vries, L.M.; Riera, C.; Scheiber, L.; Jurado, A.; Brouyère, S.; Pujades, E.; Rossetto, R.; Vázquez-Suñé, E. AkvaGIS: An open source tool for water quantity and quality management. *Computers & Geosciences* **2019**, *127*, pp.123-132. https://doi.org/10.1016/j.cageo.2018.10.012.
83. Cude, C. Oregon Water Quality Index: A Tool for Evaluating Water Quality Management Effectiveness. *JAWRA* **2001**, *37*, pp.125–137. doi:10.1111/j.1752-1688.2001.tb05480.x.
84. Curto, D.; Franzitta, V.; Guercio, A. A Review of the Water Desalination Technologies. *Appl. Sci*. **2021**, *11* (670). https://doi.org/10.3390/app11020670.
85. Da Silva Lopes, M. A.; Dória Neto, A. D.; De Medeiros Martins, A. Parallel T-SNE Applied to Data Visualization in Smart Cities. *IEEE Access* **2020**, *8*, pp.11482–11490. https://doi.org/10.1109/ACCESS.2020.2964413.
86. Daghara, A.; Al-Khatib, I.A.; Al-Jabari, M. Quality of Drinking Water from Springs in Palestine: West Bank as a Case Study. *J. Environ. Public Health* **2019**, *2019* (8631732). doi:10.1155/2019/8631732.
87. Damkjaer, S.; Taylor, R. The Measurement of Water Scarcity: Defining a Meaningful Indicator. *Ambio* **2017**, *46* (5), pp.513–531. https://doi.org/10.1007/s13280-017-0912-z.
88. Dao, D. A.; Tran, S. H.; Dang, H. T. T.; Nguyen, V.-A.; Nguyen, V. A.; Do, C. v; Han, M. Assessment of Rainwater Harvesting and Maintenance Practice for Better Drinking Water Quality in Rural Areas. *Journal of Water Supply: Research and Technology-Aqua* **2021**, *70* (2), pp.202–216. https://doi.org/10.2166/aqua.2021.076.
89. Daoud, A. K.; Swaileh, K. M.; Hussein, R. M.; Matani, M. Quality Assessment of Roof-Harvested Rainwater in the West Bank, Palestinian Authority. *Journal of water and health* **2011**, *9* (3), pp.525–533. https://doi.org/10.2166/wh.2011.148.

90. Das, D. A Case Study of Rainwater Harvesting: Its Desing, Factors Affecting and Cost Installation of AIIMS Hospital, Raipur. *SSRN Electronic Journal* **2019,** *10*. https://doi.org/10.2139/ssrn.3776112.
91. De Sousa Cordão, M. J.; Rufino, I. A. A.; Alves, P. B. R.; Filho, M. N. M. B. Water Shortage Risk Mapping: A GIS-MCDA Approach for a Medium-Sized City in the Brazilian Semi-Arid Region. *Urban Water J.* **2020**, *17* (7), pp.642–655. https://doi.org/10.1080/1573062X.2020.1804596.
92. Di Nardo, A.; Di Natale, M.; Santonastaso, G.F.; Venticinque, S. An Automated Tool for Smart Water Network Partitioning. *Water Resour. Manag.* **2013**, *27*, pp.4493–4508. DOI: 10.1007/s11269-013-0421-1.
93. Dong, J.; Wang, G.; Yan, H.; Xu, J.; Zhang, X. A Survey of Smart Water Quality Monitoring System. *Environmental Science and Pollution Research* **2015**, *22* (7), pp.4893–4906. https://doi.org/10.1007/s11356-014-4026-x.
94. Ducci, D. An Easy-to-Use Method for Assessing Nitrate Contamination Susceptibility in Groundwater. *Geofluids* **2018**, *2018*. https://doi.org/10.1155/2018/1371825.
95. Dunnette, D.A. A Geographically Variable Water Quality Index Used in Oregon. *J. Water Pollut. Control Fed.* **1979**, *51*, pp.53–61.
96. Durán-Sánchez, A.; Álvarez-García, J.; Del Río-Rama, M.C. Sustainable Water Resources Management: A Bibliometric Overview. *Water* **2018**, *10* (1191). https://doi.org/10.3390/w10091191.
97. Efron, S.; Fischbach, J.R.; Blum, I.; Karimov, R.I.; Moore, M. The public health impacts of Gaza's water crisis: analysis and policy options. *Rand Health Quarterly* **2019**, *8* (3).
98. Ejigu, M. Overview of water quality modeling. *Cogent Engineering* **2021**, *8* (1). DOI: 10.1080/23311916.2021.1891711.
99. El Alfy, M.; Lashin, A.; Al-Arif, N.; Al-Bassam, A. Groundwater characteristics and pollution assessment using integrated hydrochemical investigations GIS and multivariate geostatistical techniques in arid areas. *Water Resour Manag* **2015**, *29*, pp.5593–5612. DOI: 10.1007/s11269-015-1136-2.
100. el Baba, M.; Kayastha, P.; Huysmans, M.; de Smedt, F. Evaluation of the Groundwater Quality Using the Water Quality Index and Geostatistical Analysis in the Dier Al-Balah Governorate, Gaza Strip, Palestine. *Water* **2020**, *12* (1). https://doi.org/10.3390/w12010262.
101. Elhoseny, H.; Elhoseny, M.; Riad, A. el-din; Hassanien, A. E. A Framework for Big Data Analysis in Smart Cities. *The International Conference on Advanced Machine Learning Technologies and Applications (AMLTA2018)* **2018,** pp.405–414. https://doi.org/10.1007/978-3-319-74690-6_40.
102. Emamgholizadeh, S.; Moslemi, K.; Karami, G. Prediction the groundwater level of bastam plain (Iran) by artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS). *Water Resource Management* **2014**, *28* (15), pp.5433–5446. https://doi.org/10.1007/s11269-014-0810-0.
103. Emami, F.; Koch, M. Modeling the Impact of Climate Change on Water Availability in the Zarrine River Basin and Inflow to the Boukan Dam, Iran. *Climate* **2019**, *7* (4), pp.1-20. https://doi.org/10.3390/cli7040051.
104. Ercin, A.E.; Hoekstra, A.Y. Water Footprint Scenarios for 2050: A Global Analysis. *Environ. Int.* **2014**, *64*, pp.71–82. https://doi.org/10.1016/j.envint.2013.11.019.

105. Estrada, A.; Sánchez, C.; Pérez, J. Groundwater Contamination Due to the Use of Agrochemicals in Sugar Cane Agroecosystems. *Agroproductividad* **2020**, *13* (11). doi:10.32854/agrop.v13i11.1835.
106. European Investment Bank (EIB). *Bringing Water to Gaza;* EIB: Luxembourg, Luxembourg, 2019; Pp. 1-8.
107. Evans, S.; Jones, N.; Williams, G.; Ames, D.; Nelson, E. Groundwater Level Mapping Tool: An open source web application for assessing groundwater sustainability. *Environmental Modelling & Software* **2020**. *131*. DOI: 104782. 10.1016/j.envsoft.2020.104782.
108. Falkenmark, M.; Lundqvist, J.; Widstrand, C. Macro-Scale Water Scarcity Requires Micro-Scale Approaches. *Nat. Resour. Forum* **1989**, *13* (4), pp.258–267. https://doi.org/https://doi.org/10.1111/j.1477-8947.1989.tb00348.x.
109. Falkenmark, M.; Rockström, J.; Karlberg, L. Present and Future Water Requirements for Feeding Humanity. *Food Secur*. **2009**, *1* (1), pp.59–69. https://doi.org/10.1007/s12571-008-0003-x.
110. Farah, E.; Shahrour, I. Leakage Detection Using Smart Water System: Combination of Water Balance and Automated Minimum Night Flow. *Water Resources Management* **2017**, *31* (15), pp.4821–4833. https://doi.org/10.1007/s11269-017-1780-9.
111. Farooq, S.; Hashmi, I.; Qazi, I. A.; Qaiser, S.; Rasheed, S. Monitoring of Coliforms and Chlorine Residual in Water Distribution Network of Rawalpindi, Pakistan. *Environmental monitoring and assessment* **2008**, *140* (1–3), pp.339–347. https://doi.org/10.1007/s10661-007-9872-2.
112. Farreny, R.; Morales-Pinzón, T.; Guisasola, A.; Tayà, C.; Rieradevall, J.; Gabarrell, X. Roof Selection for Rainwater Harvesting: Quantity and Quality Assessments in Spain. *Water Res*. **2011**, *45* (10), pp.3245–3254. https://doi.org/https://doi.org/10.1016/j.watres.2011.03.036.
113. Farsani, I.F.; Farzaneh, M.R.; Besalatpour, A.A.; Salehi, M.H.; Faramarzi, M. Assessment of the impact of climate change on spatiotemporal variability of blue and green water resources under CMIP3 and CMIP5 models in a highly mountainous watershed. *Theoretical and Applied Climatology* **2019**, *136* (1-2), pp.169-184. DOI: 10.1007/s00704-018-2474-9.
114. Fell, J.; Pead, J.; Winter, K.; Aziz,F. Advancing surface water flow measurement with low-cost smart sensors. *IMIESA* **2019**, *44* (2). https://hdl.handle.net/10520/EJC-14abb99c35.
115. Ffolliott, P. F.; Brooks, K. N.; Neary, D. G. *Water Harvesting in Arid and Semi-Arid Regions*; Arizona-Nevada Academy of Scince: Arizona, USA, 2014; Pp. 41-44.
116. Fraga, I.; Cea, L.; Puertas, J. Effect of Rainfall Uncertainty on the Performance of Physically Based Rainfall–Runoff Models. *Hydrol. Process.* **2019**, *33* (1), pp.160–173. https://doi.org/https://doi.org/10.1002/hyp.13319.
117. Freeze, R. A.; Cherry, J. A.; Cherry, J. A. *Groundwater*, Prentice-Hall: New Jersey, USA, 1979; Pp. 1-604.
118. Freij, L. Climate Change and the Vulnerable Occupied Palestinian Territories. *UCLA J. Envtl. L. & Pol'y* **2021**, *39*. DOI: 10.5070/L5391052536.
119. Frichot, J. J. H.; Rubiyatno; Talukdar, G. Water Quality Assessment of Roof-Collected Rainwater in Miri, Malaysia. *Tropical Aquatic and Soil Pollution* **2021**, *1* (2), pp.87–97. https://doi.org/10.53623/tasp.v1i2.19.

120. Friedl, M. A.; Brodley, C. E.; Strahler, A. H. Maximizing Land Cover Classification Accuracies Produced by Decision Trees at Continental to Global Scales. *IEEE Transactions on Geoscience and Remote Sensing* **1999**, *37* (2). https://doi.org/10.1109/36.752215.

121. Fulton, L. v. A Simulation of Rainwater Harvesting Design and Demand-Side Controls for Large Hospitals. *Sustainability* **2018**, *10* (5). https://doi.org/10.3390/su10051659.

122. Gado, T. A.; El-Agha, D. E. Feasibility of Rainwater Harvesting for Sustainable Water Management in Urban Areas of Egypt. *ESPR* **2020**, *27* (26), pp.32304–32317, https://doi.org/10.1007/s11356-019-06529-5.

123. Gebreyess, B.; Woldeamanuel, A. A. Water Harvesting Technologies in Semi-Arid and Arid Areas. *JDMLM* **2019**, *7*, pp.1921–1928. https://doi.org/10.15243/jdmlm.2019.071.1921.

124. Gholami, V.; Khaleghi, M.R.; Taghvaye Salimi, E. Groundwater quality modeling using self-organizing map (SOM) and geographic information system (GIS) on the Caspian southern coasts. *Journal of Mountain Science* **2020**, *17* (7), pp.1724-1734. https://doi.org/10.1007/s11629-019-5483-y.

125. Gleeson, T.; Yoshihidewada, B.M.; Beek, L.H. Water balance of global aquifers revealed by groundwater footprint. *Nature* **2012**, *488*, pp.197–200. https://doi.org/10.1038/nature11295.

126. Gonçalves, N.; Valente, T.F.; Pamplona, J. Water supply and access to safe water in developing arid countries. *Journal of Earth Sciences & Environmental Studies* **2019**, *4* (2), pp.589-599. DOI: 10.25177/JESES.4.2.RA.497.

127. Goodarzi, M.; Mohtar, R.; Kiani-Harchegani, M.; Faraji, A.; Mankavi, F.; Rodrigo-Comino, J. Water Poverty Index (WPI) Evaluation in Borujerd-Dorood Watershed (Iran) to Reinforce Land Management Plans. *Pirineos* **2021**, *176*, pp.1–12. https://doi.org/10.3989/pirineos.2021.176002.

128. Gould, J.; Nissen-Petersen, E. *Rainwater Catchment Systems for Domestic Supply: Design, Construction and Implementation*, 1st edition.; IT Publications: London, UK, 1999; pp. 1-352.

129. Goyal, R. v; Patel, H. M. Analysis of Residual Chlorine in Simple Drinking Water Distribution System with Intermittent Water Supply. *Applied Water Science* **2015**, *5* (3), pp.311–319. https://doi.org/10.1007/s13201-014-0193-7.

130. Guio-Blanco, C.M.; Brito-Gomez, V.M.; Crespo, P.; Ließ, M. Spatial Prediction of Soil Water Retention in a Páramo Landscape: Methodological Insight into Machine Learning Using Random Forest. *Geoderma* **2018**, *316*, pp.100–114. doi:10.1016/j.geoderma.2017.12.002.

131. Gunkel, A.; Lange, J. New Insights into The Natural Variability of Water Resources in The Lower Jordan River Basin. *Water Resour. Manag.* **2012**, *26* (4), pp.963–980. https://doi.org/10.1007/s11269-011-9903-1.

132. Guo, B.; Wang, Z.; Yu, Z.; Wang, Y.; Yen, N. Y.; Huang, R.; Zhou, X. Mobile Crowd Sensing and Computing: The Review of an Emerging Human-Powered Sensing Paradigm. *ACM Comput. Surv.* **2015**, *48* (1). https://doi.org/10.1145/2794400.

133. Hajhamad, L.; Almasri, M. N. Assessment of Nitrate Contamination of Groundwater Using Lumped-Parameter Models. *Environmental Modelling & Software* **2009**, *24* (9). https://doi.org/10.1016/j.envsoft.2009.02.014.

134. Hallberg, G. R. Nitrate in Ground Water in the United States. *Developments in Agricultural and Managed-Forest Ecology* **1989**, *21*. https://doi.org/10.1016/B978-0-444-87393-4.50009-5.

135. Hamdan, A.A.; Almuktar, S.; Scholz, M. Rainfall-Runoff Modeling Using the HEC-HMS Model for the Al-Adhaim River Catchment, Northern Iraq. *Hydrology* **2021**, *8* (58). https://doi.org/10.3390/hydrology8020058.
136. Hanasaki, N.; Kanae, S.; Oki, T.; Masuda, K.; Motoya, K.; Shirakawa, N.; Shen, Y.; Tanaka, K. An integrated model for the assessment of global water resources - Part 2: Applications and assessments, *Hydrol. Earth Syst. Sci*. **2008**, *12*, pp.1027-1037, doi:10.5194/hess-12-1027-2008.
137. Hasan, A.; Alimari, A.; Jafar, H.; Hussein, A.; Abu Shaban, A. The Effect of Temperature and Rainfall Changes on Biophysical and Socio-Economic Status of People in Northern Jordan Valley Drylands, Palestine. In *Climate Change Adaptations in Dryland Agriculture in Semi-Arid Areas*, Springer: Singapore, 2022; pp. 43-63.
138. Hasan, N.; Driejana, D.; Sulaeman, A.; Ariesyady, H. Water Quality Indices for Rainwater Quality Assessment in Bandung Urban Region. *IOP Conference Series: Materials Science and Engineering* **2019**, *669* (12044). https://doi.org/10.1088/1757-899X/669/1/012044.
139. Hashim, H. Q.; Sayl, K. N. Detection of Suitable Sites for Rainwater Harvesting Planning in an Arid Region Using Geographic Information System. *Appl. Geomat.* **2021**, *13* (2), pp.235–248. https://doi.org/10.1007/s12518-020-00342-3.
140. He, P.; Baiocchi, G.; Hubacek, K.; Feng, K.; Yu, Y. The Environmental Impacts of Rapidly Changing Diets and Their Nutritional Quality in China. *Nat. Sustain*. **2018**, *1*, pp.122–127. https://doi.org/10.1038/s41893-018-0035-y.
141. Heiß, L.; Bouchaou, L.; Tadoumant, S.; Reichert, B. Index-based groundwater vulnerability and water quality assessment in the arid region of Tata city (Morocco). *Groundwater for Sustainable Development* **2020**, *10*. https://doi.org/10.1016/j.gsd.2020.100344.
142. Helbling, D. E.; Asce, A.M.; Vanbriesen, J. Modeling Residual Chlorine Response to a Microbial Contamination Event in Drinking Water Distribution Systems. *Journal of Environmental Engineering* **2009**, *135* (10), pp.918–927. https://doi.org/10.1061/(ASCE)EE.1943-7870.0000080.
143. Helmbrecht, J.; Pastor, J.; Moya, C. Smart Solution to Improve Water-energy Nexus for Water Supply Systems. *Procedia Eng*. **2017**, *186*, pp.101–109. https://doi.org/10.1016/j.proeng.2017.03.215.
144. Hering, J.G.; Ingold, K.M. Water resources management: what should be integrated?. *Science* **2012**, *336* (6086), pp.1234-1235. DOI: 10.1126/science.1218230.
145. Heyns, P. Water conservation in arid and semi-arid regions. *Water Resources Management* **2009**, *1*, pp.113-150.
146. Hoang, B.; Ha Ngoc, H.; Dinh, N.; Thao, N.; Ha, P.; Kandasamy, J.; Nguyen, T. Integration of SWAT and QUAL2K for water quality modeling in a data scarce basin of Cau River basin in Vietnam. *Ecohydrology & Hydrobiology* **2019**, *19* (2), pp.210-223. https://doi.org/10.1016/j.ecohyd.2019.03.005.
147. Hochman, A.; Harpaz, T.; Saaroni, H.; Alpert, P. The seasons' length in 21st century CMIP5 projections over the eastern Mediterranean. *International Journal of Climatology* **2018**, *38* (6), pp.2627-2637. https://doi.org/10.1002/joc.5448.
148. Horton, R.K. An Index-Number System for Rating Water Quality. *J. Water Pollut. Control Fed.* **1965**, *37*, pp.300–306.

149. Howard, G; Bartram, J. *Domestic Water Quantity, Service Level and Health*; WHO: Geneva, Switzerland, 2003; Pp. 1-39.
150. Hrudey, S. E.; Backer, L. C.; Humpage, A. R.; Krasner, S. W.; Michaud, D. S.; Moore, L. E.; Singer, P. C.; Stanford, B. D. Evaluating Evidence for Association of Human Bladder Cancer with Drinking-Water Chlorination Disinfection By-Products. *Journal of Toxicology and Environmental Health, Part B* **2015**, *18* (5), pp.213–241. https://doi.org/10.1080/10937404.2015.1067661.
151. Hu, J. Data Cleaning and Feature Selection for Gravelly Soil Liquefaction. *Soil Dynamics and Earthquake Engineering* **2021**, *145* (106711). https://doi.org/https://doi.org/10.1016/j.soildyn.2021.106711.
152. Huang, L.; Yin, L. Supply and Demand Analysis of Water Resources Based on System Dynamics Model. *J. Eng. Technol. Sci*. **2017**, *49* (6), pp.705-720. https://doi.org/10.5614/j.eng.technol.sci.2017.49.6.1.
153. Human Rights Council (HRC). 2021, *The allocation of water resources in the Occupied Palestinian Territory, including East Jerusalem*; HRC: Palestine, 2021; Pp. 1-17.
154. Hussain, Z.; Wang, Z.; Wang, J.; et al. A comparative Appraisal of Classical and Holistic Water Scarcity Indicators. *Water Resour Manage* **2022**, *36*, pp.931–950. https://doi.org/10.1007/s11269-022-03061-z.
155. Ighalo, J. O.; Adeniyi, A. G. A Comprehensive Review of Water Quality Monitoring and Assessment in Nigeria. *Chemosphere* **2020**, *260* (127569). https://doi.org/https://doi.org/10.1016/j.chemosphere.2020.127569.
156. Ighbareyeh, J.M.; Cano-Ortiz, A.; Carmona, E.C.; Ighbareyeh, M.M.; Suliemieh, A.A. Assessing crop yield sustainability under the climatic and bioclimatic change in the area of Palestine. *American Journal of Climate Change* **2015**, *4* (1). DOI: 10.4236/ajcc.2015.41005.
157. Iglesias, A.; Garrote, L.; Diz, A.; Schlickenrieder, J.; Martin-Carrasco, F. Re-thinking water policy priorities in the Mediterranean region in view of climate change. *Environmental Science & Policy* **2011**, *14* (7), pp.744-757. https://doi.org/10.1016/j.envsci.2011.02.007.
158. Isaac, J.; Sabbah, W. *The Intensifying Water Crisis in Palestine*; Applied Research Institute–Jerusalem (ARIJ): Jerusalem, Palestine, 2017; Pp. 1-10.
159. Jabari, S.; Shahrour, I.; El Khattabi, J. Assessment of the Urban Water Security in a Severe Water Stress Area–Application to Palestinian Cities. *Water* **2020**, *12* (7), pp.1-18. https://doi.org/10.3390/w12072060.
160. Jafari-Shalamzari, M.; Zhang, W. Assessing Water Scarcity Using the Water Poverty Index (WPI) in Golestan Province of Iran. *Water* **2018**, *10* (8), pp.1-22. https://doi.org/10.3390/w10081079.
161. Jaren, L. S.; Mondal, M. S. Assessing Water Poverty of Livelihood Groups in Peri-Urban Areas around Dhaka under a Changing Environment. *Water* **2021**, *13* (19). https://doi.org/10.3390/w13192674.
162. Jebreen, H.; Wohnlich, S.; Banning, A.; Wisotzky, F.; Niedermayr, A.; Ghanem, M. Recharge, geochemical processes and water quality in karst aquifers: Central West Bank, Palestine. *Environmental earth sciences* **2018**, *77* (6), pp.1-16. https://doi.org/10.1007/s12665-018-7440-4.
163. Jenin Municipality (JM). *Annual Report on Water Supply Service in Jenin Municipality*; JM: Jenin, Palestine, 2019; Pp. 1-5.

164. Jha, B. Cloud-Based Smart Water Quality Monitoring System using IoT Sensors and Machine Learning. *International Journal of Advanced Trends in Computer Science and Engineering* **2020**, *9*, pp.3403-3409. DOI: 10.30534/ijatcse/2020/141932020.
165. Ji, W.; Xu, J.; Qiao, H.; Zhou, M.; Liang, B. Visual IoT: Enabling Internet of Things Visualization in Smart Cities. *IEEE Network* **2019**, *33* (2), pp.102–110. https://doi.org/10.1109/MNET.2019.1800258.
166. Johannsen, I. M.; Hengst, J. C.; Goll, A.; Höllermann, B.; Diekkrüger, B. Future of Water Supply and Demand in the Middle Drâa Valley, Morocco, under Climate and Land Use Change. *Water* **2016**, *8* (8), pp.1-18. https://doi.org/10.3390/w8080313.
167. Judeh, T.; Almasri, M.; Shadeed, S.; Bian, H.; Shahrour, I. Use of GIS, Statistics and Machine Learning for Groundwater Quality Management: Application to Nitrate Contamination. *Water Resources* **2022**, *49* (3), pp.503–514.
168. Judeh, T.; Bian, H.; Shahrour, I. GIS-Based Spatiotemporal Mapping of Groundwater Potability and Palatability Indices in Arid and Semi-Arid Areas. *Water* **2021**, *13* (9), pp.1-16. https://doi.org/10.3390/w13091323.
169. Judeh, T.; Haddad, M.; Özerol, G. Assessment of Water Governance in the West Bank, Palestine. *Int. J. Glob. Environ. Issues* **2017**, *16*, pp.119–134, doi:10.1504/IJGENVI.2017.083426.
170. Judeh, T.; Shahrour, I. Rainwater Harvesting to Address Current and Forecasted Domestic Water Scarcity: Application to Arid and Semi-Arid Areas. *Water* **2021**, *13* (24). https://doi.org/10.3390/w13243583.
171. Kadam, A.; Wagh, V.; Patil, S.; Umrikar, B.; Sankhua, R. Seasonal Assessment of Groundwater Contamination, Health Risk and Chemometric Investigation for a Hard Rock Terrain of Western India. *Environ. Earth Sci*. **2021**, *80* (172). doi:10.1007/s12665-021-09414-y.
172. Kahil, M.T.; Dinar, A.; Albiac, J. Modeling water scarcity and droughts for policy adaptation to climate change in arid and semiarid regions. *Journal of Hydrology* **2015**, *522*, pp.95-109. https://doi.org/10.1016/j.jhydrol.2014.12.042.
173. Kali, S.; Khan, M.; Ghaffar, M. S.; Rasheed, S.; Waseem, A.; Iqbal, M. M.; Bilal khan Niazi, M.; Zafar, M. I. Occurrence, Influencing Factors, Toxicity, Regulations, and Abatement Approaches for Disinfection by-Products in Chlorinated Drinking Water: A Comprehensive Review. *Environmental Pollution* **2021**, *281* (116950). https://doi.org/https://doi.org/10.1016/j.envpol.2021.116950.
174. Källén, B. A. J.; Robert, E. Drinking Water Chlorination and Delivery Outcome—a Registry-Based Study in Sweden. *Reproductive Toxicology* **2000**, *14* (4), pp.303–309. https://doi.org/https://doi.org/10.1016/S0890-6238(00)00086-1.
175. Kang, D.; Lansey, K. Dual Water Distribution Network Design under Triple-Bottom-Line Objectives. *Journal of Water Resources Planning and Management* **2012**, *138*, pp.162–175. https://doi.org/10.1061/(ASCE)WR.1943-5452.0000161.
176. Karim, Md. R.; Sakib, B. M. S.; Sakib, Sk. S.; Imteaz, M. A. Rainwater Harvesting Potentials in Commercial Buildings in Dhaka: Reliability and Economic Analysis. *Hydrology* **2021**, *8* (1). https://doi.org/10.3390/hydrology8010009.
177. Karimidastenaei, Z.; Avellán, T.; Sadegh, M.; Klöve, B.; Haghighi, A. Unconventional Water Resources: Global Opportunities and Challenges. *SSRN Electronic Journal* **2022**, *10, pp.*1-35. DOI: 10.2139/ssrn.4002411.

178. Karunanidhi, D.; Subramani, T.; Roy, P.D.; Li, H. Impact of Groundwater Contamination on Human Health. *Environ. Geochem. Health* **2021**, *43*, pp.643–647. doi:10.1007/s10653-021-00824-2.
179. Kayemah, N.; Al-Ruzouq, R.; Shanableh, A.; Yilmaz, A. Evaluation of Groundwater Quality Using Groundwater Quality Index (GWQI) in Sharjah, UAE. *E3S. Web Conf.* **2021**, *241* (1005). doi:10.1051/e3sconf/202124101005.
180. Keršulienė, V.; Zavadskas, E.; Turskis, Z. Selection of Rational Dispute Resolution Method by Applying New Step-Wise Weight Assessment Ratio Analysis (SWARA). *J. Bus. Econ. Manag.* **2010**, *11*, pp.243–258. doi:10.3846/jbem.2010.12.
181. Khader, A. I.; Rosenberg, D. E.; McKee, M. A Decision Tree Model to Estimate the Value of Information Provided by a Groundwater Quality Monitoring Network. *Hydrology and Earth System Sciences* **2013**, *17* (5). https://doi.org/10.5194/hess-17-1797-2013.
182. Khaiwal, R.; Thind, P.; Mor, S.; Singh, T.; Mor, S. Evaluation of Groundwater Contamination in Chandigarh: Source Identification and Health Risk Assessment. *Environ. Pollut.* **2019**, *255* (113062). doi:10.1016/j.envpol.2019.113062.
183. Khan, M.; Shakeel, M.; Ahsan, N.; Ahmed, S.; Khan, N. Groundwater Contamination and Health Risk Posed by Industrial Effluent in NCR Region. *Mater. Today Proc.* **2021**, *124723*, pp.1–13. doi:10.1016/j.matpr.2021.02.192.
184. Khayat, S.; Geyer, S.; Hötzl, H.; Ghanem, M.; Ali, W. Identification of Nitrate Sources in Groundwater by Δ15Nnitrateand Δ18Onitrate Isotopes: A Study of the Shallow Pleistocene Aquifer in the Jericho Area, Palestine. *Acta hydrochimica et hydrobiologica* **2006**, *34* (1–2). https://doi.org/10.1002/aheh.200400615.
185. Knoll, L.; Breuer, L.; Bach, M. Large Scale Prediction of Groundwater Nitrate Concentrations from Spatial Data Using Machine Learning. *Science of The Total Environment* **2019**, *668*. https://doi.org/10.1016/j.scitotenv.2019.03.045.
186. Koirala, S.; Fang, Y.; Dahal, N. M.; Zhang, C.; Pandey, B.; Shrestha, S. Application of Water Poverty Index (WPI) in Spatial Analysis of Water Stress in Koshi River Basin, Nepal. *Sustainability* **2020**, *12* (2), pp.1-20. https://doi.org/10.3390/su12020727.
187. Krishnakumar, P.; Lakshumanan, C.; Pradeep, V.; Sundararajan, M.; Santhiya, G.; Chidambaram, S. Assessment of groundwater quality in and around Vedaraniyam, South India. *Environ Earth Sci* **2014**, *71*, pp.2211–2225. DOI: 10.1007/s12665-013-2626-2.
188. Kubicz, J.; Lochyński, P.; Pawełczyk, A.; Karczewski, M. Effects of Drought on Environmental Health Risk Posed by Groundwater Contamination. *Chemosphere* **2020**, *263* (128145). doi:10.1016/j.chemosphere.2020.128145.
189. Kumar, R.; Chatterjee, A.; Singh, M.; Singh, V. Mathematical Modelling to Establish the Influence of Pesticides on Groundwater Contamination. *Arab. J. Geosci*. **2020**, *13*, 603. doi:10.1007/s12517-020-05618-x.
190. Kumari, N. Evaluation of Groundwater Quality Index for Drinking Water in Tank Cascade Landscape. *IJLTEMAS* **2020**, *9* (8).
191. Kummu, M.; Guillaume, J.A.; de Moel, H.; Eisner, S.; Flörke, M.; Porkka, M.; Siebert, S.; Veldkamp, T.I.E.; Ward, P.J. The World's Road to Water Scarcity: Shortage and Stress in the 20th Century and Pathways towards Sustainability. *Sci. Rep.* **2016**, *6*, 1–16. https://doi.org/10.1038/srep38495.

192. Kursa, M.B. Robustness of Random Forest-Based Gene Selection Methods. *BMC Bioinform.* **2014**, *15* (8). doi:10.1186/1471-2105-15-8.
193. Kyriazis, D.; Varvarigou, T. A.; White, D.; Rossi, A.; Cooper, J. Sustainable Smart City IoT Applications: Heat and Electricity Management \& Eco-Conscious Cruise Control for Public Transportation. *IEEE 14th International Symposium on "A World of Wireless, Mobile and Multimedia Networks" (WoWMoM)* **2013**, pp.1–5.
194. Lam, K.-L.; Cheng, W.-Y.; Su, Y.; Li, X.; Wu, X.; Wong, K.-H.; Kwan, H.-S.; Cheung, P.C.-K. Use of Random Forest Analysis to Quantify the Importance of the Structural Characteristics of Beta-Glucans for Prebiotic Development. *Food Hydrocoll.* **2020**, *108* (106001). doi:10.1016/j.foodhyd.2020.106001.
195. Lee, D.; Murphy, H. Private Wells and Rural Health: Groundwater Contaminants of Emerging Concern. *Curr. Environ. Health Rep*. **2020**, *7*, pp.129–139. doi:10.1007/s40572-020-00267-4.
196. Lee, H.; Chae, M.S.; Park, J.-Y.; Lim, K.J.; Park, Y.S. Development and Application of a QGIS-Based Model to Estimate Monthly Streamflow. *ISPRS Int. J. Geo-Inf*. **2022**, *11* (40). https://doi.org/10.3390/ijgi11010040.
197. Lee, S. W.; Sarp, S.; Jeon, D. J.; Kim, J. H. Smart Water Grid: The Future Water Management Platform. *Desalination and Water Treatment* **2015**, *55* (2), pp.339–346. https://doi.org/10.1080/19443994.2014.917887.
198. Levizzani, V.; Cattani, E. Satellite Remote Sensing of Precipitation and the Terrestrial Water Cycle in a Changing Climate. *Remote Sens*. **2019**, *11* (2301). https://doi.org/10.3390/rs11192301.
199. Li, H.; Smith, C.D.; Wang, L.; Li, Z.; Xiong, C.; Zhang, R. Combining Spatial Analysis and a Drinking Water Quality Index to Evaluate Monitoring Data. *Int. J. Environ. Res. Public Health* **2019**, *16* (357). doi:10.3390/ijerph16030357.
200. Li, J.; Yang, X.; Sitzenfrei, R. Rethinking the framework of smart water system: A review. *Water* **2020**, *12* (2). https://doi.org/10.3390/w12020412.
201. Li, P.; Abbasi, T.; Abbasi, S.A. Water Quality Indices. *Environ. Earth Sci.* **2014**, *71*, pp.4625–4628. doi:10.1007/s12665-014-3141-9.
202. Li, P.; Karunanidhi, D.; Subramani, T.; Srinivasamoorthy, K. Sources and Consequences of Groundwater Contamination. *Arch. Environ. Contam. Toxicol.* **2021**, *80*, pp.1–10. doi:10.1007/s00244-020-00805-z.
203. Liou, S.-M.; Lo, S.; Wang, S. A Generalized Water Quality Index for Taiwan. *Environ. Monit. Assess.* **2004**, *96*, pp.35–52. doi:10.1023/B:EMAS.0000031715.83752.a1.
204. Liu, D.; Zhang, Y.; Jia, D.; Zhang, Q.; Zhao, X.; Rong, H. Toward Secure Distributed Data Storage with Error Locating in Blockchain Enabled Edge Computing. *Computer Standards & Interfaces* **2022**, *79* (103560). https://doi.org/https://doi.org/10.1016/j.csi.2021.103560.
205. Liu, J.; Liu, Q.; Yang, H. Assessing water scarcity by simultaneously considering environmental flow requirements, water quantity, and water quality. *Ecol. Indic.* **2016**, *60*, pp.434-441. doi: 10.1016/j.ecolind.2015.07.019.
206. Liu, J.; Yang, H.; Gosling, S. N.; Kummu, M.; Flörke, M.; Pfister, S.; Hanasaki, N.; Wada, Y.; Zhang, X.; Zheng, C.; Alcamo, J.; Oki, T. Water Scarcity Assessments in the Past, Present, and Future. *Earth's Future* **2017**, *5* (6), pp.545–559. https://doi.org/https://doi.org/10.1002/2016EF000518.

207. Liu, W.; Zhao, M.; Xu, T. Water Poverty in Rural Communities of Arid Areas in China. *Water* **2018**, *10* (4), pp.1-16. https://doi.org/10.3390/w10040505.
208. Lodwick, W.A.; Monson, W.; Svoboda, L. Attribute Error and Sensitivity Analysis of Map Operations in Geographical Informations Systems: Suitability Analysis. *Int. J. Geogr. Inf. Syst.* **1990**, *4*, pp.413–428. doi:10.1080/02693799008941556.
209. Love, S. B.; Yorke-Edwards, V.; Diaz-Montana, C.; Murray, M. L.; Masters, L.; Gabriel, M.; Joffe, N.; Sydes, M. R. Making a Distinction between Data Cleaning and Central Monitoring in Clinical Trials. *Clinical trials (London, England)* **2021**, pp.386–388. https://doi.org/10.1177/1740774520976617.
210. Lu, S.; Bai, X.; Li, W.; Wang, N. Impacts of climate change on water resources and grain production. *Technological Forecasting and Social Change* **2019**, *143*, pp. 76-84. DOI: 10.1016/j.techfore.2019.01.015.
211. Luciani, C.; Casellato, F.; Alvisi, S.; Franchini, M. From Water Consumption Smart Metering to Leakage Characterization at District and User Level: The GST4Water Project. *Proceedings* **2018**, *2* (11). https://doi.org/10.3390/proceedings2110675.
212. MacDonald, A.M.; Bonsor, H.C.; Ahmed, K.M.; et al. Groundwater quality and depletion in the Indo-Gangetic basin mapped from in situ observations. *Nat. Geosci*. **2016**, *9*, pp.762–766. https://doi.org/10.1038/ngeo2791.
213. Mahmoud, N.; Hogland, W.; Sokolov, M.; Rud, V.; Myazin, N. Assessment of Rainwater Harvesting for Domestic Water Supply in Palestinian Rural Areas. *MATEC Web Conf.* **2018**, *245* (6012). https://doi.org/10.1051/matecconf/201824506012.
214. Mahmoud, N.; Zayed, O.; Petrusevski, B. Groundwater Quality of Drinking Water Wells in the West Bank, Palestine. *Water* **2022**, *14* (3). https://doi.org/10.3390/w14030377.
215. Mair, A.; El-Kadi, A. I. Logistic Regression Modeling to Assess Groundwater Vulnerability to Contamination in Hawaii, USA. *Journal of Contaminant Hydrology* **2013**, *153*. https://doi.org/10.1016/j.jconhyd.2013.07.004.
216. Malambo, T.; Huang, Q. Rooftop Rainwater Harvesting as an Alternative Domestic Water Resource in Zambia. *GEP* **2016**, *4* (13), pp.41–57. https://doi.org/10.4236/gep.2016.413003.
217. Maqsoom, A.; Aslam, B.; Khalil, U.; Ghorbanzadeh, O.; Ashraf, H.; Faisal Tufail, R.; Farooq, D.; Blaschke, T. A GIS-Based DRASTIC Model and an Adjusted DRASTIC Model (DRASTICA) for Groundwater Susceptibility Assessment along the China–Pakistan Economic Corridor (CPEC) Route. *ISPRS International Journal of Geo-Information* **2020**, *9* (5). https://doi.org/10.3390/ijgi9050332.
218. Martins, F.; Patrão, C.; Moura, P.; de Almeida, A. T. A Review of Energy Modeling Tools for Energy Efficiency in Smart Cities. *Smart Cities* **2021**, *4* (4), pp.1420–1436. https://doi.org/10.3390/smartcities4040075.
219. Mashhadi, N.; Shahrour, I.; Attoue, N.; el Khattabi, J.; Aljer, A. Use of Machine Learning for Leak Detection and Localization in Water Distribution Systems. *Smart Cities* **2021**, *4* (4), pp.1293–1315. https://doi.org/10.3390/smartcities4040069.
220. Masindi, V.; Foteinis, S. Groundwater Contamination in Sub-Saharan Africa: Implications for Groundwater Protection in Developing Countries. *Clean. Eng. Technol*. **2020**, *2* (100038). doi:10.1016/j.clet.2020.100038.
221. Mas-Pla, J.; Menció, A. Groundwater Nitrate Pollution and Climate Change: Learnings from a Water Balance-Based Analysis of Several Aquifers in a Western Mediterranean Region

(Catalonia). *Environmental Science and Pollution Research* **2019**, *26* (3). https://doi.org/10.1007/s11356-018-1859-8.
222. Mays, D.; Scheibe, T. Groundwater Contamination, Subsurface Processes, and Remediation Methods: Overview of the Special Issue of Water on Groundwater Contamination and Remediation. *Water* **2018**, *10* (1708). doi:10.3390/w10121708.
223. McKenna, K.; Keane, A. Residential Load Modeling of Price-Based Demand Response for Network Impact Studies. *IEEE Trans. Smart Grid* **2016**, *7*, pp.2285–2294. DOI: 10.1109/TSG.2015.2437451.
224. Medici, G.; Smeraglia, L.; Torabi, A.; Botter, C. Review of Modeling Approaches to Groundwater Flow in Deformed Carbonate Aquifers. *Groundwater* **2021**, *59*, pp.334-351. https://doi.org/10.1111/gwat.13069.
225. Menzel, L.; ben Asher, J.; Ouroud, I.; Sternberg, M.; Yakir, D. *GLOWA Jordan River Phase II Final Report: An Integrated Approach to Sustainable Management of Water Resources Under Global Change*; GLOWA: Amman, Jordan, 2009; Pp.1-385.
226. Mester, T.; Balla, D.; Szabó, G. Assessment of Groundwater Quality Changes in the Rural Environment of the Hungarian Great Plain Based on Selected Water Quality Indicators. *Water Air Soil Pollut.* **2020**, *231 (*536). doi:10.1007/s11270-020-04910-6.
227. Middleton, N.J.; Sternberg, T. Climate hazards in drylands: A review. *Earth-Science Reviews* **2013**, *126*, pp.48-57. https://doi.org/10.1016/j.earscirev.2013.07.008.
228. Ministry of Foreign Affairs of the Netherlands (MoFA Netherlands). *Climate Change Profile: Palestinian Territories;* MoFA Netherlands: The Hague, The Netherlands, 2018; Pp. 1-22.
229. Mizuki, F.; Dr, K.; Dr, H. Intelligent Water System for Smart Cities. *Hitachi Review* **2012**, *61* (3), pp.147–151.
230. Mizyed, N. Climate change challenges to groundwater resources: Palestine as a case study. *Journal of Water Resource and Protection* **2018**, *10* (2). DOI: 10.4236/jwarp.2018.102013.
231. Mosley, L. *Report 579: Water Quality of Rainwater Harvesting Systems*; SOPAC: Suva, Fiji, 2005; Pp. 1-19.
232. Mudumbe, M. J.; Abu-Mahfouz, A. M. Smart Water Meter System for User-Centric Consumption Measurement. *IEEE 13th International Conference on Industrial Informatics (INDIN)* **2015**, pp 993–998. https://doi.org/10.1109/INDIN.2015.7281870.
233. Mundia, C. Assessing the Reliability of Rooftop Rainwater Harvesting for Domestic Use in Western Kenya. MSc Thesis, Southern Illinois University, Illinois, USA, January 2021.
234. Muñoz, E.; Tume, P.; Ortíz, G. Uncertainty in Rainfall Input Data in a Conceptual Water Balance Model: Effects on Outputs and Implications for Predictability. *Earth Sci. Res. J.* **2014**, *18* (1), pp.69-75. https://doi.org/10.15446/esrj.v18n1.38760.
235. Muoio, R.; Caretti, C.; Rossi, L.; Santianni, D.; Lubello, C. Water Safety Plans and Risk Assessment: A Novel Procedure Applied to Treated Water Turbidity and Gastrointestinal Diseases. *International Journal of Hygiene and Environmental Health* **2020**, *223* (1), pp.281–288. https://doi.org/https://doi.org/10.1016/j.ijheh.2019.07.008.
236. Neary, B.; Williamson, D.; Environment, M.; Wright, R. *Canadian Environmental Quality Guidelines*; Canadian Council of Ministers of the Environment: Winnipeg, MB, Canada, 2001; pp. 1–5.

237. Nguyen, D. C.; Han, M. Y. Design of Dual Water Supply System Using Rainwater and Groundwater at Arsenic Contaminated Area in Vietnam. *Journal of Water Supply: Research and Technology-Aqua* **2014**, *63* (7), pp.578–585. https://doi.org/10.2166/aqua.2014.087.

238. Nguyen, T.T.; Ngo, H.H.; Guo, W.; Nguyen, H.Q.; Luu, C.; Dang, K.B.; Liu, Y.; Zhang, X. New approach of water quantity vulnerability assessment using satellite images and GIS-based model: An application to a case study in Vietnam. *Science of the Total Environment* **2020**, *737*. https://doi.org/10.1016/j.scitotenv.2020.139784.

239. Nkiaka, E. Water security assessment in ungauged regions using the water balance and water footprint concepts and satellite observations. *Hydrology Research* **2022**, *53* (2), pp.336–352. doi: https://doi.org/10.2166/nh.2022.124.

240. Nofal, I. Geo-Database of the Ministry of Agriculture; Personal Communication. Ramallah, Palestine 2019.

241. Northcutt, C.; Jiang, L.; Chuang, I. Confident Learning: Estimating Uncertainty in Dataset Labels. *Journal of Artificial Intelligence Research* **2021**, *70*, pp.1373–1411. https://doi.org/10.1613/jair.1.12125.

242. Ntuli, N.; Abu-Mahfouz, A. A Simple Security Architecture for Smart Water Management System. *Procedia Comput. Sci*. **2016**, *83*, pp.1164–1169, https://doi.org/10.1016/j.procs.2016.04.239.

243. Ocampo-Duque, W.; Osorio, C.; Piamba, C.; Schuhmacher, M.; Domingo, J.L. Water Quality Analysis in Rivers with Non-Parametric Probability Distributions and Fuzzy Inference Systems: Application to the Cauca River, Colombia. *Environ. Int.* **2013**, *52*, pp.17–28. doi:10.1016/j.envint.2012.11.007.

244. Oki, T.; Kanae, S. Global Hydrological Cycles and World Water Resources. *Science* **2006**, *313* (5790), pp.1068–1072. https://doi.org/10.1126/science.1128845.

245. O'Neill, M.; Tijerina, D.; Condon, L.; Maxwell, R. Assessment of the ParFlow-CLM CONUS 1.0 integrated hydrologic model: Evaluation of hyper-resolution water balance components across the contiguous United States. *Geoscientific Model Development* **2020**, *14* (12), pp.1-50. DOI: 10.5194/gmd-2020-364.

246. Oni, O. The Use of Water Quality Index Method to Determine the Potability of Surface Water and Groundwater in the Vicinity of a Municipal Solid Waste Dumpsite in Nigeria. *AJER*. **2016**, *5*, pp.96–101.

247. Onwuka, S.O.; Ezugwu, C.K. Multivariate Statistical Assessment and Spatial Distribution of Groundwater Contamination in Neke and Its Environs, South-Eastern Nigeria. *Int. J. Phys. Sci.* **2019**, *14*, pp.62–80. doi:10.5897/ijps2019.4798.

248. Ortega, R.M.; Rodriguez, W.; Díaz, Z. Application of Geoelectric Parameters in the Study of Vulnerability for Groundwater Contamination. *Min. Geol.* **2020**, *36*, pp.390–403.

249. Osayemwenre, G.; Osibote, O. A. A Review of Health Hazards Associated with Rainwater Harvested from Green, Conventional and Photovoltaic Rooftops. *International Journal of Environmental Science and Development* **2021**, *12* (10), pp.289-303. doi: 10.18178/ijesd.2021.12.10.1353.

250. Palermo, S. A.; Talarico, V. C.; Pirouz, B. *Optimizing Rainwater Harvesting Systems for Non-Potable Water Uses and Surface Runoff Mitigation BT-Numerical Computations: Theory and Algorithms*, Springer International Publishing: New York, USA, 2020; pp. 570–582.

251. Palestinian Central Bureau of Statistics (PCBS). "Water Source Security: Is desalination the way to go?. Available online: https://www.pcbs.gov.ps/post.aspx?lang=en&ItemID=3944 (accessed on 18 February 2020b).
252. Palestinian Central Bureau of Statistics (PCBS). Annual Available Water Quantity in Palestine by Region and Source. Available online: http://www.pcbs.gov.ps/Portals/_Rainbow/Documents/water-E4-2018.html (accessed on 12 February 2021a).
253. Palestinian Central Bureau of Statistics (PCBS). Estimated Population in the Palestine Mid-Year by Governorate, 1997-2026. Available online: https://www.pcbs.gov.ps/statisticsIndicatorsTables.aspx?lang=en&table_id=676 (accessed on 11 May, 2021c).
254. Palestinian Central Bureau of Statistics (PCBS). *Palestinians at the End of 2020*; PCBS: Ramallah, Palestine, 2020a; pp. 1–31.
255. Palestinian Central Bureau of Statistics (PCBS). Percentage Distribution of Households in Palestine by Wastewater Disposal Method, Region, and Locality Type in 2015. Available Online: http://Www.Pcbs.Gov.Ps/Portals/_Rainbow/Documents/HHE%202015%20e%203.Htm (accessed on 1 January 2021d).
256. Palestinian Central Bureau of Statistics (PCBS). Population in Palestine. Available online: http://www.pcbs.gov.ps/site/lang__en/803/default.aspx?lang=en (accessed on 12 February, 2020c).
257. Palestinian Central Bureau of Statistics (PCBS). Quantity of Water Supply for Domestic Sector, Water Consumed and Daily Consumption per Capita in the West Bank by Governorate in 2018. Available online: https://www.pcbs.gov.ps/Portals/_Rainbow/Documents/water-E9-2018.html (accessed on 14 June, 2021b).
258. Palestinian Metrological Authority (PMA). *Climate Bulletin*; PMA: Ramallah, Palestine, 2018; Pp. 1–34.
259. Palestinian Ministry of Local Government (MoLG). Building Rooftops. Available online: https://geomolg-geomolgarconline.hub.arcgis.com/search?collection=Dataset (accessed on 18 May, 2021).
260. Palestinian Water Authority (PWA). *Annual Status Report on Water Resources, Water Supply, and Wastewater in the Occupied State of Palestine*; PWA: Ramallah, Palestine, 2011; Pp.1–97.
261. Palestinian Water Authority (PWA). *Gaza Water Status Report 2017;* PWA: Gaza, Palestine, 2018; Pp. 1-7.
262. Palestinian Water Authority (PWA). National Water Information System. Available online: http://nwis.pwa.ps:82 (accessed on 18 January, 2020).
263. Palestinian Water Authority (PWA). *Status Report of Water Resources in the Occupied State of Palestine-2012*; PWA: Ramallah, Palestine, 2013; Pp.1-22.
264. Palestinian Water Authority (PWA). *Water Authority Strategic Plan 2016-2018*; PWA: Ramallah, Palestine, 2016; Pp. 1–25.
265. Palestinian Water Authority (PWA). *Water Resources Status Report in the West Bank*; PWA: Ramallah, Palestine, 2017; Pp.1–15
266. Pasika, S.; Gandla, S. T. Smart Water Quality Monitoring System with Cost-Effective Using IoT. *Heliyon* **2020**, *6* (7). https://doi.org/https://doi.org/10.1016/j.heliyon.2020.e04096.

267. Pastuszak, M.; Kowalkowski, T.; Kopiński, J.; et al. Long-term changes in nitrogen and phosphorus emission into the Vistula and Oder catchments (Poland)—modeling (MONERIS) studies. *Environ Sci Pollut Res* **2018**, *25*, pp.29734–29751. https://doi.org/10.1007/s11356-018-2945-7.
268. Patil, N.S.; Chetan, N.L.; Nataraja, M.; Suthar, S. Climate change scenarios and its effect on groundwater level in the Hiranyakeshi watershed. *Groundwater for sustainable development* **2020**, *10*. https://doi.org/10.1016/j.gsd.2019.100323.
269. Patrão, C.; Moura, P.; Almeida, A. T. de. Review of Smart City Assessment Tools. *Smart Cities* **2020**, *3* (4), pp.1117–1132. https://doi.org/10.3390/smartcities3040055.
270. Peixoto, F. Groundwater Contamination Risk in Urban Watershed. *Mercator* **2020**, *19*, pp.1–17. doi:10.4215/rm2020.e19013.
271. Petrolo, R.; Loscri, V.; Mitton, N. Towards a Smart City Based on Cloud of Things, a Survey on the Smart City Vision and Paradigms. *Transactions on Emerging Telecommunications Technologies* **2015**, *28*. https://doi.org/10.1002/ett.2931.
272. Petropoulos, G.; Carlson, T. N.; Wooster, M. J. An Overview of the Use of the SimSphere Soil Vegetation Atmosphere Transfer (SVAT) Model for the Study of Land-Atmosphere Interactions. *Sensors* **2009**, *9* (6), pp.4286–4308. https://doi.org/10.3390/s90604286.
273. Pham, H.; Parashar, R.; Sund, N.; Pohlmann, K. A Method to Represent a Well in a Three-Dimensional Discrete Fracture Network Model. *Groundwater* **2021**, *59*, pp.281-286. https://doi.org/10.1111/gwat.13030.
274. Pickering, A. J.; Crider, Y.; Sultana, S.; Swarthout, J.; Goddard, F. G. B.; Anjerul Islam, S.; Sen, S.; Ayyagari, R.; Luby, S. P. Effect of In-Line Drinking Water Chlorination at the Point of Collection on Child Diarrhoea in Urban Bangladesh: A Double-Blind, Cluster-Randomised Controlled Trial. *The Lancet Global Health* **2019**, *7* (9), pp.1247–1256. https://doi.org/https://doi.org/10.1016/S2214-109X(19)30315-8.
275. Poonam, T.; Tanushree, B.; Sukalyan, C. Water Quality Indices- Important Tools for Water Quality Assessment: A Review. *IJAC* **2015**, *1*, pp.15–29.
276. Prasad, A. N.; Mamun, K. A.; Islam, F. R.; Haqva, H. Smart Water Quality Monitoring System. *2nd Asia-Pacific World Congress on Computer Science and Engineering (APWC on CSE)* **2015**, pp 1–6. https://doi.org/10.1109/APWCCSE.2015.7476234.
277. Preeti, P.; Rahman, A. A Case Study on Reliability, Water Demand and Economic Analysis of Rainwater Harvesting in Australian Capital Cities. *Water* **2021**, *13* (19). https://doi.org/10.3390/w13192606.
278. Qiao, C.; Ning, Z.; Wang, Y.; Sun, J.; Lin, Q.; Wang, G. Impact of Climate Change on Water Availability in Water Source Areas of the South-to-North Water Diversion Project in China. *Front. Earth Sci.* **2021**, *9* (747429), pp.1-9. https://doi.org/10.3389/feart.2021.747429.
279. Qrenawi, L.; Shomar, R. T. A. Health Risk Assessment of Groundwater Contamination Case Study: Gaza Strip. *Journal of Engineering Research and Technology* **2020**, *7*.
280. Raazia, S.; Dar, A.Q. A numerical model of groundwater flow in Karewa-Alluvium aquifers of NW Indian Himalayan Region. Model. *Earth Syst. Environ.* **2022**, *8*, pp.871–882. https://doi.org/10.1007/s40808-021-01126-3.
281. Rabeiy, R.E. Assessment and modeling of groundwater quality using WQI and GIS in Upper Egypt area. *Environmental Science and Pollution Research* **2018**, *25* (31), pp.30808-30817. https://doi.org/10.1007/s11356-017-8617-1.

282. Rahimi, O.; Murakami, K. Rooftop Rainwater Harvesting and its Efficiency in Kabul New City. *J. Jpn. Soc. Civ. Eng*. **2017**, *73* (5), pp.25-30. https://doi.org/10.13140/RG.2.2.27110.32325.
283. Ramos, H. M.; McNabola, A.; López-Jiménez, P. A.; Pérez-Sánchez, M. Smart Water Management towards Future Water Sustainable Networks. *Water* **2020**, *12* (1). https://doi.org/10.3390/w12010058.
284. Ranaee, E.; Abbasi, A. A.; Tabatabaee-Yazdi, J.; Ziyaee, M. Feasibility of Rainwater Harvesting and Consumption in a Middle Eastern Semiarid Urban Area. *Water* **2021**, *13* (15), pp.1-23. https://doi.org/10.3390/w13152130.
285. Ranjan, V.; Reddy, M. V.; Irshad, M.; Joshi, N. The Internet of Things (IOT) Based Smart Rain Water Harvesting System. *6th International Conference on Signal Processing and Communication (ICSC)* **2020**, pp.302–305. https://doi.org/10.1109/ICSC48311.2020.9182767.
286. Ranjith, S.; Anand V.; Shivapur, P.; Shiva, K.; Chandrashekarayya G.; Hiremath, D. Water Quality Model for Streams: A Review. *Journal of Environmental Protection* **2019**, *10* (12). DOI: 10.4236/jep.2019.1012097.
287. Ransom, K. M.; Nolan, B. T.; A. Traum, J.; Faunt, C. C.; Bell, A. M.; Gronberg, J. A. M.; Wheeler, D. C.; Z. Rosecrans, C.; Jurgens, B.; Schwarz, G. E.; Belitz, K.; M. Eberts, S.; Kourakos, G.; Harter, T. A Hybrid Machine Learning Model to Predict and Visualize Nitrate Concentration throughout the Central Valley Aquifer, California, USA. *Science of The Total Environment* **2017**, *601–602*, pp.1160–1172. https://doi.org/https://doi.org/10.1016/j.scitotenv.2017.05.192.
288. Rao, C.S.; Manjula, N. Determination of Water Quality Index of Some Areas in Guntur District Andhra Pradesh. *Int. J. Appl. Biol.* **2010**, *1*, pp.79-86.
289. Rasekh, A.; Hassanzadeh, A.; Mulchandani, S.; Modi, S.; Banks, M. Smart Water Networks and Cyber Security. *Journal of Water Resources Planning and Management* **2016**, *142* (1816004). https://doi.org/10.1061/(ASCE)WR.1943-5452.0000646.
290. Rasoulkhani, K.; Mostafavi, A.; Cole, J.; Sharvelle, S. Resilience-Based Infrastructure Planning and Asset Management: Study of Dual and Singular Water Distribution Infrastructure Performance Using a Simulation Approach. *Sustainable Cities and Society* **2019**, *48 (*101577). https://doi.org/https://doi.org/10.1016/j.scs.2019.101577.
291. Raza, M.; Hussain, F.; Lee, J.; Shakoor, M.; Kwon, K. Groundwater Status in Pakistan: A Review of Contamination, Health Risks, and Potential Needs. *Crit. Rev. Environ. Sci. Technol*. **2017**, *47*, pp.1713–1762. doi:10.1080/10643389.2017.1400852.
292. Richard, M.; Issac, J. *Analysis of climatic variability and its environmental impacts across the occupied Palestinian territory*; Applied Research Institute–Jerusalem: Bethlehem, Palestine, 2012, Pp. 1-12.
293. Rizeei, H. M.; Azeez, O. S.; Pradhan, B.; Khamees, H. H. Assessment of Groundwater Nitrate Contamination Hazard in a Semi-Arid Region by Using Integrated Parametric IPNOA and Data-Driven Logistic Regression Models. *Environmental Monitoring and Assessment* **2018**, *190* (11). https://doi.org/10.1007/s10661-018-7013-8.
294. Robie, J. XML Processing and Data Integration with XQuery. *IEEE Internet Computing* **2007**, *11* (4), pp.62–67. https://doi.org/10.1109/MIC.2007.96.
295. Robles, T.; Alcarria, R.; Martín, D.; Morales, A.; Navarro, M.; Calero, R.; Iglesias, S.; López, M. An Internet of Things-Based Model for Smart Water Management. *28th International Conference on Advanced Information Networking and Applications Workshops* **2014**, pp.821–826. https://doi.org/10.1109/WAINA.2014.129.

296. Rodda, H. J. E.; Demuth, S.; Shankar, U. D. E. The Application of a GIS-Based Decision Support System to Predict Nitrate Leaching to Groundwater in Southern Germany. *Hydrological Sciences Journal* **1999**, *44* (2), pp.221–236. https://doi.org/10.1080/02626669909492219.
297. Rodriguez-Galiano, V.; Mendes, M. P.; Garcia-Soldado, M. J.; Chica-Olmo, M.; Ribeiro, L. Predictive Modeling of Groundwater Nitrate Pollution Using Random Forest and Multisource Variables Related to Intrinsic and Specific Vulnerability: A Case Study in an Agricultural Setting (Southern Spain). *Science of The Total Environment* **2014**, *476–477*, pp.189–206. https://doi.org/https://doi.org/10.1016/j.scitotenv.2014.01.001.
298. Rojek, I.; Studzinski, J. Detection and Localization of Water Leaks in Water Nets Supported by an ICT System with Artificial Intelligence Methods as a Way Forward for Smart Cities. *Sustainability* **2019**, *11* (2). https://doi.org/10.3390/su11020518.
299. Romano, M.; Kapelan, Z. Adaptive water demand forecasting for near real-time management of smart water distribution systems. *Environ. Model. Softw*. **2014**, *60*, pp.265–276. https://doi.org/10.1016/j.envsoft.2014.06.016.
300. Roslan, M.K.; Kamil, Y.; Sulaiman, W.; Yusoff, A. Creation of a Ground Water Quality Index for an Open Municipal Landfill Area. *MJMS* **2007**, *1*, pp.181–192.
301. Rostad, N.; Foti, R.; Montalto, F. A. Harvesting Rooftop Runoff to Flush Toilets: Drawing Conclusions from Four Major U.S. Cities. *Resources, Conservation and Recycling* **2016**, *108*, pp.97–106. https://doi.org/https://doi.org/10.1016/j.resconrec.2016.01.009.
302. Salcedo, E.; Hoyos, S.; Esteller, M.; Morales, M. Application of Water Quality Index to Evaluate Groundwater Quality (Temporal and Spatial Variation) of an Intensively Exploited Aquifer (Puebla Valley, Mexico). *Environ. Monit. Assess.* **2016**, *188* (573). doi:10.1007/s10661-016-5515-9.
303. Sauvé, S.; Desrosiers, M. A review of what is an emerging contaminant. *Chem. Cent. J.* **2014**, 8 (15). doi:10.1186/1752-153X-8-15.
304. Savić, D.; Vamvakeridou-Lyroudia, L.; Kapelan, Z. Smart Meters, Smart Water, Smart Societies: The IWIDGET Project. *Procedia Engineering* **2014**, *89*, pp.1105–1112. https://doi.org/https://doi.org/10.1016/j.proeng.2014.11.231.
305. Schilean, A.; Giurca, I. Choosing a water distribution pipe rehabilitation solution using the analytical network process method. *Water* **2018**, *10* (484). https://doi.org/10.3390/w10040484.
306. Schilling, K. E.; Wolter, C. F. A GIS-Based Groundwater Travel Time Model to Evaluate Stream Nitrate Concentration Reductions from Land Use Change. *Environmental Geology* **2007**, *53* (2), pp.433–443. https://doi.org/10.1007/s00254-007-0659-0.
307. Schröder, J. J.; Scholefield, D.; Cabral, F.; Hofman, G. The Effects of Nutrient Losses from Agriculture on Ground and Surface Water Quality: The Position of Science in Developing Indicators for Regulation. *Environmental Science & Policy* **2004**, *7* (1). https://doi.org/10.1016/j.envsci.2003.10.006.
308. Selvaganapathi, R.; Vasudevan, S.; Balamurugan, P.; Nishikanth, C.; Gnanachandrasamy, G.; Sathiyamoorthy, G. Evaluation of Groundwater Quality and Water Quality Index in the Palacode and Pennagaram Taluks, Dharmapuri District, Tamil Nadu, India. *Int. J. Appl. Res.* **2017**, *3*, pp.285–290.
309. Sendanayake, S. Potential for Domestic Rooftop Rainwater Harvesting in the District of Colombo, Sri Lanka. *IJIR* **2016**, *2* (12), pp.231-236.

310. Shadeed, S. Spatio-Temporal Drought Analysis in Arid and Semi-Arid Regions: A Case Study from Palestine. *Arabian Journal for Science and Engineering* **2013**, *38* (9). https://doi.org/10.1007/s13369-012-0504-y.
311. Shadeed, S.; Judeh, T.; Almasri, M. Developing a GIS-Based Water Poverty and Rainwater Harvesting Suitability Maps for Domestic Use in the Dead Sea Region (West Bank, Palestine). *Hydrol. Earth Syst. Sci.* **2019**, *23*, pp.1581–1592. https://hess.copernicus.org/articles/23/1581/2019/.
312. Shadeed, S.; Judeh, T.; Riksen, M. Rainwater Harvesting for Sustainable Agriculture in High Water-Poor Areas in the West Bank, Palestine. *Water* **2020**, *12* (2), pp.1-16. https://doi.org/10.3390/w12020380.
313. Shadeed, S.; Lange, J. Rainwater harvesting to alleviate water scarcity in dry conditions: A case study in Faria Catchment, Palestine. *Water Science and Engineering* **2010**, *3* (2), pp.132-143. https://doi.org/10.3882/j.issn.1674-2370.2010.02.002.
314. Shahrour, I.; Xie, X. Role of Internet of Things (IoT) and Crowdsourcing in Smart City Projects. *Smart Cities* **2021**, *4* (4), pp.1276–1292. https://doi.org/10.3390/smartcities4040068.
315. Sheffield, J.; Wood, E.F.; Pan, M.; Beck, H.; Coccia, G.; Serrat-Capdevila, A.; Verbist, K. Satellite remote sensing for water resources management: Potential for supporting sustainable development in data-poor regions. *Water Resources Research* **2018**, *54* (12), pp.9724-9758. https://doi.org/10.1029/2017WR022437.
316. Sheikh, V. Perception of Domestic Rainwater Harvesting by Iranian Citizens. *Sustain. Cities Soc*. **2020**, *60* (102278), pp.1-16, https://doi.org/https://doi.org/10.1016/j.scs.2020.102278.
317. Sheikhy Narany, T.; Ramli, M. F.; Aris, A. Z.; Sulaiman, W. N. A.; Fakharian, K. Spatial Assessment of Groundwater Quality Monitoring Wells Using Indicator Kriging and Risk Mapping, Amol-Babol Plain, Iran. *Water* **2014**, *6* (1), pp.68–85. https://doi.org/10.3390/w6010068.
318. Shrestha, A.; Luo, W. Assessment of Groundwater Nitrate Pollution Potential in Central Valley Aquifer Using Geodetector-Based Frequency Ratio (GFR) and Optimized-DRASTIC Methods. *ISPRS Int. J. Geo-Inf.* **2018**, *7* (6). https://doi.org/10.3390/ijgi7060211.
319. Singha, S.S.; Devatha, C.P.; Singha, S.; Verma, M.K. Assessing Ground Water Quality Using GIS. *IJERT* **2015**, *4*, pp.689–694. doi:10.17577/IJERTV4IS110604.
320. Sisay, E.; Halefom, A.; Khare, D.; Singh, L.; Worku, T. Hydrological modelling of ungauged urban watershed using SWAT model. *Modeling Earth Systems and Environment* **2017**, *3* (2), pp.693-702. https://doi.org/10.1007/s40808-017-0328-6.
321. Słyś, D.; Stec, A. Centralized or Decentralized Rainwater Harvesting Systems: A Case Study. *Resources* **2020**, *9* (1). https://doi.org/10.3390/resources9010005.
322. Smithers, R.; Harrison, M.; Mimi, Z.; Hardan, K.; Abdelall, S.; Hasan, A. 2016. *National adaptation plan to climate changes;* Palestinian Environment Quality Authority (EQA): Ramallah, Palestine, 2016; Pp. 1-216.
323. Soros, A.; Amburgey, J. E.; Stauber, C. E.; Sobsey, M. D.; Casanova, L. M. Turbidity Reduction in Drinking Water by Coagulation-Flocculation with Chitosan Polymers. *Journal of Water and Health* **2019**, *17* (2), pp.204–218. https://doi.org/10.2166/wh.2019.114.
324. Stigter, T.; Ribeiro, L.; Dill, A.M.M. Application of a Groundwater Quality Index as an Assessment and Communication Tool in Agro-Environmental Policies—Two Portuguese Case Studies. *J. Hydrol.* **2006**, *327*, pp.578–591. doi:10.1016/j.jhydrol.2005.12.001.

325. Stratigea, A. The Concept of ‘Smart’ Cities – Towards Community Development? *NETCOM* **2012**, *26*, pp.375–388. https://doi.org/10.4000/netcom.1105.
326. Stringer, L.C.; Mirzabaev, A.; Benjaminsen, T.A.; Harris, R.M.; Jafari, M.; Lissner, T.K.; Stevens, N.; Tirado-von Der Pahlen, C. Climate change impacts on water security in global drylands. *One Earth* **2021**, *4* (6), pp.851-864. https://doi.org/10.1016/j.oneear.2021.05.010.
327. Sullivan, C.A.; Meigh, J.R.; Giacomello, A.M. The water poverty index: Development and application at the community scale. *Nat. Resour. Forum* **2003**, 27, pp.189-199. doi: 10.1111/1477-8947.00054.
328. SUSMAQ. *Conceptual, Steady-State and Transient-State Models of the Eocene Aquifer in the North-Eastern Aquifer Basin*; SUSMAQ: Ramallah, Palestine, 2004.
329. Tamagnone, P.; Cea, L.; Comino, E.; Rosso, M. Rainwater Harvesting Techniques to Face Water Scarcity in African Drylands: Hydrological Efficiency Assessment. *Water* **2020**, *12* (9). https://doi.org/10.3390/w12092646.
330. Tamimi, L. Rainwater Harvesting System: Quality and Impacts on Public Health. MSc Thesis, Birzeit University, Ramallah, Palestine, February 2016.
331. Tang, B.; Chen, Z.; Hefferman, G.; Wei, T.; He, H.; Yang, Q. A Hierarchical Distributed Fog Computing Architecture for Big Data Analysis in Smart Cities. *Proceedings of the ASE BigData & SocialInformatics* **2015**, *2015*. https://doi.org/10.1145/2818869.2818898.
332. Tao, Z.; Cui, Z.; Yu, J.; et al. Finite Difference Modelings of Groundwater Flow for Constructing Artificial Recharge Structures. *Iran J Sci Technol Trans Civ Eng* **2022**, *46*, pp.1503–1514. https://doi.org/10.1007/s40996-021-00698-5.
333. Taylor, R. Rethinking Water Scarcity: The Role of Storage. *Eos. Trans. Agu*. 2009, *90* (28), pp.237–238. https://doi.org/https://doi.org/10.1029/2009EO280001.
334. Tegegne, G.; Park, D.K.; Kim, Y.O. Comparison of hydrological models for the assessment of water resources in a data-scarce region, the Upper Blue Nile River Basin. *Journal of Hydrology* **2017**, *14*, pp.49-66. https://doi.org/10.1016/j.ejrh.2017.10.002.
335. Tesoriero, A. J.; Voss, F. D. Predicting the Probability of Elevated Nitrate Concentrations in the Puget Sound Basin: Implications for Aquifer Susceptibility and Vulnerability. *Ground Water* **1997**, *35* (6). https://doi.org/10.1111/j.1745-6584.1997.tb00175.x.
336. The Arab Water Council. *Vulnerability of Arid and Semi-Arid Regions to Climate Change-Impacts and Adaptive Strategies: Perspectives on water and climate change adaptation*; AWC: Cairo, Egypt, 2009; Pp. 1–16.
337. Thu Minh, H.V.; Tri, V.D.; Ut, V.N.; Avtar, R.; Kumar, P.; Dang, T.T.; Hoa, A.V.; Ty, T.V.; Downes, N.K. A Model-Based Approach for Improving Surface Water Quality Management in Aquaculture Using MIKE 11: A Case of the Long Xuyen Quadangle, Mekong Delta, Vietnam. *Water* **2022**, *14*, 412. https://doi.org/10.3390/w14030412.
338. Ton, D.T.; Smith, M.A. The U.S. Department of Energy’s Microgrid Initiative. *Electr. J.* **2012**, *25* (8), pp.84–94. https://doi.org/10.1016/j.tej.2012.09.013.
339. Toosi, A.S.; Danesh, S.; Tousi, E.G.; Doulabian, S. Annual and seasonal reliability of urban rainwater harvesting system under climate change. *Sustainable Cities and Society* **2020**, *63*. https://doi.org/10.1016/j.scs.2020.102427.
340. Tran, H.; Leonarduzzi, E.; De la Fuente, L.; Hull, R.B.; Bansal, V.; Chennault, C.; Gentine, P.; Melchior, P.; Condon, L.E.; Maxwell, R.M. Development of a Deep Learning Emulator for a

Distributed Groundwater–Surface Water Model: ParFlow-ML. *Water* **2021**, *13* (3393). https://doi.org/10.3390/w13233393.
341. Tubeileh, H.; Shaheen, H.; Aliewi, A. Modeling the Eocene Aquifer in Northern West Bank .*An - Najah Univ. J. Res. (Science)* **2006**, *20*.
342. Tyagi, S.; Sharma, B.; Singh, P. Water Quality Assessment in Terms of Water Quality Index. *Am. J. Water Resour.* **2013**, *1*, pp.34–38. doi:10.12691/ajwr-1-3-3.
343. Uddameri, V.; Silva, A.; Singaraju, S.; Mohammadi, G.; Hernandez, E. Tree-Based Modeling Methods to Predict Nitrate Exceedances in the Ogallala Aquifer in Texas. *Water* **2020**, *12* (4). https://doi.org/10.3390/w12041023.
344. United Nation (UN). Sustainable Development Goals: 17 Goals to Transform Our World. Available online: http://www.un.org/sustainabledevelopment/ (accessed on 23 July, 2021).
345. United Nations (UN). *Leave No One Behind: A Perspective on Vulnerability and Structural Disadvantage in Palestine;* UN: New York, USA, 2016; Pp.1-57.
346. United Nations (UN). *Policy Brief: Water Quality*; UN: New York, United States, 2011; Pp. 1-16.
347. United Nations (UN). *Sustainable Development Goal 6: Synthesis Report 2018 on Water and Sanitation*; UN: New York, USA, 2018; Pp. 1-195.
348. United Nations (UN). *The Besieged Palestinian Agricultural Sector;* UN; New York, USA, 2015b; Pp. 1-49.
349. United Nations (UN). *Transforming Our World: The 2030 Agenda for Sustainable Development*; UN: New York, USA, 2015a; Pp. 1-35.
350. United Nations Development Programme (UNDP). *Climate Change Adaptation Strategy and Programme of Action for the Palestinian Authority;* UNDP: Jerusalem, Palestine, 2010; Pp. 1-100.
351. United Nations Development Programme (UNDP). *Water Governance in the Arab Region: Managing Scarcity and Securing the Future*; UNDP: Sweden, 2013; Pp. 1-168.
352. United Nations Environment Programme (UNEP). *A Snapshot of the World's Water Quality: Towards a Global Assessment*, UNEP: Nairobi, Kenya, 2016; Pp. 1-162.
353. United Nations Environment Programme (UNEP). *Desk Study on the Environment in the Occupied Palestinian Territories*; UNEP: Stockholm, Sweden, 2003; pp. 1–188.
354. United Nations Environment Programme (UNEP). *State of Environment and Outlook Report for the occupied Palestinian Territory;* UNEP: Stockholm, Sweden, 2020; Pp. 1-186.
355. Urama, K.; Ozor, N. Impacts of Climate Change on Water Resources in Africa: The Role of Adaptation. *ATPS* **2010**, *29*, pp.1-29. https://rb.gy/cjfzvv.
356. Ursino, N.; Grisi, A. Reliability and Efficiency of Rainwater Harvesting Systems under Different Climatic and Operational Scenarios. *International Journal of Sustainable Development and Planning* **2017,** *12*, pp.194–199. https://doi.org/10.2495/SDP-V12-N1-194-199
357. Valipour, M.; Banihabib, M.; Behbahani, S. Comparison of the ARMA, ARIMA, and the autoregressive artificial neural network models in forecasting the monthly inflow of Dez dam reservoir. *Journal of hydrology* **2013**, *476,* pp.433-441. https://doi.org/10.1016/j.jhydrol.2012.11.017.
358. Van Vliet, M.H.; Flörke, M.; Wada, Y. Quality Matters for Water Scarcity. Nat. Geosci. **2017**, *10*, pp.800–802. https://doi.org/10.1038/ngeo3047.

359. Vanham, D.; Hoekstra, A.Y.; Wada, Y.; Bouraoui, F.; de Roo, A.; Mekonnen, M.M.; van de Bund, W.J.; Batelaan, O.; Pavelic, P.; Bastiaanssen, W.M.; et al. Physical Water Scarcity Metrics for Monitoring Progress towards SDG Target 6.4: An Evaluation of Indicator 6.4.2 "Level of Water Stress". *Sci. Total Environ.* **2018**, *613–614*, pp.218–232. https://doi.org/10.1016/j.scitotenv.2017.09.056.
360. Versini, P. A.; Pouget, L.; McEnnis, S.; Custodio, E.; Escaler, I. Climate Change Impact on Water Resources Availability: Case Study of the Llobregat River Basin (Spain). *Hydrol. Sci. J.* **2016**, *61* (14), pp.2496–2508. https://doi.org/10.1080/02626667.2016.1154556.
361. Vilane, B. R. T.; Simiso, G. An Assessment of the Quality of Rainwater Harvested Using Rooftop Rainwater Harvesting (RWH) Technologies in Swaziland **2018**, *3* (6), pp.55-64.
362. Villar-Navascués, R. A.; Fragkou, M. C. Managing Water Scarcity Futures: Identifying Factors Influencing Water Quality, Risk Perception and Daily Practices in Urban Environments after the Introduction of Desalination. *Water* **2021**, *13* (19). https://doi.org/10.3390/w13192738.
363. Vishnu, S.; Ramson, S. R. J.; Senith, S.; Anagnostopoulos, T.; Abu-Mahfouz, A. M.; Fan, X.; Srinivasan, S.; Kirubaraj, A. A. IoT-Enabled Solid Waste Management in Smart Cities. *Smart Cities* **2021**, *4* (3), pp.1004–1017. https://doi.org/10.3390/smartcities4030053.
364. Wada, Y.; Flörke, M.; Hanasaki, N.; Eisner, S.; Fischer, G.; Tramberend, S.; Satoh, Y.; van Vliet, H.; Yillia, P.; Ringler, C.; Burek, P.; Wiberg, D. Modeling global water use for the 21st century: The Water Futures and Solutions (WFaS) initiative and its approaches. *Geosci. Model Dev.* **2016**, 9, pp.175–222.
365. Wang, A.-Q.; Lin, Y.-L.; Xu, B.; Hu, C.-Y.; Gao, Z.-C.; Liu, Z.; Cao, T.-C.; Gao, N.-Y. Factors Affecting the Water Odor Caused by Chloramines during Drinking Water Disinfection. *Science of The Total Environment* **2018**, *639*, pp.687–694. https://doi.org/https://doi.org/10.1016/j.scitotenv.2018.05.188.
366. Wang, D.; Hubacek, K.; Shan, Y.; Gerbens-Leenes, W.; Liu, J. A Review of Water Stress and Water Footprint Accounting. *Water* **2021**, *13*, 201. https://doi.org/10.3390/w13020201.
367. Wang, J.; Deng, Z. Modeling and Predicting Fecal Coliform Bacteria Levels in Oyster Harvest Waters along Louisiana Gulf Coast. *Ecological Indicators* **2019**, *101*, pp.212–220. https://doi.org/https://doi.org/10.1016/j.ecolind.2019.01.013.
368. WASH Custer-State of Palestine. *The West Bank WASH Contingency Plan 2021;* WASH Custer-State of Palestine: Ramallah, Palestine, 2021; Pp. 1-41.
369. Wehbe, R.; Shahrour, I. A BIM-Based Smart System for Fire Evacuation. *Future Internet* **2021**, *13* (9). https://doi.org/10.3390/fi13090221.
370. Wellen, C.; Kamran-Disfani, A.R.; Arhonditsis, G.B. Evaluation of the current state of distributed watershed nutrient water quality modeling. *Environmental science & technology* **2015**, *49* (6), pp.3278-3290. https://doi.org/10.1021/es5049557.
371. Wilson, G.L.; Mulla, D.J.; Galzki, J.; et al. Effects of fertilizer timing and variable rate N on nitrate–N losses from a tile drained corn-soybean rotation simulated using DRAINMOD-NII. *Precision Agric* **2020**, *21*, pp.311–323. https://doi.org/10.1007/s11119-019-09668-4.
372. World Health Organization (WHO). *Guidelines for Drinking-Water Quality*; WHO: Geneva, Switzerland, 2011; Pp. 1-541.
373. World Health Organization (WHO). *Nitrate and Nitrite in Drinking-Water: Background Document for Development of WHO Guidelines for Drinking-Water Quality*; WHO: Geneva, Switzerland, 2003; Pp. 1-16.

374. World Water Assessment Programme (WWAP). The United Nations World Water Development Report; United Nations Educational, Scientific and Cultural Organization: New York, United States, 2018; Pp. 1-75.
375. Wu, L.; Gao, J.; Zhao, W.; Xu, X.; Yin, Y.; Wu, L. Quality Assessment of Rainwater and Harvested Rainwater Stored in Different Types of Cisterns. *Water Supply* **2016**, *17* (3), pp.652–664. https://doi.org/10.2166/ws.2016.144.
376. Wu, Z. Y.; El-Maghraby, M.; Pathak, S. Applications of Deep Learning for Smart Water Networks. *Procedia Engineering* **2015**, *119*, pp.479–485. https://doi.org/https://doi.org/10.1016/j.proeng.2015.08.870.
377. Xiao, Y.; Gu, X.; Yin, S.; et al. Geostatistical interpolation model selection based on ArcGIS and spatio-temporal variability analysis of groundwater level in piedmont plains, northwest China. *SpringerPlus* **2016**, *5*, (425). https://doi.org/10.1186/s40064-016-2073-0.
378. Xu, G.; Wang, T.; Wei, Y.; Zhang, Y.; Chen, J. Fecal Coliform Distribution and Health Risk Assessment in Surface Water in an Urban-Intensive Catchment. *Journal of Hydrology* **2022**, *604* (127204). https://doi.org/https://doi.org/10.1016/j.jhydrol.2021.127204.
379. Xuanhui, W.; Tailian, L.; Xilai, Z.; Hui, P.; Jia, X.; Bo, Z. Short-term prediction of groundwater level using improved random forest regression with a combination of random features. *Applied Water Science* **2018**, *8* (125), pp.1-12. doi: doi.org/10.1007/s13201-018-0742-6.
380. Yan, H.; Liu, Y.; Han, X.; Shi, Y. An evaluation model of water quality based on DSA-ELM method. *16th International Conference on Optical Communications and Networks (ICOCN)* **2017**, pp.1-3. doi: 10.1109/ICOCN.2017.8121280.
381. Yang, Y.; Zhu, Y.; Wu, J.; Mao, W.; Ye, M.; Yang, J. Development and application of a new package for MODFLOW-LGR-MT3D for simulating regional groundwater and salt dynamics with subsurface drainage systems. *Agricultural Water Management* **2022**, *260*. https://doi.org/10.1016/j.agwat.2021.107330.
382. Yoon, H.; Jun, S.; Hyun, Y.; Bae, G.; Lee, K. A comparative study of artificial neural networks and support vector machines for predicting groundwater levels in a coastal aquifer. *Journal of Hydrology* **2011**, *396* (1-2), pp.128-138. https://doi.org/10.1016/j.jhydrol.2010.11.002.
383. Yousefi, M.; Saleh, H. N.; Yaseri, M.; Mahvi, A. H.; Soleimani, H.; Saeedi, Z.; Zohdi, S.; Mohammadi, A. A. Data on Microbiological Quality Assessment of Rural Drinking Water Supplies in Poldasht County. *Data in Brief* **2018**, *17*, pp.763–769. https://doi.org/https://doi.org/10.1016/j.dib.2018.02.003.
384. Yu, Z.; Zhu, T.; Zhang, J.; Ge, M.; Fu, S.; Lai, Y. Fog Harvesting Devices Inspired from Single to Multiple Creatures: Current Progress and Future Perspective. *Adv. Funct. Mater*. **2022**, *2200359*, pp.1-20. https://doi.org/10.1002/adfm.202200359.
385. Zabidi, H.A.; Goh, H.W.; Chang, C.K.; Chan, N.W.; Zakaria, N.A. A Review of Roof and Pond Rainwater Harvesting Systems for Water Security: The Design, Performance and Way Forward. *Water* **2020**, *12* (3163). https://doi.org/10.3390/w12113163.
386. Zafarzadeh, A.; Amanidaz, N.; Seyedghasemi, N. Relationship between Turbidity and Residual Chlorine and Microbial Quality of Drinking Water. *Medical Laboratory Journal* **2014**, *8* (3).
387. Zakar, M. Z.; Zakar, R.; Fischer, F. Climate Change-Induced Water Scarcity: A Threat to Human Health*. *South Asian Stud.* **2012**, *27* (2), pp.293-312.

388. Zhang, B.; Cui, B.; Zhang, S.; et al. Source apportionment of nitrogen and phosphorus from non-point source pollution in Nansi Lake Basin, China. *Environ Sci Pollut Res* **2018a**, *25*, pp.19101–19113. https://doi.org/10.1007/s11356-018-1956-8.
389. Zhang, S.; Zhang, J.; Jing, X.; Wang, Y.; Wang, Y.; Yue, T. Water Saving Efficiency and Reliability of Rainwater Harvesting Systems in the Context of Climate Change. *Journal of Cleaner Production* **2018b**, *196*, pp.1341–1355. https://doi.org/https://doi.org/10.1016/j.jclepro.2018.06.133.
390. Zhang, S.; Zhang, J.; Yue, T.; Jing, X. Impacts of climate change on urban rainwater harvesting systems. *Science of the Total Environment* **2019**, *665*, pp.262-274. https://doi.org/10.1016/j.scitotenv.2019.02.135.
391. Zhao, J.; Zhou, B.; Butler, J. P.; Bock, R. G.; Portelli, J. P.; Bilén, S. G. IoT-Based Sanitizer Station Network: A Facilities Management Case Study on Monitoring Hand Sanitizer Dispenser Usage. *Smart Cities* **2021**, *4* (3), pp.979–994. https://doi.org/10.3390/smartcities4030051.
392. Zheng, J.F.; Jiao, J.D.; Zhang, S.; Sun, L.P. An optimization model for water quantity and quality integrated management of an urban lake in a water deficient city. *Urban Water Journal* **2017**, *14* (9), pp.922-929. https://doi.org/10.1080/1573062X.2017.1301500.
393. Zhou, Q.; Chen, C.; Zhang, G.; Chen, H.; Chen, D.; Yan, Y.; Shen, J.; Zhou, R. Real-time management of groundwater resources based on wireless sensors networks. *Journal of Sensor and Actuator Networks* **2018**, *7* (1). DOI: 10.3390/jsan7010004.