



**DEVELOPMENT OF URBAN GROWTH AND WATER MANAGEMENT
MODELS IN NASIRIYAH CITY, IRAQ USING GIS AND MACHINE LEARNING
TECHNIQUES**

By

HANOON SADEQ KHALEEF AH HANOON

**Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia,
in Fulfilment of the Requirements for the Degree of Doctor of Philosophy**

January 2024

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DEDICATION

To the noble soul of the Prophet Muhammad, whose teachings inspire humanity to seek knowledge. To the cherished memory of my father, the loving spirit of my mother, and my sister, whose unwavering support and nurturing guidance shaped my journey.

And

To my esteemed teachers, whose dedication has bestowed upon me the invaluable gift of the finest education.



Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment
of the requirement for the degree of Doctor of Philosophy

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January 2024

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Urbanisation and water scarcity risk (WSR) have obstructed sustainable development goals globally. However, traditional approaches in this field do not include a listening concept to people who are vulnerable to water shortage risk and environmental vulnerability when making important decisions. In addition, techniques to measure the overlapping risks of water shortage and environmental vulnerability that threaten urban communities has yet to be developed. Therefore, the current study includes four objectives. The first objective is to develop a comprehensive vulnerability assessment (CVA) to determine vulnerable urban areas. This technique was created by combining three fuzzy logic functions, i.e. fuzzy analytic hierarchy process, fuzzy linear membership, and fuzzy overlay gamma. The second objective is to develop a new machine learning model to predict urban water shortage risk based on public participation (PP), namely WSRPP. The third objective is to develop a new approach to forecast urban boundary growth using ML and GIS, namely UGBF. The last objective is to develop a hybrid model prediction of environmental vulnerability (EV)

and WSR, called WSREV model. The hybrid model includes the integration of the three techniques mentioned above (i.e. CVA, WSRPP and UGBF) coupled with Water Evaluation and Planning Model (WEAP). Nasiriyah City in southern Iraq was selected as the study area. Results revealed the following: A total of 11 sectors in the city, as well as over 175,000 people or 25% of the entire population, reside in regions with a high degree of vulnerability. Additionally, 26% live in 17 sectors with very high WSR. The urban area ratio was increased by about 10%, i.e. from 2.5% in the year 1992 to 12.2% in 2022. Moreover, the city will be expanded by 34%, 25% and 19% by the years 2032, 2042 and 2052, respectively. The prediction scenarios showed by the year 2052, under high population growth coupled with the RCP 8.5 path of climate change (HP-RCP 8.5), about 34% of the city's area will be located under a very high to high degree of risk. By contrast, the situation under the manage measure scenario and RCP 4.5 path of climate change (MS-RCP 4.5) will be only 9% of the city's area under a **very high to high degree of risk.**

Keywords: public engagement; water-shortage risk; machine learning; GIS; urban growth prediction

SDG: water-shortage risk; machine learning; GIS; urban growth prediction

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

**PEMBANGUNAN PERTUMBUHAN BANDAR DAN MODEL
PENGURUSAN AIR DI BANDAR NASIRIYA, IRAQ MENGGUNAKAN
TEKNIK GIS DAN PEMBELAJARAN MESIN**

Oleh

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Pembangunan dan risiko kekurangan air (WSR) telah menghalang matlamat pembangunan bandar secara global. Walau bagaimanapun, pendekatan tradisional dalam bidang ini tidak memasukkan konsep dengan daripada umum yang berisiko pada risiko kekurangan air dan pencemaran alam sekitar ketika membuat keputusan yang penting. Tambahan pula, teknik untuk mengukur risiko pertindanan kekurangan air dan kerentanan persekitaran yang mengancam komuniti bandar masih belum dibangunkan. Oleh sebab itu, kajian ini merangkumi empat objektif. Objektif pertama adalah untuk membangunkan penilaian kerentanan yang komprehensif (CVA) bagi menentukan kawasan bandar yang rentan. Teknik ini telah direka dengan menggabungkan tiga fungsi logik kabur, iaitu proses hierarki analitik kabur, keahlian linear kabur, dan gama tindakan kabur. Objektif kedua adalah untuk membangunkan pembelajaran mesin baharu bagi meramal risiko kekurangan air bandar (WSR) berdasarkan penglibatan awam (PP), iaitu WSRPP. Objektif ketiga adalah untuk membangunkan pendekatan baharu bagi meramalkan pertumbuhan persempadanan

bandar menggunakan ML dan GIS yang dinamai UGBF. Objektif terakhir adalah untuk membangunkan model peramalan hibrid bagi kerentanan persekitaran (EV) dan WSR, iaitu model WSREV. Model hibrid tersebut merangkumi integrasi tiga teknik yang dinyatakan di atas (iaitu, CVA, WSRPP dan UGBF) beserta dengan Model Penilaian dan Perancangan Air (WEAP). Bandar Nasiriyah, di selatan Iraq telah dipilih untuk dijadikan kawasan kajian. Dapatan memperlihatkan yang berikut: Sejumlah 11 sektor di bandar, di samping lebih 175,000 penduduk atau 25% keseluruhan populasi, menetap di wilayah dengan tahap kerentanan yang sangat tinggi. Tambahan pula, 26% tinggal di 17 sektor dengan WSR yang sangat tinggi. Ratio kawasan bandar telah meningkat lebih kurang 10%, iaitu daripada 2.5% pada tahun 1992 kepada 12.2% pada tahun 2022. Di samping itu, bandar tersebut akan berkembang, masing-masing sebanyak 34%, 25% dan 19% pada tahun 2032, 2042 dan 2052. Senario peramalan menunjukkan bahawa menjelang tahun 2052, di bawah pertumbuhan populasi yang tinggi ditambah pula dengan laluan perubahan iklim RCP 8.5 (HP-RCP 8.5), lebih kurang 34% kawasan bandar akan ditempatkan di bawah risiko yang sangat tinggi hingga ke tahap risiko yang tinggi. Sebaliknya, situasi di bawah senario pengukuran pengurusan dan laluan perubahan iklim RCP 4.5 hanya merupakan 9% daripada kawasan bandar di bawah risiko sangat tinggi hingga ke tahap risiko tinggi.

Kata Kunci: SDG; water-shortage risk; machine learning; GIS; urban growth prediction

SDG; Srisiko kekurangan air; pembelajaran mesin; GIS; ramalan pertumbuhan bandar

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LIST OF ABBREVIATIONS

WSR	water shortage risk
PP	public participation
LULCC	Land use–land cover change
GIS	Geographic information system
RS	Remote sensing
MCDM	Multi criteria decision making
MODM	Multi objective decision making
ML	Machine learning
CVA	comprehensive vulnerable assessment
WSRPP	water shortage risk and public participation technique
WEAP	Water evaluation and planning model
UGBF	urban growth boundary forecasting technique
WSREV	prediction model of environmental vulnerability (EV) and WSR
SDGs	Sustainable development goals
AHP	Analytic Hierarchical Process
FL	fuzzy logic
FLM	fuzzy logic membership
FOG	fuzzy overlay gamma
KSI	Keywords, Sequences and Importance
SQL	Similarity, Quality, Recent technique
PPGIS	Public participation and GIS
MLP	Multilayer perceptron
SVM	Support vector machine algorithm
RF	Random forest algorithm
KNN	K-nearest neighbour algorithm

NBC	Naïve Bayes classification
AB	AdaBoost algorithm
AI	Artificial intelligence
CA	Cellular automata
MC	Markov chain
ANN	Artificial neural network
UGBs	Urban growth boundary(s)
PEST	parameter estimation tool
DU	Depleted uranium
ED	Environmental domain
UD	Urban domain
BD	Building domain
SD	Social domain
Ve	Environmental vulnerability
Vb	building vulnerability
Vu	Urban vulnerability
Vs	social vulnerability
Va	Aggregated vulnerability
Vt	Comprehensive vulnerability
WLC	weighted linear combination function
DST	Decision support tool
PCC	Proximity to urban centre
PWP	Proximity to water pipelines
PSN	Proximity to sewage networks
PMR	Proximity to main roads
PD	Population density

GDP	Gross domestic product
PR	Proximity to the river
S	Slope
DEM	Elevation
SCP	Semi-automatic classification plugin
IES	Iraqi environment standards
WWTPs	Wastewater treatment plant(s)
R^2	Coefficient of determination
OC	Overall accuracy
ACC	Accuracy
RC	Reference scenario
BAUS	Business-As-Usual scenario
ES	Ecological security scenario
CLP	Cultivated land protection scenario
RUD	Rapid Urbanization Development
NG	Nature growth
MS	Management scenario
HP	High population scenario

CHAPTER 1

INTRODUCTION

1.1 Background

Rapid urbanisation driven by uncontrolled population growth coupled with climate change has caused many problems worldwide, e.g. pollution, water shortage risk (WSR), crowded traffic, poor sustainability and exhaustion of natural resources (Rossell, 2021). Consequently, urban regions have grown at the expense of natural habitats and water resources, resulting in the deterioration of the natural environment (Islam, Hossain and Majed, 2021). Climate change has directly affected water supply, and the effect is evident in densely inhabited dry and semiarid areas, putting large parts of humanity at risk of water shortages (Rafiei, Gharechelou and Golian, 2022).

Due to the vast array of assessment factors, understanding urban water management, such as the amount and purity of potable water, water governance, sanitation, human well-being, water supply, socioeconomic variables, environmental and natural health, water management and WSR, is challenging (Chapagain et al., 2022). However, given the increasing strain on urban water consumption, numerous studies have attempted to describe how internal and exterior challenges combine to cause WSR in urban areas (Asghar et al., 2019).

These two types of challenges are closely related to WSR, which has the internal challenge of unequal water distribution between communities and the external challenge of climate change and national water management regarding splitting water allocation amongst cities (Yousuf et al., 2018). Although climate change has an impact

on the availability of water, other variables (e.g. population development, urbanisation, infrastructure, living standards and geographic disparity) are placing even more stress on the distribution mechanism (Amin et al., 2018).

Water supply amounts amongst a city's neighbourhoods have variance due to the spatial inequality phenomenon in the water supply. Given that public participation (PP) has become a critical component of land-use planning, it has been sanctioned by international law as a means of engaging the state, civil society and individuals in making decisions (Badiora & Ojo, 2021). Therefore, formal decision-making processes should be modified to empower local residents to participate in exploring risks and selecting solutions (Aubert et al., 2020).

Geographic information system and multicriteria decision making (GIS-MCDM) are one of the main decision-making topics that attempt to find the best choice by examining several variables throughout the selection process (Taherdoost & Madanchian, 2023). Recent bodies of research successfully conducted geographical analysis for maximising resource allocation using combined GIS and machine learning (GIS-ML) as a modern method. However, human perspectives have not been included in ML language yet. Furthermore, when it comes to multicriteria decision-making, both methods fail to account for land use land cover change LULCC processes brought about by urbanisation.

Future hazard situations must be estimated on the basis of land-use change patterns to make choices about the optimum process for identifying the overall risk of environmental contamination and WSR (Aniah et al., 2023). To forecast the overall

risk, however, an appropriate modelling method should be developed to simulate urban growth. These techniques should be easily incorporated with the optimum techniques and should be integrated with WSR. Therefore, the main goal of the current study is to develop models of urban growth and water management using GIS and machine learning.

1.2 Problem Statement

Although vulnerability theory can be applied to detect susceptible urban areas by considering various variables that have an impact on urban populations, scholars have ignored environmental issues and water scarcity risk (WSR) that are associated with urban vulnerability (Gerundo, Nesticò, et al., 2020; Ruá et al., 2021). In this context, many studies have used the multicriteria decision-making (MCDM) technique to evaluate the various factors that affect urban areas. The analytic hierarchical process (AHP) stands out amongst more than 15 MCDM techniques presently used (Zolfaghary, Zakerinia and Kazemi, 2021). However, AHP uses sharp values, and its findings are clouded by uncertainty; thus, fuzzy AHP (FAHP) has evolved as an improved form of AHP to better represent human thinking (Malakar, 2021).

As for the use of geographic information systems (GIS) for urban planning, fuzzy logic (FL) functions are by far the most successful implementation of geographic analysis (Perera *et al.*, 2021). Fuzzy logic duties vary; fuzzy linear membership (FLM) can be used with FAHP to standardise decision-making criteria and turn factors into fuzzy values between 0 and 1 (Parsian *et al.*, 2021). Furthermore, fuzzy overlay gamma (FOG) has become the most important function in (GIS) to analyse the impacts of several sets' variables (Mallick *et al.*, 2021). To this end, the first objective of the

current thesis introduces a new approach namely, comprehensive vulnerability assessment (CVA). It includes integration of FAHP, FLM and FOG to overcome the uncertainty. This approach considers environmental vulnerability (EV) as a considerable driving factor of total vulnerability ignored by previous studies. However, using GIS-MCDA for the optimisation process has a few drawbacks.

The GIS-MCDA method takes more time, effort, resources and cost than what is strictly necessary. Machine learning models can accurately forecast WSR in urban regions. Given the difficulties in interpreting its results, traditional ML methods are not preferred for detecting outliers in relevant hydrological variables (S. Wang et al., 2022). However, human perspectives are not included in ML decisions, despite the need of including the views of those who are vulnerable or at danger. Thus, the second objective of the current thesis presents public participation (PP) as a new tool to develop a model that can predict WSR in urban regions, namely, WSRPP. However, a model that simulates urban growth is still needed for making wise decisions based on machine learning (ML).

In the context of urban growth simulation, the cellular automata (CA) model is favoured over other simulation methods because it can anticipate local urban expansion efficiently and accurately (Kamaraj & Rangarajan, 2022). However, combining CA-ANN with optimisation approaches to achieve a sustainable site choice for varied activities involves complicated procedures (Ghosh et al., 2021). Although many operations are required for a single task, such as downloading Landsat imagery, classifying land cover and simulating urban expansion, it cannot reliably anticipate farther out than three decades. However, the process of simplifying this technique into

a training model is a subject that must be investigated. Therefore, the third objective of the current thesis introduces urban growth boundaries (UGBs) as a simple tool to develop a new machine learning model called urban growth boundary forecasting (UGBF). It integrates UGBs and ML algorithms as a straightforward model for controlling and monitoring urban growth.

Future scenarios that used urban sprawl simulations did not fully consider environmental concerns and water security risk (Zhang *et al.*, 2020). Development plans must be enhanced, and land and water resource management must be integrated; however, most studies have failed to quantify the sustainability impact of urbanisation and water crisis adequately (B. Gong & Liu, 2020; P. Kumar *et al.*, 2022). Therefore, the fourth objective of the current study presents a hybrid model by integrating three techniques that were developed in previous objectives (i.e. CVA, WSRPP and UGFB) with the WEAP model. The hybrid model considers the LULCC dynamic, water simulation and PP to predict EV and WSR up to the year 2052 under different scenarios, including high population growth and climate changes.

1.3 Research Objectives

The study aims to develop models utilizing GIS and machine learning for urban growth and water management in Nasiriyah City, Iraq. It focuses on identifying vulnerable areas, assessing water scarcity risk, and predicting urban expansion. This approach integrates public participation with advanced analytics to guide sustainable urban and water resource planning. Therefore, four objectives were included in this thesis:

- 1- To determine vulnerable urban areas using a comprehensive vulnerability assessment model.
- 2- To develop a water security risk model using public participation (PP) and ML algorithms.
- 3- To develop an urban growth model using GIS and ML algorithms.
- 4- To develop a hybrid prediction model of the overall risk of water scarcity risk and environmental pollution.

1.4 Scope and Limitation of the Research

The main scope of this study is to develop urban growth and management water models considering vulnerable areas. This study proposes a scientific strategy that promotes public participation (PP) at various stages of the decision-making process to address water shortages in metropolitan areas. However, this thesis focuses solely on assessing water security risks within the boundaries of the study area, Nasiriyah, a city located in southern Iraq, with water pollution falling outside the scope of the research. Additionally, the research scope focuses on developing an urban growth model integrating GIS and machine learning techniques, encompassing a comprehensive vulnerability assessment based on social, urban, building, and environmental parameters. In addition, the scope of the thesis involves the evaluation of several scenarios, including climate change, high population growth, and various management scenarios, aimed at predicting water scarcity trends up to the year 2052. Consequently, data within the city's boundaries that are relevant to the research objectives are required. However, the data period ranged from 1984 to 2021 due to the accessibility of the required data.

Several limitations have emerged during this study. Firstly, accessing data about social vulnerability at the household level was challenging due to stringent constraints, high population density, and the expansive size of the study area. Secondly, obstacles arose in obtaining necessary data related to the management regulations of the local water supply system, impeding the identification of all key driving factors of water scarcity risk. Additionally, restrictions were encountered in conducting public interviews with residents within the study area of Nasiriyah City, which hindered efforts to assess the level of service provided by government agencies. Moreover, the onset of the COVID-19 pandemic further complicated the participatory planning process, exacerbating existing challenges.

1.5 Thesis Organisation

The thesis is divided into five chapters as follows:

The first chapter introduces the research topic and describes briefly the background of the study, the problem statement and scientific gaps, the research questions and the study objectives. In addition, it includes the contribution and importance of the current study. The literature review is in the second chapter. It is a summary of the most important previous studies related to the subject of the thesis. This chapter offers a discussion of the studies that have already been conducted, the gaps in the literature and the methodologies that were used. It also contains the limitations and challenges in the scope of the topic. In addition, it includes the definitions of keywords of the thesis topic.

The third chapter is the methodology. It contains the overall flowcharts of the methodology. This chapter describes the study area and the data collection process,

data management and analysis. It explains how the methods were developed for this study and how the ML models were trained. In addition, the validation results and model calibration processes are explained. The fourth chapter presents the results and discussion. It contains the results of the four techniques that were developed on the basis of the objectives of the current study. It also contains maps, charts, and validation results. In addition, this chapter contains the analysis and discussions of results.

The fifth and final chapter presents the conclusion and recommendations. This part summarises the study's major results and makes recommendations for future research.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter reviews the literature concerning water management and urban growth models. It delineates three critical components essential for model development: defining the research topic or subject, outlining techniques necessary for its creation and validation, and identifying parameters for measuring changes and validating the models. The literature review starts with a comprehensive urban expansion and water management overview. The subsequent part scrutinizes parameters, analysing driving factors like urban vulnerability, growth patterns, and water scarcity risks. The concluding section investigates the application of GIS, remote sensing, multi-criteria decision techniques, and machine learning algorithms. Moreover, it discusses various verification methods employed in studies on land use classification, urban growth simulation, and water system simulation. Finally, the chapter concludes with a synopsis of the literature review, including tables summarizing techniques, parameters utilized, and associated limitations.

2.2 Subject

This part delves into the research topic, i.e., water management and urban growth. It reviews how urban sprawl affects cities and leads to water crises in semi-arid areas such as Iraq. Urban sprawl puts pressure on communities, particularly in managing water resources. The expansion of cities exacerbates water shortages, increasing the demand for water and straining existing supplies and infrastructure. It is crucial to

address how urban sprawl affects water management and the sustainability of cities, especially in regions with limited water resources like Iraq.

2.2.1 Urban Growth

The evident shift in natural land cover due to urban growth is noticeable. Over the past few decades, the expansion of built-up areas has persisted, reducing green spaces and water reserves. Understanding the dynamics of urban growth necessitates identifying the driving factors behind urban expansion. Population growth is the most important driving force of urban growth (Dutta and Guchhait, 2020; Mansour). Another factor was the operations of the military that have contributed to the demolition and destruction of landscape, especially in conflict areas, such as Iraq (Saleem, Corner and Awange, 2018). However, regarding human and environmental protection, the conflict between sustainable development and urban growth has created a severe problem. Therefore, sustainable development is a crucial objective that must be achieved to prevent the exhaustion of those non-renewable resources. (Hunt & Shahab, 2021; Guiwen Liu et al., 2019).

2.2.2 Water Management

Given the rising issues of controlling water resources, which include climate change, urbanisation and resource depletion, majority of the world's regions have experienced severe water shortages. Sustainable urban water with decreased supply and unpredictability demand is an important concept of individuals' lives and city resilience in the case of drought (Z. H. Wang et al., 2019). Whilst water management is essential to the long-term sustainability of natural resources, the criteria of

sustainability required for intergenerational (cross-generational) justice are still not included in water management considerations (J. Xu et al., 2019).

Urban planners are often faced with the difficulty of combining all feasible water resource management strategies to provide sustainable solutions under various situations (Tabassum et al., 2020). According to (Fan et al., 2020), using environmental security scenarios allows for the development of quantitative indicators for sustainability. Therefore, improving water supply by integrating adaptability into urban design is a considerable obstacle to fostering sustainable urban development and societal resilience (Tsegaye et al., 2020).

2.2.2.1 Iraq's Water Crisis

The climate of Iraq is the semitropical and semidry type. Iraq was a rich country in water resources until a few decades ago. Almost all Iraqi people rely on the surface waters of the Euphrates and Tigris Rivers, which have their sources in upstream neighbouring countries (Ewaid et al., 2019). The rapid population growth in transboundary Euphrates and Tigris river countries, coupled with high agricultural demands and dam construction, has led to water deficits and poor water quality (Yousuf et al., 2018).

Given that the population rises swiftly and urbanisation continues fast, water resources in Iraq might decline, and water deficiencies would speed Iraq's desertification rate with a more enormous freshwater deficit (Ewaid et al., 2020). Based on the literature, Iraq's severe water deficit will be at extreme levels by 2050 (Ewaid & Abed, 2017). Therefore, the need to decrease demand, develop water

resource management, and control the main crops' water provisions is urgent because cultivation is the first consumer of water in Iraq.

2.3 Techniques (Geospatial engineering)

In the ISO/TC 211 series of standards, geospatial engineering is described as the 'discipline dealing with the gathering, distribution, storage, analysis, processing, and display of geographic data or geographic information'. Geospatial analysis tools illuminate urbanization's impact on nature and resource waste (Kazak, 2018). Advancements in remote sensing, statistics, and models have critically unveiled the substantial impact of LULCC on global environmental change, igniting widespread interest in examining urban sprawl and its repercussions (Malek & Verburg, 2020). However, more adaptability in dealing with and mitigating the consequences of urbanisation may be achieved if monitoring land use is improved using modern geospatial engineering solutions across the globe. (Mitchell et al., 2021).

2.3.1 Geography Information System (GIS)

Geography information system is an information technology system that saves all of the digital data in one spot, allowing for the data to be retrieved and analysed quickly and effectively in the form of reactive maps. Initially conceived for scientific analysis, GIS has expanded beyond its initial scope and is now utilized across various fields. Its standout feature is its capacity to efficiently gather and handle large amounts of geographical and attribute data concurrently (Mahmoud et al., 2019). Generally, GIS encompasses four fundamental functional components:

1. “Data acquisition”: This process involves converting geospatial data into a format **compatible** with computer systems for efficient interpretation.
2. “Storage and Maintenance of Data*”: Crucial for managing extensive and complex spatial datasets, this aspect reduces the size, cost, and time associated with data transfer, filtering, and storage while ensuring data quality and reliability.
3. “Data manipulation and analysis”: Encompassing the collection, integration, and visualization of diverse geographical datasets, this facilitates comprehension and prediction of spatial patterns, serving as a fundamental method for extracting valuable insights from geographic data.
4. “Data presentation”: Following data manipulation and analysis, this involves structuring information visually to enhance understanding. It plays a pivotal role across various fields, enabling effective communication of findings derived from data analysis. Figure 2.1 illustrates the essential functional components of GIS.

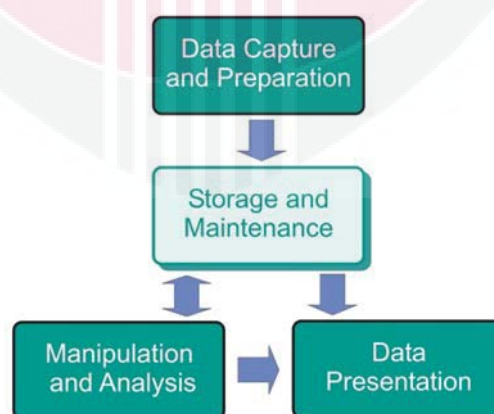


Figure 2.1 : Functional components of GIS

2.3.2 Remote Sensing

The term ‘remote sensing’ or ‘RS’, refers to the science of detecting the features of Earth’s surface and estimating the geo-biophysical qualities of those characteristics via the use of electromagnetic radiation as a method of contact (Reddy, 2018). It supplies data about Earth’s surface features at different spatial–temporal levels through satellite images (Rai et al., 2020). Remote sensing has passed through three major stages: the earliest generation included a group of satellites that can obtain a low spatial resolution (1 km–100 m); the second generation included a group of satellites that could increase the spatial resolution to 30–10 m; the latest generation of satellites were more proficient in observing Earth’s surface with a great spatial resolution, i.e. 5–0.5 m, as shown in Figure 2.2 (Kadhim et al., 2016). However, the platform of USGS ([https:// earthexplorer.usgs.gov/](https://earthexplorer.usgs.gov/)) provided a primary dataset for almost the studies that investigated Earth’s surface changes (P. Liu et al., 2020).

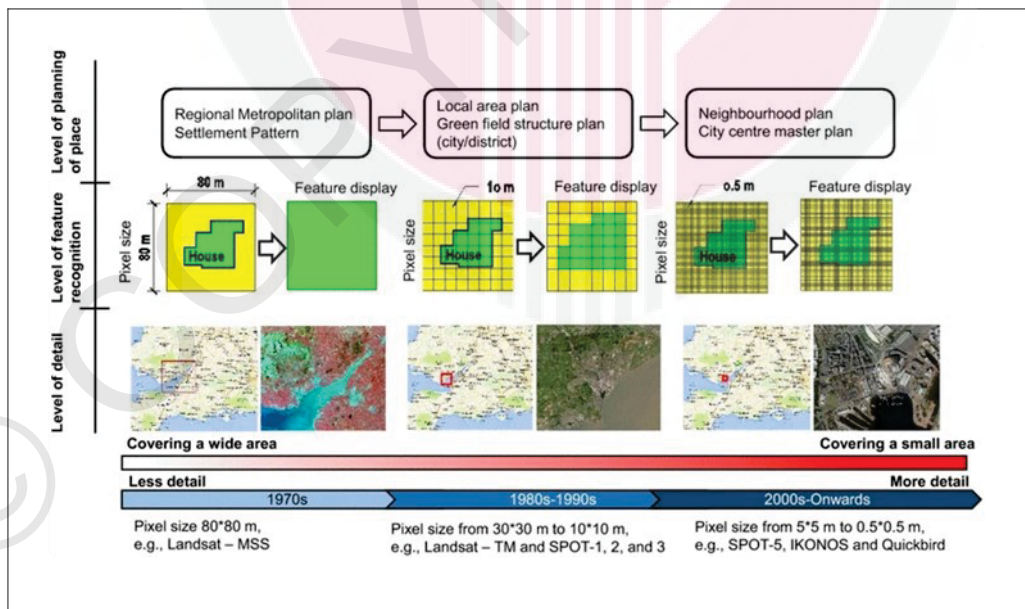


Figure 2.2 : Stages of the improvement of remote sensing

2.3.2.1 Integration of GIS and RS

Remote sensing has been universally applied in creating suitable models for examining the link between urbanization growth and land use. However, RS cannot provide detailed vertical or horizontal information for geographic features. Therefore, using GIS is a great solution that bridges this gap (Yoo et al., 2020). The integration of RS and GIS has been a valuable tool to collect and analyse geospatial data of urban planning, and it is an efficient approach for mapping and representing urban areas at various spatial levels (Olorunfemi et al., 2020). It gives promisingly accurate and positive results for monitoring urban developments and can measure and explain the various LULCCs that took place over the previous period (Gopal et al., 2016). Moreover, that integration of RS, GIS and land accounting techniques can analyse the reality of the situation, predict the future land cover change and discover implications for ecological sustainability (Akubia et al., 2020).

2.3.2.2 RS and GIS Applications for Monitoring Earth's Surface

Remote sensing (RS) and GIS could classify Landsat TM and Landsat ETM+ imagery into various LULCC classes. As a result of the combination of GIS and RS technologies, the internal driving forces of LULCC can be analysed, the spatial-temporal dynamics landscape for the past period can be investigated, and the trend of land use and environmental quality can be simulated (S. Liu et al., 2019). The integration confirmed a remarkable adverse relationship between land surface temperature and vegetation cover and stated that the sprawl of human settlements has increased surface temperature (Aldhshan & Shafri, 2019).

2.3.2.3 Satellite Image Classification Techniques

Common satellite image classification techniques are classified into automatic, manual and hybrid (Yusoff et al., 2017). In addition, satellite images could be classified in a semiautomated way. Although most techniques are under the first category, selecting appropriate classification techniques is based on the requirements of the study (Abburu & Babu Golla, 2015). With the help of field validation, supervised maximum likelihood can achieve high accuracy of urban sprawl analysis, as shown in the flowchart (Figure 2.3[a]) that was adopted by (A. Rahman et al., 2011). By contrast, (Mahmoud et al., 2019) stated that the unsupervised classification technique can also achieve satisfying accuracy land cover classification when the results are compared with the actual situation.

(Elias et al., 2019) used the hybrid classification technique to analyse LULCC in Ethiopia from the year 1985 to 2015, with the help of a handheld Garmin GPS and GCPs generated from Google Earth, and to increase the resolution of LULCC classification. Although several platforms can provide high-spatial-resolution RS images for LULCC mapping, an effective method that has the capability to produce highly accurate LULCC corresponding to the resolution of those images is still rare (Tong et al., 2020).

Most scholars adopted the accuracy of LULCC maps as the most important criterion to select the appropriate classification technique (Adel et al., 2020; Yusoff & Muharam, 2015). Thus, (Talukdar *et al.*, 2020) conducted another study to assess the classification accuracy of six ML algorithms: random forest (RF), support vector machine (SVM), artificial neural network (ANN), fuzzy adaptive resonance theory-

supervised predictive mapping (Fuzzy ARTMAP), spectral angle mapper (SAM), and Mahalanobis distance (MD) (Figure 2.3[b]). The study conclusively demonstrated that RF outperformed all other ML models in terms of accuracy.

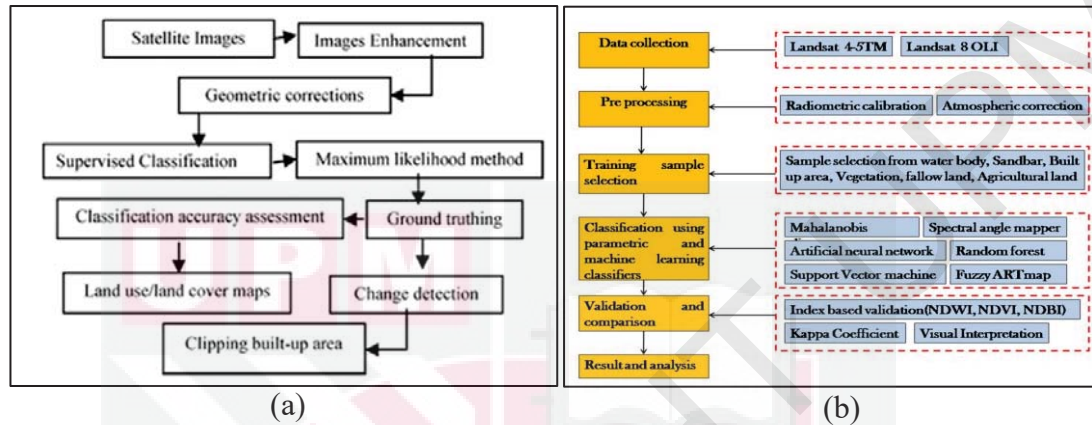


Figure 2.3 : (a) Classification of LULC using supervised maximum likelihood (b) Classification of LULC using machine learning algorithms

2.3.3 GIS and Public Participation

At the beginning of its existence, public participation and GIS (PPGIS) operated with basic equipment, such as paper maps, pencils and stickers, amongst other things. These days, PPGIS techniques are included in what is known as geoparticipation, which may be defined as the use of GIS for participatory mapping (Bąkowska-Waldmann & Kaczmarek, 2021). Public participation and GIS approaches can assist residents in achieving civic maturity, a sense of agency and social growth (Jankowski *et al.*, 2021). Meeting various planning demands is sufficiently adaptable, and it can mature into a more solid participatory planning support system (Kahila-Tani *et al.*, 2019).

Public participation and GIS can be used as a primary or secondary data collection method (Alattar et al., 2021). It makes a substantial contribution to our understanding of how people interact with their immediate surroundings and what they seek from it (Kivinen et al., 2018). Public participation and GIS also contributes to the development of alternative modes of public involvement, the engagement of a broader audience and the promotion of open communication between citizens and decision-makers (Kahila-Tani, Kytta and Geertman, 2019). However, the inability to read maps and the scarcity of consistent cartographic material were big challenges; thus, face-to-face interactions are required (Schernewski et al., 2019; L. Yu et al., 2020). Whilst enhanced participation is possible with the use of online and GIS tools, such procedures are extremely susceptible to shifting situations, as well as the mandate and continuity of support from management authorities (Van Cauwenbergh et al., 2018).

2.3.3.1 Public Participation Motivations

To achieve widely accepted PP by communities, the process should consist of four elements: participation of interests, knowledge, discussion and participation in activities and processes (Haqbeen et al., 2021). Whether public engagement should be initiated primarily by individuals or by authorities or politicians is a matter of disagreement (Kantola & Tuulentie, 2020). However, the general assumption is that persons affected by decisions have a right to be part of the decision-making process (Empidi & Emang, 2021). Residents who have an awareness of the effects of decisions tend to engage in participatory behaviour to avoid the severe consequences of pollution (S. Yu et al., 2021). In this case, people know why they engage and how the results will be relevant. Consequently, PP coordinators should consider involving the

most affected individuals, and participants should have access to their gathered data and project outcomes (M. Zhao et al., 2018).

2.3.3.2 Data Collection and Public Participation

Engaging individuals in planning and place governance is a long-standing global challenge. Planners need the experience of suitable mechanisms to touch broader societies of participants. However, people cannot engage in consultation and planning procedures in poor nations, particularly war-torn ones, due to location, time, gender, and security difficulties; thus, implementing bottom-up participation theories is difficult (Haqbeen et al., 2021). In this case, Internet mapping platforms can be used to support researchers in assembling information (Kotus & Rzeszewski, 2020).

Policymakers and spatial planning specialists usually mention a lack of participation awareness and practical skills (Somarakis & Stratigea, 2019). However, a lack of Internet literacy is a primary challenge (Van Cauwenbergh et al., 2018). Therefore, citizen data collectors require simple-to-use tools and computer interfaces to assist them in summarising and visualising PP results and assessing data quality (A. Gray et al., 2021). The usage of a smartphone is one of many available solutions that accelerate the data collection process and empower numerous people of all ages, educational levels and professional backgrounds (Salvati et al., 2021). However, the public involvement values of inclusion, transparency, interactivity and continuity that should govern e-consultations remain unimplemented (Bąkowska-Waldmann & Kaczmarek, 2021). Therefore, formal decision-making processes should be modified to the unique requirements of mass participation. To empower citizens to participate in decision-

making, updating data on the webpage is a considerable challenge related to dynamic information precision and effectiveness (Sang et al., 2021).

2.3.4 Delphi Technique

Several scientific studies use the Delphi approach to include stakeholders in assessment formulation. The Delphi technique is a sort of expert judgement in which a panel of recognised authorities discusses a problem using a predetermined set of questions (Choi & Cho, 2021). It is often used to raise up debates on contentious issues. Thus, this approach begins with numerous phases of brainstorming, when participants email or call in their first thoughts utilising the questionnaire to reach a consensus at the end of the process (Vulto et al., 2020).

According to the literature, the Delphi technique is used to explain expert panel views based on a systematic questionnaire prepared by researchers to estimate weight coefficients and score the weights of different aspects according to their respective circumstances (S. Yang et al., 2023). A total of 10 panellists are required to reduce mistakes and increase dependability; 8–12 panellists are adequate (J. Kim et al., 2020). However, if the specialists are too few, agreeing on enough issues is difficult; if there are too many, it is time consuming. Studies often include 10–30 professional participants in Delphi panels, which reduce error and enhance dependability (Varela & Domingues, 2021). Using experts' assessment, this number validates theories in undeveloped situations (Olivero et al., 2022).

2.3.5 Models of Simulation and Optimisation

Simulation of LULCCs in metropolitan regions and their surrounding aids sustainable urban planning. Researchers recognise the relevance of spatial modelling and optimisation in designing conversion scenarios and improving sustainable city operations, but application software approaches leave them out (Eicker et al., 2020). If these techniques can be used in real time, old approaches may be phased out (Batty, 2018). Land-use simulation and optimisation models can describe water consumption for each land use and incorporate useful information to improve water-simulation models (Rufino et al., 2021).

One of the most common land use and cover simulation models, on the one hand, is the Cellular Automata (CA) model, which leads to the creation of a decision support system (DSS) tool used as a specialised knowledge-based tool (Kazak, 2018). Cellular Automata can anticipate sprawl-related built-up status at the expense of other land-use classifications in future years (Yatoo et al., 2020). Markov chain, on the other hand, may maximise numerous effective environmental planning and management strategies (Xiang et al., 2021).

Water evaluation and planning (WEAP) is the simulation of a water model that has several benefits for assessing water systems. To simulate this system, water demand, supply, and transmission items are used (Bouznad et al., 2020). Moreover, WEAP has algorithms that mimic rainfall runoff from basins and sub-basins using climatic time-series data. Additionally, WEAP models are simpler to utilise and have simpler operating systems than measured general equanimity models (Gengyuan Liu et al., 2021). It provides a coordinated strategy for using a scenario generation tool and a

water balance database to assess water management policies and stakeholder procedures (Arfa Saleem et al., 2021).

River basin planning and management (RIBASIM) is a distinct integrated model that helps design river basin water distribution and simulates water supply and demand based on different scenarios to achieve sustainable water management (El Harraki et al., 2021). It also allows manual optimisation by changing water supply sources. However, it is frequently used as a reliable method of conducting the water-accounting procedure (Pedro-Monzonís et al., 2016). The soil and water assessment tool (SWAT) simulates water quantity and quality and evaluates land use and climate change's environmental impacts (Arjomandi et al., 2021a). (Jha et al., 2020) used groundwater flow simulation model and optimisation to construct favourable exploration-scale water management strategies.

In addition, (Handayanto et al., 2018) used a genetic algorithm (GA), particle swarm optimisation and local search to obtain the best land use whilst modelling LULCC using NARXNET and the land change modeller. To improve the collection of locally provided urban ecosystem services, (Elliot et al., 2019a) performed a new study to build a combination model that uses MILP and LULCC implementation scores. In addition, many studies have taken advantage of GIS to support simulation and optimisation models and made judgements on sustainable development in metropolitan areas (Price et al., 2018).

For future studies, the optimisation model may be strengthened by using some open-source tools, such as GeoSOS for ArcGIS, which provides full capabilities for

optimising, modelling and bringing the terrestrial model and the dynamic process into visual form (X. Li et al., 2017). Furthermore, local parameters, such as population and accessibility, should be added to optimisation models to improve decision-making for sustainable development (Guzman et al., 2020; Mohamed & Worku, 2020a).

2.3.5.1 Optimisation Techniques

2.3.5.1.1 Multicriteria Decision Model

Optimisation may be described as a decision support system (DSS) with certain limitations in which the goal is to acquire the most advantage from the available resources to obtain the best possible outcomes (Anuj Kumar & Pant, 2023). Whilst numerous strategies for optimising land use have been established (e.g. multiobjective decision making [MODM]), multicriteria decision model (MCDM) is a key decision-making tool that aims to choose the best option using several criteria during the voting process (Taherdoost & Madanchian, 2023).

Multicriteria decision model may assist in finding a good option for a certain challenging circumstance (Anuj Kumar & Pant, 2023), whereas MODM may be used to evaluate continuous choices with established constraints in the form of decision variable vectors (Abhishek Kumar et al., 2017). Although the number of choices under consideration may distinguish multiattribute decision-making (MADM) from MODM, both have comparable qualities. MODM is a subdiscipline of MCDM that deals with decision-making situations in which several competing goals must be evaluated at the same time, and the range of possibilities is extensive and implicitly constrained by restrictions (Thies et al., 2019).

Multicriteria decision model divides any issue into five major levels: the objective, available preferences and alternatives, criteria, and results. Multicriteria decision model has been created in many different ways to consider the implications of criterion selection and weighting on the choices that are ultimately made (Roy & Kar, 2022). However, more than 15 different MCDM methods exist, and three of them are notable (i.e. AHP, analytical network process and multiattribute utility theory) (Diaz-Balteiro et al., 2017). In MCDM, all methods follow the same rule, that is, they are used to produce criterion weightings by examining relevant criteria (Ghorbanzadeh et al., 2018).

2.3.5.1.2 Analytic Hierarchy Process

In the year 1970, Thomas Saaty invented Analytic Hierarchy Process (AHP). Throughout the last four decades, it has been extensively utilised and acknowledged as a tool for dealing with difficult decision-making issues in various sectors (Anuj Kumar & Pant, 2023). It is importance analysis for issues involving a vast number of options when it is difficult to achieve a pairwise comparison of the options, and it is based on the additive weighting model (Malczewski, 2006). Therefore, it was commonly used and coupled with GIS by many scholars to facilitate the identification and classification process of the possible solutions to the problem of optimal land use and water supply evaluation (Alvarado et al., 2016).

Analytic Hierarchy Process-based MCDA coupled with RS and GIS achieved a satisfying accuracy result in many fields, especially in selecting areas susceptible to hazard (Jhariya et al., 2020). Therefore, using AHP and GIS has been increasing as a robust spatial DSS in various fields, including the suitability assessment of land use

(Zolfaghary et al., 2021). Whilst AHP demonstrated more uncertainty in criterion weight assignment, the FAHP technique showed satisfactory results and reduced the burden of many spatial analyses (Caprioli & Bottero, 2021).

Nevertheless, fuzzy AHP (FAHP) has evolved as an improved form of AHP that mirror people thinking because AHP uses crisp values, and its findings are unclear (Malakar, 2021). Decision-makers may evaluate indications with different degrees of relevance that come from FAHP to help them determine the best options and indicators (Hanine et al., 2021). The FAHP methodology addresses uncertainty values that are associated with vulnerability indicators, but the AHP method produces satisfying results (Caprioli & Bottero, 2021).

2.3.5.1.3 Fuzzy Logic and Analytic Hierarchy Process

GIS has made Fuzzy logic (FL) the most effective spatial analytic tool for urban planning. Fuzzy logic can assess the many degrees of membership for intricate subjects involving doubt, such as the indices of vulnerability (Gerundo, Marra, et al., 2020). Fuzzy logic offers various means. One of these functions is FLM, which may be used with MCDA to standardise criteria for making intelligent judgements and transform various parameters into fuzzy 0–1 values (Parsian *et al.*, 2021).

The fuzzy overlay (FO) technique is used for multicriterion overlay analysis of numerous aspects linked with different sets. It examines the relationship between the minor criteria of several important criterion sets (Baalousha et al., 2021). However, several important FO functions enable the cell-by-cell overlay process to combine fuzzy membership values for many variables (Bianchini *et al.*, 2019). The most

important function that is produced when a fuzzy product value is multiplied by a fuzzy sum value called FOG. The gamma power is applied to both values. FOG adjusts the relationship between the fuzzy sum value increase and the fuzzy product value decline (Mallick *et al.*, 2021).

2.3.5.2 Integration of GIS and Multicriteria Decision Model

Several methods, such as MCDM, can determine vulnerability in urban settings, which evaluates numerous variables that add to city complexity (Assumma *et al.*, 2021; George *et al.*, 2022). To handle numerous challenging geographical issues, MCDM is frequently integrated into GIS. Additionally, such integration is more effective in assisting the decision-making process due to the availability of RS data and specialised perspectives (Billaud *et al.*, 2020; Ferretti, 2021). This model can aggregate data from several geographical aspects into a single measure index and analyse the situation and its ecological impacts (Ghorbanzadeh *et al.*, 2018). However, the integration of GIS and MCDM has been used as the main technique for spatial modelling for exploring vulnerable urban areas (Feizizadeh *et al.*, 2021). GIS and MCDM provides visualisation of the spatial variability of the driving forces; therefore, it can describe spatial injustices between different parts of urban areas (Cordão *et al.*, 2020)..

2.3.5.3 Integration of GIS and Machine Learning

Based on the literature, Multicriteria Decision Model (MCDM) and Machine Learning (ML) algorithms are the most widely used analysis methods for flood, fire and landslide risk maps and for choosing project locations (S. Wang *et al.*, 2022). Multicriteria Decision Model and Machine Learning, two of the most remarkable and fast-growing artificial intelligence fields, may assist urban planners in making

judgements (Martyn & Kadziński, 2022). Each assessment approach has merits and downsides. On one hand, MCDM has significant disadvantages. The unnecessary complexity of the optimization process requires additional time, effort, resources, and implementation costs (P. Kumar et al., 2022). Its results are associated with uncertainty and subjective bias stemming from expert opinions. In contrast to MCDM, ML boasts stronger predictive capabilities, thus outperforming MCDM in terms of prediction performance (Gudiyangada Nachappa et al., 2020; Khosravi et al., 2019). On the other hand, the primary advantage of integrating GIS and ML approaches is the improved performance of resulting susceptibility maps, along with faster data processing times (Iban & Sekertekin, 2022). ML exhibits greater accuracy in classification compared to MCDM.

Most scholars prefer the integration of GIS and machine learning (GIS-ML) for spatial analysis and location optimization. Machine learning (ML) is commonly used for trend identification and prediction from large datasets, requiring careful pre-application processes such as data collection, algorithm selection, model training, and validation. With numerous ML algorithms in water management and urban planning, selecting the appropriate algorithm is crucial. Performance metrics, interpretability, dataset size, data linearity, format, and training/prediction time are considered for algorithm suitability (M. Zhu et al., 2022). This review thus focuses on examining the most relevant algorithms to the study's topic, as elaborated in the subsequent sections.

- **Multilayer Perceptron (MLP)**

Multilayer perceptron (MLP) has been extensively utilised for pattern recognition or classification, utilising a backpropagation technique to model learning. MLP has

three-layer, input, hidden and output layers. Thus, data are feedforwarded from the input layer to the output layer via hidden layers (Dam et al., 2022). The weights are adjusted by this method until the network produces an output that is as close to the desired output as possible (Güneş et al., 2021). In reality, neural networks with one hidden layer, and seldom two, exhibit great performance (Bansal et al., 2018). The risk of overfitting and longer calculation times are caused by a high number of hidden layers (Ajdadi et al., 2016). Furthermore, trial and error may be used to determine how many neurons are present in the hidden layer (Zarei et al., 2017).

- **K-Nearest Neighbour (KNN)**

In the field of data mining, the k-nearest neighbour (KNN) ML model is frequently used. It uses a basic ML method to fit the dataset (Niño-Adan et al., 2022). Given its effectiveness and familiarity, many academicians have advised utilising it to solve various categorisation issues. It is a popular ML strategy that is straightforward and does not rely on any parameters, and it has been used in various pattern recognition applications (Sun et al., 2022). Euclidean distance is frequently used in KNN-based approaches to compare the training–testing model similarity. On the basis of estimated similarities, KNN was developed, identifying the testing model’s output label as the one with the most votes amongst the k-neighbours (Gou et al., 2022).

- **Support Vector Machines (SVM)**

Regression and nonlinear classification may be conducted using Support Vector Machines (SVM), a group of supervised ML models with a connected kernel function (Mehmood & Asghar, 2021). It is utilised in various fields, including time series, regression, character recognition and classification (clustering). In its most basic form,

SVM operates on the statistical theory's 'structure risk minimal' premise (Hong et al., 2022). Given that the SVM applies the structural risk reduction concept, it can avoid the overfitting problem (W. Gong et al., 2015). Moreover, it may be modified to convert nonlinear input into linear input using a kernel function and then solve problems (e.g. linear problems) (Güven & Şimşir, 2020). Nevertheless, SVM can handle weighted instances and perform incremental–decremental learning (Gâlmeanu and Andonie, 2022).

- **Naive Bayes Classification (NBC)**

Naïve Bayes classification (NBC) is a probabilistic technique with strong feature independence. It is predicated on the assumption of attribute independence. In contrast to conventional techniques, which only provide the most probable class, it can predict and generate data across various classes. Whilst NBC works easily, SVM and MLP and other algorithms need several variables, which must be carefully discovered and tweaked for improved results (Balaji et al., 2020). Additionally, NBC is a superior option for the categorisation of urban vulnerability due to its substantial nonlinearity in comparison with SVM (Yao & Ye, 2020).

- **Random Forest (RF)**

Random forest algorithm (RF) refers to the many decision trees, which comprise the integrated ML model. It incorporates the findings of each decision tree using a special combination approach to produce a classifier with strong generalisation skills. This method creates subgroups from initial training data. These subsets train many base classifiers, whose votes decide the best classification results (Dai et al., 2022). In Random forest, tree predictors are mixed, with each tree relying on random vector

values separately and having a comparable distribution (Virro et al., 2022). Despite its excellent fitting and generalisation capabilities, the underlying notion of this model is easy to comprehend (Feng et al., 2022). (Yagoub et al., 2022) has demonstrated that selecting RF properties may considerably improve prediction accuracy. Random forest can manage massive data multidimensionality whilst being quick and sensitive to overfitting, according to previous studies (Dachuan Zhang et al., 2019).

- **AdaBoost (AB)**

AdaBoost algorithm (AB) is an ensemble learning method that builds a strong classifier from weak learners whilst minimising noise susceptibility. It can regulate, speed up and simplify applications. AB repeatedly weights each training dataset variable; thus, the sample weights are changed until the model meets its prediction accuracy requirement or the maximum number of iterations (Hang Liu et al., 2022). To reduce training failures and provide accurate predictions, each iteration trains data samples based on the classifier's weights (Pal et al., 2022). It works best when used to enhance Deep Tree performance on binary classification problems.(Aslam et al., 2022).

- **Linear Regression (LR)**

Linear regression (LR) is a simple but powerful ML-supervised learning approach that uses a linear formula to find a problem's optimal straight line. LR can predict a target variable (dependent variable) by utilising feature variables (independent variables). Target values are usually time-series variables (Shi et al., 2021). LR can help find patterns in experimental data and benchmark and evaluate new analytic procedures (Zakeri et al., 2020). The LR model may utilise the logistic function to connect land-

use class (a dependent variable) to its driving force (independent variables) to mine CA conversion rules (Raju & Laxmi, 2020).

- **Shapley Additive Explanations Model (SHAP)**

SHapley Additive exPlanations (SHAP) is an interpretable ML model that can understand a wide range of complex models by visualising and describing the convoluted causal link between the driving forces and the prediction. Although the SHAP technique is often used to understand the output of any ML model, it is utilised to interpret how the independent variables of the most accurate are related to the dependent variables (Grbčić et al., 2022). It helps display the significance of each attribute in ML models used visually to understand the mechanism of any model, as well as the contribution of each criterion to the decision based on Shapley values (G. Xu et al., 2022).

2.3.5.3.1 Multicollinearity Analysis

Datasets have many problems that must be preprocessed before they can be used to train ML algorithms. Although missing values, outliers and un-normalised and imbalanced datasets are serious issues that must be addressed, the multicollinearity problem between the independent variables has the most effect on the ML results (Bayhan & Bayhan, 1998). When two or more independent variables in a regression model have substantially linked, multicollinearity emerges, which may compromise the stability of the model (Sundus et al., 2022). It makes the model particularly sensitive to changes in the input variables, which might result in bad predictions or overfitting when nontraining set inputs are utilised (Ching et al., 2021).

When outliers and multicollinearity exist in a regression model dataset, the least squares estimator fails (Arum et al., 2023). However, the large magnitude of the input attributes hinders the ML performance and has a negative influence on the classification results (Chan et al., 2022). From this point forward, feature reduction is a required preprocessing strategy before using ML models to remove irrelevant criteria and apply the best prediction model (Gao et al., 2019).

2.3.5.4 Simulation Methods

2.3.5.4.1 Cellular Automata (CA)

Cellular automata (CA) and Markov models -FLUS, CA linked with the Markov chain (MC), Artificial Neural Network (ANN)- based Cellular automata (CA) and Random Forest (RF) have been used to simulate transition potential routes and LULCC and predict urban growth. Furthermore, the University of Illinois Land-use Evolution and Effect Assessment Model was used to simulate population density and dispersion (Allam et al., 2020). Each model offers a unique strategy to address dynamically complicated LULCC. Cellular automata was used because it can predict small-scale urban growth efficiently and effectively (Kamaraj & Rangarajan, 2022). Cell and cell space, cell size and shape, transition rule and cell neighbour are the four basic factors that make up the bulk of CA's core work, which also includes state and time (Wang and Wang, 2022).

Cellular automata applies the same transition rules to all model cells for urban expansion modelling. Given that the model ignores changes in spatial heterogeneity, such systems are prone to over- or undersimulation, leading to the amalgamation of several conversion-rule mining strategies. linear regressing (LR), Markov chain (MC),

and Artificial intelligence (AI) are the three main categories of such strategies (A. Khan & Sudheer, 2022). Unfortunately, consistent mechanisms for creating transition rules remain lacking. (Littidej et al., 2022). Therefore, landscape-driven, patch-based CA is a new method proposed by (Lin et al., 2023); this method simultaneously assesses landscape similarity and cell-by-cell agreement.

Linear regression (LR) makes it challenging to demonstrate that changes in land use are not necessarily linear. This approach typically produces faulty conversion rules, and rules derived from this method are frequently incorrect (Mitsova et al., 2011). However, when it comes to providing spatial and temporal information on dynamic LULCC, the second kind of model (CA-MC) is the gold standard. By combining the CA and MC models, we have a powerful simulation of land cover change that considers time and space (Küçük Matcı et al., 2022). The third group (CA-AI) includes tree-based decisions, SVM, ant colony algorithms, genetic algorithm (GA), and ANN (Quanli Xu et al., 2021).

In contrast to MC, ANN could accurately characterise nonlinear, spatially uncertain land-use changes, thereby improving CA model transformation procedures (Pu, 2021). Artificial Neural Network-based Cellular automata (ANN-CA) has utilised GIS and RS together to enhance urban growth forecasting processes and to better monitor LULCC over time (Rimal et al., 2018). Cellular automata method requires complex techniques to be combined with land use optimisation strategies to arrive at a sustainable conclusion on a suitable site for different activities (Ghosh et al., 2021). However, the CA model was used to set UGBs to regulate urban sprawl (Jin et al., 2023).

2.3.5.4.2 Urban Growth Boundaries (UGBs)

Green belts, urban service borders and urban growth boundaries (UGBs) are only a few of the tools used all over the globe to steer urban expansion in a sustainable direction (J. Yang et al., 2019). However, many studies have looked at the function of the UGBs (Jun Li & Zuo, 2022). Urban growth boundaries helps restrict urban expansion and prepare for future urban development. Thus, it has been used as a planning or policy tool in many nations, including China, Saudi Arabia, the United States and Switzerland, to govern urban development and stop the city's unplanned growth (Bajracharya & Sultana, 2022). In addition, in the 20th century, Maryland, Florida, Minnesota and Oregon, as well as cities in Australia, Korea, Canada and India, embraced UGB to guide sustainable urban expansion (Hepinstall-Cymerman et al., 2013).

Whilst the concept of UGB is the same in developed and developing nations, its implementation in developing countries has been restricted (Schuster Olbrich et al., 2022). Thus, given the distinctions in the nature of urban growth, the design and implementation of the UGB in developing countries would need radically different methods in comparison with developed countries (Seto et al., 2011). By contrast, UGBs have been used worldwide to help urban planners decide where and how to create new communities (Lai et al., 2022). Whilst it is generally agreed that it is useful for monitoring city development and controlling sprawl, it may profit from using urban growth models or land-use change simulation models, such as CA (X. He et al., 2019).

2.3.5.4.3 Hydrologic Simulation Models

To analyse water demand, water resource system analysis, water resource planning and management, as well as water balance and water allocation policies, many models have been developed (e.g. Crop Water and Irrigation Requirement, WO-Source Energy Balance Model, Resource Allocation Model, RIBASIM, Modular Simulator for river basin, Water Resource System Simulator, SWAT and WEAP). In comparison with generic equanimity models that can be measured, WEAP models are more user friendly and have simpler operating mechanisms (Al-Juaidi & Al-Shotairy, 2020). It can accurately replicate river runoff, water intake stations and water transfer distances (Amin et al., 2018). Moreover, WEAP can model the gap between demand and supply factors to learn how different climate change and population growth scenarios would affect water allocation management techniques (Nguyen et al., 2021).

After reviewing the relevant literature, several researchers settled on the WEAP model as the most promising option for estimating the effects of the present severe climatic conditions and for informing process changes in the planning and management of irrigation water in the future (Alamanos et al., 2020b). It is beneficial, simple to use, economical and widely accessible to the water resource community. Similar to other models, WEAP needs climate data and land-use information to investigate demand-and-supply water relations during the assessment of any possible scenario (Kuntiyawichai & Wongsasri, 2021). In addition, the population is an essential factor that has to be fed into WEAP to simulate water demand (Nguyen et al., 2021). The WEAP model can effectively predict the population growth and the total demand under various anticipated scenarios based on the critical assumption of the consumption per capita. Additionally, it serves the goals of modelling various

characteristics of decision analysis by using a water algorithm formula for proper water resource management planning (Halder et al., 2021).

2.3.5.4.4 Water Evaluation and Planning (WEAP) System

The Stockholm Environment Institute (SEI), a non-profit research centre at Tufts University in Somerville, Massachusetts, established WEAP in 1988. WEAP provides scenario-based models and methodologies to solve water administration problems in the natural watershed, canals, reservoirs and streams. It models basin and sub-basin rainfall–runoff using climatic time-series data (Asghar et al., 2019). Recently, WEAP has been used in different countries by many scholars to simulate demand and water supply under different situations with robust performance; results were supported by clear visuals (Alamanos et al., 2020a; Leong & Lai, 2017).

Although the input data have limitations, the previous studies showed that the WEAP model provided a solid basis for evaluating water resources under extreme weather conditions and rapid population growth (Hellegers et al., 2013). WEAP was used by Chamizo-Checa et al. (2020) to evaluate water demand and supply, and the validation result showed that modelling values were matched with the observed discharge data of the Tula River during the study period (Chamizo-Checa et al., 2020). Thus, many studies confirmed that the performance of WEAP was robust (Opere, Waswa and Mutua, 2022). Water Evaluation and Planning (WEAP) is software that can correctly simulate; it perfectly predicts discharges calculated in the measuring station with an average absolute error smaller than 10% (Molina Sánchez et al., 2022).

Water Evaluation and Planning is equipped with a technology known as parameter estimation tool (PEST), which may compare results with historical data and automate WEAP parameter change for reliability. It is a nonlinear parameter that serves as a one-of-a-kind calibration tool. It executes a model's control as many times as needed whilst altering its parameters until the gaps between the selected model's simulations and observed data are decreased in the direction of weighted least squares (Eryani et al., 2022). As a result, the WEAP model has the potential to be a powerful tool for quickly examining water surfaces whilst considering population and weather dynamics. In addition, Stockholm Environment Institute (SEI) developed a technique using R shiny to validate and calibrate the model. It is called the WEAP calibration and ensemble with R tools.

2.3.5.4.5 Soil Moisture Method

WEAP uses five methods to estimate river water: soil moisture method, irrigation demands only method, rainfall runoff method (simplified coefficient method), plant growth method and MABIA method (Ahmadaali et al., 2018; Ahmed et al., 2021). The soil moisture technique simulates the hydrological cycle well. This approach requires precipitation, temperature, plant cover, relative humidity, latitude and evapotranspiration (Ougougdal et al., 2020). The WEAP model generates hydrological cycle components using climatic time data by simulating rainfall runoff at the catchment area surface. Using certain processes, the approach estimates evapotranspiration, surface runoff, subsurface runoff, percolation and base flow. It also defines the plant cover and soil type (Abera Abdi & Ayenew, 2021). In this method, two layers are used to illustrate the basin. The top bucket is the root zone, in which the hydrological model calculation was based on. The bottom bucket is the deep

zone, in which the hydrological model estimation was based on, as shown in Figure 2.5. To run the soil moisture method, hydrological parameters that are listed in Table 2.1 should be defined (Amin et al., 2018).

Table 2.1 : List of required hydrological parameters for the soil moisture

Parameter	Acronym
“Crop coefficient”	KC
Z1	/
Z2	/
“Deep Water Capacity”	DWC
“Deep Conductivity”	DC
“Resistance Runoff Factor”	RRF
“Root Zone Conductivity”	RZC
“Soil Water Capacity”	SWC
“Preferred Flow Direction”	PFD

(de O. Vieira & Sandoval-Solis, 2018)

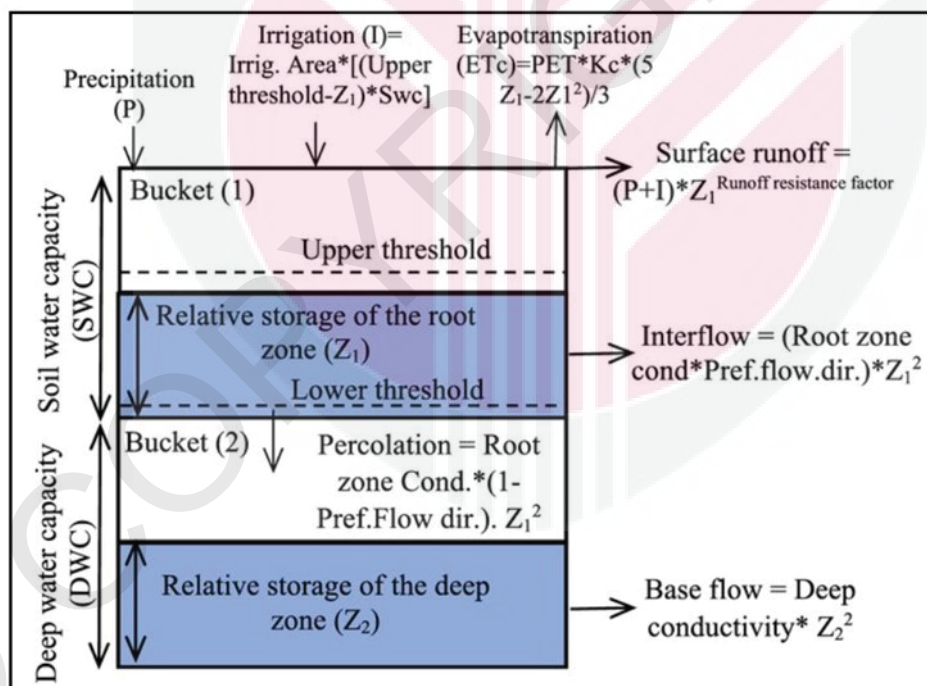


Figure 2.4 : Conceptual diagram and equations incorporated in the soil moisture method

2.3.6 Scenarios of Urbanisation and Water Management

Scenarios that include economic development and ecological security show leaders the feasibility, opportunity and challenges of accomplishing long-term sustainability objectives (Xue et al., 2018). Several researchers advised pursuing the governance (Gov) scenario long-term because it is environmentally sustainable and economically beneficial for places with runaway population growth and rapid urbanisation (Ruben et al., 2020). Hence, safeguarding water resources and green space under homogenous urbanisation should assist semiarid nations avoid water deficits (Bigurra-Alzati et al., 2021).

The urban landscape layout has been modified using land-use scenario dynamics to prevent encroaching on vital natural areas and corridors (Z. Liu et al., 2020). Similarly, protecting cultivated land has had a favourable influence on the consequences of land-use change on ecosystem services (Lang & Song, 2019). Although a scenario of urban densification has been a suitable solution due to limited land and reduction of greenhouse gas emissions, it increases air pollution, which extensively accelerates the spread of a pandemic (Khavarian-Garmsir et al., 2021). Additionally, the combination of MCDA and what-if scenario analysis (WISA) provides versatile tools for evaluating numerous policy choices and comparing and contrasting them with other alternatives to achieve aims and make unbiased decisions (Gorgoglione et al., 2019). Therefore, further simulations of land usage under diverse financial, social, demographic, geophysical and climatic scenarios are needed (Dou Zhang et al., 2020a).

2.3.6.1 Climate Change Scenarios

The Intergovernmental Panel on Climate Change (IPCC) has found that urban climate change effects, vulnerabilities and dangers have grown in all dimensions, economic situations and site features (Manapragada et al., 2022). In addition, IPCC has established that climate change is occurring, and sea level increase is likely (Aguilera-Vidal et al., 2022). Therefore, IPCC has recognised some of the causes of climate change and proposed worldwide mitigation strategies (Baek et al., 2013). IPCC developed four scenarios for the 21st century that show how greenhouse gas (GHG) emissions and atmospheric concentrations, air pollutant emissions and land use may change (Muhury et al., 2023). RCP2.6, RCP4.5 and RCP6.0 are tight mitigation and moderate, whereas high GHG emission scenarios are RCP8.5 (VIEIRA et al., 2023). However, climate prediction is an extremely complicated subject, and predicting how each place will react over the next several decades is difficult (Fürtön et al., 2022).

2.3.6.2 Climate Envelope Models

Climate envelope models (CEMs) have been used at regional scales to map crop distributions in relation to climatic factors and to produce estimates about changes in cropping area suitability by adding outputs from future climate change scenarios (Pokhrel et al., 2014). CEMs can be helpful in understanding species and habitat responses to climate change because it identifies critical links between climate change and relevant responses (Betts et al., 2015). Several different modelling categories have been using atmosphere–ocean global circulation models and/or Earth system models to simulate future changes based on different RCP scenarios (Baek et al., 2013). However, HadGEM2-ES, a modern Earth system model, now includes many land-

surface processes that are crucial to understanding climate change consequences. It analyses climate change, interactions and feedbacks whilst running (Singh et al., 2017).

2.4 Parameters

The literature stresses that characteristics of neighbourhoods, socio-economic conditions, and natural factors are key factors impacting urban growth and water management. Additionally, changes in water supply and demand and population density patterns significantly shape strategies for managing water resources. Recognizing these factors is crucial for developing thorough models for managing water and promoting urban growth. Subsequent sections overview the factors associated with urban expansion, water scarcity, and urban vulnerability, offering valuable insights to devise a new methodology for managing urban growth and water resources.

2.4.1 Urban Growth Driving Factors

Land use and land cover change is heavily influenced by neighbourhood, social and natural factors. Neighbourhood elements include closeness to metropolitan areas, major roads and urban centres (Q. Wang & Wang, 2022). Population and GDP are examples of socioeconomic forces (Küçük Matcı, Çömert and Avdan). Topography and environmental characteristics, such as elevation, slope and aspect, are examples of natural elements (Kamaraj & Rangarajan, 2022).

2.4.1.1 Neighbourhood Factors

Urban areas are dispersed amongst areas close to well-developed districts. Urban development is considerably influenced by factor of proximity to urban centres. It works in tandem with other factors and operates spatiotemporally to promote urban expansion across the city (Wu et al., 2006). Urban centres are desirable locations to start enterprises and build new communities (Megahed et al., 2015). The closeness to major pipelines and drainage networks are an appealing spatial feature for urban expansion because new homes are often built around these metropolitan areas to maximise the available infrastructure and utilities (Mansour et al., 2022). Moreover, a city is often grown in the direction of major roadways because closeness to major roads is a crucial determinant for growth (Traore & Watanabe, 2017). Therefore, modifications to highway entrances and exits, as well as road landscape designs, have considerable effects on geographic closeness (R. Yang et al., 2021).

2.4.1.2 Socioeconomic Factors

Density of population and Gross domestic product (GDP) are socioeconomic variables affecting LULCC globally (Past et al., 2022). Growth in population raises land demand; hence, considerable impacts on LULCC are anticipated (Ashwini & Sil, 2022). As urban areas make up most of a nation's economy, they grow and change faster than rural areas. By 2050, urban areas are expected to have quadrupled.

2.4.1.3 Natural Driving Factors

Elevation, slope and river proximity are the three most often used natural elements in urban development forecasting (Kamaraj and Rangarajan, 2022). They collaborate

with other LULCC driving factors. Lowland locations are less prone to urbanisation because building costs in low regions are higher due to the demand for huge quantities of backfilling. However, steeply sloping areas have a reduced proclivity to become urban (Dachuan Zhang et al., 2019). Moreover, proximity to the river is a critical factor for urban growth, particularly in arid locations where surface water is essential for settlement growth (Mansour *et al.*, 2022). Urban areas are commonly built beside rivers because water promotes the building of many urban community and sustainable development activities (Mengistu *et al.*, 2022).

2.4.2 Driving Forces of Water Scarcity Risk

Researchers have debated the causes driving urban of water scarcity risk (WSR). (Millington, 2018) argued that hydroclimatic circumstances, as well as technological, social and socioeconomic challenges, are major motivators of WSR. (Cordão et al. 2020) pointed out that WSR in municipalities is linked to issues, such as population growth, urbanisation, climate change, water supply and demand imbalances, unequal distribution of city services amongst neighbourhoods and economic difficulties. Social injustice, changing demographics and economy, increased water use, weak system pressure, inadequate energy and water scarcity are the seven causes.

Environment, geography, geology, economy, climate and society were all considered by (Noori et al., 2022) as factors related to WSR. In addition, (Krueger et al., 2019) identified several factors that contribute to WSR: the volume of water assigned to an urban area; the infrastructure for purifying, saving and distributing water; the financial budget for infrastructure construction and maintenance; and leadership effectiveness for managing and operating the water supply. According to (Liu et al., 2022), a close

relationship is found between WSR and the energy power supply. Consequently, several driving factors related to WRS were reviewed as follows:

2.4.2.1 Unmet Water Demand

Depending on water supply and demand priority, the amount of water delivered to each demand node along the river might vary, leading to ‘unmet demand’ (Dallison et al., 2021). However, cities’ water demands are often calculated as a function of their populations and average daily water use (Mena et al., 2021). Therefore, the volume of water should be adequate to maintain water treatment facilities (WTPs) working effectively and producing enough water for all shared districts. If the water in the rivers is insufficient to satisfy the city’s demands, then the demand will be unmet. Consequently, increased unmet demand raises WSR (Ward et al., 2019).

2.4.2.2 Proximity to the River Basin

In metropolitan environments, the distance between the river and the water reservoirs is one of the most important factors determining the WSR (Savari et al., 2022). However, illegitimate subscriptions, water leaks and pipe accidents increase loss with distance. Thus, cities that use reservoirs far from rivers are more susceptible to water shortages than others (Wee & Aris, 2022).

2.4.2.3 Proximity to Pumping Station

The high water pressure often causes water leakage in the neighbourhoods closest to the pumping station (PS) than in those further away (Zhuang & Sela, 2020). Neighbourhoods farther from pumping stations are more vulnerable to WSR (Eryiğit

& Sulaiman, 2022). Thus, housing between the pumping stations and the city's outskirts obtain adequate water pressure.

2.4.2.4 Proximity to Major Pipes

Water pressure is stronger in areas close to big pipelines compared with those at the ends of the pipes. Consequently, communities close to major water pipelines often have water, and they are better than the others. As a result, a negative linear connection is found between proximity to major pipes and water supply volumes (Hashemi et al., 2020).

2.4.2.5 Age of the Network Pipes

The operating life of water pipelines in any urban area greatly influences their efficiency (Latif et al., 2022). When a pipe ages, the inside surface becomes rougher because of the build-up of different components, which has a detrimental impact on the efficiency of the pipes. Hence, as the pipes become older, the water supply's efficiency declines (Zielina et al., 2022).

2.4.2.6 Capacity of Reservoir

Controlling the effectiveness of delivering water to the neighbourhood depends on reservoir capacity. Nonetheless, balance between the population and the reservoir capacity must be maintained (Moossa et al., 2022). Long-term development plans should consider this equation, and decision-makers should connect population increase and urban expansion to the necessary urban water capacity. As a result, danger is decreased by increasing reservoir capacity (Pissarra et al., 2021).

2.4.2.7 Electricity Supply

Water systems need enough electrical power dependability to provide constant service. To maintain water flow into city neighbourhoods, WTP and PS primarily depend on energy. Unexpected water service cutbacks result from recurrent power outages (Y. Liu et al., 2022). Given that even brief power outages may have considerable effects on certain utilities, having redundant supplies or backup generators lowers the risk. Nonetheless, a positive linear link is found between WSR and power interruptions (Yan et al., 2022).

2.4.2.8 Population

Water consumption has grown as a result of population growth and other reasons, including climate change (Xiang et al., 2021). When predicting the unmet urban water demand and urban expansion, the pace of population increase is a key element (Tabassum et al., 2020). Population and water use are closely connected, and the need for water is the result of multiplying water usage per person multiplying the population. Urban water supplies, for instance, may be considerably affected by factors, such as population growth and increased demand (Bakhtiari et al., 2020). Thus, a neighbourhood with a higher population is more vulnerable to water scarcity than other neighbourhoods.

2.4.2.9 Population Density

Population density puts a water supply system (WSS) under relative pressure. A positive linear connection occurs between a neighbourhood's population density and

WSR; consequently, greater density districts exert more pressure on WSS than lower density districts although having the same population (X. Chen *et al.*, 2020).

2.4.2.10 Unemployment Ratio

Experts in urban water supply claim that unemployment affects the amount of residential water that can be stored. Homes in wealthy areas are often outfitted with enough water reserves (van Leeuwen, 2017). When water shortage occurs, private reservoirs are a great resource for locals. Nonetheless, when the water supply is cut off, households in low-income areas commonly run dry (Valencia et al., 2022).

2.4.3 Effects of Urbanisation

Substantial scientific literature has confirmed the negative influences of urban sprawl on natural resources, such as cultivation, forest, surface, groundwater quality and energy resources. Consequently, the advantages provided by nature to humans in urban settings are known as urban ecosystem services, which are under risk due to rapidly expanding urbanisation (Elliot et al., 2019b). Therefore, many activities are accompanied by urban sprawl, threatening urban communities with serious environmental impacts, which are reviewed in the section below.

2.4.3.1 Weapon Effects and War

The major driving force for environmental change in Iraq was the military factor that converted farmland to transportation and a massive expansion in military camps. Radioactive materials, including depleted uranium (DU), which were routinely stored in the USA military base (Camp Taji) near Nasiriyah City, leaked into the environment

(Savabieasfahani et al., 2020). The expanse of radioactive elements in the region of the impact would expose urban communities to high risk (Durakovic, 2017; Mahdi et al., 2020).

2.4.3.2 Construction Industries

The brick industry and other construction industries are one of the most polluting industries in developing countries and have a vital negative impact on the environment (Le and Nguyen, 2019). When more people move to metropolitan areas, the demand for bricks increases. Consequently, the number of factories, which are major pollution sources, increases (Çelik et al., 2019; Solgi et al., 2019), in addition to the negative effect of land erosion because of mining and the continuous utilisation of land (Herlambang et al., 2019). Consequently, brick factories have adverse environmental influences, such as air pollution, excessive energy consumption and waste production (Zhang *et al.*, 2018).

2.4.3.3 Impact of Oil Industries on the Environment

Rapid population growth and increased demand for energy have led to highly adverse effects on water and the environment. Toxic pollutant emissions by oil refinery factories are affecting the water environment, where phenol and its derivatives are the most considerable environmental pollutants (Hesas et al., 2019). Oil refineries cause water and environmental pollution because refinery pollutants include a wide range of compounds at varying quantities, from ammonia to sulphones to phenol to hydrocarbons (Farag, Soliman and Abdel-Fattah, 2018). In short, the oil refinery factories and other oil-related industries have greatly influenced the environment, including soil, water and sediments of the larger area (Makri *et al.*, 2020).

2.4.3.4 Impact of Sewage on the Environment

According to a United Nations report, in developing countries, over 80%–90% of the wastewater pollutes surface and groundwater, which is a primary reason for environmental contamination that threatens community health (Fayomi et al., 2019). Industrial wastewater emulating the sewage of a municipality showed sharp toxicity in association to all bioindicators and belonged to the third toxicity level (Bezverbna & Załęska-Radziwiłł, 2018). In addition, wastewater treatment plants WWTPs could be hotspots for antimicrobial expansion, which harms aquatic habitats. In addition, hospital effluents constitute a distinct category of waste that is extremely hazardous because they include a myriad of drug residuals and infectious agents (Deepnarain *et al.*, 2020).

2.4.3.5 Impact of Landfill on the Environment

Globally, urbanisation and the growth of large conurbations is the main reason of the solid waste problem. Food waste, plastic trash and technological waste contribute to soil and water contamination, mostly via landfill leachate (Rezapour et al., 2018). In addition, many studies have proven that the leachate from municipal solid waste landfills can be a source of contaminants for adjacent areas (Vaverková *et al.*, 2018).

2.4.3.6 Effects of Poultry on the Environment

Given that urbanisation continues to increase rapidly, the demand for animal origin–industrial livestock and poultry production is expected to keep rising, leading to a considerable environmental pollution source (Hu et al., 2017). Animal husbandry's pollution emission is a global concern because it worsens environmental pollution

(Han et al., 2020) . Pollution from livestock and poultry husbandry activities dangerously threatens the regular trade of agricultural goods, regional environmental security and sustainable development.

2.4.3.7 Urban Growth and the COVID-19 Pandemic

In light of the rapid spread of the COVID-19 pandemic, societies all over the globe, from cities to rural areas, have had to re-evaluate their behaviour. COVID-19 has placed a focus on the interdependence of environmental, social and economic factors, highlighting the complexity of the relationships amongst these three elements. Its rapid expansion across the world has stimulated interdisciplinary research on issues of urban design and public healthcare (Hanmao Liu & Wang, 2021). Poorly controlled urban expansion has increased human density and ecological biodiversity, making the pandemic favourable (Platto et al., 2021). Thus, the pandemic was most severe in megacities, where rapid urbanisation has created substantial challenges with access to public amenities and the availability of medical services (Molina, 2021; P. Zhao et al., 2020). As a response, policymakers should make future plans that minimise migration from rural to urban areas. Although this phenomenon obstructed traditional business, it has increased remote business interactions, which were previously rare (Hariyani & Pratama, 2021; Lonati et al., 2021). Polycentric urban scenarios may affect socioeconomic growth and environmental approaches at various scales, although they may be better for pandemic isolation and quarantine (Xingjian Liu et al., 2018).

2.4.4 Sustainability Indicators

Global environmental change and sustainability generate critical issues, including identifying vulnerable populations and areas susceptible to the ongoing environmental

changes. Understanding these dynamics is essential for effective mitigation and adaptation strategies to safeguard both ecosystems and human communities. In a sustainable context, several initiatives, such as the water–energy–food nexus strategy, attempted to invest in sustainable ecosystem services to ensure vulnerable area access to essential services (Urbinnati *et al.*, 2023). (Ezbakhe *et al.*, 2019) suggested assessing the five normative elements of the human rights to water and sanitation (access, availability, quality, acceptability and affordability) to reduce service delivery problems for vulnerable communities. Various approaches for designing indicators that can define, evaluate and address vulnerability from complete viewpoints have been proposed by integrating traditional data sources with modern Earth observation data (Papathoma-Köhle *et al.*, 2019; Abascal *et al.*, 2022). Some researchers have proposed deprivation indices to measure deprivation in urban areas, such as the English indices of deprivation (IoD 2019) (Ministry of Housing Communities and Local Government, 2019). Others, such as (Lynch & Mosbah, 2017) have improved sustainability local indices to measure sustainability comprehensively. However, a body of studies adopted vulnerability theory as basic to measure sustainability indicators (Kang *et al.*, 2020).

2.4.5 Vulnerability Theory

Numerous urban planners utilize vulnerability theory to advance Sustainable Development Goals (SDGs), operating on the premise that risk results from the multiplication of threat by vulnerability. To identify potentially vulnerable communities, (Hazell, 2020) listed 10 topographic, demographic and land cover factors. Similarly, (Ge *et al.*, 2019) developed 16 social vulnerability indicators in four major categories: health, cultural, economic and social inequalities. In addition, to

assess vulnerable urban regions, (Ruá et al., 2021) used four domains: urban, building, sociodemographic, and socioeconomic. In another study, (Gerundo, Nesticò, et al., 2020) developed mitigation indicators for three key dimensions, namely, social domain, building domain and urban domain, to measure vulnerability indices. Similarly, (Gerundo, Marra, et al., 2020) organised three dimensions (social domain, urban domain and building domain) to create a composite vulnerability index for defining risky urban regions.

2.4.5.1 Vulnerability Indicators

Vulnerability is defined as a diminished ability to adapt to, resist and recover from threats (United Nations, 2003; Vučić et al., 2021). Hence, urban vulnerability may be defined as the process that results from the interaction of several disadvantageous conditions, making it difficult to overcome the unusual circumstances of urban areas (Huedo et al., 2021). The sensing and measurement of these parameters are critical tasks that must be completed prior to adopting vulnerability mitigation strategies (Garcia-almirall, 2021). However, most models used in this scope overlook ecological problems that are associated with urbanisation and even disregard Strategic Environmental Assessment (SEA), which is an effective technique for assessing environmental damages due to human activities to keep urban development sustainable (J. A. Thornton *et al.*, 2022). However, vulnerability theory is the best measuring technique because it can combine social, urban, building and EV indicators into one indicator to better understand the present situation and aid mitigation actions (Galderisi & Limongi, 2021).

2.4.5.1.1 Environment Domain

Quantifying the resilience of urban populations in the face of pollution risks from a wide range of sources is the goal of environmental vulnerable (EV) metrics. One way to classify the origins of pollution is into ‘point sources’ and ‘nonpoint sources’ (Dargahi et al., 2017). Industrial sites, power plants, landfills, brick factories and wastewater treatment plants are all examples of point sources of pollution that may be located and studied (WWTPs) (Motalebi Damuchali & Guo, 2020). Nonpoint sources of pollution, on the other hand, are more challenging to identify and manage. Polluting substances are released at several locations at once (Mahdi et al., 2020).

2.4.5.1.2 Building Domain

Previous statistical investigation that used quantitative and qualitative indicators revealed that the financial sector, government regulations and city size are most responsible for an urban environment’s susceptibility (Ribeiro et al., 2022). The main detrimental impacts of informal construction are the lack of amenities, such as unpaved roads (a major contributor to dust pollution) and public sewage and solid waste treatment facilities (Nassar & Elsayed, 2018). However, urban areas may be designated as vulnerable zones due to factors, such as the infrastructure, shape and density of a community, as well as its location (Abascal et al., 2022).

2.4.5.1.3 Urban Domain

Urban density, population density and green public spaces are directly or indirectly connected to vulnerability indicators and have the greatest influence on urban design (Mouratidis & Yiannakou, 2022). To prioritise measures that vulnerable people are

most needed, combining population and housing density and inadequate infrastructure maps helps pinpoint vulnerable areas with high vulnerability indicators (L. E. Thornton et al., 2022).

2.4.5.1.4 Social Domain

Researchers define social susceptibility as ‘the vulnerability of an individual or a community to an adverse event’ (Pasi et al., 2018). Studying social vulnerability focuses on identifying the issues and causes of social inequality that increase vulnerability at the household and community levels (Goto et al., 2022). However, the important social variables, which could measure the vulnerability of communities, include access to health care, education and employment possibilities (Guan, Liu and Dong, 2022; Sarker, 2022).

The uncontrolled growth exacerbates water demand, presenting a formidable obstacle to effective water management. Since it is imperative to safeguard natural resources sustainably, the glaring omission of water-sharing concerns from sustainable development guidelines underscores a stark failure in promoting intergenerational justice and addressing pressing environmental equity issues.

Numerous scholars have utilized various techniques and diverse parameters to identify vulnerable areas and conduct comprehensive risk assessments, as detailed in Table 2.2. The widespread use of the Multicriteria Decision-Making (MCDM) technique underscores its dominance in evaluating the myriad factors influencing urban areas. However, while MCDM-GIS offers a systematic approach, its reliance on subjective weighting and simplification of complex urban dynamics may pose limitations in

capturing the full spectrum of urban challenges and opportunities. Thus, the Fuzzy Analytic Hierarchy Process (FAHP) has emerged as a refined version of MCDM, offering a solution to better align with human cognition and decision-making processes. However, the bulk of models used in this context neglect urbanisation's ecological issues (Josimović, Cvjetić and Manić, 2021).

In contrast to the integration of MCDA-GIS, GIS-ML improves susceptibility map performance and decreases data processing time (Iban & Sekertekin, 2022). The predictive power of ML algorithms is greater than MCDA, making ML models more effective counterparts (Gudiyangada Nachappa *et al.*, 2020). Nevertheless, both techniques are entrenched in uncertainty, casting doubt on the reliability of their outcomes. Amidst this uncertainty, leveraging GIS functionality could potentially enable public engagement, facilitating a deeper understanding of the inherent ambiguities surrounding vulnerability indices (Giuffrida *et al.*, 2019). Despite this potential, the efficacy of GIS in addressing public concerns and navigating uncertainty within vulnerability assessments warrants further exploration and validation.

In spite of numerous efforts to advance water management techniques, existing frameworks conspicuously lack the integration of public participation (PP), as evidenced by Table 2.3. This oversight raises concerns about the adequacy of current approaches in capturing the diverse perspectives and stakeholder interests crucial for effective and sustainable water governance. Therefore, the integration of public participation and GIS (PPGIS) fills a crucial gap in scientific understanding by offering a solution that fosters alternative modes of public involvement, engages a broader audience, and promotes open communication between citizens and decision-

makers. This approach not only enhances the inclusivity and transparency of decision-making processes but also leverages machine learning capabilities to analyse and interpret geospatial data more effectively, leading to more informed and sustainable outcomes.

Ensuring water availability for both immediate and future needs within a sustainable urban context hinges on accurately forecasting water supply and demand amidst urban sprawl (Chini & Stillwell, 2020). In light of this critical imperative, existing efforts by numerous academics have predominantly concentrated on developing optimization and simulation models, such as the CA model, CA-Markov, and CA-ANN, considering several parameters to monitor urban growth, as detailed in Table 2.4. However, the integration of these models with comprehensive water resource management strategies remains a pressing challenge, highlighting potential gaps in addressing the complex interplay between urban expansion and sustainable water governance.

Notwithstanding the utilization of urban sprawl simulations, future scenarios have largely overlooked critical environmental considerations and water security concerns, which are essential for attaining sustainable objectives. The inadequacy persists as development plans lack necessary enhancements, and integration of land and water resource management remains lacking across various scenarios, including those addressing climate change. Regrettably, the majority of studies have faltered in adequately quantifying the sustainability ramifications of urbanization and the impending water crisis, as evidenced in Table 2.5. This deficiency underscores a

glaring gap in comprehensively addressing the profound impacts of urban expansion and water scarcity on sustainable development agendas.

Table 2.2 : Techniques, factors and limitations in analyzing vulnerable regions within a sample of literature

Study	Techniques	Parameters	Limitation
(Ruá, Huedo, Civera, et al., 2019)	"GIS and panel of experts"	"Urban domain, building domain, socio-demographic, and Socio-economic domain"	The selection of panel experts may introduce biases based on their expertise, perspectives, and biases.
(Malekmohammadi & Jahanishakib, 2017)	"Hybrid of the hydrogeomorphic approach and driver-pressure-state-impact-response (DPSIR) model"	"Agricultural activities, settlements and urban areas, drought, tourism, population growth, and mining activities."	Estimating vulnerability indicators and applying the DPSIR framework often involves subjective judgment and uncertainty.
(Ge et al., 2019)	"Projection pursuit cluster (PPC) model"	"Health inequality, cultural inequality, economic inequality social inequality."	PPC requires substantial computational resources and time, particularly when exploring multiple parameter settings or conducting sensitivity analyses.
(Kang et al., 2020)	"GIS and logistic regression (LR) analysis."	"Social vulnerability, sociodemographic variables."	Logistics analysis involves complex optimization and decision-making processes related to various parameters, which may require specialized models and expertise beyond traditional GIS capabilities.
(Hazell, 2020)	"Principal component analysis (PCA) and (GIS-MCDM)"	Socioeconomic and ecological indicators.	PCA assumes that the relationship between variables is linear, which may not always hold true for complex environmental systems.
(Gerundo, Nesticò, et al., 2020)	"AHP and GIS"	"Social, building, and urban dimensions."	Biased weightings of parameters by using AHP can lead to skewed vulnerability assessments and unreliable results
(Parsian et al., 2021)	"RS,GIS,and AHP"	"Elevation, slope, rainfall, the main river, topographic, wetness index (TWI), LULC, soil type, and NDVI"	A lack of reliable and comprehensive data on factors such as environmental pollution can undermine the accuracy of AHP analysis.
(Ruá, Huedo, Cordani, et al., 2019)	"SWOT and Correct, Adapt, Maintain and Explore (CAME)"	"Building density, green areas, energy efficiency-accessibility-conservation, socio-demographic, population, socio-economic, level of education."	While CAME provides a structured framework for model evaluation, it may have limitations in terms of its applicability to complex hydrological models like SWAT
(Ruá et al., 2021)			

Table 2.3 : Techniques, parameters, and limitations associated with water modeling in a sample of studies

Study	Techniques	Parameters	Limitation
(Cordão et al., 2020)	“MCDM-GIS”	“Population, topography factors, neighbourhood factors, water supply level, and monthly income.”	Inaccurate or biased weightings that are extracted by MCDM may lead to skewed risk assessments and unreliable results.
(Ougougdal et al., 2020)	“Statistical downscaling model (SDSM) and the water assessment and planning tool (WEAP).”	“Climate data, hydrological data, land use/land cover data, and socio-economic.”	Both SDSM and WEAP require extensive parameters, so; obtaining high-quality data at appropriate spatial and temporal resolutions can be challenging, especially in data-scarce regions or areas with limited monitoring infrastructure.
(Alamanos et al., 2020b)	“WEAP and IWR-MAIN’s software and GIS”	“Meteorological data, water pricing, users’ income, level of education, family members, floor and residence size variables.”	Calibrating these models can be time-consuming and computationally intensive, and may require specialized expertise in hydrology, engineering, and modeling.
(D. Zhu & Chang, 2020)	“Criteria Importance Through Intercriteria Correlation (CRITIC)”	“Environment factors, society, Economy and Institution factors”	CRITIC does not explicitly consider uncertainty in criteria importance rankings or decision outcomes
(Asghar et al., 2019)	WEAP	“Socio-economic factors, climate data ,water demand and supply, and population”	Using WEAP does not adequately account for non-climatic factors that influence water scarcity, It needs other models
(Bano et al., 2020)	“STELLA Architect”	Socio-hydrologic , fund balance, consumer behaviour and infrastructure conditions.	STELLA may oversimplify the representation of hydrological processes such as infiltration, runoff generation, groundwater flow, and water quality dynamics, leading to potentially inaccurate simulations of water behavior.
(Alwan et al., 2020)	“RS and GIS-based Multi-Criteria Evaluation (MCE)”	“Soil types, land cover, runoff , slope and distance to the river.”	MCE may not explicitly consider trade-offs or conflicts between criteria, particularly when criteria are competing or mutually exclusive.
(Yilmaz et al., 2019)	“Regional Climate Model system; the revision-4283 (RegCM4)”	“Hydrological parameters, climate data, land use, land cover, soil types, and topography factors.”	RegCM4 may not fully account for human-induced changes in land use, land cover, and water management practices that can significantly influence water scarcity risk.

Table 2.3 : Continued

(Löwe et al., 2020)	“Hydraulic simulation tool”	“Annual flow volumes, combined sewer overflows, exceedances of hydraulic pipe capacity, surcharge volumes, population, building density, and building size”	Hydraulic simulation tools typically focus on simulating hydraulic behavior and infrastructure performance, but may not explicitly consider non-hydraulic factors that influence water management decisions.
(Arjomandi et al., 2021b)	“MCDM,SWAT and GIS”	“Economic, Social, and Environmental criteria”	Integrating SWAT with MCDM techniques requires careful consideration of how to incorporate model outputs and decision criteria effectively. Ensuring consistency and compatibility between the hydrological model and decision-making framework can be challenging.
(Chapagain et al., 2022)	“An integrated urban water security assessment framework”	“Water supply sanitation, climate data, hydrological data, water and socio- economic productivity, ecosystem and environment, water related disaster, and water governance”	The integrated assessments rely on diverse datasets from various sectors; however, data availability and quality can vary significantly between regions and may be incomplete, outdated, or inconsistent, impacting the accuracy and reliability of the assessment.

Table 2.4 : A sample of papers related to urban growth modeling: techniques, parameters, and constraints

Study	Techniques	Parameters	Limitation
(W. Wang et al., 2020)	“Urban growth boundary(s) UGBs, Ant colony optimization (ACO),GIS,(AHP)”	“Terrain condition, traffic conditions, population density, water supply , and risk of geological hazards.”	ACO algorithms may face challenges in efficiently handling large-scale urban simulations due to their computational complexity, potentially restricting their practical use in real-world urban planning scenarios.
(Ruben et al., 2020)	“Cellular Automata-Markov (CA–Markov)”	“Slope, elevation, distance from road, distance from motorway, distance from water bodies, and distance from railway”	The model's predictive accuracy and ability to simulate realistic urban patterns may be limited, particularly in rapidly evolving urban environments where parameters such as socioeconomic factors, policy interventions, and environmental factors play significant roles

Table 2.4 : Continued

(Rufino et al., 2021)	“GIS and Cellular Automata”	“Distance to city centre, distance to main roads, distance to belt highways, distance to other cities, population density, inherent dynamic (changes)”	GIS-based cellular automata models may struggle to capture the intricate interactions between various urban growth factors and spatial patterns, leading to potential inaccuracies in the simulation results.
(Dou Zhang et al., 2020b)	“Markov model, future land use simulation FLUS, ANN.GIS”	Geographical factors, climatic data, economic and social factors.	Combining multiple modelling techniques requires careful parameterization, calibration, and validation, which can be time-consuming and challenging.
(Guo et al., 2020)	“GIS , ISPRS ,Google Earth (GE) and deep learning”	“Node index, transportation, place index, land use types, green index”	Deep learning models trained on specific urban areas or periods may not generalize well to new locations or future periods. This limitation can restrict the applicability of GIS-based deep learning models for urban growth prediction in different contexts or for long-term forecasting.
(S. Wang et al., 2022)	“LR, (MCE), (CA)-Markov “	“Natural factors Socioeconomic factors Neighbourhood factors Elevation”	MCE and CA models may struggle to capture the complexity and non-linear nature of these processes, leading to potential inaccuracies in long-term projections.
(Yatoo et al., 2022)	“(CA) and artificial neural network (ANN) with GIS ,RS”	“Demographic factors,socio-economic, distance to ways, and rivers, and elevation,”	CA-ANN models can integrate spatial and non-spatial data, but selecting the parameters and input variables requires careful consideration.

Table 2.5 : A sample of past research scenarios, models, and findings employed in urban growth and water management

Study	Models	Scenarios	Findings
(Qiurong Xu et al., 2019)	“Future urban regional environment” (FUTURE) “Integrated valuation of environmental services and trade-offs” (InVEST)	Status quo (SQ) and Urban planning development (UPD)	UPD scenarios present solutions that seem to significantly lessen the adverse impacts of urban growth on ecosystem services.
(Deal et al., 2017)	“land-use evolution and impact assessment” (LEAM)	Reference scenario (RC) and Agricultural preservation (AP)	Using LEAM simulation scenarios in terms of real county spatial and population distributions helps improve the results of Planning Support Systems (PSSs).

Table 2.5 : Continued

(Türk & Zwick, 2019b)	“Inquired land assignment” (ILAM)	Sustainable best land usage and Urban development land use optimization	With minor adjustments, ILAM model may be used in a variety of domains and at lower planning practice levels.
(Guiwen Liu et al., 2019)	Cellular automata (CA) and gap rent theory	“Natural growth” (NG), “Government development” (GOV) and “Geological protection” (GP)	Economic factors can improve the CA model results.
(Mohamed & Worku, 2020b)	“ CA, Markov chain (MC) and AHP	“Ecologically sensitive” (ESS) and “Business as usual” (BAUS)	Hybrid CA-Markov and AHP is useful technique for monitoring urban growth dynamics.
(Lang & Song, 2019)	“The integrated valuation of ecosystem services and trade-offs tool” (InVEST) and “land use and its effects at small region extent” (CLUE-S)	(RC), “Rapid urbanization” (RUD), “Ecological security” (ES) and “Cultivated land protection” (CLP)	A hybrid of the InVEST and CLUE-S models has a strong ability to simulate land use change, and it can evaluate ecosystem services under several future scenarios.
(Ruben et al., 2020)	CA-MC	BAUS and Gov	The validation results showed that the CA-Markov model can be utilised to simulate land use and land cover under BAUS and Gov scenarios.
(Dou Zhang et al., 2020a)	FLUS and Markov	“Ecological protection” (EP) and (NG)	The integration of the Markov model with the FLUS model can project the future demand for each land-use type, as well as predict land-use patterns based on EP and NG scenarios.
(Zuzheng Li et al., 2020)	“CA, MC and GeoSOS”, (FLUS) and “Integrated valuation of ecosystem service and trade-offs” (InVEST)	BAU, “Ecological protection” (ELP) and RUD	The simulation of land usage has some limitations. In this case, the transition rules of the GeoSOS-FLUS model remain unchanged
(Ojwang et al., 2017)	WEAP	RC, Management scenario and RCP 4.5	WEAP is an effective tool for interpreting the complex water demand-supply system
(El Harraki et al., 2021)	“River basin planning and management” (RIBASIM) and the genetic algorithm (GA) opti	Various scenarios	RIBASIM is a more complex tool than WEAP and its result is associated with uncertainty

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Introduction

The methodology chapter characterises the study area, explains the collection and analysis data process and describes the developing technique process required to achieve the research objectives. In the context of data collection, the integration method between the remote sensing images, spatial data and statistical data is also explained. In addition, GIS database design and preprocessing data have been clarified. The spatial analysis processes via various GIS techniques used in this research are explained. In this chapter, the novel approach of the CVA of vulnerable urban region is described after the environmental local standard was clarified. Similarly, the novel techniques that were used to innovate the modern technique based on ML and PP to forecast ‘water scarcity risk’ (WSRPP) are demonstrated. Moreover, materials and methods that were used to develop the UGBF technique, which integrates ML models and GIS, were explained. This chapter also describes the development of the hybrid technique that was applied to predict WSR and EV under various future scenarios up to 2052. Furthermore, validation methods that were used to validate the study results are explained in this chapter.

3.2 Overall Methodology

This research focuses on developing urban growth and water management models to define vulnerable urban areas towards sustainable cities. Figure 3.1 shows the overall methodology that was used in this thesis. It includes four main objectives. It started with the CVA of urban region under ecological threats, fast urbanisation and

considerable population increase to determine vulnerable urban areas. This assessment applies the hybrid of FAHP, FLM and FOG to minimise the uncertainty in the process of generating and classifying vulnerability indicators. The next objective is to develop a model of WSR prediction based on the integration of PP and ML models to predict water deficit hazards in urban regions called WSRPP.

The model can predict WSR applying ML algorithms directly, or it can utilise the WLC technique. SVM, MLP, KNN, RF and NBC are the five ML algorithms used for this. The Shapley additive explanation model was added to interpret the findings. Furthermore, WEAP was utilised to simulate unmet water demand as a driving factor of WSR in urban areas. The third objective was to develop a novel method called UGBF. UGBF can easily be combined with optimising land-use strategies to help decision-makers to choose appropriate alternatives. It can simulate city expansion for a long period.

In this phase, three primary procedures were implemented: (1) supervised classification procedure using RF, (2) prediction of urban growth using the ANN-CA model, and (3) integration of ML algorithms and UGB tools to forecast UGBs. Four ML algorithms, namely, LR, RF, KNN and AB, were all part of the ML model. The fourth objective was to develop techniques to predict WSR and EV under various future scenarios up to 2052. The three types of techniques (i.e. CVA, WSRPP and UGBF) that were developed in this work and WEAP were integrated to produce the final risk based on vulnerability theory. The role of the WEAP model is to allocate a water amount for each supply node and demand under several scenarios, including climate change scenarios. Furthermore, the processes of validation were used at each

level to ensure model performance by measuring relevant indices to verify the sequential outcomes in this study.

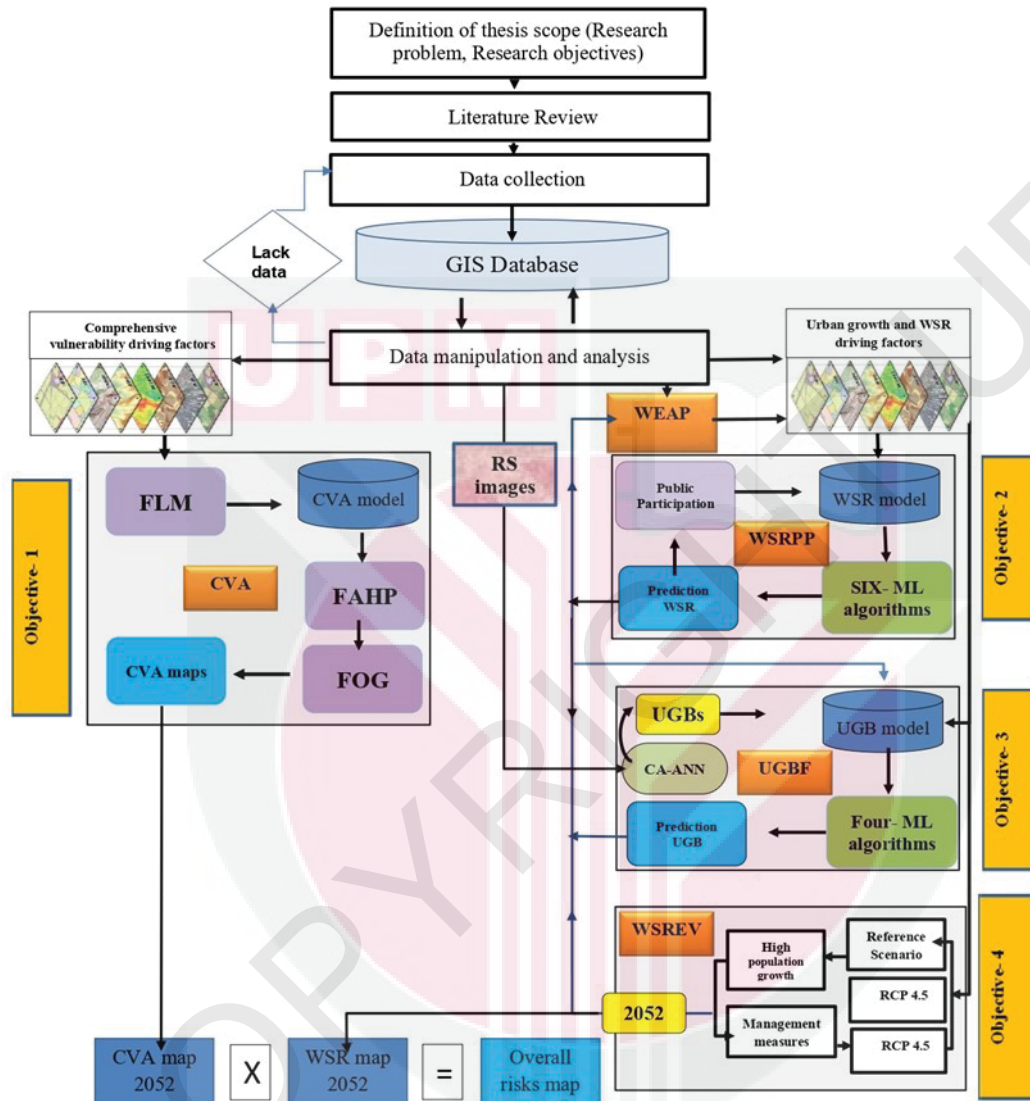


Figure 3.1 : Overall methodology

3.3 Study Area

For this thesis, Nasiriyah City in Southern Iraq was chosen as a study area. It is a sample of Iraqi cities because the urban features of Iraq are consistent throughout the whole country. Nasiriyah City, situated as the capital of Dhi-Qar province beside the majestic Euphrates River (as depicted in Figure 3.2), holds a pivotal geographic position approximately 370 km southeast of Baghdad, the capital of Iraq. Within its bounds lies the ancient city of Ur, dating back to 4000 BCE, a site of immense archaeological significance. In 2016, Ur was rightfully inscribed on UNESCO's prestigious World Heritage List, further highlighting its profound cultural and historical importance. Notably, Ur is revered as the birthplace of the prophet Abraham, serving as the genesis of his divine mission. This sacred site is acknowledged as a pivotal nexus of religious convergence, a testament to its enduring impact on the tapestry of human history.

Nasiriyah is well-positioned to take advantage of many of the development opportunities due to its strategic placement near the major highway and in the intercity train corridor between Baghdad and the Iraqi ports. The administrative region of the city is situated at 31°16'00" N–30°47'00" N, 46°00'00" E–46°28'00" E, and the average elevation is 4 m above mean sea level. The total area is 145,000 ha, of which 46,000 ha was assigned for Nasiriyah City expansion. According to the municipal census of 2021, over 700,000 people are living in 93 various neighbourhoods. The city has suffered from the severe effects of wars. The most dangerous site, i.e. the Khamisiyah site, where chemical weapons and DU were used, is located about 17 km from its borders (G. C. Gray et al., 1999; Shewale, 2011). Rapid urban development,

high population growth, emigration to the city and poor urban planning have brought this risky location closer to city settlements.

Urban water for Nasiriyah City is supplied from the Gharraf River, located around 40 km away due to the excessive saltiness of the Euphrates River that passes in the centre of the city. More than a million people live along the Gharraf River, a tiny tributary of the Tigris River, with majority of them mostly dependent on agriculture. The city's ecosystem has also been affected by climate change; in recent years, summertime highs in the area have reached 52 °C, causing severe and frequent water shortages in the research region.

Most areas within the city grapple with persistent water shortages stemming from external and internal factors. Externally, the impact of climate change and national water management policies play a significant role. Climate change-induced phenomena such as rising temperatures and decreased precipitation exacerbate water demand while diminishing available water resources. Concurrently, national water management practices, including the allocation of water quotas among cities, directly affect the city's water supply. Internally, inequities in water distribution between neighbourhoods exacerbate the issue. Spatial disparities in water access create variations in supply levels across different city sectors. While some areas remain relatively unaffected by water scarcity, even amidst unfavourable hydro-climatic conditions, others are disproportionately vulnerable, experiencing scarcity despite conducive environmental circumstances. This interplay of external environmental factors and internal disparities underscores the complex dynamics contributing to water scarcity risk within the city.

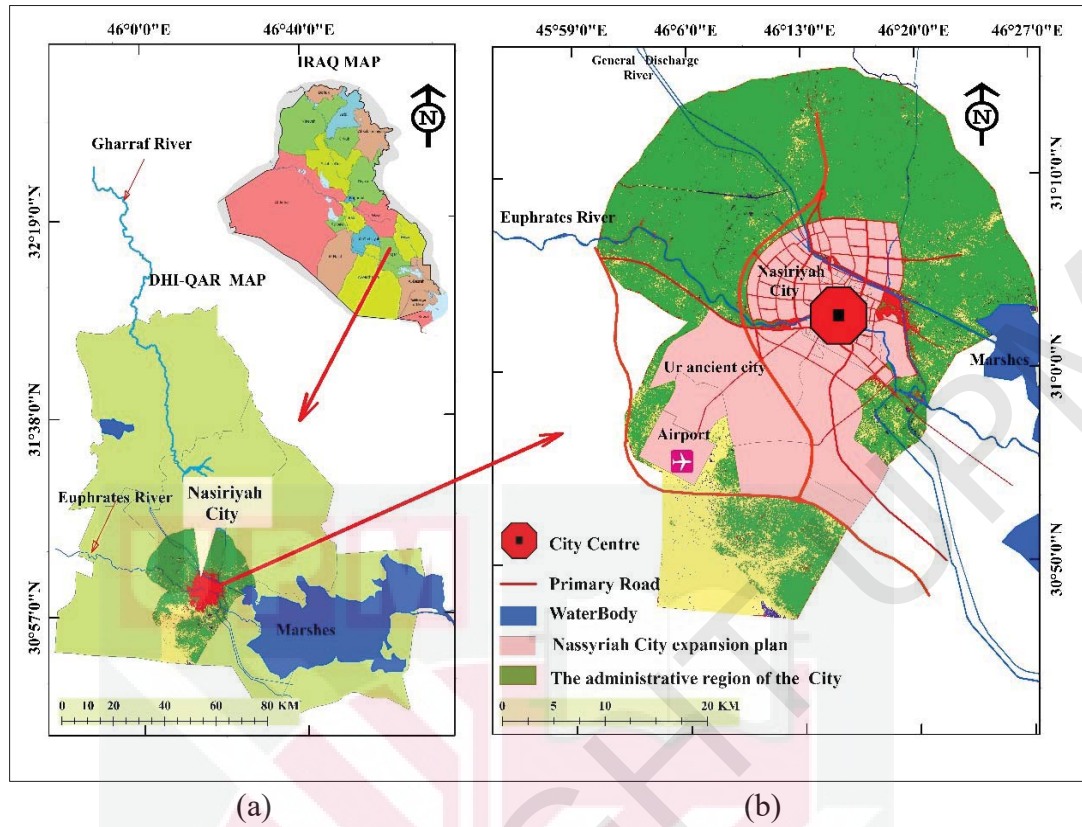


Figure 3.2 : (a) Dhi-Qar province map; (b) the study area (Nasiriyah City)

3.4 Data Collection and Spatial Analysis

Given the urban fabric complexity and overlapping nature, the data collection phase of this research took the longest period and required the most effort. In this stage, different types of data, i.e. RS images, spatial dataset and statistical data, were collected. Remote sensing imagery and a geographical dataset with accompanying description data were the two primary types of data gathered for this thesis. First, we used data from the US Geological Survey (USGS) and the European Union's Earth observation programme (<https://scihub.copernicus.eu>) to acquire multispectral Landsat TM and OLI aerial imagery covering the entire research region for 1992, 2002, 2012, 2021 and 2022.

The greatest overcast threshold was set at 5% throughout the picture downloading process to obtain photos with exceptionally low cloudiness or cloud-free images. To assure integrity, all Landsat data from the same or around dates were utilised. Then, a geographical dataset was gathered from various sources to identify the elements that increase urbanisation and the likelihood of a water crisis. Land survey work using GPS was required to find missing data and locate various geographic features.

On the one hand, considering that climatic information supplied by NASA/Prediction of World Wide Energy Resources (POWER) can be utilised in scientific research with a high degree of trust (Kuntiyawichai & Wongsasri, 2021). Climate information for the study region for the years 1984 to 2021 was acquired from NASA/POWER. On the other hand, the Iraq Meteorological Department provided data for the years 2022 through 2052. Table 3.1 lists the types of data collected for this work. After collecting the data, the GIS database was designed. Subsequently, data management and analysis were undertaken.

Table 3.1 : Data collected

Data	Satellite and Sensor	Acquisition Date	Stripe	Resolution	Sources
Remote sensing images	Sentinel 2	2021/11/14	167/039	10 m	European Union's Earth observation programme (https://scihub.copernicus.eu , (accessed on 5 December 2021))
		2021/10/2	167/038		
	Landsat 5 (LT05 TM)	13 October 1992	167 / 039	30 m	USGS (https://earthexplorer.usgs.gov , (accessed on 6 November 2022))
	Landsat 5 (LT05 TM)	13 October 1992	167 / 038	30 m	
	Landsat 7 (LE07 ETM)	1 October 2002	167 / 039	(15–30) m	
	Landsat 7 (LE07 ETM)	1 October 2002	167 / 038	(15–30) m	
	Landsat 7 (LE07 ETM)	12 October 2012	167 / 039	(15–30) m	

Table 3.1 : Continued

	Landsat 7 (LE07 ETM)	12 October 2012	167 / 038	(15–30) m
	Landsat 9 (LC09-OLI_TIRS)	8 October 2022	167 / 039	(15–30) m
	Landsat 9 (LC09-OLI_TIRS)	8 October 2022	167 / 038	(15–30) m
			(30°–31°)N and (45°– 46°) E	1-ARC
DEM	EntityID: SRTM1N31E045V32000	11 February		
Data	Description	Source	Accuracy	
Pléiades 1, product name: ORTHO, 2014	The images were utilised to validate land use classes and the boundary of old neighbourhoods and to increase the resolution of image classification.	Iraqi General Survey Authority	0.50 m	
Land use—streets, districts and water networks, 2021	The data were analysed spatially to classify land use classes, street case (asphalt or dusty) and wastewater discharge system (sewage network systems or home septic tanks).	Office of the Municipality of Nasiriyah City, Iraq	2 m	
Master plan of Nasiriyah City	The shape files were analysed to compare actual land use with the master plan of the city on the basis of urban planning indicators.	Office of Urban Planning, Nasiriyah City, Iraq	2 m	
Pipeline wastewater, manhole sewages, pump stations and water treatment stations (WTSs)	They were manipulated spatially to determine the locations of polluted sources (WWTPs) and pump stations of wastewater. Spatial analysis of infrastructure distribution in the city was conducted.	Office of Sewage Department in Dhi Qar	2 m	
Poultry sites, protein factories and animal feeds	They were treated spatially and then entered within the sub-criteria of the environment domain.	Agriculture Directorate of Dhi Qar, Iraq	5 m	
Polluted industrial projects	They were analysed spatially and listed under point-source pollution (sub-criteria of the environment domain).	Dhi Qar Investments Office (Iraq)	5 m	
Polluted sites (2021)	They were manipulated and integrated with spatial data and then organised under point-source pollution.	Dhi Qar Environment Office (Iraq)	1 m	
Health care centres and hospitals (2021)	The data were analysed spatially and then compared with urban planning indicators before being entered into the sub-criteria of social domain.	Ministry of Health (Dhi Qar office, Iraq)	2 m	
Schools (2021)	The same previous processes were performed.	Ministry of Education (Dhi Qar office, Iraq)	2 m	
Unemployment rate 2021	Data were entered into the sub-criteria of social domain.	Iraqi Ministry of Planning, Department of Statistics	Neighbourhood scale	

Table 3.1 : Continued

Population housing census (2021)	Data were entered as sub-criteria of urban domain.	Ministry of Planning/Statistics Office	Neighborhood scale
Population census (2021)	Data were used to extract two conditional factors	Department of Statistics in Ministry of Planning	Neighborhood scale
Site survey using GPS (2022)	The work was required to validate data, increase the resolution of the geographic features of locations and complete missing data.	Author	2 m
Site survey using drone images (February,	They were used for the digitalisation of informal settlements.	Author	2 m
Land use shapefiles (SHF) of streets, districts borders and class of land uses	Shapefiles were used to extract land use classes, neighbourhoods' borders and street paths	Nasiriyah City Municipality, Iraq	2 m
Shapefiles and raster for the WSS (2021)	Data were used to generate network pipeline paths and determine the pipeline diameters and locations of the reservoirs, WTP and PS	Dhi-Qar Water Directorate	2 m
Master plan of Nasiriyah City	Shapefiles were used to validate neighbourhoods' borders, streets paths, pipeline paths and land use	The Office of Urban Planning, Nasiriyah City, Iraq	2 m
Shapefiles of network river	The shapefiles were used to extract location demand nodes, gauge location, and Garraf River path and its branches	Ministry of Irrigation/Dhi-Qar (Iraq)	5 m
Hydrological data (1990–2022)	Gharraf River's monthly discharge was used to model the WEAP, and hydrological parameters were used to estimate the conditional factor	Ministry of Irrigation/Dhi-Qar (Iraq)	±5%
Climate data (1984–2021)	Climate data were required for the WEAP model	(NASA/POWER) website, (https://power.larc.nasa.gov , (accessed on 21 April 2022)).	-
Site surveying work using GPS	The survey was needed to check locations of PS, reservoirs data, pipeline paths, WTP, piping division, and gauges of rivers	Author	2 m
Road network (1992, 2002, 2012, 2021, 2022)	Generate the raster of PMR	Nasiriyah City's Department of Urban Planning, Iraq	2 m

Table 3.1 : Continued

Rivers network (1992, 2002, 2012,2021, 2022)	Shapefile was utilised to produce the raster of PR	Ministry of Irrigation/Dhi-Qar, Iraq	5 m
Water pipeline (1992, 2002, 2012, 2021, 2022)	Extract the raster of PWP	Dhi-Qar Water Directorate	2 m
Sewage pipeline (1992, 2002, 2012, 2022)	Shapefile was utilised to extract the raster of PSN	Sewage Department Office in Dhi-Qar, Iraq	2 m
GDP (1992, 2002, 2012, 2022)	Generate the raster of GDP	Department of Statistics in Ministry of Planning	/
Auxiliary information (master plan for Nasiriyah City)	Validate the LULC classification and identify city expansion and street, central city and neighbourhoods	Nasiriyah City's Department of Urban Planning, Iraq	/
Coordinates for several factories	Input data to predict UGBs	Dhi-Qar Environment Office (Iraq)	(2 m)
City Maps different scale	Validation of images classification; Distribution spatial analysis pattern; Matching shapefiles, Digitization of missed geographic features	Nasiriyah City's Department of Urban Planning, Iraq	Scale: 1/25000 1/10000 1/2500
Meteorological data (climate data)	Climate data to Set up WEAP model	Iraq Meteorological Department	/
Climate data mode (2022-2052)	Climate data for RCP4.5, RCP8.5 paths based HadGEM2-ES, to simulate future the hydrologic model under RCP 4.5, RCP8.5 paths	Ministry of Irrigation (MWR)	/
Gharrf river discharge (2023-2052)	The data based on HadGEM2-ES model, it required to set up WEAP for simulate future and current unmet water demand	Ministry of Irrigation (MWR)	/
Demand water	It is required to set up WEAP model	Ministry of Irrigation (MWR)	/

3.4.1 GIS Database Design and Management

Generally, the management and pre-processing of data is as important as the data collection stage in the GIS projects. This stage included several processes, as shown in Figure 3.3 : 1) data filtration to omit redundant data; 2) data processing to make the

filtered data more organised and readable; 3) data analysis to examine, audit and inspect it to be more accurate; and 4) information extraction, in which non-spatial data are linked in the database with spatial data to reconfigure data and save them to obtain and elicit information. As a result, the primary dataset was produced, which was required to extract the driving factors of vulnerability, water shortage risk and urban growth. In addition, the various driving factors were organized into relevant categories in order use them to achieve the study objectives.

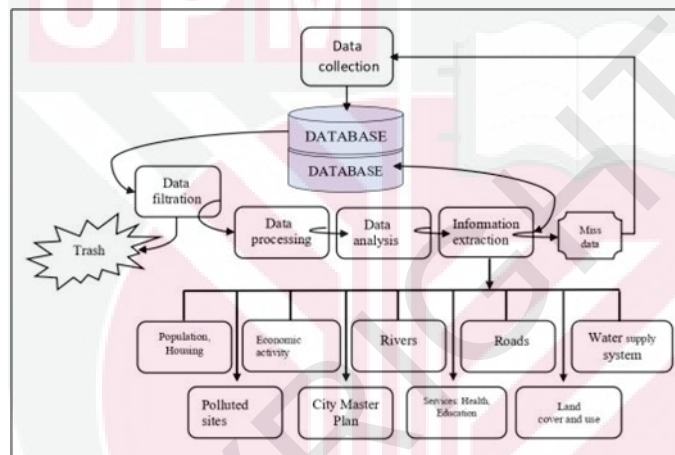


Figure 3.3 : Data pre-processing in GIS

3.4.2 Spatial Analysis Processes

After the collected data were organised into relevant categories, two types of spatial analysis technique were performed in accordance with the type of data (continuous and discrete) to generate required driving forces as well as themes layers for this study. In this study, most data that belong to the environment pollution is continuous. Given that all polluting projects and the DU landfill represent point sources of pollution (PSPs), their effects could be continuous across the study area with a different degree based on distance from the source. Therefore, two sequential operations, namely,

Euclidean distance and fuzzy membership function (FM), were conducted to generate driving forces of each phenomenon. In contrast, the data are distributed inside the boundaries of neighbourhoods on the basis of actual quantities are discrete data. Therefore, rasterization and normalisation function were applied to prepare the driving factors.

3.4.2.1 Euclidean Distance and Rasterization

In a GIS project, rasterization and Euclidean distance are typically used to convert vector geometries (points, lines, and polygons) into raster images. Rasterization is used on discrete spatial data, whereas Euclidean distance is used on continuous geographical data (L. Wang et al., 2022). As a result, seven driving factors were constructed from the collected data using the rasterization tool based on specified data: population, population density, unemployment ratio, unmet water demand, electric supply, age of the network pipes and capacity of reservoirs. These driving factors had distinct units, and they were normalised to a common range (from 0 to 1) in the modelling using the linear interpolation Equation (3.1) (Carver, 1991). The normalisation technique allows for expressive comparisons, with 1 representing ‘high risk’, 0.5 representing ‘medium risk’ and 0 representing ‘low risk’. By contrast, the Euclidean distance is a useful function based on the Pythagorean theorem, which calculates the Euclidean distance to the nearest source for each cell in a raster dataset using Equation (3.2) (Zihao Li et al., 2021).

$$yi = \frac{(xi - x.min)}{(x.max - x.min)} \quad (3.1)$$

Where $0 \leq y_i \leq 1$, and x_i is the value of any pixel in the raster.

$$d = \sqrt{[(X_2 - X_1)^2 + (y_2 - y_1)^2]} \quad (3.2)$$

Where d is the distance between the specific feature and the remaining sites.

3.5 Developing Comprehensive Vulnerability Assessment (Objective 1)

Comprehensive vulnerability assessment (CVA) is a new approach that was developed in the first objective framework of the current study. CVA can detect vulnerable urban sectors under ecological threats, fast urbanization, and significant population increase. This assessment applies the hybrid of fuzzy AHP (FAHP), fuzzy linear membership (FLM) and fuzzy overlay gamma (FOG) to minimize the uncertainty in the process of generating and classifying vulnerability indicators. Figure 3.4 shows flowchart of methodology (CVA).

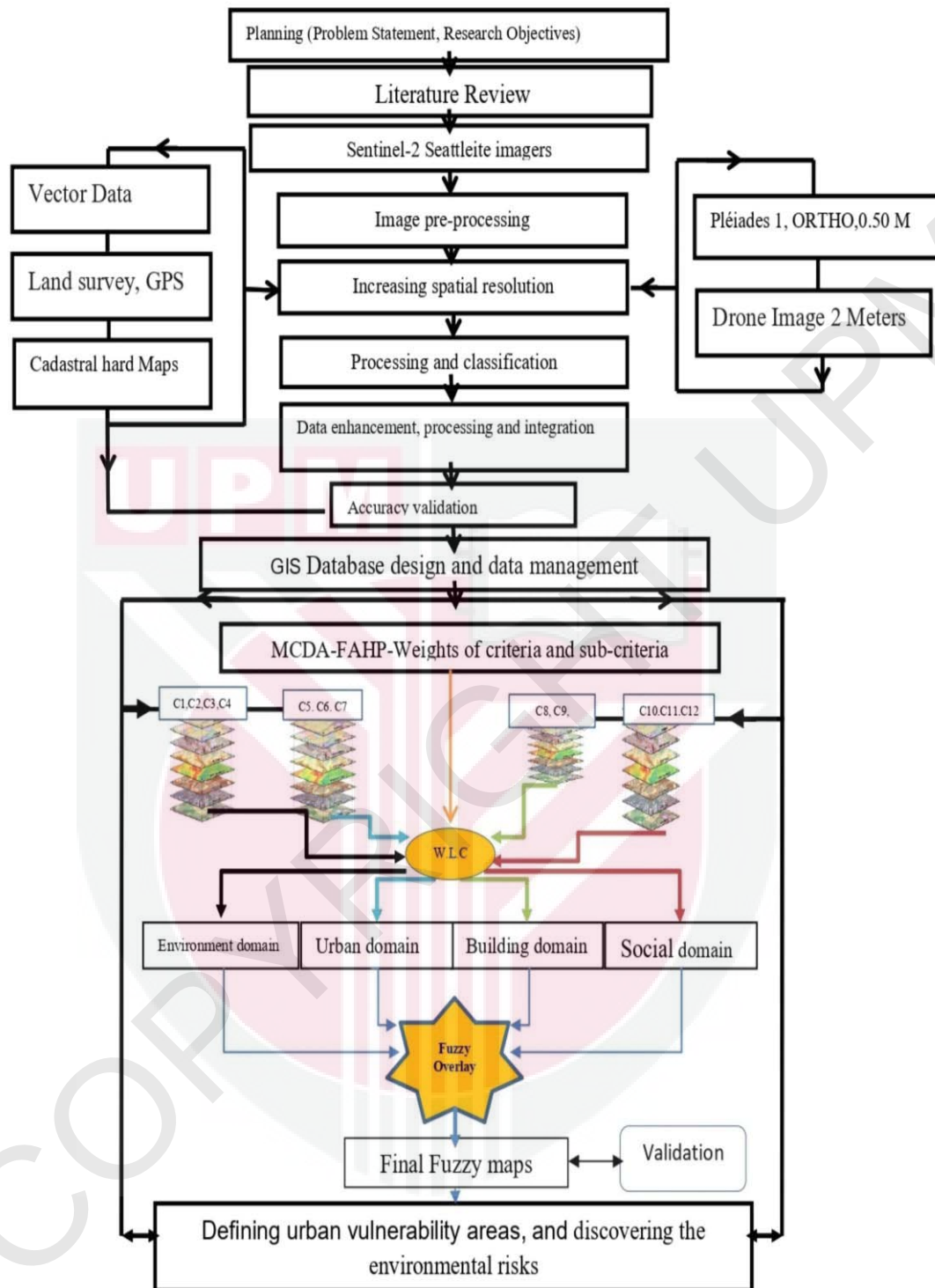


Figure 3.4 : Flowchart of Comprehensive Vulnerability Assessment (CVA)

3.5.1 Criteria Vulnerability Selection

Collecting data associated with many indicators is extremely difficult; hence, the vulnerability assessment process can be accomplished using different indicators based on local conditions or data availability (Kang et al., 2020). However, a comprehensive vulnerability assessment based on vulnerability theory was performed for the study area (Nasiriyah City, Iraq) to define vulnerable urban areas by measuring the effects of multiple criteria that are strongly associated with urban communities. Thus, 12 sub-criteria were selected depending on the literature review, local urban and environmental indicators and data availability. The Delphi technique was applied to approve the relevant criteria for vulnerability indicators. The sub-criteria were categorised into four major domains: environment (ED), urban (UD), building (BD) and social (SD) (Figure 3.5).

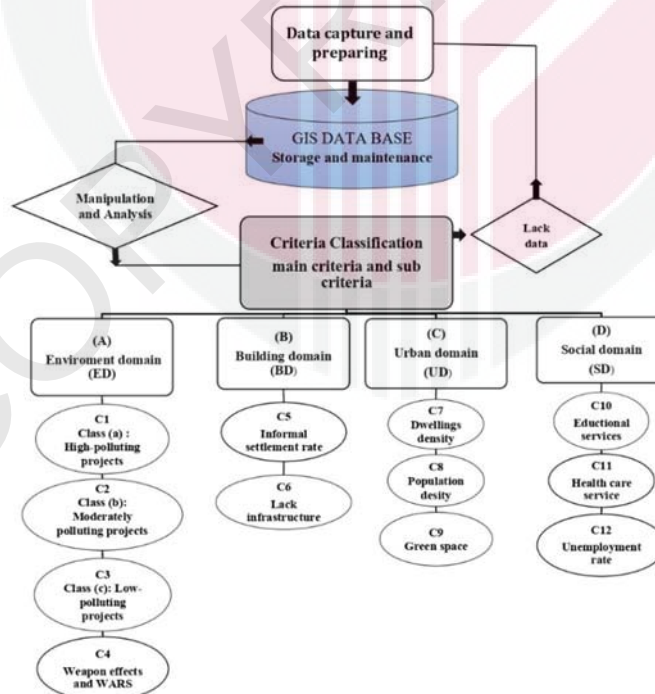


Figure 3.5 : Generating driving factors of comprehensive vulnerability

3.5.1.1 Environment Domain (ED)

The current study applied the local environmental standards number (3-2011) that adopted by the Iraqi Ministry of Environment. These standards determine buffer zones with different radius on the basis of pollution degree. However, residential neighbourhoods located inside buffer zones are considered urban areas exposed to pollution risks. Local environmental standards classify point-source pollution into three categories.

3.5.1.1.1 Class A: High-polluting projects (C1)

This category includes many polluting projects, such as oil refineries, iron industries, WWTPs, brick factories, thermal power plants and landfill sites. Table 3.2 lists some types of high-polluting projects with their respective buffer zone on the basis of the classification of local environmental indicators in Iraq.

Table 3.2 : Samples of high-polluting projects (Class A)

Activity types	Buffer zone radius (km)
Dangerous landfill	15
Oil refinery	10
Gas plant	10
Factories of aluminum and cables	10
Thermal power station	5
Iron plant	5
Brick factory	5
Protein feed factory	3
Asphalt plant	5
Landfill	2
WWTPs	2

3.5.1.1.2 Class B: Moderately Polluting Projects (C2)

This class involves polluting projects that affect the environment less than Class A projects, such as the poultry industry, plastic manufacturers, gas turbine power plants,

concrete manufacturers, flour mills and date canning factories. Table 2.3 provides several types of moderately polluting projects with their respective buffer zone radius based on Iraqi environment indicators.

Table 3.3 : Samples of moderately polluting projects (Class B) in accordance with Iraqi environment standards

Activity types	Buffer zone radius (m)
Flour mill processing plant	1000
Gas power plant	1000
Wire plant	1000
Poultry industry	1000
Poultry slaughter	1000
Sandwich panel industry	1000
Woolen textile factory	500
Concert plant	500
Plastic and paint plant	500

3.5.1.1.3 Class C: Low-Polluting Projects (C3)

This class includes polluting projects that affect less than Class B projects, such as wastewater pumping stations, oil stores and industrial complexes. Table 3.4 presents some types of low-polluting projects and their respective buffer zone on the basis of Iraqi environmental indicators.

Table 3.4 : Samples of the low-polluting projects (Class C) in accordance with Iraqi environment standards

Activity types	Buffer zone radius (m)
Site of oil stores	500
Vehicle industrial complex	500
Pumping station of wastewater	20

3.5.1.1.4 Effects of Weapons and War (C4)

In the current study, the weapon effect was defined as a polluting factor within the environmental domain. Thus, evaluating weapon effects on the environment of the

study area was performed in accordance with Iraqi environment standards, which determined the buffer zone of dangerous landfills as mentioned in Table 3.2.

3.5.1.2 Building Domain (BD)

Two sub-criteria were adopted in the current study to define vulnerable neighbourhoods within the building domain: (1) the ratio of informal settlements (C5) and (2) the lack of infrastructure at the neighbourhood scale (C6).

3.5.1.3 Urban Domain (UD)

In the current study, vulnerability indicators, including dwelling density (C7), population density (C8), and green area (C9), were classified under the urban domain to define vulnerable urban areas in the study area.

3.5.1.4 Social Domain (SD)

Therefore, data for three criteria, namely, education services (C10), health care services (C11), and unemployment ratio (C12), were collected in the current study to define social vulnerability indicators in accordance with the local urban planning indicators of Iraq (Table 3.5).

Table 3.5 : Iraqi urban planning standards

Facility	Maximum access distance from dwellings to facility (m)	Number of units/populations
Nursery	300	1 per 2400–3600 capita
Kindergarten	300	1 per 2400–3600 capita
Primary school	500	1 per 2400–3600 capita
Intermediate school	500	1 per 9600–14400 capita
Secondary school	800	1 per 9600–14400 capita
Health centre	800	1 per 9600–14400 capita
Open space	/	6.25 m ² per capita
Streets	/	11.6% to 26% from total area
Population density per hectare	/	250 persons per hectare (p/h)
Housing density	/	42 dwellings per hectare (d/h)

3.5.2 Delphi Technique

The criteria and sub-criteria that were defined from the literature review were reviewed by an expert panel by using the Delphi method to endorse the criteria that are most relevant to vulnerability indicators. An expert panel was carefully selected. It consisted of 22 qualified experts, 6 experts from the environment domain, 10 experts from the urban planning department and 6 experts from the construction domain. The experts participated in multiple meetings organised to integrate viewpoints into a group consensus. After each round, the answers were summarised and transferred to the experts. They were allowed to modify their responses in the next rounds, depending on how they analysed the group opinion. The result of this method was that nearly all the criteria and sub-criteria were approved as relevant to urban vulnerability indicators.

3.5.3 Fuzzification and Generating Driving Factors

After the collected data were organised into four primary datasets (urban, building, social and environment), two types of spatial analysis technique were performed in

accordance with the type of data (continuous and discrete) before the weighted linear combination function (WLC) was applied to produce vulnerability indicators for each domain environmental vulnerability (Ve), building vulnerability (Vb), Urban vulnerability (Vu) and social vulnerability (Vs), as shown in Figure 3.6. For continuous data, a negative FLM function was used to standardise the sub-criteria of the environment domain (effects of Classes A, B and C and DU) into fuzzy values between 0 and 1 on the basis of Formula (3.3). Figure 3.7 illustrates negative and positive FLM functions, i.e. Formula (3.4).

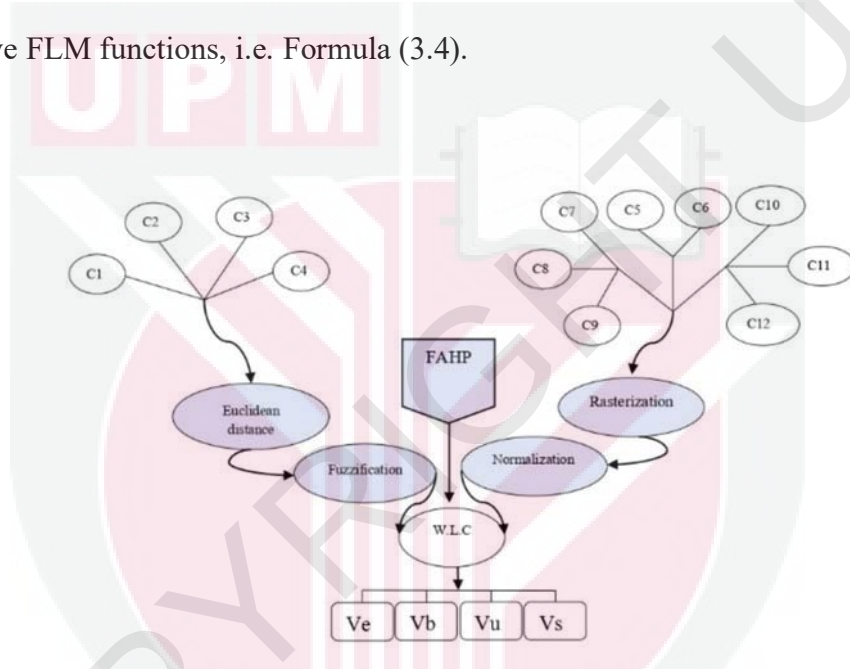


Figure 3.6 : Generating vulnerability indicators

$$f(x) = \begin{cases} 1 & x < 0 \\ \frac{(Max-x)}{(Max-min)} & min < x < ma \\ 0 & if \ x > \ max \end{cases} \quad (3.3)$$

$$f(x) = \begin{cases} 1 \text{ or } 0 & x > \ max \\ 0 \text{ or } 1 & x < \ min \\ \frac{(X - Min)}{(Max - Min)} & min < x < ma \end{cases} \quad (3.4)$$

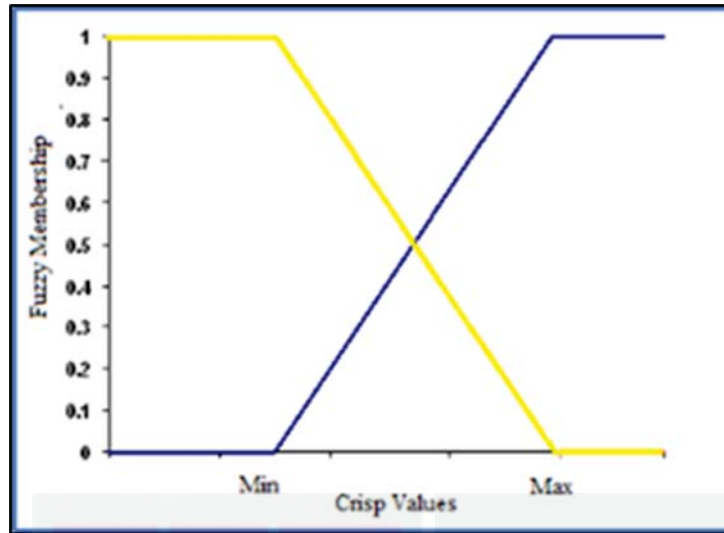


Figure 3.7 : The negative and positive FLM functions

3.5.3.1 Fuzzy Analytic Hierarchy Process

Fuzzy Analytic Hierarchy Process were selected and used in the current research. The Analytic Hierarchy Process method was firstly applied to organise the hierarchical form and calculate the consistency ratio (CR) when investigating the consistency degree between the weights of different values. Subsequently, the FAHP technique was used to obtain the criterion weights of the major domains (environment, urban, building and social) and the sub-criteria in accordance with the following sequential steps:

- 1- Creating a pairwise comparison matrix. A pairwise comparison matrix was prepared on the basis of the questionnaire survey results. Nine experts compared the relevant criteria with vulnerability indicators. The related weights of these criteria based on AHP were computed. To examine the consistency grade between the weight values of various parameters, CR was calculated using the three formal (3.5, 3.6 and 3.7). The results showed that the CR values were less than 0.1; thus, the pairwise comparison matrices were suitable.

(3.5)

$$\lambda_{max} = \frac{1}{n} \sum_{i=1}^n \frac{(a_{ij} \times w_i)}{w_i},$$

where (a_{ij}) is a pairwise comparison matrix element, and (w_i) is the weight value of each parameter.

$$CI = \frac{(\lambda_{max} - n)}{(n-1)} \quad (3.6)$$

$$CR = \frac{CI}{RI} \quad (3.7)$$

CI denotes the consistency index, whilst RI represents the mean of the random index that was calculated in accordance with Saaty's rating RI (1–10) (M. X. He & An, 2016).

- 2- The comparative importance hierarchy values are crisp in AHP. Thus, crisp values were transformed into fuzzy numbers in this step on the basis of the triangular fuzzy membership equation, i.e. Formula (3.8). Fuzzy value is described by three determinations $\{a, b, c\}$, as illustrated in Figure 3.8.

$$\mu_{triangle}(x) = \begin{cases} 0, & x < a \\ \frac{x-a}{b-a}, & a \leq x \leq b \\ \frac{b-x}{c-b}, & b \leq x \leq c \\ 0, & x > c \end{cases} \quad (3.8)$$

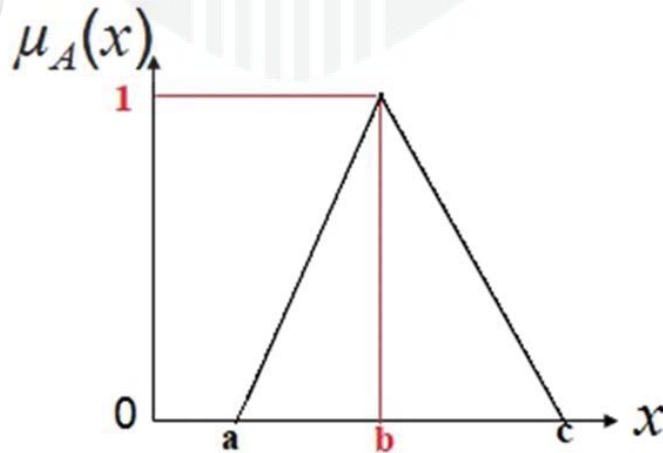


Figure 3.8 : Triangular fuzzy membership equation

- 3- In this step, the fuzzy geometric mean value ($\tilde{r}$) of every criterion was calculated using Formula (3.9).

$$\tilde{r}_i = \Pi_{j=1}^n (\tilde{A}_{ij})^{1/n} = \{\tilde{A}_{i1} \times \tilde{A}_{i2} \times \tilde{A}_{i3} \times \tilde{A}_{i4} \dots \tilde{A}_{in}\}^{\frac{1}{n}} \quad (3.9)$$

“Where ($\tilde{A}_{ij}$) is fuzzy comparison matrix of dimension i to criterion j ”

$$\tilde{w}_i = \tilde{r}_i \times (\tilde{r}_1 + \tilde{r}_2 + \tilde{r}_3 + \tilde{r}_4 + \dots \tilde{r}_n)^{-1} \quad (3.10)$$

- 4- The fourth step is the determination of the fuzzy comparative weight of each criterion, as follows:
- 5- Determining the weights of the crisp values by using the centre of area (COA) method based on Formula (3.11).

$$w_i = \frac{(L\tilde{w}_i + M\tilde{w}_i + U\tilde{w}_i)}{3} \quad (3.11)$$

$$W_{ni} = \frac{w_i}{\sum_{i=1}^n w_i}, \sum w_i = 1, w_i > 0 \quad (3.12)$$

- 6- The final step is the standardisation of the relative weights (w_i) by applying Formula (3.12), and lastly, collecting the final weight (W_{ni}). Table 3.6 provides the final results.

Table 3.6 : Results of the FAHP method

Major Criteria	Major Weight	Sub-criteria	Sub-weight	Partial Weight = Sub-weight × Major Weight
Environment domain (A)	0.441	Class A (c1)	0.221	0.097
		Class B (c2)	0.128	0.057
		Class C (c3)	0.076	0.034
		Weapon effects (c4)	0.575	0.254
		Subtotal	1.000	0.441
Building domain (B)	0.271	Informal settlements (c5)	0.644	0.175
		Lack of infrastructure (c6)	0.356	0.097
		Subtotal	1.000	0.271
Urban domain (C)	0.144	Population density (c7)	0.491	0.071
		Housing density (c8)	0.255	0.037
		Green space (c9)	0.255	0.037
		Subtotal	1.000	0.144
Social domain (D)	0.144	Health services (c10)	0.255	0.037
		Educational services (c11)	0.255	0.037
		Unemployment rate (c12)	0.491	0.071
		Subtotal	1.000	0.144
Total	$\Sigma = 1$		$\Sigma = 1$	1.000

3.5.3.2 Weighted Linear Combination Technique (WLC)

By using WLC, the acquired weights from FAHP were entered on the basis of Formula (3.13) to aggregate each group of sub-criteria into a single layer. The results were four individual vulnerability maps: environmental vulnerability (Ve), building vulnerability (Vb), social vulnerability (Vs) and urban vulnerability (Vu).

$$V_{e,b,u,s} = \sum_{i=1}^n c_i w_i (q_i) \quad (3.13)$$

where n is the number of sub-criteria, (w_i) is the relative weight of a sub-criterion (c_i) and (q_i) is the amount of a sub-criterion (c_i).

3.5.4 Final Fuzzy Map

3.5.4.1 Aggregated Vulnerability (Va)

In accordance with theory of vulnerability, the aggregated vulnerability (V_a) is the product of the three vulnerability domains: urban, social and building, $V_a = V_u \cdot V_s \cdot V_b$ (Gerundo, Nesticò, et al., 2020). FL was used to consider uncertainty in the classification and combination of vulnerability indicators. Similarly, the FO tool was used to examine the potential of an event relevant to various sets in a multicriteria overlay examination. Although FO specifies which sets a phenomenon is possibly a member of, it also examines the relationships amongst members of various sets (Baalousha et al., 2021). The FO tool was applied two times (fuzzy product and fuzzy sum) to obtain the best indicator of vulnerability by calculating FOG using Formula (3.14), as shown in Figure 3.9.

$$V_{a,t} = \{\prod_{c=1}^n f_{(c)}\}^{1-\gamma} \cdot \{1 - \prod_{c=1}^n (1 - f_{(c)})\}^{\gamma} \quad (3.14)$$

where n is the number of input rasters, $f_{(c)}$ is the value of the pixel of each input raster, γ is gamma (0.90) and $V_{a,t}$ is the fuzzy gamma map of aggregation vulnerability and comprehensive vulnerability.

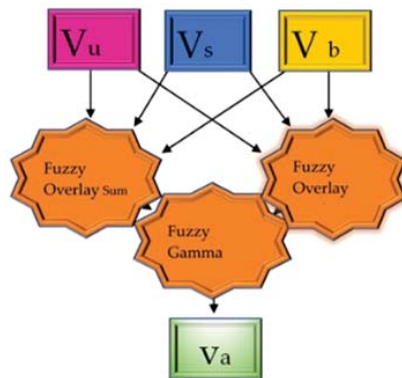


Figure 3.9 : Method for creating an aggregate vulnerability map

3.5.4.2 Comprehensive Vulnerability Maps (Vt)

The final fuzzy map presents a comprehensive vulnerability map of the study area that was produced by multiplying the environment vulnerability indicators (V_e) by the aggregated vulnerability indicators (V_a) on the basis of vulnerability theory in accordance with Formula 3.15 by using FOG, as shown in Figure 3.10.

$$V_t = V_u * V_s * V_b * V_e \quad (3.15)$$

To reduce evaluation subjectivity, two different scenarios of the overall vulnerability maps were proposed. In the first scenario, each of the four domains (environment, urban, social and building) was weighted with the obtained value from the FAHP method. In the second scenario, each of the four domains had the same value.

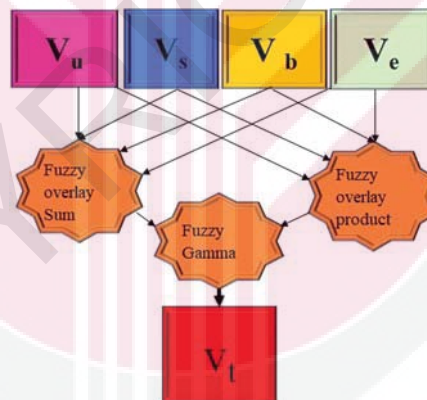


Figure 3.10 : Method for creating a comprehensive vulnerability map

3.5.4.3 Jenks Optimisation Method (JNB)

To understand vulnerability maps produced in this study and characterise the data visually, the Jenks natural breaks (JNB) classification technique was used to reclassify the numerical values of spatial data. The JNB technique utilises an algorithm that aims to minimise the deviation of weight in each type from the type average (J. Chen et al.,

2013). Similarly, this algorithm attempts to increase the deviation of weights from the average of the other types on the basis of Formula (3.16) (Alkhodari et al., 2021; Osaragi, 2002). Consequently, the vulnerability maps were reclassified into five classes (very high, high, medium, low and very low) to enable decision makers to interpret the results easily.

$$GVF = \frac{(SDAM - SDCM)}{SDAM} \quad (3.16)$$

where GVF is between 1 and 0, and it presents the goodness of different proper variables; SDAM represents the total of the squared deviations from the average of the current array; SDCM represents the total of the squared deviations from the average of each type.

3.6 Developing Water Scarcity Risk and Public Participation Technique (Objective 2)

In the second objective, a novel approach called WSRPP based on public participation (PP) and ML was developed to detect WSR in urban areas. PP of local residents was proposed as a new technique in the urban water management. WSRPP can detect WSR in two ways, namely, direct prediction using ML models and the weighted linear combination (WLC) function in GIS. The trained model of ML was built from independent and dependent variables. Ten driving factors were adopted for the independent variables based on the literature review, local experts' opinions, and data availability, to detect WSR in urban areas. By contrast, the Public Participation results of the evaluation of water shortage risk were adopted as dependent variables, as explained in Figure 3.11 (the methodology flowchart). This work was carried out in Nasiriyah City, Iraq.

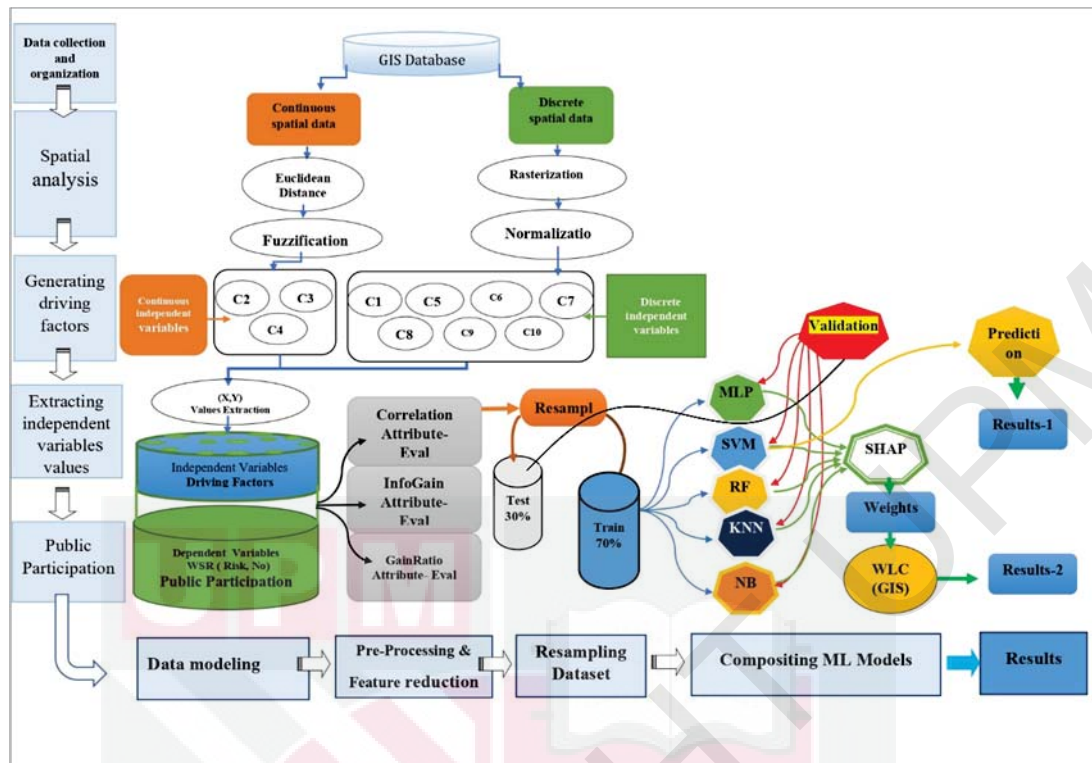


Figure 3.11 : The methodology flowchart of developing WSRPP technique

3.6.1 Criteria Selection of Water Scarcity Risk (WSR)

This study highlighted the spatial analysis of essential factors to supplying homes with potable water. This process, which is usually used by most countries worldwide, passes through many stages via a system known as water supply system (WSS), which runs from water sources to homes. Water reservoirs, water treatment plants (WTP), pumping stations (PS), electricity-supply facilities, pipeline networks, and indoor water storage are the essential components that make up this system. However, it is difficult to dispense with any part of the WSS. In other words, if any part of it breaks, the water supply to houses will be cut off. Therefore, spatial driving factors that reflect the roles of the components of WSS were adopted in this study. Consequently, the ten criteria listed below were chosen based on the literature review, the effect degree of each criterion on the WSS, local experts' opinions and data availability.

- 1- Unmet demand (C1), 2- Proximity to the river basin (C2), 3- Proximity to PS (C3), 4- Proximity to major pipes (C4), 5- Age of the network pipes (C5), 6- Capacity of reservoir (C6), 7- Electricity supply (C7), 8- Population (C8), 9- Population density (C9), 10- Unemployment ratio (C10).

3.6.2 Generating Driving Factors

GIS was implemented to supply inputs, spatial data analysis and WSR visualisation at a neighbourhood scale. GIS techniques can generate driving factors from the primary database based on the relationship between geographic features and WSR. In this study, several spatial-analysis techniques were used to derive the driving factors of WSR, such as Euclidean distance and Rasterization, Fuzzification, and Normalization.

3.6.2.1 Fuzzy Large and Near Membership

Fuzzy large membership and fuzzy near membership are two major spatial analytic functions used in this study (Baalousha et al., 2021). On the one hand, when larger input values are more probable to be part of the set, the fuzzy large function is employed, where values higher than the midpoint have a higher probability of membership, and values less than the midway have a declining membership (Arab & Ahamed, 2022). As a consequence, this function was applied against the raster dataset of two relevant criteria (proximity to the river basin and proximity to the main pipelines) based on the relationship in which the WSR degree increases with the distance from the main pipelines or river basin to householders or WTP based on Equation (3.17), as shown in Figure 3.12 a. The fuzzy near function, on the other hand, is most useful when membership is close to a given value (J. Liu et al., 2021).

The function is defined by a midpoint that defines the set's centre (Kritikos & Davies, 2015). On the basis of Equation (3.18) and as shown in Figure 3.12 b, membership reduces from 1 to 0 as values travel away from the midpoint in positive and negative directions (M. M. Rahman & Szabó, 2022). As a result, the criterion of proximity to PS was determined using fuzzy near membership. This criterion defined the neighbourhoods in the study area that are near to the centroids of the distances between the PS and the edges of the pipeline network. Conversely, the area near the PS has high water pressure, which causes pipes to leak; the area at the pipeline network's edges has a lower water pressure.

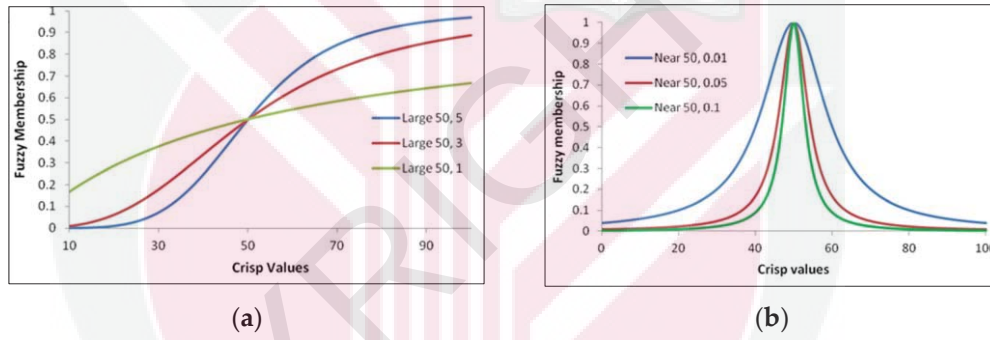


Figure 3.12 : (a) Fuzzy large membership; (b) fuzzy near membership.

$$u(x) = \frac{1}{1 + \left(\frac{x}{f2}\right)^{-f1}} \quad (3.17)$$

$$u(x) = \frac{1}{1 + f1(x - f2)^2} \quad (3.18)$$

where $f1$ is the spread of the function, $f2$ is the midpoint and $u(x)$ is the membership value of category x .

3.6.3 Public Participation Process

Risk levels in urban areas that are evaluated by stakeholders or experts are often associated with uncertainty and subjective bias in experts' opinions. Subjective bias in water management presents a multifaceted challenge due to the sensitivity of ensuring equitable water distribution. This bias often originates from experts' predisposed mindsets or attitudes, which can result in judgments that stray from logical conclusions. Experts may be influenced by a range of factors, including their background, motivations, training, experience, and organizational culture.

Human perspectives are usually ignored in ML judgments, although the opinions of people exposed to vulnerability or risk are an important factor in decision-making. Therefore, participation of residents was adopted in this approach as a new technique for overcoming subjectivity bias and ensuring the proactive evaluation of the mitigation process in urban areas that face WSR. However, the safety requirements associated with COVID-19 presented complex challenges to conducting interviews with the public. Therefore, in this study, mobile phones were used to connect with local residents with the help of the local administration of Nasiriyah City (the study area).

The advantage of mobile technology for data acquisition is relevant when local-authority resources are lacking and when more expensive data-collection methods cannot be used (Salvati et al., 2021). The technique of cluster sampling was employed to facilitate public participation in the study. This sampling method is typically utilized in scenarios where the population is extensive and the region is divided into non-overlapping clusters, such as neighbourhoods within a city.

As a result, fifty neighbourhoods out of the total ninety-three were meticulously chosen as the city sample. These neighbourhoods were systematically categorized into four distinct regions: north, south, west, and east of the city. Participation in the study was contingent upon meeting rigorous criteria, which included being officially registered with the local water management office, attaining adulthood (over 18 years old), holding a minimum level of education (equivalent to at least a high school diploma), and demonstrating proficiency in utilizing the WhatsApp application to accurately share their home's location.

Consequently, a minimum of ten individuals from each neighbourhoods were enlisted as representatives to assess Water Scarcity Risk (WSR). A total of 575 individuals were involved in this initiative, with an average of two engagements per person. Initially, participants were briefed about the mission and questionnaire, followed by a second interaction to provide their household locations and responses.

Regrettably, only 43 women actively participated in the public engagement process. This disparity can be attributed to entrenched customs and traditions within the city, where men predominantly undertake interactions with strangers or government agencies to address communal issues. Subsequently, local experts meticulously analysed the collected data and identified 35 neighbourhoods vulnerable to water scarcity risk. This determination underscores the urgent need for targeted interventions to alleviate water scarcity challenges in these susceptible areas.

3.6.4 Data Model in Machine Learning (ML)

Nasiriyah City in Iraq, with a total of 93 neighbourhoods and the 10 criteria related to WSR, was selected as an input dataset of the ML model to predict WSR and extract the weights of relevant criteria to water shortage in urban areas. The data model and independent and dependent variables were first organised. Feature-reduction process was conducted, and a collection of six ML models were then constructed to predict uncertainty in the dependent variable. The independent variables were the values of the 10 criteria, which were extracted by a specific geospatial tool into the GIS environment. By contrast, the dependent variables were the evaluation of the WSR (high risk, low risk) of the city neighbourhoods by their residents' participation through PP. This assessment adopted the result of PP, which was organised by the local municipal council of Nasiriyah City (the study area) to evaluate the WSS in the city.

3.6.5 Constructing ML Models

Several ML models were selected to predict WSR, with the aid of two common ML applications, Weka[®] and Orange[®]. On the one hand, data pre-processing was conducted using Weka software (Chou et al., 2021). Data pre-processing refers to the preparation of the original data for usage by an ML model, which includes data integration, reduction, cleaning and transformation. On the other hand, the ensemble of ML models was built using Orange software, including MLP, SVM, KNN, RF, NB and SHAP models.

3.6.5.1 Feature Reduction Using Weka Software

In this study, three types of attribute evaluator were used: InfoGainAttributeEval, GainRatioAttributeEval and CorrelationAttributeEval, which were provided by Waikato Environment for Knowledge Analysis, Weka software, version 3.8.6. InfoGainAttributeEval is a single-attribute examiner that employs the ranker algorithm, which measures the information gain of the selected attributes according to the stated classes using a discretisation approach (Albagmi et al., 2022).

GainRatioAttributeEval is another evaluator, which identifies the factor value by measuring the gain ratio in relation to the output (Sivatha Sindhu et al., 2012). CorrelationAttributeEval calculates the Pearson correlation coefficient between the output and input of attributes (Amirruddin et al., 2022). In addition, the algorithm's 10-fold cross-validation approach was used to improve the performance, decrease error rates and boost efficiency (Otchere et al., 2021). Each attribute evaluator, however, evaluates the independent variables based on their mean value expressed as a number between 0 and 1 (Almeida et al., 2013).

3.6.5.2 Modelling with Orange Software Application

The model dataset was resampled into two parts. 70% of the dataset was training dates. It consisted of the independent variables, which were the nine related criteria endorsed by the attribute evaluator functions, whereas the dependent variables were the evaluation of WSR in the city neighbourhoods by their residents' opinion (high risk, non-risk). In addition, 30% of the dataset was used as the testing model to evaluate the training model using six indicators (i.e., precision, sensitivity (recall), specificity, F1-

score, classification accuracy (ACC) and area under the curve (AUC) measures) to assess how well the models performed.

Once the ML algorithms were run, the performance metrics for each model were measured to evaluate the goodness of fit of the different ML models; consequently, the result analysis supports the selection of five suitable algorithms among different ML models, namely, MLP, SVM, NBC, KNN, and RF. In addition to this typical method, different algorithms were tested on testing datasets to select suitable ML algorithms for the model dataset, and several other factors were considered, the most important of which were interpretability, dataset size, data linearity, data format and training and prediction times.

On the one hand, after the team of ML models was trained using the training model, it was able to predict WSR for the study area, as well as any other urban area. On the other hand, the SHAP model provided the weights of independent variables (nine criteria) and illustrated the contribution of each factor visually. Those weights were entered in WLC in GIS to produce WSR maps of the study area with another method. The average weight of the five models was used to produce the final map.

However, in this study the hidden layer of MLP model was set to one layer with 6 hidden neurons based on Equation (3.19) (Azoff, 1993). In addition, SVM can handle weighted instances and perform incremental–decremental learning based on Equation (3.20) (Gálmeanu & Andonie, 2022; Otchere et al., 2021). Therefore SVM were set as follows: the number of tolerance (0.001), iteration limit was (100) and regression loss epsilon (0.1).

$$n = (i + o)/2, \quad (3.19)$$

where i is the input layer, and n represents the number of neurons in the hidden layer(s).

$$f(x) = w^T \varphi(x) + b \quad (3.20)$$

where b denotes the deviation vector, w is the weight and $\varphi(x)$ is the function of non-linear mapping.

Furthermore, RF parameters were set as follows: the number of trees was 10, the minimum sample was 5 and the limit depth of individual trees was 15. KNN was set as follows: the number of neighbours was 10 and the metrics were Euclidean.

3.6.6 Water Scarcity Risk Validation

Validation is the most crucial step in any ML modelling process. In this study, a portion of the 30% test dataset was used to evaluate the performance of the five models, and validation results were compared using several validation indicators, such as precision, sensitivity (recall), specificity, F1-score, Accuracy (ACC) and AUC measures based on Equations (3.21)–(3.26) (Onah et al., 2021). Generally, precision indicates the proportion of relevant instances amongst the retrieved instances; sensitivity (recall) denotes how effectively a model can detect positive instances; specificity represents how effectively it discovers negative instances; and accuracy is expected to denote how well it identifies both categories (Ajdadi et al., 2016).

The F1-score is the harmonic mean of accuracy and recall calculated using Equation (3.25) (Kordnoori et al., 2021). AUC presents the area under the receiver operating

characteristic (ROC) curve, which is determined using Equation (3.26). It is a useful parameter for assessing the performance of a classifier and measuring a classifier's ability to avoid false categorisation (Hashem et al., 2021). In addition, the overall performance of the models was confirmed using the ROC accuracy evaluation parameter (Lee et al., 2020).

$$\text{Precision} = \frac{Tp}{Tp + FP} \quad (3.21)$$

$$\text{Sensitivity (Recall)} = \frac{Tp}{TP + FN} \quad (3.22)$$

$$\text{Specificity} = \frac{TN}{TN + FP} \quad (3.23)$$

$$\text{Accuracy (ACC)} = \frac{Tp + TN}{Tp + TN + FP + FN} \quad (3.24)$$

$$F1 - \text{score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (3.25)$$

$$AUC = \frac{1}{2} \left(\frac{Tp}{TP + FN} + \frac{TN}{TN + FP} \right) \quad (3.26)$$

T , F , P and N represent true, false, positive and negative. TP , TN , FP and FN are true positive, true negative, false positive and false negative.

3.6.7 Production of Water Scarcity Risk Maps

In this study, WSR maps were produced in two ways in GIS. The first way is a simple traditional method to present the prediction results of ML models directly. Thus, five maps were produced based on the result of the five algorithms used in this study. The second way is using the WLC function. It was applied six times in total, yielding six urban WSR maps. WLC aggregated the layers of criteria and their associated weights which were obtained individually from each model to produce five maps; the sixth

map (the final map) was produced using the average weights based on Equation (3.27) (Malczewski, 2004).

Furthermore, using the Jenks natural breaks (JNB) classification method in GIS, the maps were divided into five classifications of urban water vulnerability (very high, high, moderate, low and very low). Finally, the evaluation process between the two ways was conducted using the evaluation indicators to validate the results.

$$WSR = \sum_{i=0}^n c_i w_i (q_i), \quad (3.27)$$

where n represents the number of criteria, w_i represents the weight criterion (c_i), q_i is the value of a criterion (c_i) and WSR is the risk of water shortage.

3.7 Developing Urban Growth Model (Objective 3)

The practical basis of this study depends on the capabilities of ML algorithms to develop a land use simulation technique. Thus, this study proposes a simple novel technique called urban growth boundary forecasting (UGBF), to improve spatial decisions made by optimisation land use techniques that seek optimal sites for various human activities. Several techniques were applied to achieve this goal: (1) Nasiriyah City, Iraq was chosen as the study area; (2) Landsat images for three periods, i.e. 1992, 2002, 2012 and 2022, were downloaded; (3) supervised classification technique using RF was applied to classify Landsat images for the years 1992, 2002, 2012 and 2022; (4) ANN-CA simulation technique was used to predict the city expansion for the next three decades (2032, 2042 and 2052); (5) the UGB technique was delineated using

simulated maps; (5) a dataset model was generated using UGBs to train ML algorithms on urban growth trend. Figure 3.13 shows the overall flowchart of the methodology.

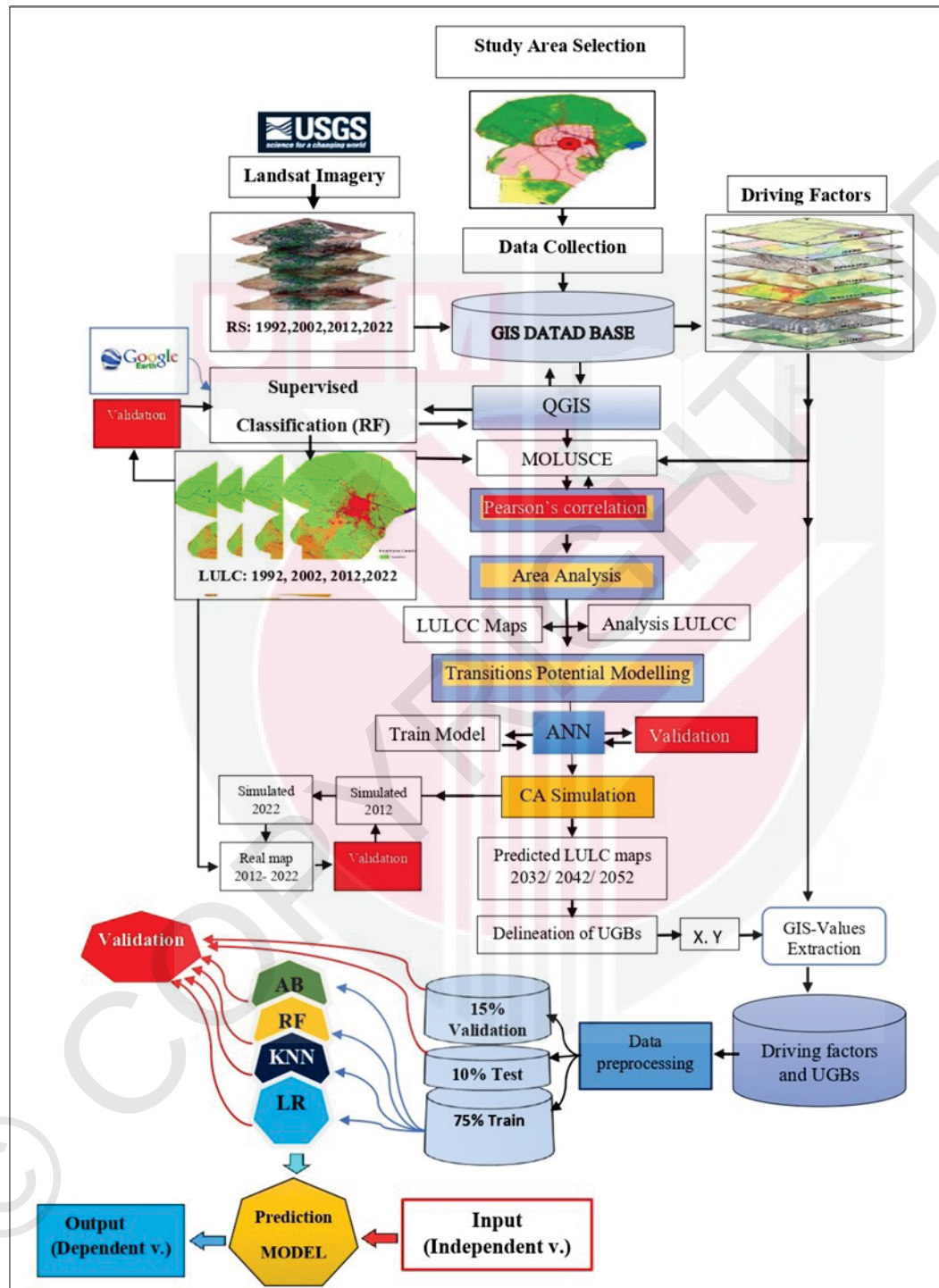


Figure 3.13 : Methodology for developing UGBF technique

3.7.1 Driving Forces of Urban Growth

The driving variables of LULC and urban growth rates vary regionally throughout the globe; thus, different driving variables are used to generate transition potential routes on the basis of the characteristics of each region. On the basis of the literature review and local experts' opinions, several driving forces were selected in this study:

- This study hypothesised that the land use change ratio somewhat decreases with the increase in distance from several geographic features, such as (main roads, urban centres, water pipelines, sewage networks). Therefore, proximity to main roads (PMR), proximity to urban centres (PCC), the proximity to existing water pipelines (PWP) and sewage networks (PSN) were adopted as neighbourhood driving factors.
- Gross domestic product (GDP) and Population density (PD) were adopted as the socioeconomic driving factors that lead to future expansion in the study area.
- Elevation, slope (S) and proximity to the river (PR) are the most common natural factors used to predict urban growth (Kamaraj & Rangarajan, 2022; Lai et al., 2022). Thus, elevation, S and PR were adopted as natural driving factors in this study.

3.7.2 GIS-Based Classification of Landsat Images

In this work, supervised classification with RF was used to classify Landsat images from the years 1992–2002, 2002–2012 and 2022. This process included several steps that were divided into three main stages: generating training samples, training the algorithm and developing the prediction model (classification maps). To generate accurate training samples, on the one hand, band combination was applied to generate true-colour composites and a false-colour composite for each Landsat image of four different land use classes (vegetation, bare land, waterbodies and urban); on the other

hand, a sufficient and equal number of training plots for each class were carefully selected to acquire the most realistic land cover coverage. This was accomplished with the assistance of ancillary information platforms, such as Google Earth, to aid in the understanding of geographical characteristics (Padma et al., 2022).

In the training algorithm stage, each Landsat image and its corresponding training samples were defined to train the RF algorithm. The percentage of the training model was set as 70%. After making sure that values of overall accuracy and kappa were perfect, the LULC classification stage was initiated. During this stage, the final LULC maps for the years 1992, 2002, 2012 and 2022 were produced with four classes. For the accuracy assessment, the semi-automatic classification plugin (SCP) technique in QGIS was used to validate LULC classifications based on reference layers (ground truth).

3.7.3 Predicting Urban Boundary (s) Growth

The QGIS 2.18 program and MOLUSCE plugin were utilised for simulating urban growth. In addition to cellular automaton (CA) strategy, the MOLUSCE plugin included four forecasting methods: Artificial Neural Network (ANN), multicriteria evaluation, weights of evidence and LR (P. Wang et al., 2021). Artificial Neural Network (ANN) and CA were integrated in this work to analyse the LULCC of the study area for the period of 1992–2022 and to predict LULCCs for 2032, 2042 and 2052. Several independent variables were used for this experiment: P, GDP, DEM, S, PMR, PCC, PWP, PSN and PR. The MOLUSCE plugin provided several well-known techniques to assess the relationship between LULCC and independent variables. In this step, Pearson's correlation was applied because it is the most used method for

fuzzy numbers. It was adopted to check the degree of multicollinearity among independent variables; the results show that all driving factors are adequate for future land cover simulations, except for three independent variables, i.e., elevation, PD and GDP, due to the level of multicollinearity.

The current study used a 10-year gap between two maps since Cellular automata (CA) model can benefit from more extended time between two maps rather than just a short gap. A longer time interval allows for a more pronounced observation of changes in urban growth patterns, capturing larger-scale trends and developments. This extended period provides the model with more comprehensive data to analyse and predict future urban expansion accurately. Additionally, a 10-year gap may better reflect significant socio-economic changes, policy interventions, and natural processes influencing urban growth, leading to more robust and reliable predictions.

With a gap of 10 years, change analysis and transition potential modeling for the years 1992–2022 made it possible to prepare a simulation for city expansion growth for the years 2032, 2042, and 2052. Therefore, spatiotemporal changes, as well as the LULC transition between research periods (1992–2002, 2002–2012 and 2012–2022) were computed, and three LULCC maps were created. Furthermore, transition potential modelling was generated using the ANN. To prepare for the simulation process, several parameters, such as iteration value, number of hidden layers and learning rate, must be determined.

The primary task was to train ANN and choose appropriate parameter values using empirical data; thus, empirical data were used to calibrate CA models via repeated

runs of the same model with various parameter combinations to determine optimal parameter values. Once sufficient model validation results were achieved, the following parameters were selected whilst forecasting: 1000 iterations, a neighbourhood value of 3 pixels, a learning rate of 0.001, hidden layer of 10 and 0.05 momentum.

In the simulation process, CA was applied to simulate the LULCC of 2012 by inputting the LULC for 1992 and 2002, whereas the LULCC in 2002–2012 was used to simulate the map of year 2022. The MOLUSCE plugin provides a kappa validation approach and a comparison of real and simulated LULC maps to verify the model and prediction accuracy (Muhammad et al., 2022). After obtaining good standard evaluation results, the LULC maps for years 2012 and 2022 were used in the CA technique to predict the LULC for the year 2032. In addition, the LULCs for years 2002 and 2022 were applied to simulate the LULCs for year 2042. Furthermore, the predicted maps for 2032 and 2042 were utilised to predict the LULC for year 2052.

3.7.4 Structuring the Training Machine Learning Model

In this stage, a simple urban growth prediction technique was developed. Firstly, the results of the ANN-CA technique were used to delineate the UGB lines for the years 2022, 2032, 2042 and 2052, and train an ensemble of ML algorithms on the urban growth trends. Each polyline of UGBs was converted to point shapefile with equal distances, whereas the city centre was defined as the base point of the UGBs. Then, the technique of extracting multivalues from points in GIS was used to extract the values of the variable layers.

The six values were used as independent variables in the dataset model, whereas the yearly date of urban growth was selected as the dependent variable (outcome). The dataset was subjected to several types of data preprocessing, the most important of which were handling missing values, removing outliers and extreme values, dealing with imbalanced classification issues using the synthetic minority oversampling technique and applying the feature reduction process to exclude redundant independent variables using multicollinearity analysis as a final check.

In the multicollinearity analysis process, the values of the tolerance and variance inflation factor (VIF) were calculated as the final check of the level of multicollinearity among independent variables using SPSS software. The analysis revealed that the level of correlation among the seven independent variables is within an acceptable range, the tolerance values are greater than 0.1 (0.25 to 0.83) and the VIF are less than 10 (1.20 to 4.02). Then, a data sampler tool was used to divide the dataset into three parts: 70% training samples, 15% validating samples for unbiased evaluation of the model and 10% testing samples for evaluation of the model.

Once the ML algorithms were run, the performance metrics for each model were measured to evaluate the goodness of fit of the different ML models; consequently, the result analysis supports the selection of four suitable algorithms among different ML models, namely, RF, KNN, AB and LR. In addition to this typical method, different algorithms were tested on validation datasets to select suitable ML algorithms for the model dataset, and several other factors were considered, the most important of which were interpretability, dataset size, data linearity, data format and training and prediction time.

3.7.5 Spatial Applicability of the Novel ML Model

To apply the novel technique spatially, a sample of six polluting factories was selected to predict UGBs and validate the buffer zone. According to Iraqi Environment Standards (IES) (specifically, number 3-2011) which has been adopted by the Iraqi Ministry of Environment, buffer zones must be left between UGBs and pollution-causing projects, as shown in Table 3.7, to protect urban communities from harmful gas emissions. Similar to the previous section (structuring the training ML), the seven values of driving factors were extracted for each specific location of the six selected projects on the basis of their coordinates by using the GIS analysis technique to generate the prediction model. The model was included from seven attributes (driving factors) as independent variables, whereas the dependent variable was the yearly date of UBG, which is an unknown value that would to be predicted by running trained ML algorithms.

Table 3.7 : Sample of polluting factories and buffer zones according to IES

Project Types	Radius of Buffer Zone (km)
Oil refinery	10
Landfill	2
WWTPs	2
Plastic and paint plant	0.5
Sandwich panel industry	1
Industrial area	1

3.7.6 Validation Urban Growth Prediction Results

In the classification stage, the trained model of classification was validated by the RF algorithm on the basis of two evaluation metrics, namely, overall accuracy (OC) and kappa coefficient. Equations (3.28) and (3.29) show the calculation method of OC and kappa (Basheer et al., 2022; Kamaraj & Rangarajan, 2022; Past et al., 2022).

Furthermore, the final classification maps for the years 1992, 2002, 2012 and 2022 were validated by the SCP technique. In the following stage, i.e., LULC prediction, the simulated maps for the years 2012 and 2022 were validated on the basis of the real maps for the same years.

$$OC = \frac{TC.P}{TS.P} * 100, \quad (3.28)$$

Where: OC denotes overall accuracy, TC.P is the total number of properly identified pixels and TS.P is the total number of sample pixels.

$$kappa\ coefficient = \frac{O.A - C.A}{1 - C.A}, \quad (3.29)$$

where O.A is the overall accuracy and C.A is the chance agreement.

In the model prediction stage, the evaluation process of the goodness of fit of regression ML models was applied, and several metrics were measured each time the model was run. As a result, after running the four ML algorithms, i.e., RF, KNN, AB and LR, the following performance metrics were achieved for each model: coefficient of determination (R^2), mean absolute error (MAE) and root-mean-squared error (RMSE) based on Equations (3.30–3.32) (Almalki et al., 2021; Jaime et al., 2022). In a regression ML model, R^2 reflects the fraction of the dependent variable's variation that has been explained by the model's independent variables (Gonzalez & Arsanjani, 2021). Furthermore, for each ML model, MAE and RMSE describe the divergence between actual and observed data points and anticipated data points (S. W. Kim et al., 2020). For validation, 15% of the dataset was used as a validation set for unbiased evaluation to perform model selection; in addition, 10% of the testing set was applied to determine if the final model chosen by the validation set can adapt well to new, unseen data.

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (3.30)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n}} \quad (3.31)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (3.32)$$

where y_i is the equivalent real value, $\hat{y}_i$ denotes the predicted value of the i -th sample and n denotes the total number of samples or errors.

3.8 Predicting Overall Risk (Objective 4)

This stage presents a novel technique for predicting the future risk under various scenarios called WSREV. The method includes integrating four techniques; three of them (i.e. CVA, WSRPP and UGBF in addition to WEAP) were developed in previous objectives. The role of the WEAP model is to allocate a water amount for each supply node and demand site based on various parameters, e.g. population, the agricultural area, water consumption, water availability and priority. It computes unmet water demand and requirements for each demand site on the Gharraf River Basin, Southern Iraq, and then it simulates water supply and demand for the Nasiriyah City neighbourhoods under three main scenarios, i.e. reference scenario, climate change scenario based on RCP 8.5 and RCP 4.5 and their dependent scenarios (high population and management scenario). Figure 3.14 shows the flowchart of the methodology for the final stage.

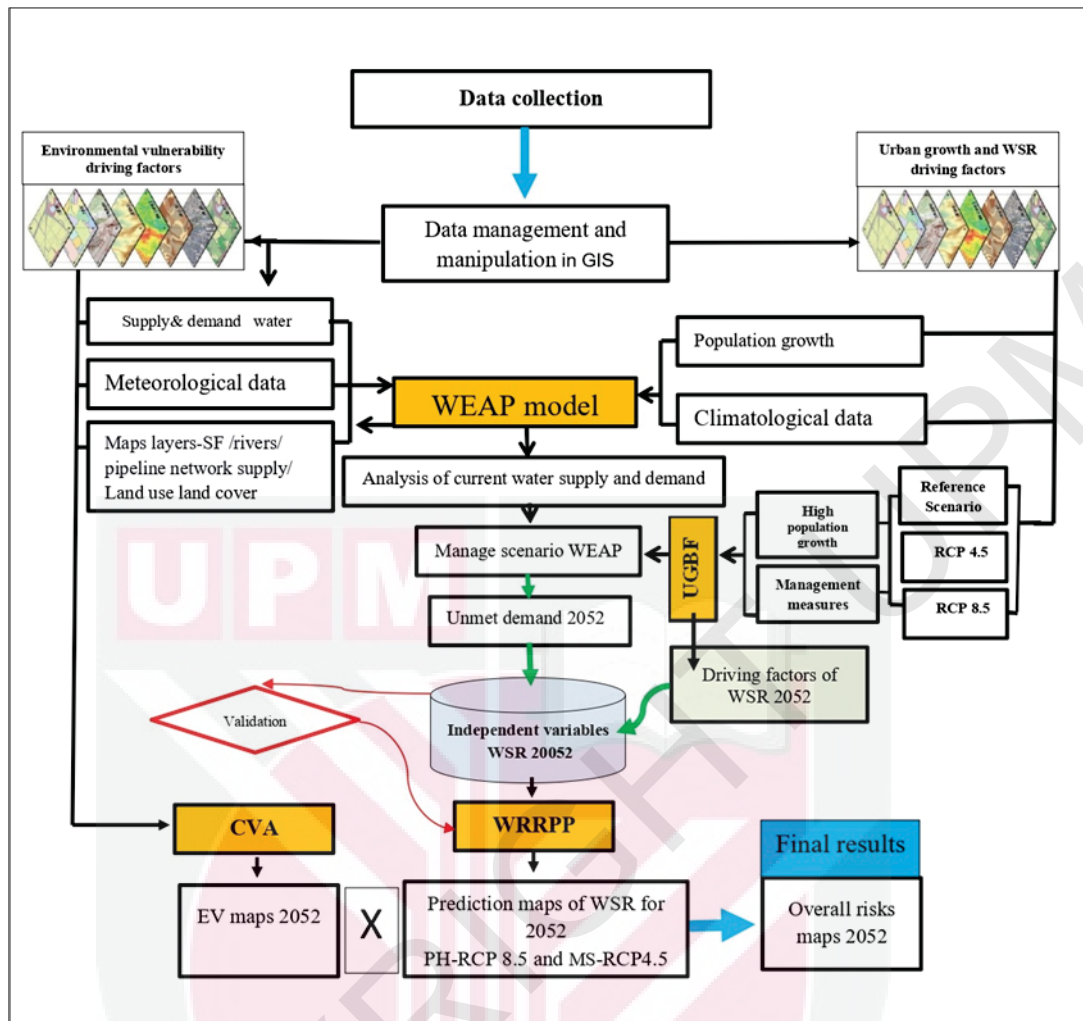


Figure 3.14 : Methodology of comprehensive risk prediction

3.8.1 Water Evaluation and Planning (WEAP) System Setup

Given that unmet water demand was established as a factor influencing WSR in this study, a hydrological model was created using WEAP tools to assess the value of unmet water demand for Nasiriyah City and the Gharraf River Basin area. To operate the WEAP model, the geographic features of the Gharraf Basin were defined as geographic layers after processing operations were conducted by GIS application.

The geographic layers included paths of the Gharraf river and its branches, demand nodes and 44 water demand positions. Moreover, sites of four catchments were

identified inside the model. The model linked all geographic features with high efficiency by using transmission links. The demand sites distributed along the Gharraf River, which are irrigation, domestic and industrial.

The domestic demand sites included the study area, Nasiriyah City, and all the states of Dhi-Qar Province that are sharing the water of the Gharraf River as the essential domestic water resource. In addition, the Basra Canal, which transmits water from the main river to Basra Province, was considered in this model. After the calibration and validation results were validated, the results were displayed: unmet demand water, delivered supply and required demand times.

The first step of modelling WEAP was data input associated to the study area, e.g. time of research, study area border, real water supply and demand, current situation and future scenarios. The water supply nodes and demand sites for surface water (domestic, agriculture and industrial) were defined in the model; in addition, land cover and multifactor, such as monthly precipitation, temperature, wind, humidity, coldness fraction, runoff and infiltration, were entered for hydrological modelling of the Gharraf River using the soil moisture method.

3.8.1.1 Demand Sites

To calculate current demand for different states of Dhi-Qar Province, including Nasiriyah City, data of various activities at disaggregated level were entered. Whilst irrigation demand was calculated on the basis of water demand per hectare, domestic water demand was calculated on the basis of water consumption per person. The model analysed water demand by multiplied the annual activity level by annual water use

rate for each sector based on Formula 3.33. In this study, the 2021 census of population was used to compute total water demand at the neighbourhood level. Furthermore, the water need for urban and rural regions was 109.5 cubic metres per capita per year.

During the season, the average water demand was 300 L per day. The minimum domestic demand was on January (141 L/capita per day), and the maximum water demand on July and August was 494.5 L/capita per day. Water demand varies by month due to rising temperatures; January usually is a cold winter season, and the temperature decreases to 3°, whereas July and August are the hot summer season, and the temperature increases to 49°. The increasing temperature causes a rise in water use by the population. Thus, the monthly variation was defined to calculate water demand per month. In addition, the agricultural area is divided into two main types based on the water consumed crop area and palm area, as listed in Table 3.8.

Table 3.8 : Requirement for irrigation water Crops water demand and palm

Plant	From	To	M3/ha	Water demand plus lose 30%- 25% (m3/y/ha)
Crop-Wheat	15-Oct	3-May	9571	12442.3
Crop-Maize	16-Apr	8-Aug	9600	12480
Crop-Others	8-Aug	15-Jan	4000	5200
Total				30122.3
Palm	1-May	1-Oct	6776	8470
Palm	1-Oct	1-May	6963	8703.75
Total				17174

$$AnnualDemand = \sum_{Br} (TotalActivityLevel(Br) \times WaterUseRate(Br)) \quad (3.33)$$

3.8.1.2 Catchment Sites

The land cover classes of four catchment sites around the Gharraf River in the study area were entered. The total catchment area of the four sites is the 385765.775 ha categorised into five groups, as shown in Table 3.9. In addition, climate data, temperature, precipitation, wind, humidity and cloudiness fraction from 1984 until 2021 were uploaded inside the WEAP model.

Table 3.9 : Catchments area of Gharraf river

Types land	Catch-1 Fajer (ha)	Catch-2 Naseer (ha)	Catch-3 Rafayi (ha)	Catch-4 Shatra (ha)
Barren lands	4382.28	34053.25	5476.35	800.9125
Crops	43875	19581.25	46068.75	15935
Palm	4370.7425	3559.125	5309.6	6586.475
Urban	3122.6325	1599.025	3111.5	2042.69
Vegetation	61271.07	34728.725	75839	14052.3975
Total area (ha)	117021.725	93521.375	135805.2	39417.475

3.8.1.3 Streamflow data

In the present study, the daily discharge data of the Gharraf River at Dhi-Qar Province from the year 1990 to June 2022 were entered into WEAP model. In addition, the expected quota water of the Gharraf River from the national water for the period of 2023–2052 under climate change scenarios was obtained from the Ministry of Water Resources, Iraq. Data were summarised into monthly time steps, entered into the WEAP model and visually represented. Missing data were filled by using the linear interpolation algorithm existing in the WEAP model. To obtain findings and determine if the demand for water would be supplied at all demand locations, the time series approach was used to compute the quantities of supply given at each node along the river.

3.8.1.4 Soil Moisture Method

In this work, the soil moisture technique was used to estimate the Gharraf River flows after inputting several variables, such as precipitation, temperature, plant cover, relative humidity, and latitude, evapotranspiration, were determined. The method adopted concept the soil of Gharaf basin into two layers. The top bucket represents the root zone, for which the hydrological model was derived using Formula 3.34 (Ru et al., 2022). The bottom bucket is the deep zone, where the hydrological model was calculated using Formula 3.34.

$$Rd_j \frac{dz_{1,j}}{dt} = P_e(t) - PET(t)K_{c,j}(t) \left(\frac{5z_{1,j} - 2z_{1,j}^2}{3} \right) - P_e(t)z_{1,j}^{RRF_j} - f_j K_{s,j} z_{1,j}^2 - (1 - f_j) k_{s,j} z_{1,j}^2 \quad (3.34)$$

“Where $(Rd_j \frac{dz_{1,j}}{dt})$ is the change in soil moisture; $z_{1,j} = [1,0]$ is Z_1 is an estimate of the soil moisture content in the top bucket, P_e is the effective precipitation (in mm), $PET(t)$ is the, potential evapotranspiration (in mm per day), $k_{c,j}$ is the crop coefficient for area j , RRF_j is the Runoff Resistance Factor of the land cover, $f_j k_{s,j} z_{1,j}^2$ is the intermediate flow, and $(1 - f_j) k_{s,j} z_{1,j}^2$ represents percolation”.

$$S_{max} \frac{dz_2}{dt} = \left(\sum_{j=1}^N (1 - f_j) k_{s,j} z_{1,j}^2 \right) - K_{s2} z_2^2 \quad (3.35)$$

“Where K_{s2} is the saturated conductivity of the lower store (mm/time) and S_{max} is the depth of percolation from the top layer, and Z_2 is an estimate of the soil moisture content in the bottom bucket”.

3.8.1.5 Calibration Process Using Parameter Estimation Tool (PEST)

Parameter Estimation Tool (PEST) was run many times to control the model whilst its parameters were modified until the gaps between the simulation model and observed data were reduced. It is a nonlinear parameter that serves as a one-of-a-kind calibration tool that is an important technique equipped in WEAP. In this study, nine soil and land use-related parameters, which are listed in Table 3.10, were calibrated using PEST. These parameters are essential variables to run the soil moisture method for modelling water.

Table 3.10 : Contains default values of the hydrological parameters

Parameter	Default
Crop coefficient kc	1
Z1	35 %
Z2	35 %
Deep Water Capacity (DWC)	950 mm
Deep Conductivity (DC)	20 mm/month
Resistance Runoff Factor (RRF)	3
Root Zone Conductivity (RZC)	10 mm/month
Soil Water Capacity (SWC)	500 mm
Preferred Flow Direction (PFD)	0.15

3.8.1.6 Calibration and Validation of the Hydrological Model

In this study, WEAP calibration and ensemble with R tool were used to validate and calibrate the model. Water discharge from two gage stations was used, namely gage 3 and gage 5. Whilst gage station 3 is located in the middle distance of the river at 31°53'0.48" N, 46° 3'27.14"E, gage station 5 is located at the end of the river at 31°26'45.29" N, 46°10'34.07" E. A period of 6 years (1/12/2012–1/12/2018) served as the calibration period for the model, and a further 3 years (1/12/2019–1/12/2021) was used to validate the model. In this method, the flow measured at the two hydrometric gage stations was contrasted with the flow estimated by the model. To evaluate the

model's calibration and validation findings quantitatively, the Nash–Sutcliffe efficiency (NSE), normalised root mean square error (NRMSE), percent bias (PBIAS) and coefficient of determination (R²) were measured to check the accuracy based on Formulas 3.36–3.39.

$$R^2 = \frac{[\sum_{i=1}^n (Q_{o,i} - \bar{Q}_o)(Q_{s,i} - \bar{Q}_s)]^2}{\sum_{i=1}^n (Q_{o,i} - \bar{Q}_o)^2 \sum_{i=1}^n (Q_{s,i} - \bar{Q}_s)^2} \quad (3.36)$$

$$NSE = 1 - \frac{\sum_{i=1}^n (Q_o - Q_s)_i^2}{\sum_{i=1}^n (Q_{o,i} - \bar{Q}_{mean})^2} \quad (3.37)$$

$$NRMSE = \frac{\sqrt{\frac{1}{N} \sum_{i=1}^N (Q_{o,i} - Q_{s,i})^2}}{\bar{Q}_o} \quad (3.38)$$

where Q_o is the initially measured discharge, and Q_s is the simulated discharge. Q_{mean} is the mean observed data over the simulation period.

$$PBIAS = \frac{\sum_{i=1}^n (Q_{obs} - Q_{sim})}{\sum_{i=1}^n Q_{obs,i}} * 100 \quad (3.39)$$

when Q is discharge and PBIAS is optimised to zero, it estimates the average propensity of simulated values to be larger or lower than observed values.

3.8.2 Scenario Management

After making sure that the results of the calibration and valuation were within acceptable limits according to the standards and previous studies, WEAP was moved to the management scenario interface to analyse the model with several ranges of ‘what if’ questions. The WEAP model incorporates tools for creating various scenarios and then simulating them in the future to answer various ‘what if’ questions

and compare them to the current situation (Ougougdal et al., 2020). In this study, two types of scenarios, i.e. independent and dependent, were generated.

3.8.2.1 Independent Scenarios

This type included the main scenarios that have a distinct path, and each one has its own hydrological and climate data. In this study, three main scenarios were created.

- 1- Reference scenario. By default, WEAP divided the modelling period (2022–2052) into two divisions. The first is the ‘current account’, which was the initial year 2022. It is the base year in which all the expression of the model were entered, and the scenarios were generated from this year. The second division is called reference (2023–2052). It is considered the reference scenario (RC), which depends on current accounts and inherits expression from it. In general, RC is a scenario that suggests that what if the current situation won't be changed.
- 2- Climate change RCP4.5. It is classified as a moderate scenario by the IPCC. It is one of the anticipated climate future paths in which all countries of the globe reduce emissions simultaneously and successfully. However, in this study, the hydrological data and climatic conditions expected under RCP 4.5 based on the HadGEM2-ES model were entered into this analysis, whereas the remaining data were inherited from the current accounting year 2022.
- 3- Climate change RCP8.5. It was dubbed the ‘worst path’ by the IPCC. It refers to the carbon concentration, which, at an average of 8.5 watts per square metre, produces global warming and a temperature increase of roughly 4.3 °C by 2100. Nevertheless, in this work, the hydrological data and climatic variables under RCP 8.5 that were projected on the basis of the HadGEM2-ES mode were fed into WEAP 1, whereas the remaining data were inherited from the current accounting year 2022. In this study, each main scenario (independent scenario) was linked with two dependent scenarios.

3.8.2.2 Dependent scenarios

This type includes sub-scenarios in which the hydrological and climate data of the main scenario that are linked with were used to simulate the water surface, whereas one or more parameters inherited from the current accounting year would be changed as follows:

- (a) High population scenario (HP). It represents the scenario where population growth increases from 2.5% to 5%. In this scenario, the data of river discharges and the climate data of the main scenario linked with it were used to simulate the water surface. At the same time, the other expressions were inherited from the current account with changing population growth rate to 5%.
- (b) Management scenario (MS). It is a set of suggestions and measures to address the difficulties of drought and water shortage in the Gharraf Basin. These measures were proposed after analysing the current water management mechanism of the Gharraf Basin and the challenges it faces, and they are as follows: The measures aim to give the high priority for domestic demand, reductions in the basic agricultural water use and the basic drinking water use. In an MS, the river discharges and climate data of the main scenario linked with it were used to simulate the model. Meanwhile, the other required parameters were inherited from the current account with some modifications based on the following suggestions:
 - 1- The first suggestion is the priority. Under the WEAP concept, competing demand locations are allotted water according to their demand priority. The demand priority is linked to the demand site and can be adjusted depending on the water management plan. Priorities are set to vary from 1 to 99 by default; for example, demand sites with priority 99 will fill only if water remains after all other higher-priority demands 1 to 98 have been met. Even though agricultural demand consumes more than 90% of the Gharraf River, causing water shortages in urban areas, all sectors have been given equal priority in the past and current plans established by local water management. Thus, in the MS, the priority hypothesis was applied. What

if domestic demands take higher priority than agricultural demands? In this scenario, as a suggestion, domestic demand received priority 1, whereas agricultural and industrial demand received priority 2.

- 2- The second suggestion is changing the linkage method that is currently adopted for wastewater disposal, in which the water is transported to the sea through drainage canals. The suggestion aims to return a minimum of 50% of domestic water demand to the system by water treatment processing instead of throwing it into the sea.
- 3- The third suggestion is decreasing irrigation water consumption by using modern techniques for irrigation, leading to a reduction of about 20% of the water required for each hectare and a change of reference parameters as listed in Table 3.11:

Table 3.11 : Presents the water demand of the irrigation sector before and after the suggested decreasing measures

Plant	From	To	M3/ha	Water demand plus lose 30% (m3/y/ha)	Decreasing 20%
Corp-Wheat	15-Oct	3-May	9571	12442.3	9953.84
Corp- Maize	16-Apr	8-Aug	9600	12480	9984
Crop-Others	8-Aug	15-Jan	4000	5200	4160
Total				30122.3	24098
Palm	1-May	1-Oct	6776	8470	6776
Palm	1-Oct	1-May	6963	8703.75	6963
Total				17174	13739

- 4- The fourth suggestion is changing the connection method that is currently adopted for the disposal of agricultural drainage water by returning a minimum of 20% of irrigation water consumed to the system instead of throwing it into the sea.

3.8.3 Predicting Water Scarcity Risk (WSR) for the Year 2052

In this step, the simulation result for the year 2052 that was conducted in the third stage was analysed to determine the city's neighbourhoods in the year 2052. As a

result, they will increase from 93 in 2022 to 188 neighbourhoods by 2052. Then, the nine driving factors of WSR were generated on the basis of the simulated map of Nasiriyah City for the year 2052. The driving factors which were endorsed in the second stage are unmet demand (C1), proximity to the river basin (C2), proximity to PS (C3), proximity to major pipes (C4), age of the network pipes (C5), capacity of the reservoir (C6), electricity supply (C7), population density (C8) and unemployment ratio (C10).

However, WSR was predicted under two scenarios, one with a high negative effect (HP-RCP 8.5) and the other with a low negative effect (MS-RCP 4.5), to demonstrate how effective the proposed measures within the framework of MS are in dealing with climate change. The novel ML model and PP, which was trained in the second stage, was also used to predict WSR for the year 2052. As result, two WSR maps were produced. The first map was under HP-RCP 8.5, and the other was under MS-RCP4.5.

3.8.4 Forecasting Overall Risk for the Year 2052

In this step, overall future risks that are related to WSR and environmental pollution were predicted on the basis of the concepts ($\text{Risk} = \text{threat} \times \text{vulnerability}$), according to Hazell (2020); that is, the EV generated in the first stage multiplied by the potential threat (WSR) for the year 2052. As a result, two risk maps were produced: one map under HP-RCP 8.5 and the other under MS-RCP 4.5.

3.9 Summary

The summary of the methodology is as follows:

- As a case study for this thesis, Nasiriyah City in Southern Iraq was chosen. It covered the Ur archaeological site, the capital of Mesopotamia (4000 BCE). The city has suffered from urbanisation, in addition to the effects of wars where chemical weapons and DU were deployed across the city. Furthermore, most parts of the city experience water scarcity due to external and internal factors.
- This study adopted two major categories of data: RS imageries and spatial datasets coupled with statistical data. RS images were downloaded from the USGS website and from Sentinel-2 images from European Union's Earth observation programme. In addition, the spatial dataset was collected from different reliable sources to extract the driving factors of urban growth, WSR and urban vulnerability. In addition, survey work was needed to determine missing data and check the locations of different parts of the study area. Climate data were collected from reliable sources, such as the NASA/POWER.
- Two main types of spatial analysis techniques were performed in accordance with the type of data (continuous and discrete) to generate the required information, various driving forces layers and other GIS layers for this study. On the one hand, two main functions in the GIS environment, namely, Euclidean distance and fuzzy membership function, were conducted to generate the driving forces from continuous data. On the other hand, rasterisation and normalisation functions were applied to prepare the driving factors from the discrete data that were distributed inside the boundaries of neighbourhoods.
- The study developed four approaches to achieving four main objectives within a sustainable city framework. The first approach is developing a comprehensive urban vulnerability assessment by integrating three functions of FL: FAHP, FLM and FOG. The second one is a novel approach based on ML and PP to detect WSR in two ways, namely, prediction by using ML

models directly and using the WLC function in GIS. The third is a novel technique that can predict urban sprawl for a long time and can be simply integrated with optimisation techniques for land-use techniques to make suitable decisions. For this objective, three main processes were applied: supervised classification process using RF, prediction of urban growth using a hybrid method combining ANNs and CA and development of a novel technique based on ML and UGB tool to predict urban sprawl. The final approach is a hybrid to predict overall risk by the year 2052. It integrates four techniques based on vulnerability theory. Three of them were mentioned above, and the fourth is the WEAP model. In addition, several future scenarios, including climate change scenarios, were proposed to predict the overall risk that will occur in the study area by the year 2052. Furthermore, at each stage of this study, the validation process was conducted by measuring performance metrics with the appropriate ML algorithms.

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1 Comprehensive Vulnerability Assessment (CVA)

The results of CVA were six vulnerability maps at the neighbourhood scale of the study area (Nasiriyah City). 1- Urban vulnerability map (Vu), 2- social vulnerability map (Vs), 3- building vulnerability map (Vb), 4- aggregated vulnerability map (Va), three domains (urban, social and building), 5- environmental vulnerability map (Ve) and 6- final fuzzy map (Vt), overall vulnerability maps (urban, social, building and environment). To provide understandable vulnerability maps, JNB classification was used to classify the study area into five classes, depending on the proposed vulnerability indicators, starting from a very high vulnerability region to a very low vulnerability region.

4.1.1 Urban Vulnerability Map

Figure 4.2 is the urban vulnerability map (Vu) was produced by the overlapping of sub-criteria, namely, dwelling density (C7), population density (C8) and green space ratio (C9), as shown in Figure 4.1. It shows that 13 neighbourhoods of the city are located in the very high vulnerability region. More than 196,928 persons, i.e. 28% of the city's total population, are located in this region. In addition, 8 neighbourhoods with more than 89,000 persons, or 12% of the total population, are located in the high vulnerability region.

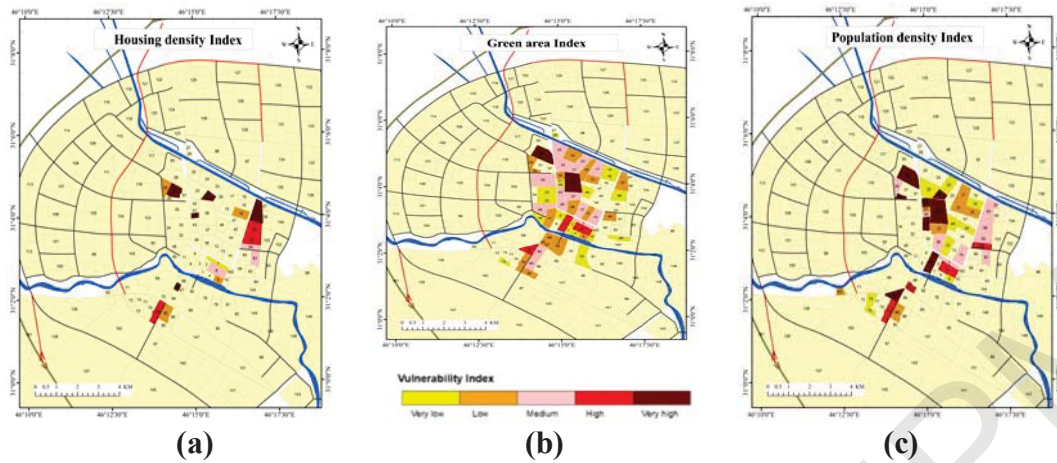


Figure 4.1 : Sub-criteria of the urban domain: (a) Housing density (C7) (b) Green space ratio (C8) and (c) Population density (C9)

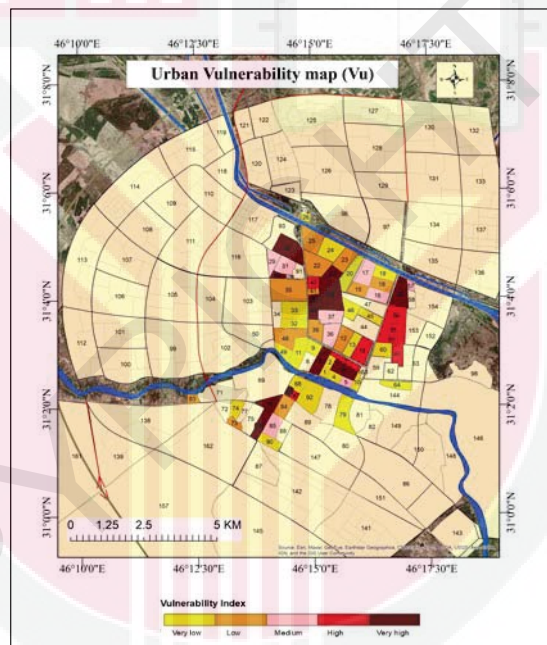


Figure 4.2 : Urban vulnerability map (Vu)

4.1.2 Social Vulnerability Map

By using the same technique in the previous section, the social vulnerability map (Vs) (Figure 4.4) was produced by overlapping sub-criteria, namely, education services (C10), health care services (C11) and unemployment rate (C12), as shown in Figure

4.3. In the gathering process of sub-criteria, each criterion is multiplied by the relevant weight obtained from FAHP to produce Vs.

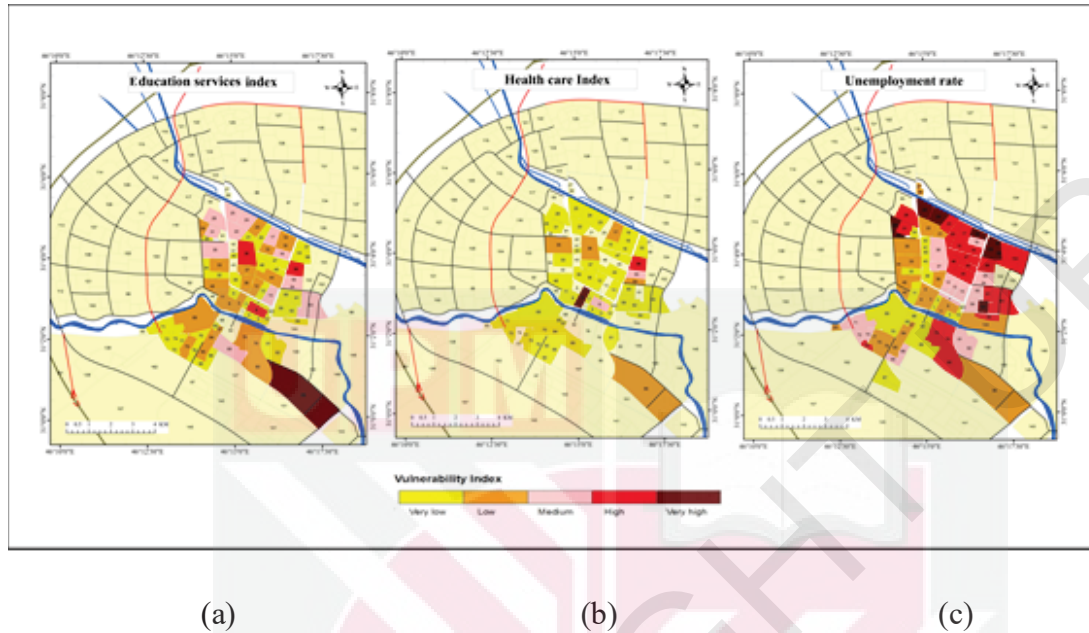


Figure 4.3 : Sub-criteria of the social domain: (a) education index (C10), (b) health care index (C11) and (c) unemployment rate (C12)

As shown in Figure 4.4, 10 neighbourhoods of the city are located in the very high vulnerability region. These neighbourhoods are home to more than 197,559 people, i.e. 28% of the total population. In addition, 18 neighbourhoods with more than 172,000 residents, i.e. about 24% of the total population, are located in the high vulnerability region.

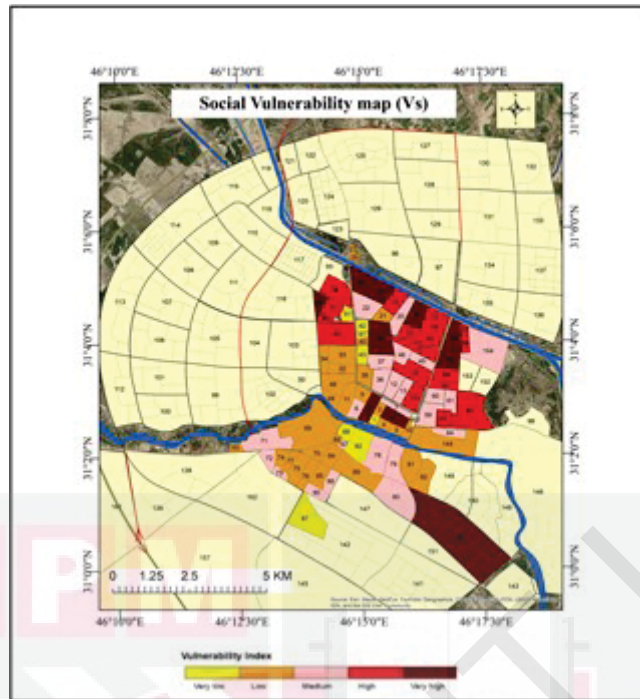


Figure 4.4 : Social vulnerability map (Vs)

4.1.3 Building Vulnerability Map

The building vulnerability map (Vb) was created by overlapping two sub-criteria, i.e. informal settlement rate (C5) and the lack of infrastructure rate (C6) by using the same technique mentioned earlier, as depicted in Figures 4.5 and 4.6. The later shows that three neighbourhoods of the city are located in the very high vulnerability region. These neighbourhoods have more than 23,000 residents, i.e. 3% of the city's total population. In addition, only seven neighbourhoods with more than 36,000 residents, i.e. 5% of the total population, are located in the high vulnerability region.

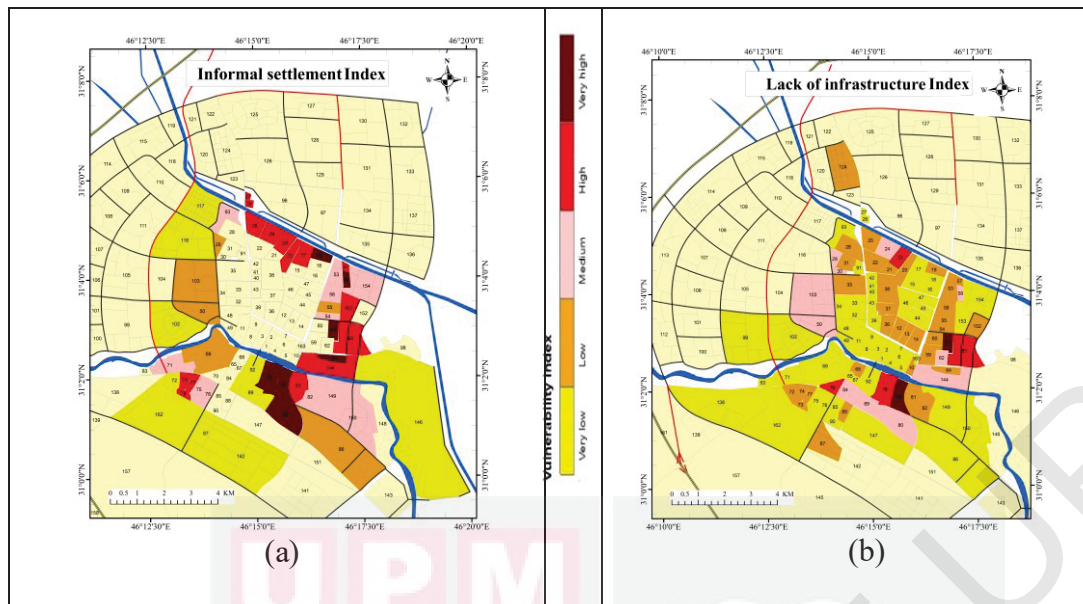


Figure 4.5 : Sub-criteria of the building domain: (a) informal settlement rate (C5) and (b) lack of infra-structure rate (C6)

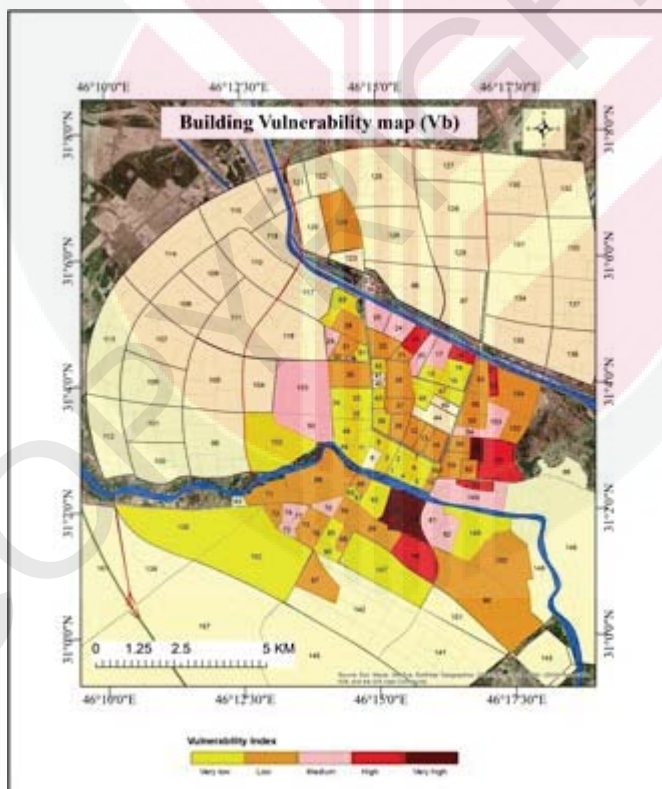


Figure 4.6 : Building vulnerability map (Vb)

4.1.4 Aggregated Vulnerability Map (Va)

The aggregated vulnerability map (Figure 4.7) was produced by multiplying Vu, VS and Vb using the FOG technique. It shows that six neighbourhoods of the city are located in the very high vulnerability region. These neighbourhoods have more than 106,000 residents, or 15% of the total population. In addition, 17 neighbourhoods with more than 204,000 people, or 29% of the total population, are existing in the high vulnerability area. Table 4.1 provides the spatial distribution of the population on the basis of the proposed vulnerability indicators.

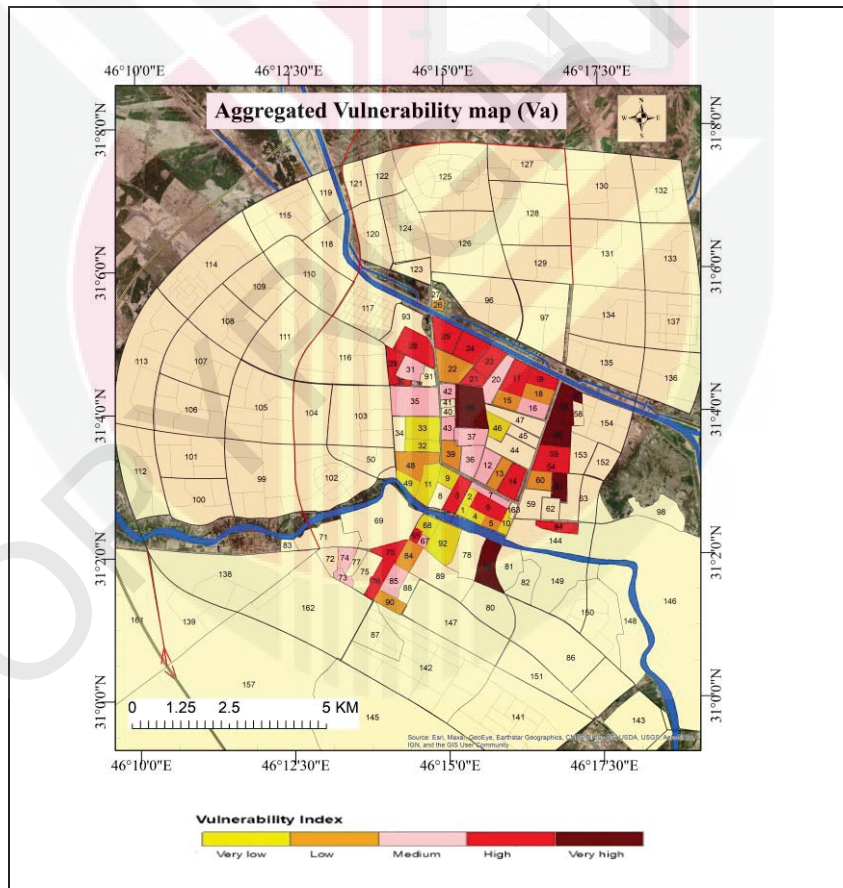


Figure 4.7 : Classification of city neighbourhoods on the basis of the aggregated vulnerability indicators (Va)

Table 4.1 : Classification of the city neighbourhoods on the basis of the aggregated vulnerability indicators

Vulnerability indicators	Number of neighbourhoods	Neighbourhood code	Population (person)	Ratio from the total population	Area (hectares)
Very high	6	38, 53, 56, 57, 62 and 79	106,809	15%	267
High	17		204,762	29%	557
Medium	14		119,185	17%	433
Low	11		77,596	11%	329
Very low	13		61,194	9%	366

4.1.5 Environmental Vulnerability Map (Ve)

The overlapping of sub-criteria, i.e., high sources of pollution (C1), moderate sources of pollution (C2), low sources of pollution (C3) and effects of weapons and wars, DU landfill (C4), produced the environmental vulnerability map, as shown in Figures 4.8, 4.9 and 4.10. The environmental vulnerability map classifies the study area into five, as mentioned earlier. For higher accuracy, the values of pixels were extracted from the boundaries of each neighbourhood on the basis of its coordinates. Figure 4.10 shows that six neighbourhoods of the city are located in the very high vulnerability area. More than 68,660 people, i.e. 9.7% of the total population of the study area, are living in these neighbourhoods, which are exposed to environmental risks. In addition, eight neighbourhoods with more than 38,000 residents, or 5.4% of the total population, are located in the high vulnerability region.

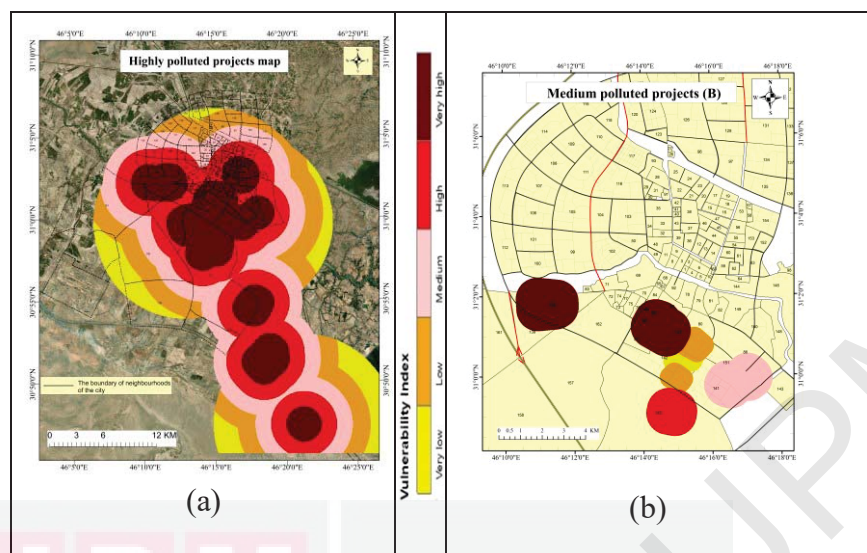


Figure 4.8 : Sub-criteria of the environmental domain: (a) map of the high sources of pollution (C1) and (b) map of the moderate sources of pollution (C2).

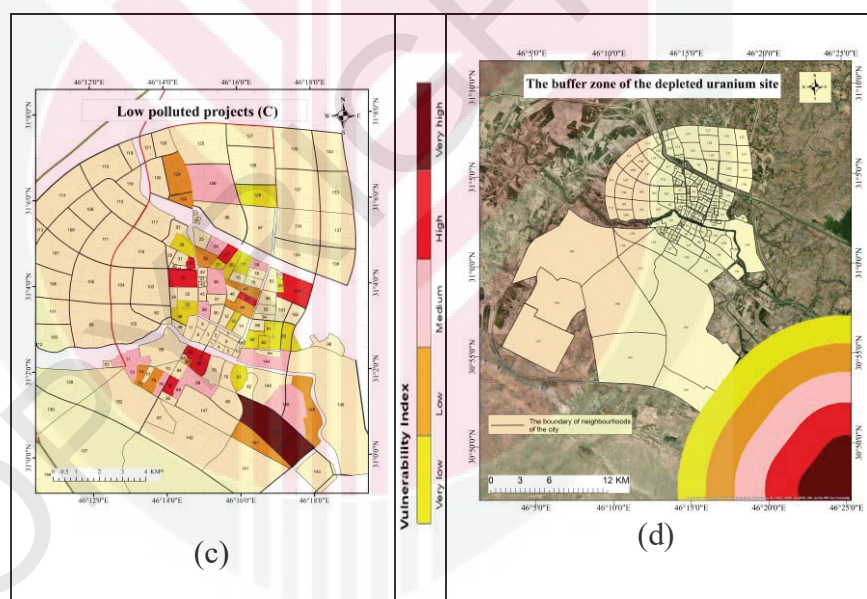


Figure 4.9 : Sub-criteria of the environmental domain: (c) map of the low-polluting projects (C3) and (d) buffer zones of DU landfill (C4)



Figure 4.10 : Environmental vulnerability map (Ve)

4.1.6 Comprehensive Vulnerability Map (Vt)

Based on two scenarios, two maps of the comprehensive urban vulnerability (Vt) were produced. In the first scenario each of the four domains (environment, urban, social and building) was weighted with the obtained value from the FAHP method while in the second scenario, each of the four domains had the same value. However, both maps were produced by using the FOG function based on Function $V_t = V_u * V_s * V_b * V_e$. Figure 4.11 shows the first scenario of the comprehensive vulnerability map (Vt) in which 11 city neighbourhoods are located in the very high

vulnerability region. They are home to more than 175,000 residents, or 25 % of the total population of the study area. Furthermore, 12 neighbourhoods with more than 115,000 residents, or 16% of the total population, are located in the high vulnerability region, as indicated in Table 4.2. Simultaneously, the second scenario results showed that only 5 neighbourhoods with 104,000 residents, i.e. 15% of the total population, are located in the very high vulnerability region. Furthermore, 15 neighbourhoods with more than 202,208 persons, or 29% of the total population, are located in the high vulnerability region, as shown in Figure 4.12. Table 4.3 provides the second scenario results.

Table 4.2 : First classification scenario of city neighbourhoods on the basis of the comprehensive vulnerability index (Vt)

Vulnerability-y indicators	Number of neighbourhoods	Neighbourhood code	Population	Ratio from the total population	Area (hectares)
Very high	11	6, 38, 53, 54, 55, 56, 57, 61, 76, 79, 85	175,678	25%	431
High	12	3, 14, 17, 19, 21, 23, 24, 30, 64, 67, 70, 73	115,841	16%	336
Medium	14	7, 20, 25, 28, 29, 31, 35, 36, 37, 43, 65, 74, 84, 90	145,345	21%	503
Low	13	5, 10, 12, 13, 15, 16, 18, 22, 39, 42, 60, 68, 92	93,033	13%	388
Very low	11	1, 2, 4, 9, 11, 26, 32, 33, 46, 48, 49	39,649	6%	293

Table 4.3 : Second classification scenario of city neighborhoods on the basis of the comprehensive vulnerability index (Vt)

Vulnerability indicators	Number of neighborhoods	Neighbourhood code	Population	Ratio from the total population	Area (hectares)
Very high	5	38, 53, 54, 56, 61	104,844	15%	255
High	15	3, 6, 14, 17, 21, 23, 28, 29, 30, 55, 57, 70, 76, 79, 85	202,208	29%	509
Medium	15	7, 16, 19, 20, 24, 25, 31, 35, 36, 37, 43, 64, 65, 67, 73	120,049	17%	484
Low	15	5, 10, 12, 13, 15, 18, 22, 39, 42, 48, 60, 68, 74, 84, 90	107,780	15%	430
Very low	11	1, 2, 4, 9, 11, 26, 32, 33, 46, 49, 92	34,665	5%	302

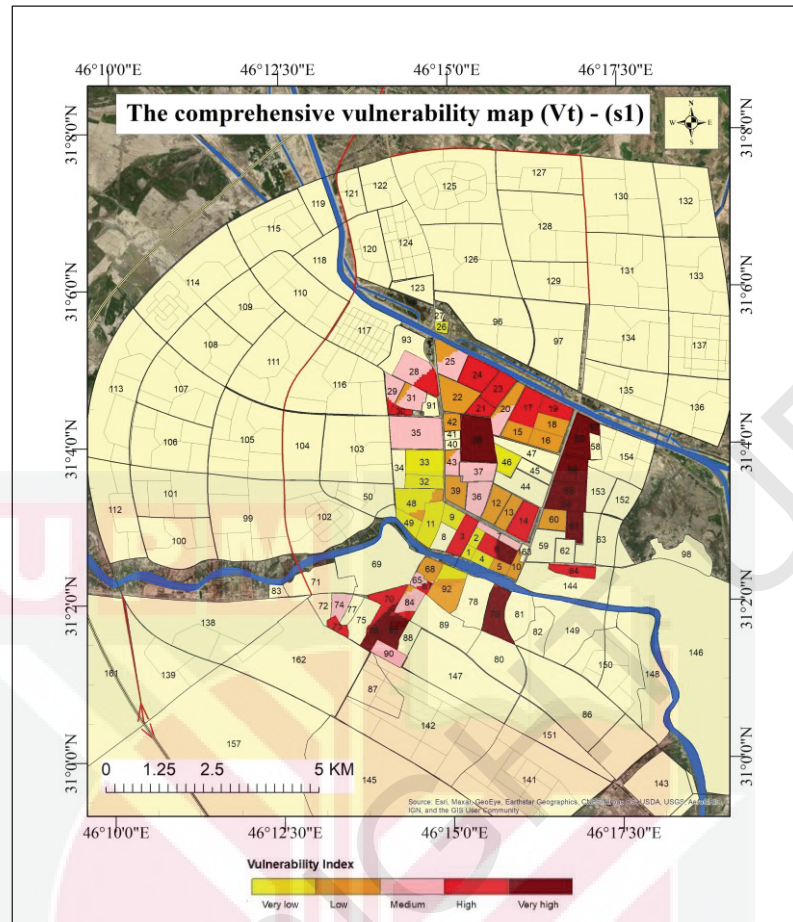


Figure 4.11 : First classification scenario of the comprehensive vulnerability index (Vt)

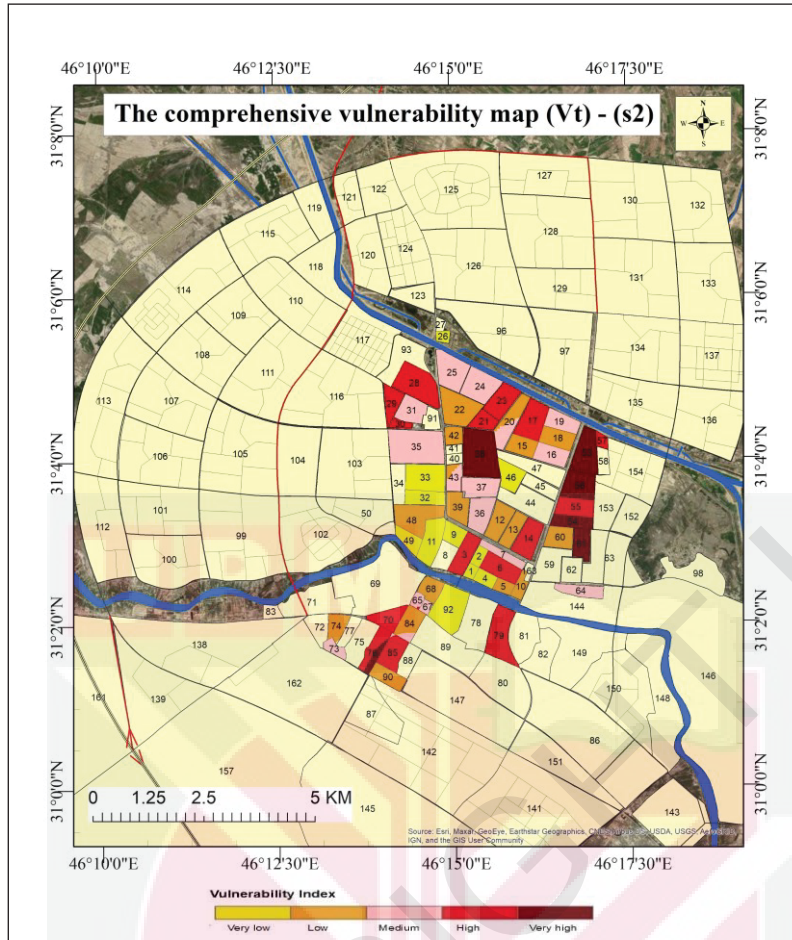


Figure 4.12 : Second classification scenario of the comprehensive vulnerability index (Vt)

4.1.7 Validation of Comprehensive Vulnerable Assessment

4.1.7.1 Using Machine Learning (ML)

The ML technique was used to verify the accuracy and robustness of the comprehensive vulnerability map (Vt). ML is a technique that uses a small part of data (testing dataset) to evaluate a large part of the same dataset (a trained sample) (Y. Chen et al., 2020). However, the naïve Bayes (NB) classifier that is available in Weka software was applied on the basis of Formula (4.1) (Ko, 2017).

$$P\left(\frac{A}{B}\right) = \frac{P\left(\frac{B}{A}\right) P(A)}{P(B)} \quad (4.1)$$

$P(A/B)$ presents the posterior likelihood, where (A) is the probability of the hypothesis, and (B) presents the observed event. $P(B/A)$ presents probability: the probability of the proof given that the probability of a hypothesis is correct.

The validation result showed that correctly classified instances were 90.4762%, and the kappa statistic value was 0.8786. Thus, the level of agreement of the classification results has been proven as ‘almost perfect’. If the kappa value is between 0.80 and 1, then the result is interpreted as an ‘almost perfect agreement’ (McHugh, 2012).

4.1.7.2 Spatial Analysis Validation

Three aerial photos of the study area were acquired, i.e., drone imagery (2009), Pleiades 1 ORTHO (2014) and Sentinel 2 imagery (October 2021), to validate the result of the comprehensive vulnerability map (V_t), as shown in Figure 4.13. Six neighbourhoods from the eleven located in the very high vulnerability region (61, 54, 55, 56, 53 and 57) were spatially analysed as a sample to validate the vulnerability indicator results.

Figure 4.13 shows the neighbourhoods located in the buffer zone of the main WWTP of the city, a high pollution source. In addition, the streets of this area are dusty (unpaved streets), and more than half of the total dwellings are informal housing. Compared with the other neighbourhoods, those are the most vulnerable areas. Consequently, the spatial analysis confirmed the validity of the results.

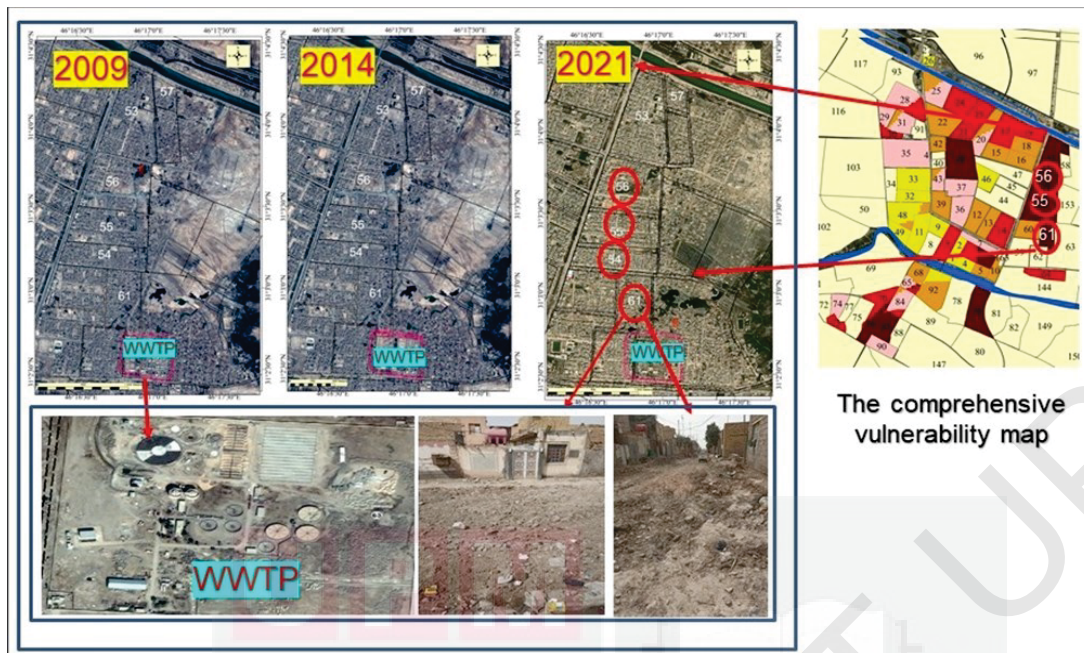


Figure 4.13 : Spatial analysis process for the region under very high vulnerability

4.1.7.3 Sensitivity Analysis

Sensitivity analysis was used to investigate model sensitivity to different criterion weights. It is typically applied as a mechanism for assessing the responses of a model to modifying the input parameters and evaluating the reliability of the obtained results. Thus, model outcomes are substantial if the study results are altered once the input weights of the criteria are different. In this study, a sensitivity analysis process was applied to demonstrate the effect of different weights on classification outcomes to verify the robustness or sensitivity of the proposed model versus the relative importance of the major criteria. In addition, sensitivity analysis addresses the hypothesis that the study results will be changed if another scenario is used. In this context, another scenario was prepared in which the weights of the major criteria were changed. Consequently, the classes of the city's neighbourhoods were changed once the new weighted values were inputted, as illustrated in Figure 4.14. Consequently, the sensitivity analysis process confirmed that the model results are robust.

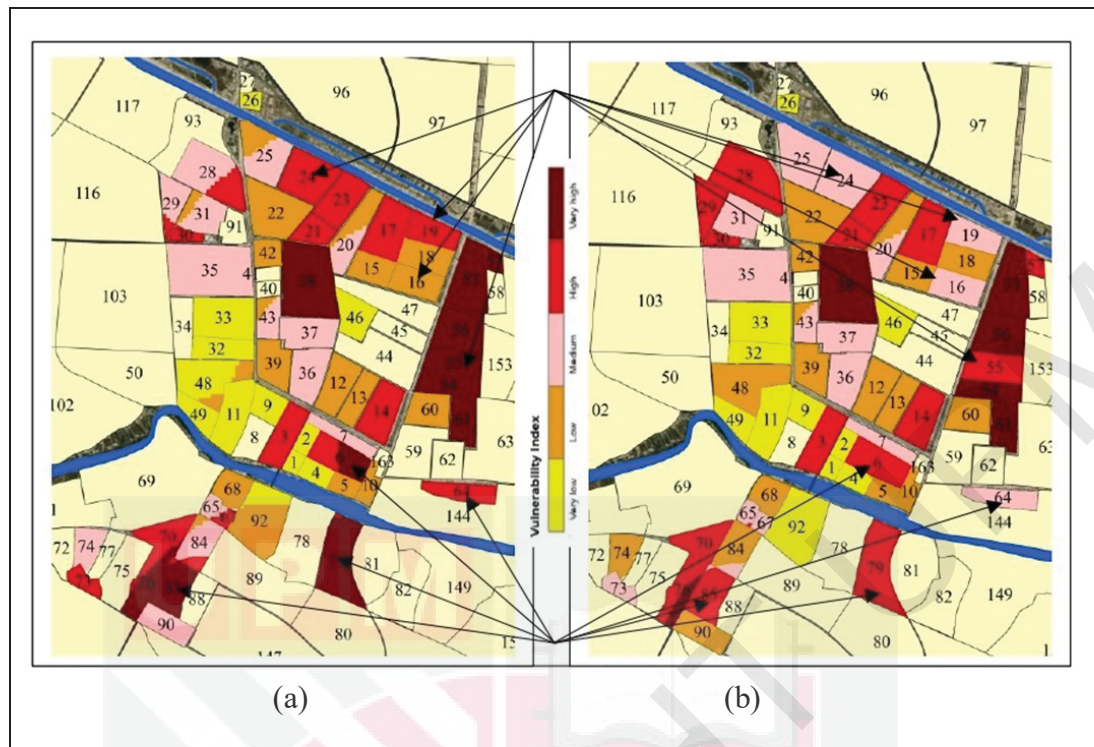


Figure 4.14 : Change in a neighbourhood's classification between the first scenario in (a) and the second scenario in (b)

4.1.8 Discussion of Comprehensive Vulnerability Assessment

Previous studies used different methods to define vulnerable urban areas, and they adopted various criteria that are relevant to vulnerability assessment. Some scholars, such as (Hazell, 2020), classified criteria into three categories (topographic, land cover attribute and demographic). Whilst others, such as (Gerundo, Marra and de Salvatore, 2020), classified criteria into social, urban and building domain. Similarly, (Ruá et al. 2021) classified criteria into four categories: socioeconomic, sociodemographic, urban and building. However, most of these approaches have disregarded potential environmental issues in urban areas due to urbanisation and human activities. By contrast, they focused primarily on financial and social criteria for studying land use change. Furthermore, the simulation results were difficult to utilise in optimising land use on Earth (Jingzhi Li et al., 2021).

In contrast with conventional approaches, the current study suggests a new approach called CVA that is capable of measuring comprehensive vulnerability indicators (V_t), including environmental vulnerability indicators. Compared with previous techniques in which classical theory based on the logic of crisp sets was used, FL was used in the CVA technique to consider the uncertainty in the classification and combination of vulnerability indicators. In addition, the FOG function was applied to produce the final fuzzy map to compromise the rising effect of fuzzy sum and the lessening effect of fuzzy product to obtain the best result.

In contrast with previous methods that used various criteria derived only from the existing literature, CVA suggested a sober approach to confirm the relevance of the criteria with the actual reality of vulnerable urban areas. The proposed approach includes three sequential phases, starting with selecting relevant criteria from the literature review, using the Delphi technique to arrive at the group's opinion to endorse those criteria and intersecting the endorsed criteria with national urban and environmental indicators. In this study, the JNB algorithm was employed to classify the degree of vulnerability, ensuring clear and comprehensible outcomes. Subsequently, the NBC algorithm was utilized to validate the classification results. Moreover, to mitigate the impact of subjectivity bias, two distinct scenarios of the overall vulnerability maps were generated.

The results indicated that the city neighbourhoods suffered from environmental pollution and regional marginalisation visually and statistically. A large area of the city is suffering from pollution effects, wherein residential land use is overlapped with polluted industrial use because of rapid urbanisation and poor land use. In addition, the comprehensive vulnerability maps showed that many neighbourhoods were

located in very high and high vulnerability regions. However, the west part of the city, in accordance with future city expansion based on the master plan approved by local authorities, is located in a region with environmental pollution. By contrast, the north part of the study area is outside the region with environmental pollution, and thus, it is suitable for future city extension. Therefore, a conclusion can be drawn that local urban planning standards and environmental legislation have been disregarded in the planning stage of urban activities.

In the context of the comparability criterion between Nasiriyah City, i.e., the case study, and other Arab cities, the study presented results that were consistent to a certain extent with those of other studies that were conducted to define vulnerable urban areas in Egyptian cities. For example, a study conducted by (Effat, Ramadan and Ramadan , 2021) in Assiut City, Egypt, revealed that informal settlement rate, population density, urban growth rate and lack of essential services are the most significant criteria that raise the vulnerability degree in urban areas. Similarly, another study conducted by (Waly, Ayad and Saadallah, 2021) in Alexandria City, Egypt indicated that demographic characteristics, infrastructure indicators, urban domain, unemployment and poverty are the most consequential factors that led to urban vulnerability in the city.

However, CVA can evaluate urban areas more realistically due to adopted comprehensive vulnerability indicators, which include environmental indicators that are integrated with social, urban and building indicators. Therefore, CVA can be more reliable as a decision support system for analysing urban areas, allocating the required financial resources and efficiently executing mitigation processes for the most vulnerable Arabic urban areas and developing countries.

In summary, compared with previous techniques, CVA is based on vulnerability theory contributes to identifying priority areas of intervention, exhibits novelty and makes a significant contribution to Earth's sustainability. CVA integrates the aggregated vulnerability indicators coupled with environment vulnerability indicators, thus, it can build a robust database and guide for the comprehensive vulnerability assessment, which is improved to be a decision support system for determining priority areas of intervention within complicated urban areas. In addition, this system optimises public spending for mitigating vulnerability because local authorities responsible for city services frequently have insufficient financial resources.

Why is defining vulnerable urban areas necessary before starting with intervention procedures? Evaluating a city's situation before implementing intervention procedures has many reasons. 1 - To identify the magnitude of the problem and explain why a comprehensive plan for mitigating city problems with four dimensions (urban, social, building and environment) is urgently needed. 2 - To define the priority of the intervention based on accuracy vulnerability indicators. 3 - To prepare a spatial database for observing vulnerability indicators when implementing the intervention plans for mitigating the adverse effects of urbanisation and human activities.

4.2 Prediction of Water scarcity risk

4.2.1 Feature reduction results

The results of using the three ranking algorithms, InfoGainAttributeEval, GainRatioAttributeEval and CorrelationAttributeEval, provided insight into the degree of importance of each criterion of the 10 criteria to the output class, as shown in Table 4.4. However, the factors are ranked based on their average merit, which is

given as a value between 0 and 1. The attributes with low merit (a threshold of 0.1) were discarded. Furthermore, the evaluation process applied, which was conducted by NB, confirmed that the performance of CorrelationAttributeEval was more accurate than the other two. As result, only one independent variable (population) was discarded.

Table 4.4 : Performance of the three ranking attributes using 10-fold cross-validation

No	Attributes	InfoGain AttributeEval	GainRatio AttributeEval	Correlation AttributeEval
1	Capacity of reservoir	0.615	0.621	0.739
2	Proximity to river	0.339	0.346	0.641
3	Unmet demand	0.339	0.346	0.652
4	Proximity to pipelines	0.196	0.298	0.241
5	Age of the network pipe	0.258	0.193	0.283
6	Electricity supply	0.191	0.294	0.223
7	Proximity to PS	0.149	0.262	0.364
8	Unemployment ratio	0.011	0.024	0.312
9	Population	0	0	0.1
10	Population density	0	0	0.126

4.2.2 Performance of ML Models

The accuracy of the training models was 0.923, 0.923, 0.923, 0.885 and 0.846 based on SVM, MLP, RF, KNN and NB algorithms, respectively. On the one hand, the dataset (conditional factors) was entered into the models to predict the WSR level of all study areas directly. On the other hand, the SHAP model gathered the weights of conditional factors to use them in the WLC methods to produce WSR maps with another technique (Figure 4.15).

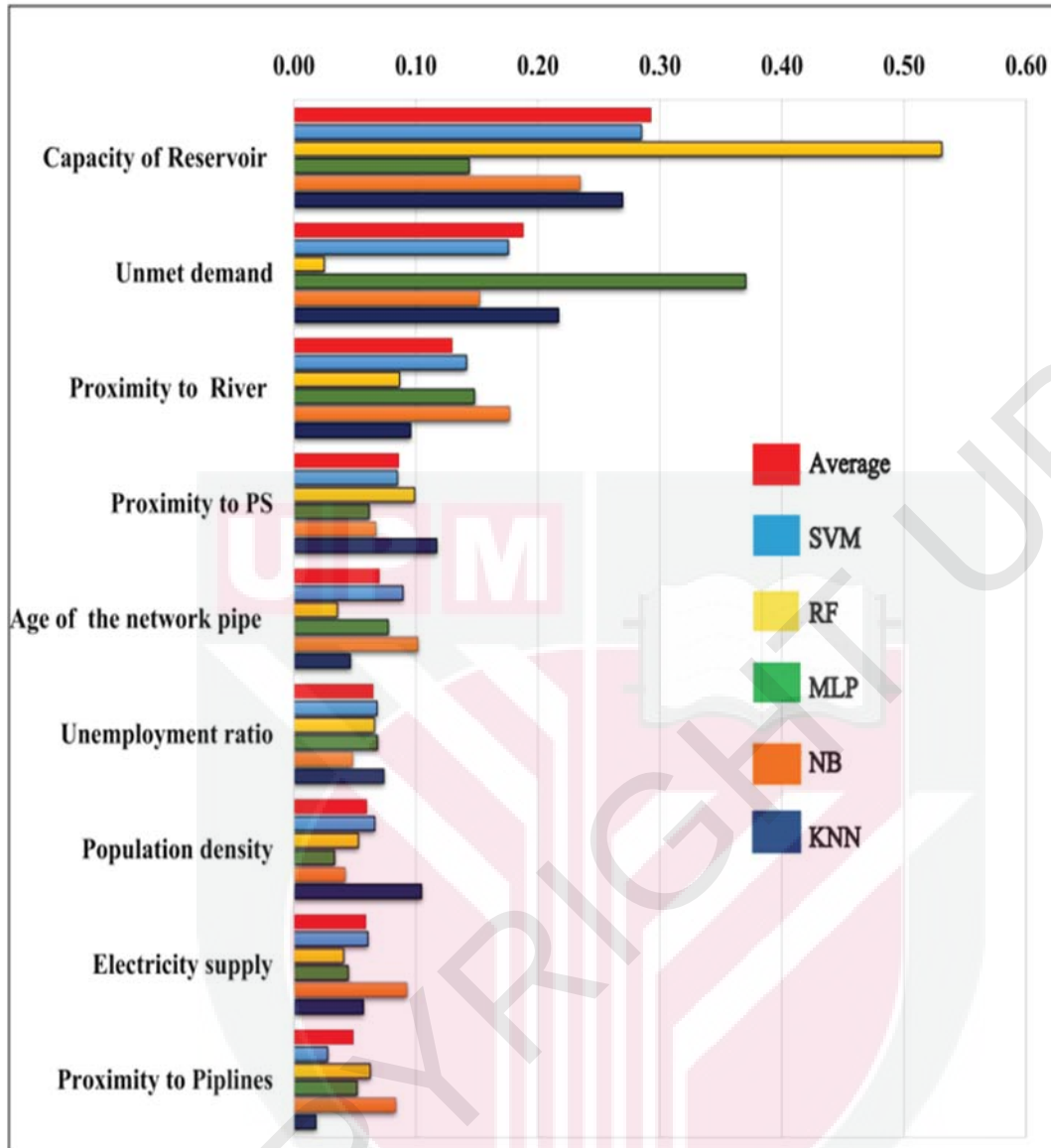


Figure 4.15 : Weights of criteria

4.2.3 Water Scarcity Risk Maps

The results of the prediction process were directly represented using the GIS application; thus, five WSR maps were produced based on the ML model used, as illustrated in the left side of Figures 16-20. Furthermore, the WLC technique was applied five times in the GIS environment to generate five WSR maps for Nasiriyah City with another technique, as shown in right side of Figures 4.16–4.20. In these

processes, the set weights of the criterion were changed according to the ML model each time.

The classification of each map produced by WLC was evaluated using the corresponding ML algorithm. The ACC was 78%, 84%, 85%, 90% and 96% for the produced maps from weights of NB, RF, KNN, MLP and SVM models, respectively (Table 4.5). To reach high accuracy, the average weights produced by the five ML models were applied to the WLC function to create the final map (Figure 4.21), the accuracy of which was higher than the others, as shown in Figure 4.24. According to the final map, 26% of the city's population, who are living in 17 neighbourhoods, are under very high WSR, 13%, who are living in 18 neighbourhoods are under high WSR, and the rest are under moderate to very low risk, as shown in Figure 4.22.

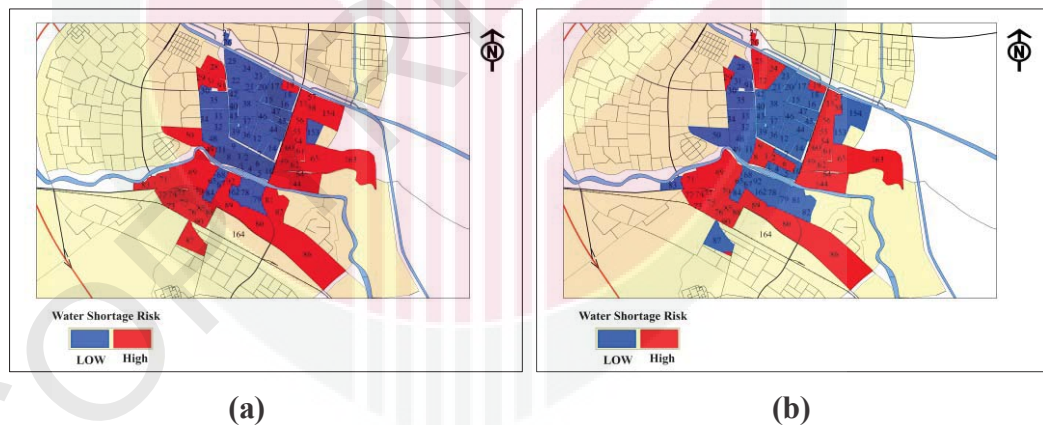
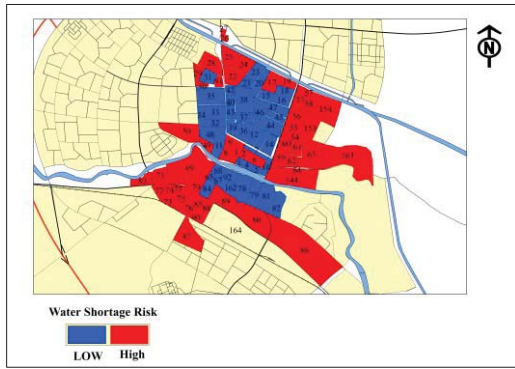
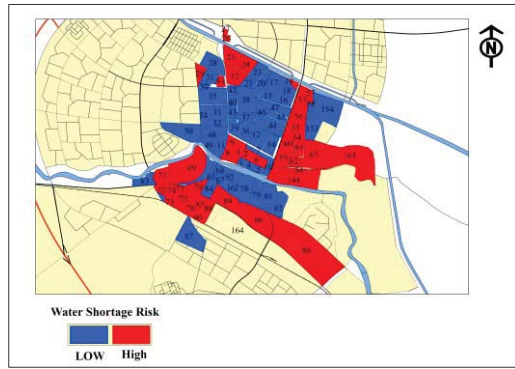


Figure 4.16 : NB algorithm outputs (a) WSR map: direct representation, (b) WSR map: WLC technique

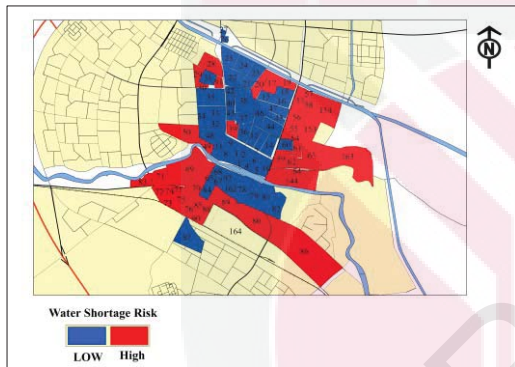


(a)

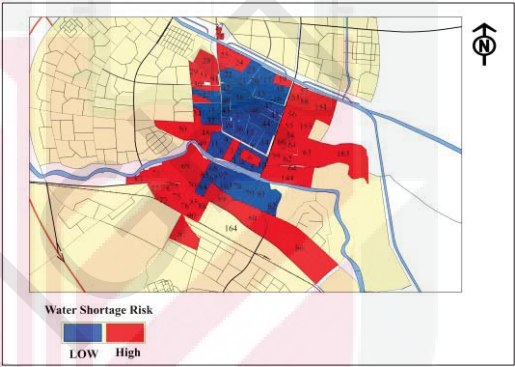


(b)

Figure 4.17 : RF Algorithm Results (a) WSR map: direct representation, (b) WSR map: WLC technique

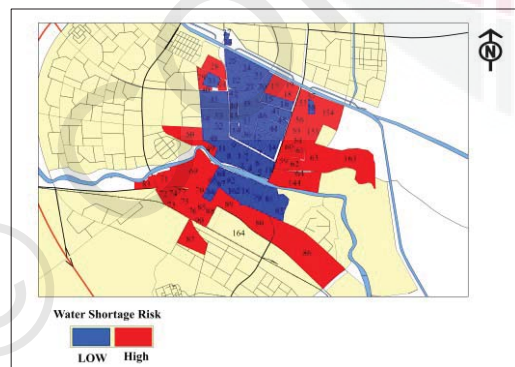


(a)

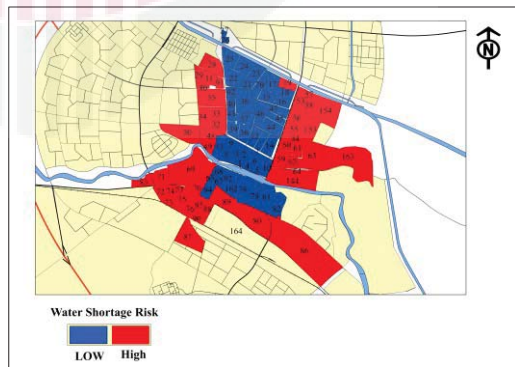


(b)

Figure 4.18 : KNN algorithm outputs (a) WSR map: direct representation, (b) WSR map: WLC technique



(a)



(b)

Figure 4.19 : MLP algorithm outputs (a) WSR map: direct representation, (b) WSR map: WLC technique

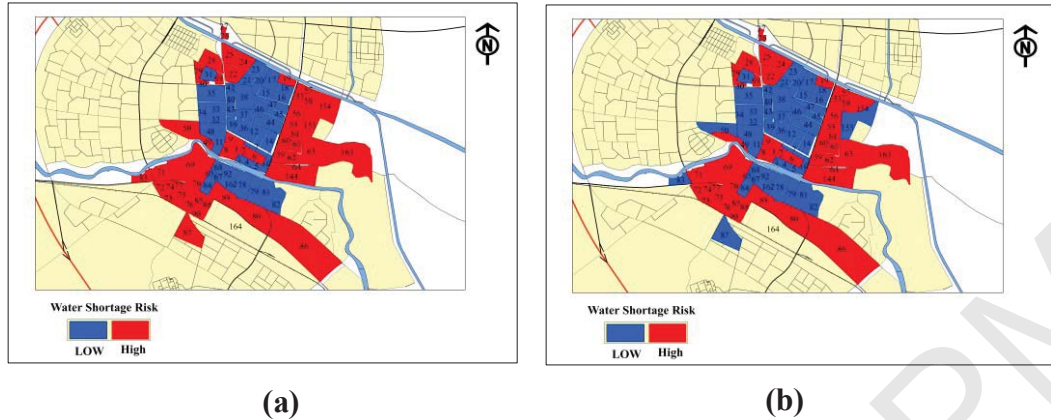


Figure 4.20 : SVM algorithm outputs a) WSR map: direct representation, (b) WSR map: WLC technique

Table 4.5 : Evaluation of classification of maps (b) in Figures 16–20 using the corresponding ML algorithm

Model	AUC	ACC	F1	Precision	Recall
NB	0.875	0.777	0.747	0.738	0.756
RF	0.889	0.84	0.831	0.755	0.925
KNN	0.864	0.851	0.844	0.927	0.776
MLP	0.954	0.904	0.897	0.951	0.848
SVM	0.962	0.957	0.958	0.92	1

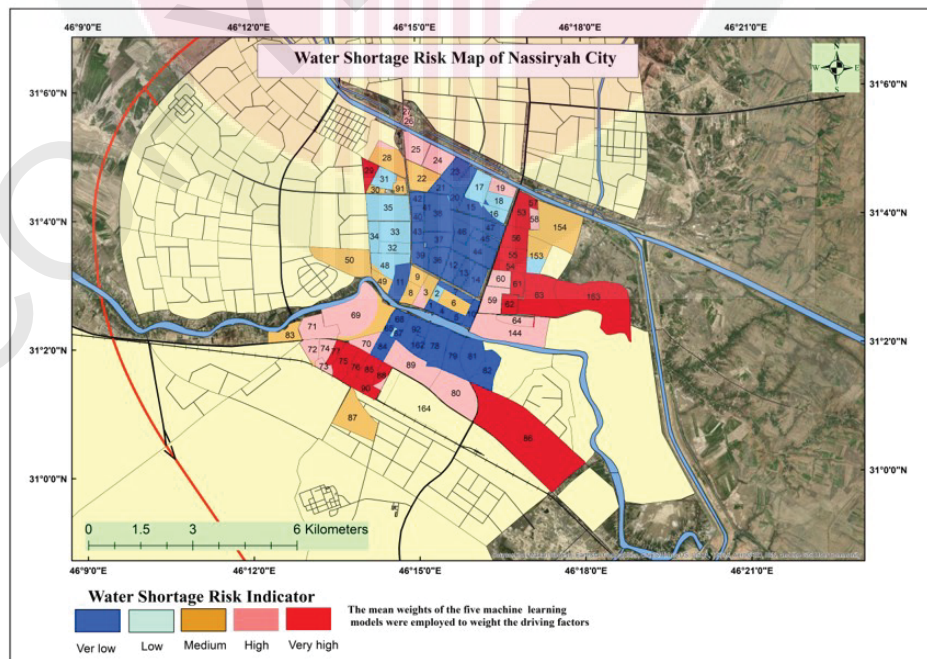


Figure 4.21 : Final WSR map classified into five categories (Very high, High, Medium, Low and Very low)

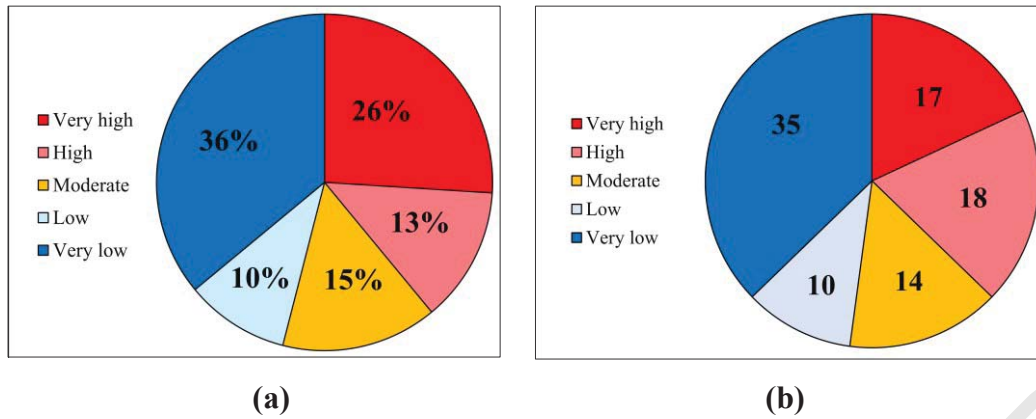


Figure 4.22 : (a) Distribution of population ratio based on WSR classes. (b) Distribution of city neighbourhoods based on WSR classes

4.2.4 Validation of Water Scarcity Risk Maps

An evaluation process was applied in each stage of this work. Firstly, the NB algorithm was applied with the method of 10-fold cross-validation to validate the feature-reduction stage. The result demonstrated that the performance accuracy of CorrelationAttributeEval was about 93% while the accuracy of InfoGainAttributeEval and GainRatiAttributeEval were 91.67% and 91.25%, respectively. Then, the trained model was evaluated using the five ML models (NB, RF, KNN, SVM and MLP) using a testing dataset via a confusion matrix. Six validation indicators were calculated: AUC, ACC, F1, precision, recall and specificity, as shown in Table 4.6 and Figure 4.23.

Despite the fact that the trained model evaluated by MLP was the best in terms of AUC values, the ACC values of the five ML models proved that the dataset was almost perfect. In the next stage, the six maps produced by entering the gained weight from the ML models into the WLC technique were evaluated by applying the corresponding ML model. The ACC was 78%, 84%, 85%, 90% and 96% for the produced maps from weights of NB, RF, KNN, MLP and SVM models, respectively (Table 4.5).

Furthermore, the final map that applied the average weights of the five models and the WLC technique achieved higher accuracy than the other five weights, as is seen in Figure 4.24.

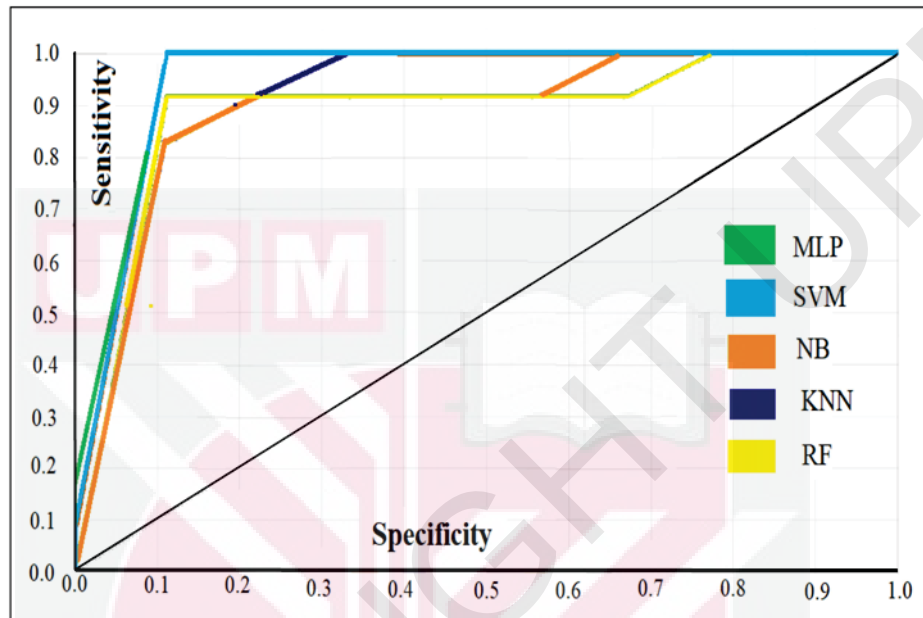


Figure 4.23 : Specificity and Sensitivity of WSR model

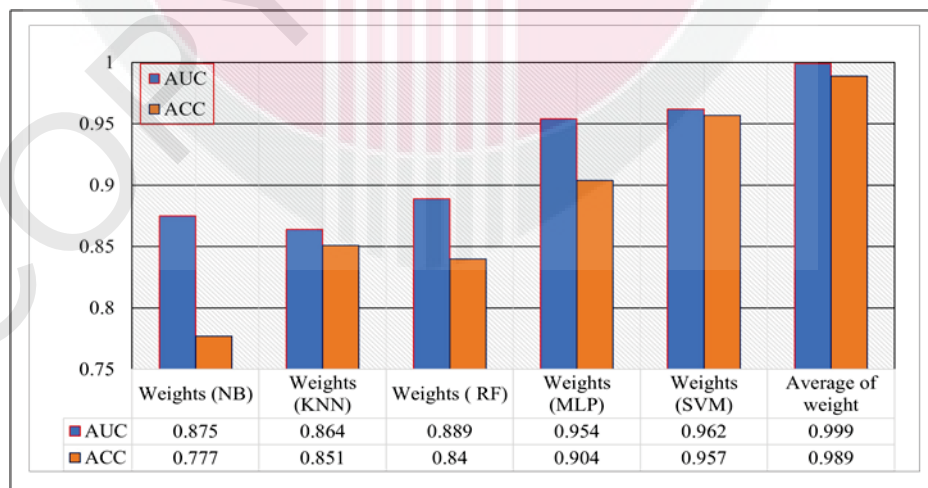


Figure 4.24 : Area under curve (AUC) and the accuracy (ACC)

Table 4.6 : Model evaluation using the testing dataset

Model	AUC	ACC	F1	Precision	Recall	Specificity
MLP	0.940	0.923	0.917	0.917	0.917	0.929
SVM	0.934	0.923	0.917	0.917	0.917	0.929
KNN	0.9116	0.885	0.869	0.909	0.833	0.929
RF	0.893	0.923	0.917	0.917	0.917	0.929
NB	0.875	0.846	0.846	0.786	0.917	0.786

4.2.5 Discussion of Water Scarcity Risk Prediction

This study highlights the water supply problem in urban areas by analysing the external and internal challenges that cause WSR. In urban areas, the external challenges are represented by climate change and quota city shares of water, whereas the internal challenges are represented by inequity in water management amongst city neighbourhoods.

Although the first challenge can be understood using traditional hydrological models, obtaining a deep understanding of the second challenge by conventional methods that adopt experts' opinions to determine the vulnerable urban areas is difficult due to subjectivity bias. Therefore, a research question is proposed in this study, that is, Are the opinions of people who are vulnerable to WSR nearer to reality than the opinions of experts? To address this problem, this study used PP to present a novel approach in detecting urban areas that are vulnerable to WSR by integrating ML and GIS called WSRPP. The new approach in this study shows that people's opinions match the combined impact of WSR driving forces, as depicted in Figure 4.22-b. It reveals that 35 neighbourhoods achieved high to very high WSR levels, in line with the public participation assessment findings.

The results of this work (Tabel 4.5) revealed that WSRPP technique that used the integration of PP with ML and GIS is an effective technique for exploring urban risks, in general, and WSR, especially. All five ML models that were used in this work indicated that the accuracy of the dataset was almost perfect. The accuracy of the dataset was 0.923, 0.923, 0.885, 0.923 and 0.846 by performing MLP, SVM, KNN, RF and NBC, respectively. Although the ML models predicted the WSR for the study area effectively, determining the real effects of the continuous factors, proximity to PS, proximity to main pipelines and proximity to rivers of the study area is difficult due to the effects of continuous factors that could not be obstructed by borders of neighbourhoods. Therefore, this study suggested that the average weights that were extracted by multiple ML models could resolve this issue (W. Li et al., 2021).

This suggestion would be convincing if the result of comparison between classifications based on the ML prediction method and the WLC, which uses the average weights, were validated. However, the ACC of the five maps of WSR that were produced individually from the weights of NB, RF, KNN, MLP and SVM algorithms was 78%, 84%, 85%, 90% and 96%, respectively, compared with the classification that was produced directly by model prediction. Although the ACC of the map produced using the weights of the SVM model achieved a high accuracy (96%), the final WSR map using the average weights of the five models achieved 99%, as shown in Figure 4.24. Furthermore, this approach successfully displayed the effects of the continuous factors that could not be obstructed by the neighbourhood's borders across the study area, as shown in Figure 4.25. Therefore, the results endorsed the capability of the novel approach to detecting WSR with high accuracy.

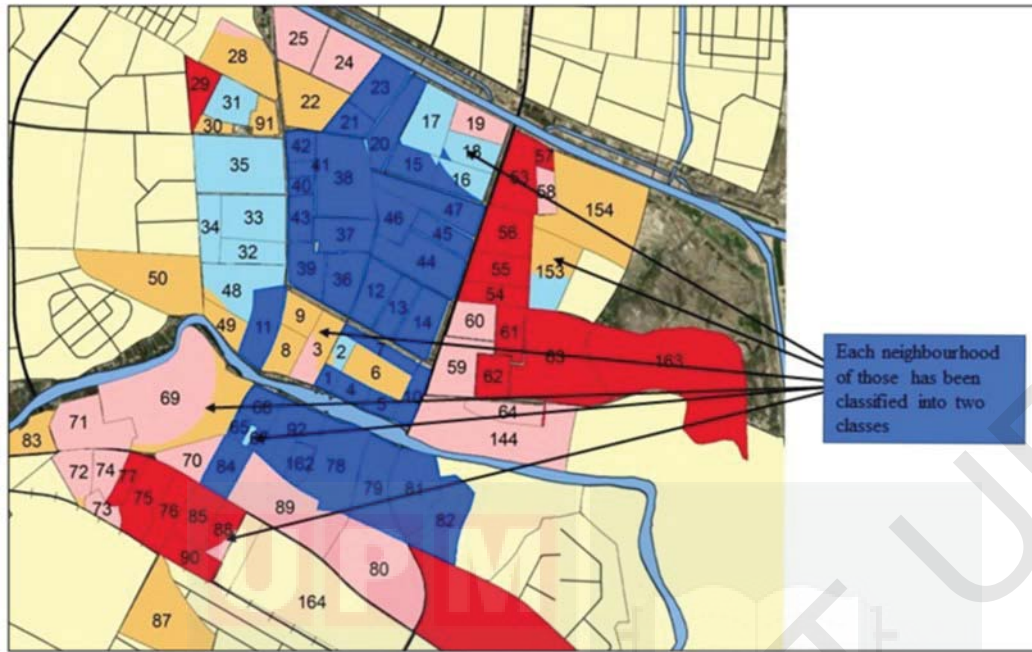


Figure 4.25 : The effects of continuous factors

The analysis process of the driving factors conducted by the SHAP model showed that the criteria of the capacity of reservoirs, unmet water demand and proximity to the river gained the highest weights (29%, 19% and 12%, respectively) amongst the other criteria, as shown in Figure 4.15. Thus, 60% of the decision depended on only these three criteria, whereas all six criteria contributed to only 40% of the decision.

The decision maker should consider this conclusion when the mitigation processes of WSR are taking place. However, the results demonstrated that a variation in water supply existed in this single city due to the spatial distribution of the urban WSS. The final map showed that 26% of the city's population, who are living in 17 neighbourhoods, were under very high WSR; 13%, who are living in 18 neighbourhoods, were under high WSR and the rest are under moderate to very low risk, as shown in Figure 4.22. This result endorsed the hypothesis of this study: that

the inequality in water distribution management within the same urban area is a significant challenge leading to WSR.

Different from traditional approaches, WSRPP considered all contributing factors for supplying water, beginning from the river to the house, to analyse the actual reasons for WSR in urban areas (Amin et al., 2018; Cordão et al., 2020; Ougougdal et al., 2020). In addition, compared with recent research, this study adopted the theoretical analysis of the mitigation of WSR by decreasing water losses; therefore, this analysis was adopted in the deriving process of the relevant criteria, such as the proximity to PS and the proximity to the river (Ahmadi et al., 2020; Rufino et al., 2021). Furthermore, modern techniques were applied (i.e., fuzzy large membership and fuzzy near membership) in the derivation process (Kordnoori *et al.*, 202).

In the risk-management field, machine-learning models are often assumed to be applicable to similar spatial environments of interest. Therefore, the proposed training model was built from the spatial analysis of essential components of a conventional water supply system (WSS) which is usually used by most countries worldwide. The training model included several independent variables, namely, 10 spatial driving factors that reflected the roles of WSS components, which run from water sources to homes, and a dependent variable, that is, the water situation of each sector of an urban area. In addition, the quality of the model's execution was improved using three types of attribute evaluators to remove irrelevant driving factors and apply the best prediction model. Therefore, the model was carefully organized to achieve high accuracy in other water-scarcity risk-estimation studies in similar spatial environments.

The proposed approach can be generalised to other fields to support decision makers in reducing the degree of vulnerability in urban areas in developed and developing countries. However, the accuracy of the required data is difficult to guarantee in this study. On the one hand, the WSS within a city is complex. On the other hand, the PP approach in developing countries faces many limitations in collecting people's opinions regarding the main service provided by the government. Although the uncertainty ratio was associated with the results due to the accuracy of collected data, the novel approach interpreted the results in a clear form, which allows decision makers to support the proactive exploration of urban WSR and select appropriate alternatives at the right time.

4.3 Simulation of Urban Growth

4.3.1 Classification of Landsat Image

The supervised classification techniques (RF in QGIS) classified the Landsat images from 1992, 2002, 2012 and 2022 with high accuracy. The minimum of kappa values was 88%, and the minimum OA was 93%. The outcomes indicate that the observed LULCC are predominantly rapid across Nasiriyah City from the year 1992 to 2022 and turned into urban areas at the expense of other land use classes. The urban area ratio increased by about 10%, i.e., from 2.5% in the year 1992 to 12.17% in 2022. The urban sprawl was at the expense of vegetation (6.82%), bare land (2.83%) and water (0.02%), as shown in Figures 4.26 and 4.27. This change was a result of migration from rural areas to the city, in addition to the fact that the study area is the economic centre of about 2 million people.

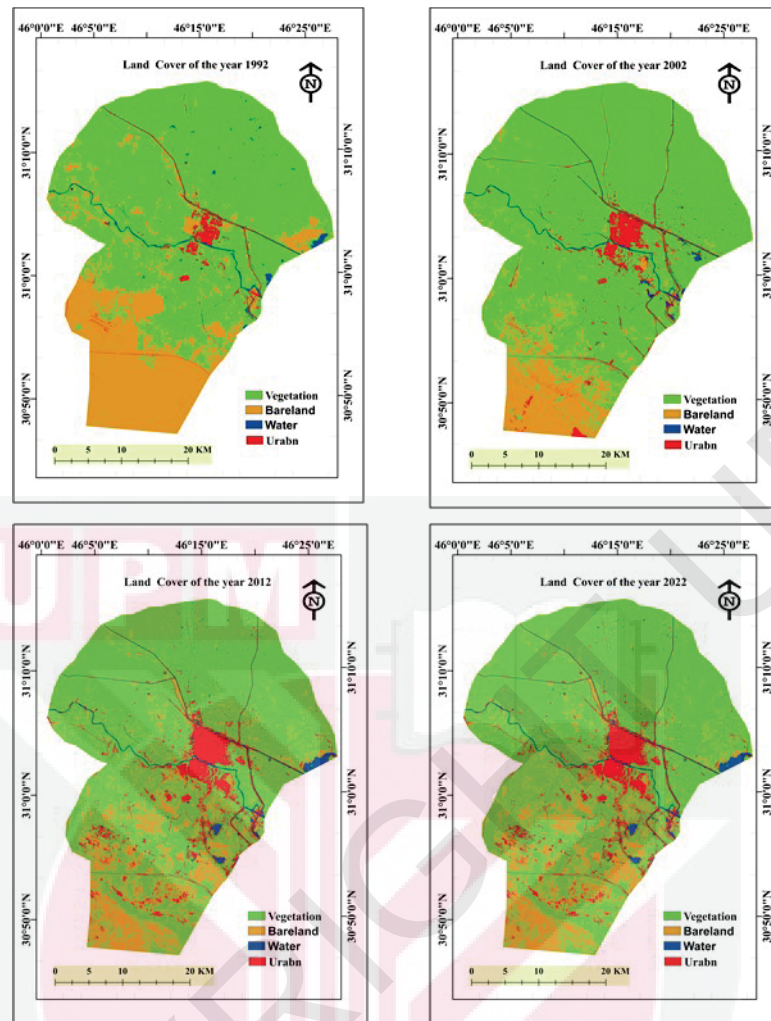


Figure 4.26 : Land use and Land cover (LUC) maps of the study area for 1992–2022

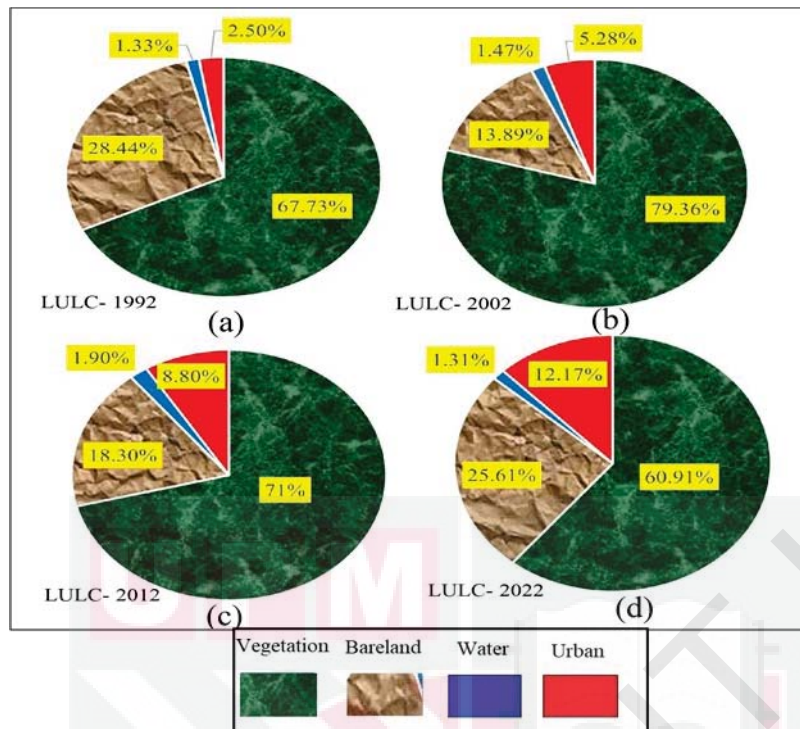


Figure 4.27 : LULC changes for four time periods: (a) 1992, (b) 2002, (c) 2012, and (d) 2022

4.3.2 Prediction of Urban Growth Boundaries

Cellular automata (CA) prediction models require at least two sequences of temporal maps of LULC to operate effectively. These sequences represent the changes in LULC over time. The first map serves as the system's initial state, depicting the starting configuration of cell states. The second map helps to capture the system's subsequent states as it evolves over time, usually through iterative updates based on predefined rules. By comparing the initial state with the subsequent states, CA prediction models can analyse the system's dynamic behaviour and make predictions about its future states.

In the current study, to simulate the LULC of 2012, the LULC for 1992 and 2002 was used, whereas the LULCC in 2002–2012 was used to simulate the map of the year

2022. The results reveal that the accuracy of performance of ANN-CA is an ‘almost perfect agreement’, with an overall kappa value of 90.3% and 80.2% for the simulated maps of years 2012 and 2022, respectively, based on the maps of the same years. The prediction result for the following three decades (2032, 2042 and 2052) supports the historical trend of urbanisation at the expense of considerable quantities of vegetation area. The urban area ratio of the general region increased by about 7.92 %, i.e., from 12.17% in the year 2022 to 20.09% in 2052. Urban sprawl occurred at the expense of vegetation (7.63%) and water (0.29%). Meanwhile, the city would be expanded by 34%, 25% and 19% by the years 2032, 2042 and 2052, respectively, as shown in Figure 4.28. These results were required for delineating UGB lines for the years 2022, 2032, 2042 and 2052 to train the ensemble of ML algorithms on the urban growth trends, as shown in Figure 4.29.

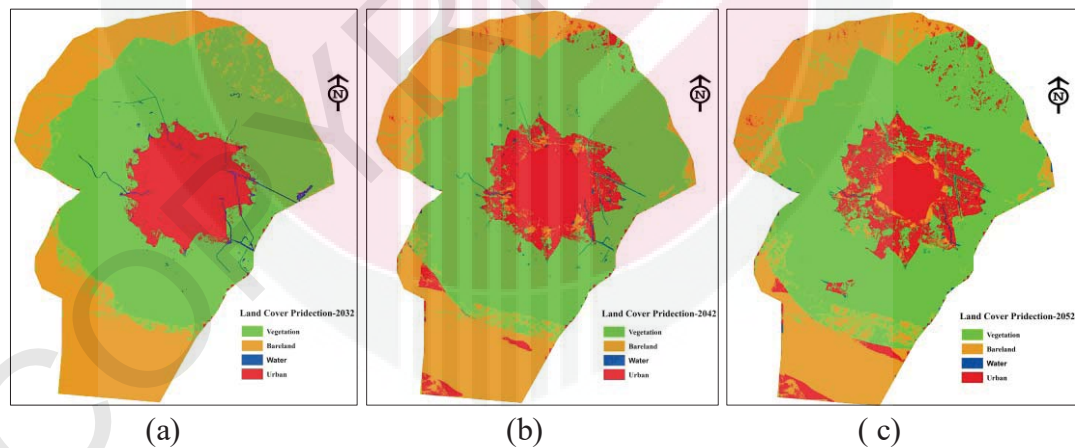


Figure 4.28 : Predicted LULC of the study area for the period 2032–2052: (a) 2032, (b) 2042, (c) 2052

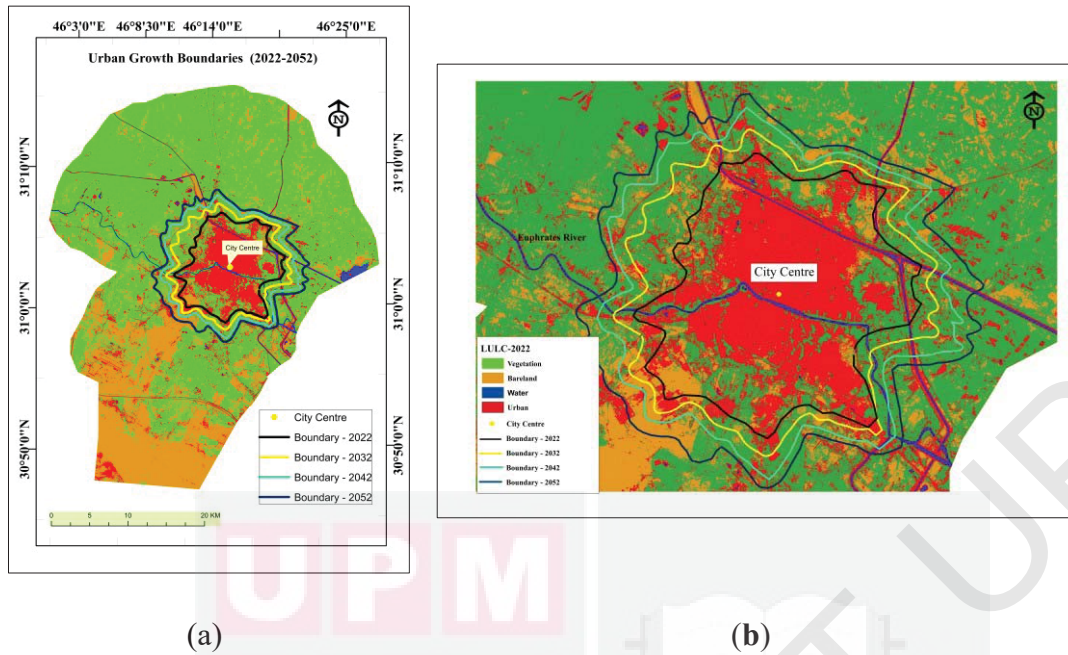


Figure 4.29 : (a) the movement of UGBs; (b) the city expansion for years 2022, 2032, 2043 and 2052

4.3.3 Spatial Applicability of the Novel ML Model

The results of spatial applicability confirm that the novel ML model is effective, according to the validation metrics that were measured by the four ML algorithms. On the one hand, the test score result reveals that the values for the coefficient of determination (R^2) are 98%, 96%, 90% and 89%, which were measured by AB, RF, KNN and LR, respectively. On the other hand, the validation score result reveals that the values of R^2 are 100%, 99%, 89% and 88%, which were validated by AB, RF, LR and KNN, respectively. In addition, the predicted results proven by the novel approach are efficient in supporting decision systems regarding land use optimisation, especially selecting pollution-causing project sites. It accurately determined the date of the intersection of UGBs with the buffer zone of the sample of the pollution-causing projects that were selected in this work. The results predicted are as follows:

1. The urban growth boundary already reached the location centre of project No. 1 (oil refinery) in the year 2021, indicating that the location centre of the oil refinery violates IES. According to IES, the buffer zone between UGBs and an oil refinery must be 10 km to protect the urban community from gas emissions.
2. The urban growth boundary was intersected with a buffer zone around the Project No. 2 (WWTP). in the year 2016 and will reach its location centre in the year 2022. Although the project is presently under construction, it violates the IES, which enforces a 2 km buffer zone.
3. The urban growth boundary intersected the buffer zone around the Project No.3 (landfill site) in the year 2013, and it will reach the location centre by the year 2030. Therefore, the location of this project must be moved in accordance with the IES, which enforces 2 km as a buffer zone from the UGB. Based on local environmental reports, the majority of Nasiriyah City residents suffer from the bad smell and smoke released from this site.
4. The urban growth boundary will intersect with the buffer zone around the Project No. 4 (plastic and paint factory) in the year 2038, and it will reach the location centre by the year 2043. The factory must be moved to a farther site by the year 2038 due to IES, which enforces 500 m as a buffer zone from the UGB.
5. The urban growth boundary will intersect with the buffer zone around the Project No. 5 (sandwich panel factories) in the year 2046, and it will reach the location centre by the year 2056. The factory must be moved by 2046 due to IES, which enforces 1 km as a buffer zone of from the UGB.
6. The urban growth boundary will intersect with the buffer zone around the project No. 6 (industrial area) in the year 2087, and it will reach the location centre by the year 2092. Its location is suitable based on IES, which enforces 1 km as a buffer zone of from the UGB. Figure 4.30 shows the prediction results regarding the sample of the pollution-causing projects that were selected in this study.

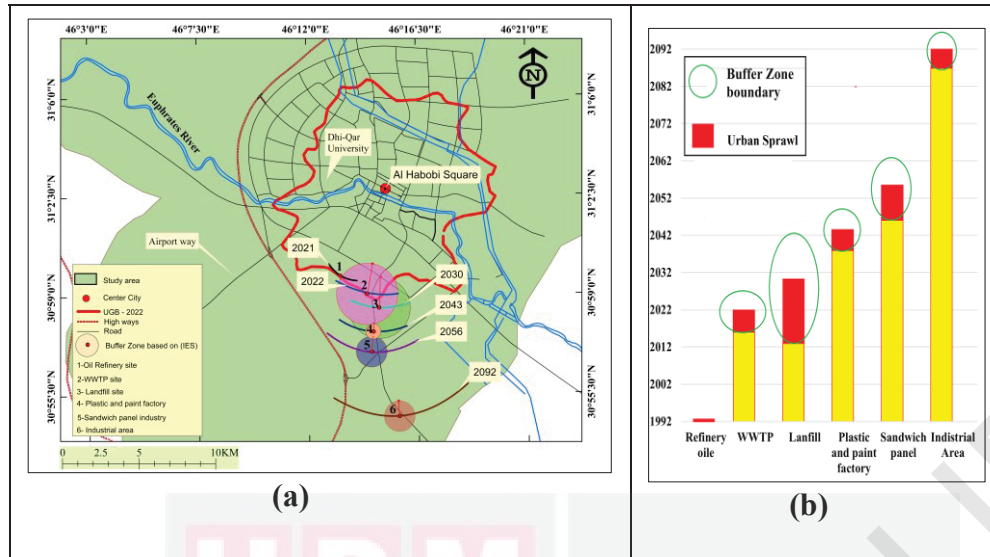


Figure 4.30 : (a) the buffer zones and forecasted UGBs over time; (b) movement of UGBs

4.3.4 Validation of Urban Growth Model

In this work, the validation results reveal that the ML model was run with high accuracy, and the performance indexes were measured to validate the sequential results of each stage. The indexes indicated that the performance of the techniques used in this study was almost perfect. Firstly, the accuracy performance of Landsat image classification was validated with high accuracy in the two steps, i.e., model training using RF and final LULC classification using SCP in QGIS, as listed in Table 4.7.

Secondly, to calibrate the ANN-CA technique, the LULCs for 2012 and 2022 were simulated; thus, the accuracy of the simulation maps was validated on the basis of the real maps of the same years and was in ‘almost perfect agreement’, as it also listed in Table 4.7. Finally, in predicting the UGB stage, the trained model was validated using the four ML algorithms, i.e., RF, KNN, AB and LR, using the testing set (10%) and validation set (15%) via a confusion matrix test, as shown in Figure 4.31.

Table 4.7 : Performance evaluation of the LULC classification stage

Years	Overall Accuracy of the Training Model [%]	Kappa of the Training Model	Overall Accuracy of Classification [%]	Kappa Classification	Kappa of Simulation Maps
1992	99.64	0.993	99.94	0.999	/
2002	94.07	0.902	96.3127	0.9307	/
2012	89.99	0.844	93.2061	0.8838	0.903
2022	93.77	0.880	97.7284	0.9617	0.802

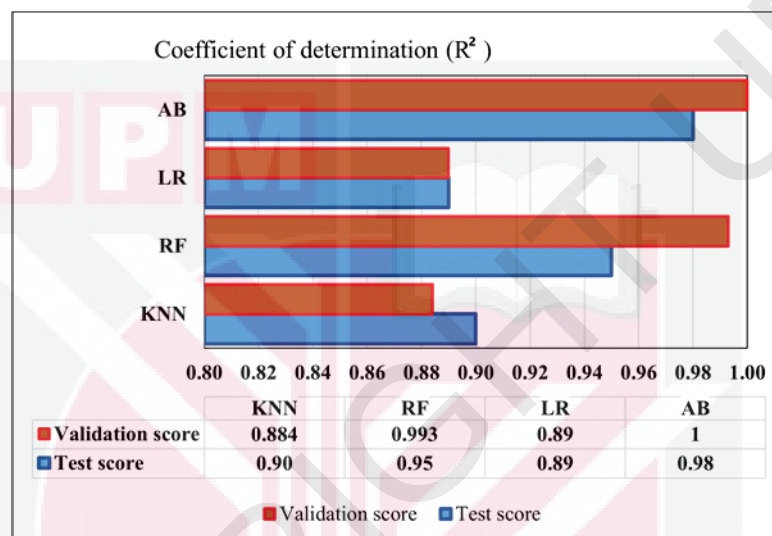


Figure 4.31 : Values of the coefficient of determination (R^2) of the trained model

4.3.5 Discussion of the Urban Growth Prediction

The urban communities near pollution-causing factories are exposed to risks of environmental pollution (Bseibsu et al., 2022). To mitigate possible counteractions, substantial research has proposed appropriate solutions, including many land use optimisation methods. The most common methods of spatial optimisation are GIS-MCDM and the integration of GIS and ML models along with RS data. However, in both approaches, the spatial decision is made on the basis of multicriteria, most of which are spatial dynamic factors; however, the practical principle of these approaches does not consider dynamic LULCC due to urban growth. Consequently, a city would

likely sprawl close to the pollution-causing projects that were selected, causing considerable effects on sustainability. Therefore, a novel technique was proposed in this study to solve the above-mentioned problem called urban growth boundary forecasting (UGBF) . It presents urban growth boundary(s) (UGBs) as a simple tool to predict and monitor urban sprawl.

The findings of this work reveal that the novel approach (UGBF) is highly efficient for the proactive prediction of potential long-term environmental effects, as well as the detection of environmental impacts at present. The overall result shows that the Nasiriyah City expansion (the study area) is haphazard and unplanned, resulting in disastrous effects on urban and natural systems. The urban sprawl would continue towards the area on which built or proposed industrial projects violate local environmental standards (IESs), which aim to protect urban communities from environmental pollution.

The analysis result shows that the urban area ratio increases by about 10%, i.e., from 2.5% in the year 1992 to 12.2% in 2022. This change was at the expense of vegetation (6.7%), bare land (2.84%) and water (0.02%). Furthermore, the prediction results reveal that the city will expand by 34%, 25% and 19 % by the years 2032, 2042 and 2052, respectively. In addition, the land use assessment result for the sixth site confirms that the novel technique can forecast city expansion until 2092. It is one of the advantages that the present study seeks. The validation results confirm that the performance of UGBF is effective, according to the validation metrics that were measured by the four ML algorithms, i.e., AB, RF, LR and KNN. The coefficient of determination (R^2) values ranged from 88% to 100%.

In contrast to conventional and modern approaches of LULC optimisation and simulation, UGBF can effectively validate and support the decision-making process regarding long-term land use planning. Nevertheless, their advantages cannot be underestimated, although their results are often associated with uncertainty (Ademulegun *et al.*, 2022; Aghmashhadi *et al.*, 2022; Rahman and Szabó, 2022).

The practical principle of almost all land use optimisation methods is similar, that is, their outcome is driven by multicriteria, which contribute different factors to the decision-making process. However, most of these criteria are dynamic spatial factors that change over time due to the impact of urban sprawl (Xiaoyang Liu *et al.*, 2022; Saha *et al.*, 2021). Given that this change is neglected when using land use optimisation techniques, the decisions that are made on the basis of multicriteria would be converted from strong to weak over time. To overcome this issue, simulation techniques could be applied because these techniques provide a comprehensive perspective of current and future development opportunities (Muhammad *et al.*, 2022).

Although ANN-CA is the most effective technique, which has been recently commended by many scholars (Saha *et al.*, 2021; Tripathy & Kumar, 2019), integrating it with land use optimisation approaches to make a sustainable decision regarding a suitable site for various activities is complex. It requires multiple operations that must be conducted in sequential steps when a suitable location for a specific activity is chosen. Whilst most strategic industrial projects, such as oil refineries, power energy electricity and WWTP, are designed to work for multiple decades, all prediction techniques are restricted to predict over three decades with acceptable accuracy. To bridge these gaps, the novel approach based on ML and GIS was developed. The results of this study confirm that using UGBF can avoid the

probability of incorrect decisions that cost a high amount when their consequences are corrected.

The advantages and disadvantages of the proposed approach are arguable. To what extent the novel technique may be used to forecast urban sprawl in other cities has yet to be answered. Each city has spatial properties, i.e., area of the city, distance from the city centre to UGB, design of roads and proximity of the rivers from built-up areas. The novel model predicts UGB on the basis of these properties and the historical trend of LULCC that can be obtained from the archive of Landsat images. Therefore, the model can be applied to another city with its own spatial properties.

Another argument that could spark discussion is that although UGBF can monitor urban growth with high accuracy, the other factors that contribute to the selection of optimal sites are neglected. The main aim of developing this approach was to overcome the limitations of the land use optimisation technique. This novel technique can be applied before using either GIS-MCDM or GIS-ML to exclude the sites that would be covered by city expansion in the future.

UGBF can discover planning problems of projects that were built in the past, and it can predict potential environmental problems of projects under construction and even the proposed location of planning projects. Therefore, it can be a DST for land use optimisation, especially in selecting sites of pollution-causing projects. This technique is necessary for scholars and urban planners who are interested in sustainable development goals (SDGs).

4.4 Prediction of Overall Risk

4.4.1 Water Demand

The model result showed that the maximum monthly water demand for the period of 2023–2052 under the main scenario (RC, RCP 4.5 and RCP 8.5) and their dependent scenarios (HP and MS) will be in July (1258, 1308 and 1032 mcm, respectively). In addition, the minimum monthly water demand for the same period under the same scenarios will be in March (364, 383 and 300 mcm), as shown in Figure 4.32(a). Meanwhile, the model calculated the yearly water demand for the period of 2022–2052. In the current year (2022), the yearly water demand of overall site demand was 11,032 mcm. The yearly water demand under the three main scenarios will be 11,158, 11,319 and 11,525 mcm for the years 2032, 2042 and 2052, respectively, whereas under the HP scenario will be 11,314, 11,775 and 12,525 for the years 2032, 2042 and 2052, respectively. In addition, under the MS scenario, it will be 9,044, 9,205 and 9,411 mcm for the years 2032, 2042 and 2052, respectively, as shown in Figure 4.32(b).

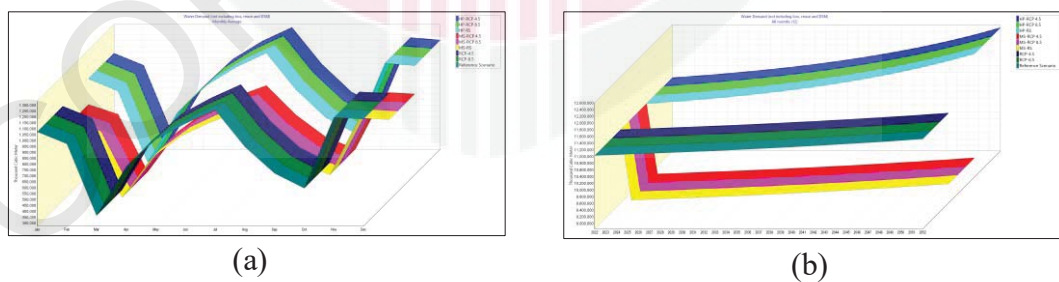


Figure 4.32 : (a) monthly water demand; (b) yearly water demand

4.4.2 Unmet Water Demand

The model results showed that unmet demand values vary. Each scenario has its own behaviour; thus, nine different values were obtained, as shown in Figure 4.33. To analyse the result, the unmet water demand was divided into three groups based on the main scenarios (RC, RCP 4.5 and RCP 8.5).

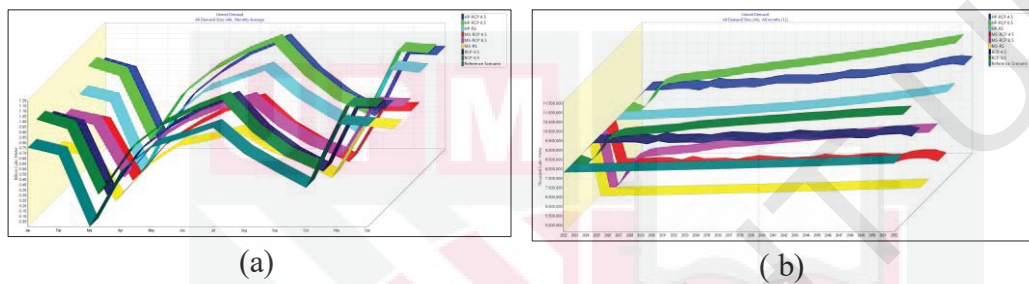


Figure 4.33 : (a) monthly unmet demand; (b) yearly unmet demand

4.4.2.1 Group 1: Reference Scenario and Its Dependent Scenarios

The model result showed that the maximum monthly unmet demand for the period of 2022–2052 under the reference scenario and its dependent scenarios (RS, H-RS and MS-RS) will be in November (978, 1003 and 711 mcm, respectively). In addition, the minimum monthly water demand for the same period under the same scenario will be in March (1.9, 17 and 1.4 mcm under RS, H-RS and MS-RS, respectively), as shown in Figure 4.34 (a). In addition, the result analysis of the water situation under RS, HP-RS and MS-RS showed that suggesting measures according to MS (MS-RC) will have a remarkable effect on the yearly unmet water demand amount. In the current year (2022), the unmet demand of overall site demand was 7,817 mcm.

The unmet demand water under RC will be 7,939, 8,094 and 8,301mcm for the years 2032, 2042 and 2052, respectively. The unmet demand water under the HP-RS

scenario will be 8,090, 8,551 and 9,303 mcm for the years 2032, 2042 and 2052, respectively. In contrast, under the MS-RC scenario, unmet demand water for the year 2032, 2042 and 2052 will be (5273, 5421, and 5612) mcm, respectively, as shown in Figure 4.34 (b).

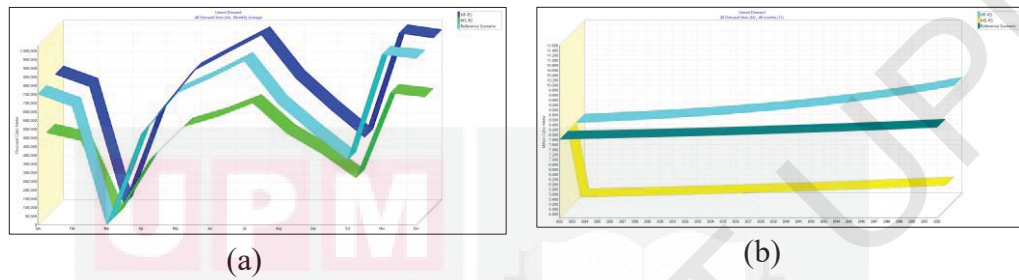


Figure 4.34 : (a) Monthly unmet water demand under RC and its dependent scenarios (MS-RC and HP-RC), and (b) yearly unmet water demand

4.4.2.2 Group 2: RCP 4.5 Scenario and its Dependent Scenarios

The model result showed that the maximum monthly unmet demand for the period of 2022–2052 under the RCP 4.5 scenario and its dependent scenarios (RCP 4.5, HP-RCP 4.5 and MS-RCP 4.5) will be on July (1045, 1096 and 775 mcm, respectively). In addition, the minimum monthly water demand for the same period under the same scenarios will be in March (138, 156 and 28 mcm under RCP 4.5, H-RCP 4.5, and MS-RCP 4.5, respectively), as shown in Figure 4.35 (a).

The model calculated the yearly unmet demand for the study period. In the current year (2022), the unmet demand of overall site demand was 7,818 mcm. Under RCP 4.5, the unmet demand water was 8486, 8651 and 8798 for the years 2032, 2042, and 2052, respectively. Under the HP-RCP 4.5 scenario, the unmet demand (8,644, 9,109 and 9,800) for the year 2032, 2042 and 2052 respectively. Furthermore, under the MS-

RS scenario, the unmet demand was 5,800, 5,958 and 6,095 mcm for the years 2032, 2042 and 2052, respectively, as shown in Figure 4.35 (b).

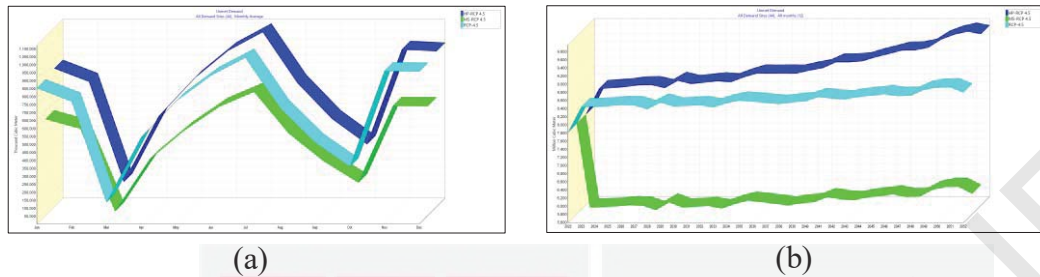


Figure 4.35 : (a) Monthly unmet water demand under RCP 4.5 and its dependent scenarios (MS-RCP4.5 and HP-RCP 4.5), (b) yearly unmet water demand

4.4.2.3 Group 3: RCP 8.5 Scenario and its Dependent Scenarios

The model result showed that the maximum monthly unmet demand for the period of 2022–2052 under the RCP 8.5 scenario and its dependent scenarios (RCP 8.5, HP-RCP 8.5 and MS-RCP 4.5) will be in July (1,122, 1,172 and 866 mcm); in addition, the minimum monthly water demand for the same period under the same scenarios will be in March (225, 243 and 141 mcm, respectively), as shown in Figure 4.36 (a). Meanwhile, the yearly unmet demand was calculated for period (2022–2052). In the current year (2022), the unmet water demand of the overall site was 7,818 mcm. Under RCP 8.5, the unmet water demand was 9,585, 10,059 and 10,434 mcm for the years 2032, 2042 and 2052, respectively. In addition, the unmet water demand under the HP-RCP 8.5 scenario was 9,743, 10,517 and 11,437 mcm for the years 2032, 2042 and 2052, respectively. Under the MS-RS scenario, the unmet water demand was 7,150, 7,689 and 8,089 for the years 2032, 2042 and 2052, respectively, as shown in Figure 4.36 b.

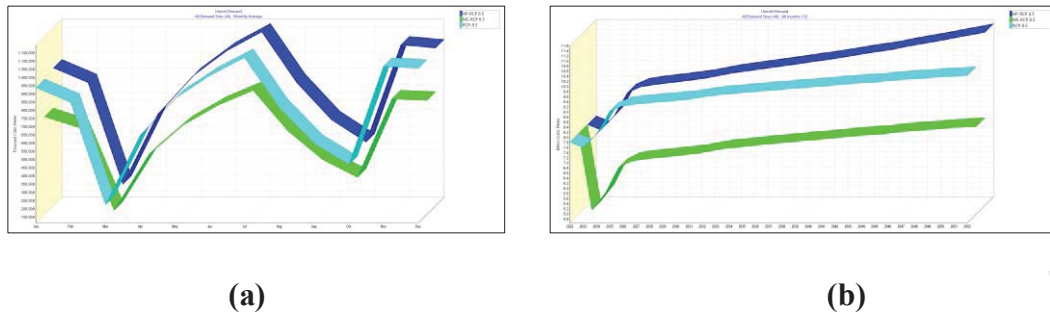


Figure 4.36 : (a) Monthly unmet water demand under RCP 8.5 and its dependent scenarios (MS-RCP8.5 and HP-RCP8.5), (b) yearly unmet water demand

4.4.3 Water Demand Based on Sectors

The water demand from the Gharraf basin was divided into three sectors: irrigation, domestic and industrial. Although the major amount of water demand goes to irrigation activities in all scenarios, the percentage will vary based on the proposed scenario. In the main scenarios (RC, RCP 4.5 and RCP 8.5), the result analysis showed that the percentage of water demand for the agricultural sector will be 94%, 93% and 91% in the years 2023, 2042 and 2052, respectively, as shown in Figure 4.37 (a,b and c). In the HP scenarios, the percentage of water demand of the agricultural sector will be 93%, 89% and 84% in the years 2023, 2042 and 2052, respectively, as shown Figure 4.37(d,e and f). In the MS, the percentage of water demand of the agricultural sector will be 93%, 92% and 89% in the years 2023, 2042 and 2052, respectively, as shown in Figure 4.37(g,h and i).

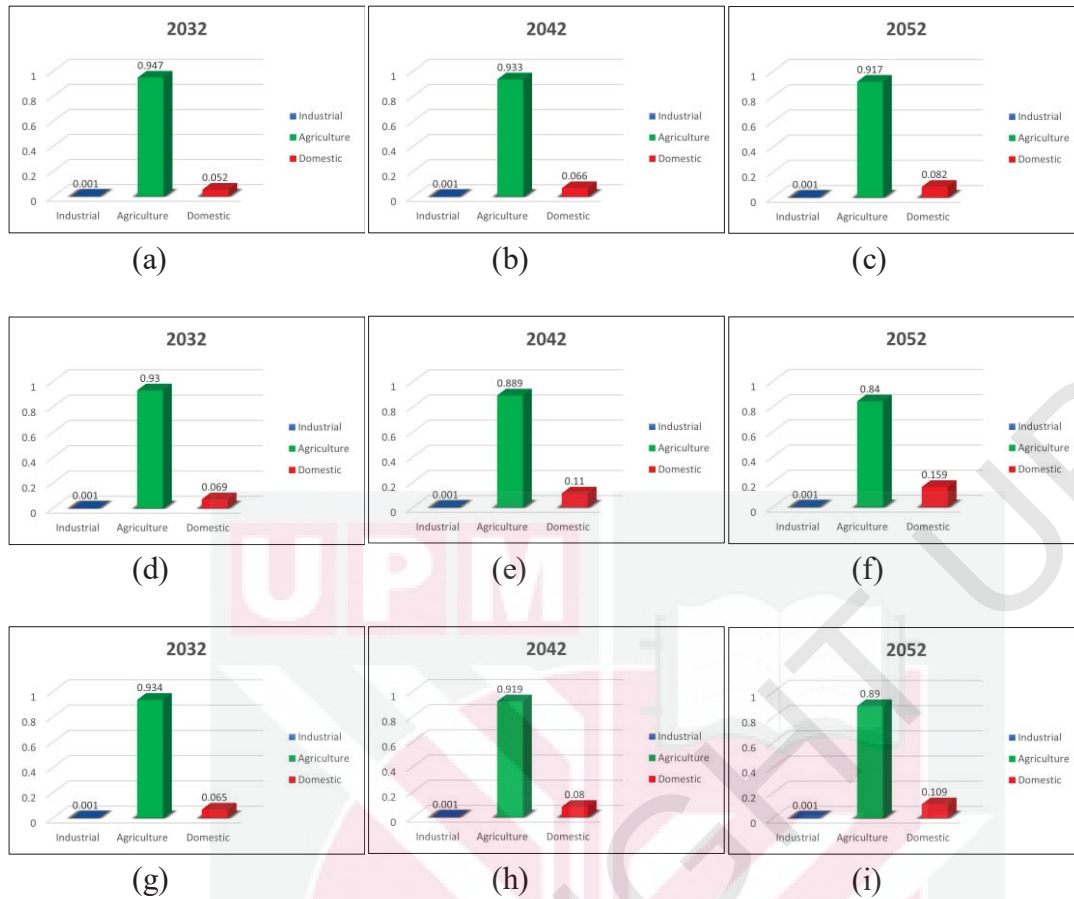


Figure 4.37 : (a,b,c) water demand based on sectors, under the main scenarios (RC, RPC 4.5 and RCP8.5), (d,e and f) water demand based on sectors under the high population scenario, (g,h and i) water demand based on sectors under the management scenario

4.4.4 Unmet Demand Based on Sectors

The result analysis revealed that the maximum unmet demand of the agricultural sector will be under HP-RCP 8.5, whereas the minimum unmet demand will be under the MS-RC scenario. By contrast, the minimum unmet demand of the domestic sector will be under MS-RC, MS-RCP4.5 and MS-RCP 8.5, whereas the maximum unmet demand will be under the same scenario (HP-RCP 8.5), as shown in Figure 4.38. Although the water situation of the Gharraf Basin will be difficult under HP-RCP 8.5 for all sectors, the proposed measures according to the MS scenario will relieve this situation. Consequently, the WSR of Nasiriyah City was predicted under two

scenarios; the first one has a high negative effect (HP-RCP 8.5), and the other will relieve this effect (MS-RCP 4.5) to highlight the extent to which the proposed measures within the framework of MSs are effective to face climate change.

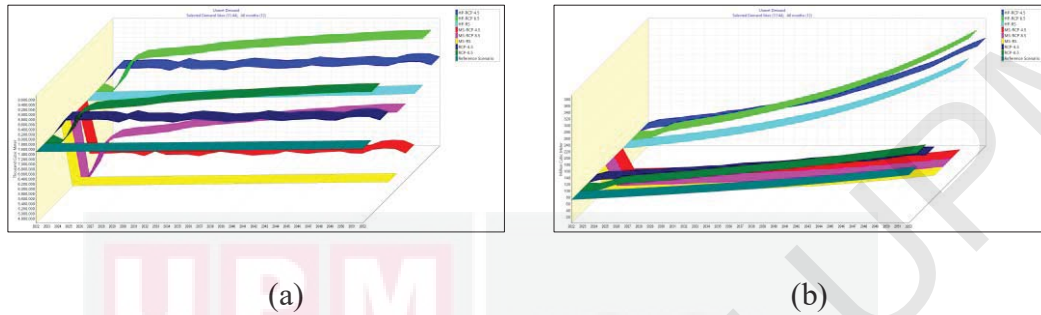


Figure 4.38 : (a) Unmet demand for the agricultural sector, (b) unmet demand for the domestic sector

4.4.5 Prediction of Overall Risks for the Year 2052

4.4.5.1 Forecasting WSR under HP-RCP 8.5

Under HP-RCP 8.5, the population growth was proposed to be 5%; thus, the city population will increase up to 3,305,358 by the year 2052. Under HP-RCP 8.5, the water situation of the Gharraf Basin will be difficult. Based on the HadGEM2-ES model, the expected monthly average precipitation in the 2052 will be about 10.87 mm/month, whereas in 2023, it will be about 12 mm/month, and the expected maximum temperature will be 50.20° in the year 2052; by contrast, in the same month of the year 2023, it will be 48.65°. The share of the Gharraf River in the national waters will be reduced by almost half. The unmet water demand of Nasiriyah City will be 91% for most demand sites. Therefore, 185 of the 188 city neighbourhoods will be at drought risk. The remaining three sites have independent water sources (industrial and education areas), as shown in Figure 4.39.

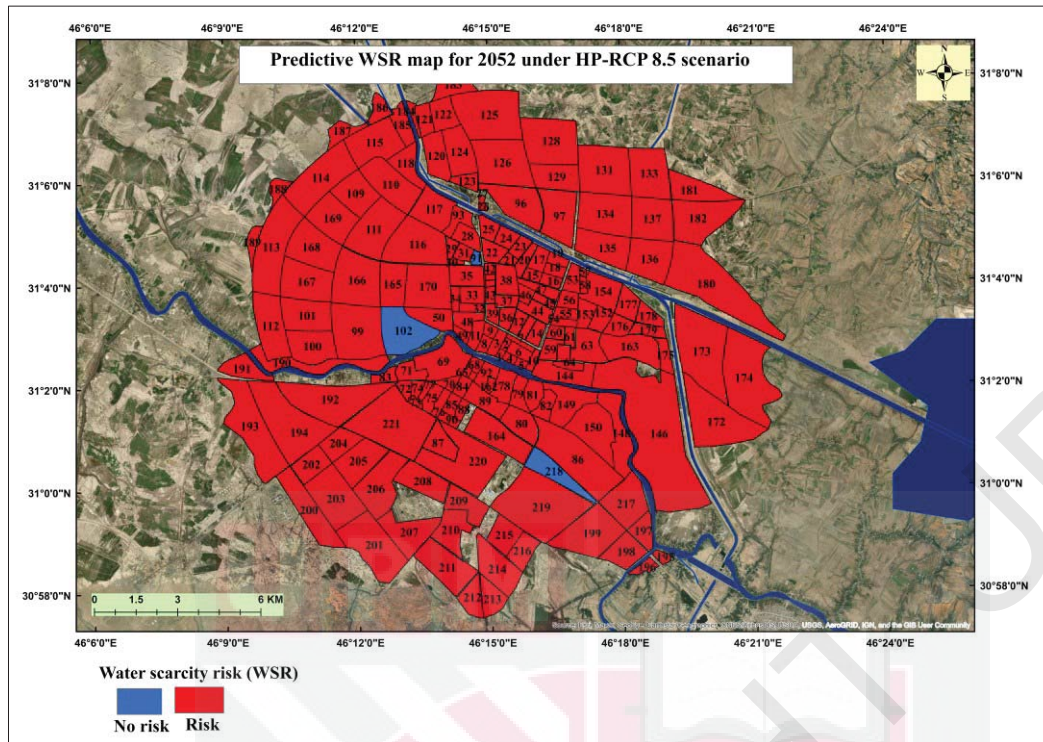


Figure 4.39 : WSR for the year 2052 under the HP-RCP 8.5 scenario

4.4.5.2 Forecasting WSR under MS-RCP 4.5

Based on RCP 4.5 and the HadGEM2-ES model, the expected monthly average precipitation in the year 2052 will be about 13.8463 mm/month, and the expected maximum temperature will be 49.54°. By contrast, in the year 2023, the expected monthly average precipitation will be about 13.4 mm/month, and the expected maximum temperature degree will be 48.50°.

The model results showed that the proposed measures in MS under RCP 4.5 will be effective. On the basis of a 2.5% population growth and the census of 2021 (728,367), the city population was simulated to be about 1,565,994 by 2052. In that year, the effects of the proposed measures of water rationalisation will be evident, and the unmet water demand will decrease from 91% to 9%–55%. In 2052, the prediction result using the integrated ML and public engagement showed that 114 of 188 of city

neighbourhoods will suffer from water deficit. This part of the city will be about 16,801 ha, and it will accommodate about 70% of the population. Most of the expansion areas located in the south and southwest will suffer from water scarcity, as shown in Figure 4.40.

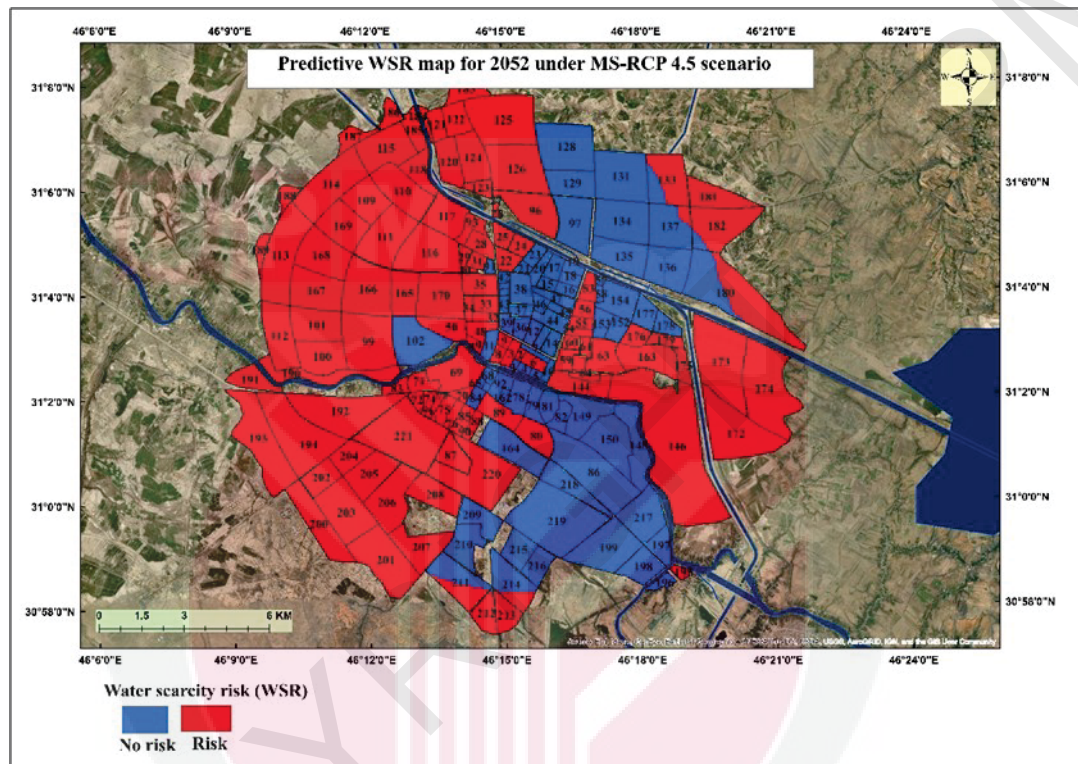


Figure 4.40 : WSR for the year 2052 under the MS-RCP 4.5 scenario

4.4.6 Final Result of the Integration Models

4.4.6.1 Forecasting Overall Risks under HP-RCP 8.5

After calculating the overall future risk based on the concept (i.e. Risk = threat × vulnerability), EV multiplied by the potential threat (WSR), the prediction result of future risk showed an intensive risk threat to the sustainability of the city. By the year 2052, 34% of the city's area will be located under a very high and high degree of risk of pollution and water scarcity. This area will accommodate 920,000 persons, about

27% of the city population. It is located in the southern and southwestern parts of the city. In Figure 4.41, the risk map classified the city into five categories: very low, low, moderate, high and very high.

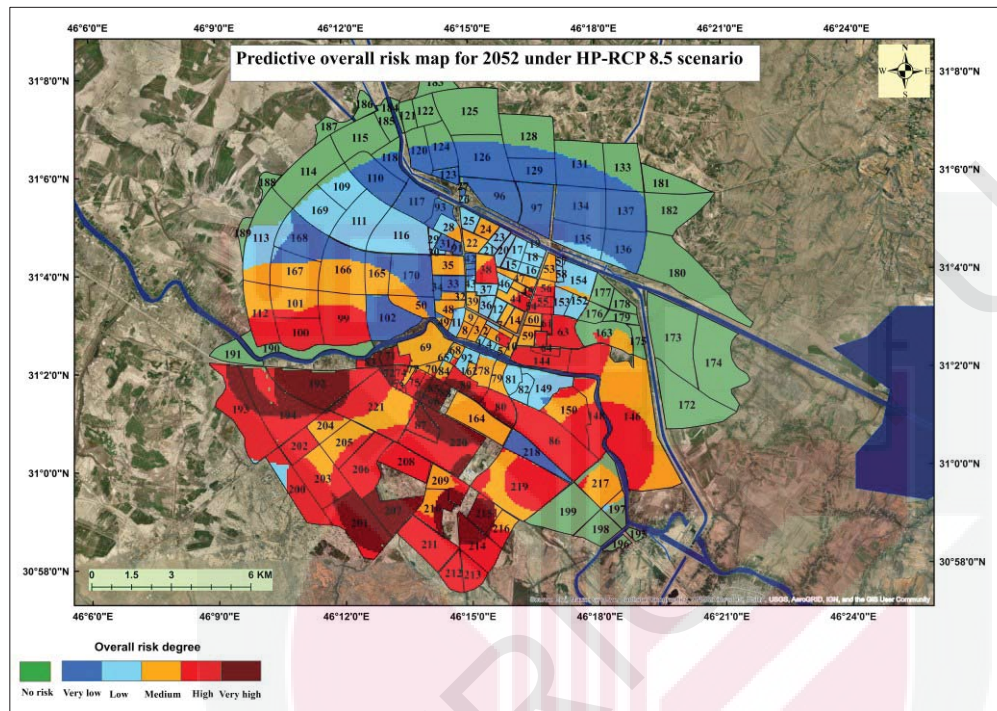


Figure 4.41 : The overall risks map of Nasiriyah City for the year 2052 under the HP-RCP 8.5 scenario

4.4.6.2 Forecasting Overall Risk under MS-RCP 4.5

Under MS-RCP 4.5, the prediction result of future risk showed that by the year 2052, 9% of the city's area will be located under a very high and high degree of risk of pollution and water scarcity. This area will accommodate about 136,000 persons, about 8.6% of the city population. It is located in the southern and southwestern parts of the city. In Figure 4.42, the risk map classified the city into five categories: very low, low, moderate, high and very high.

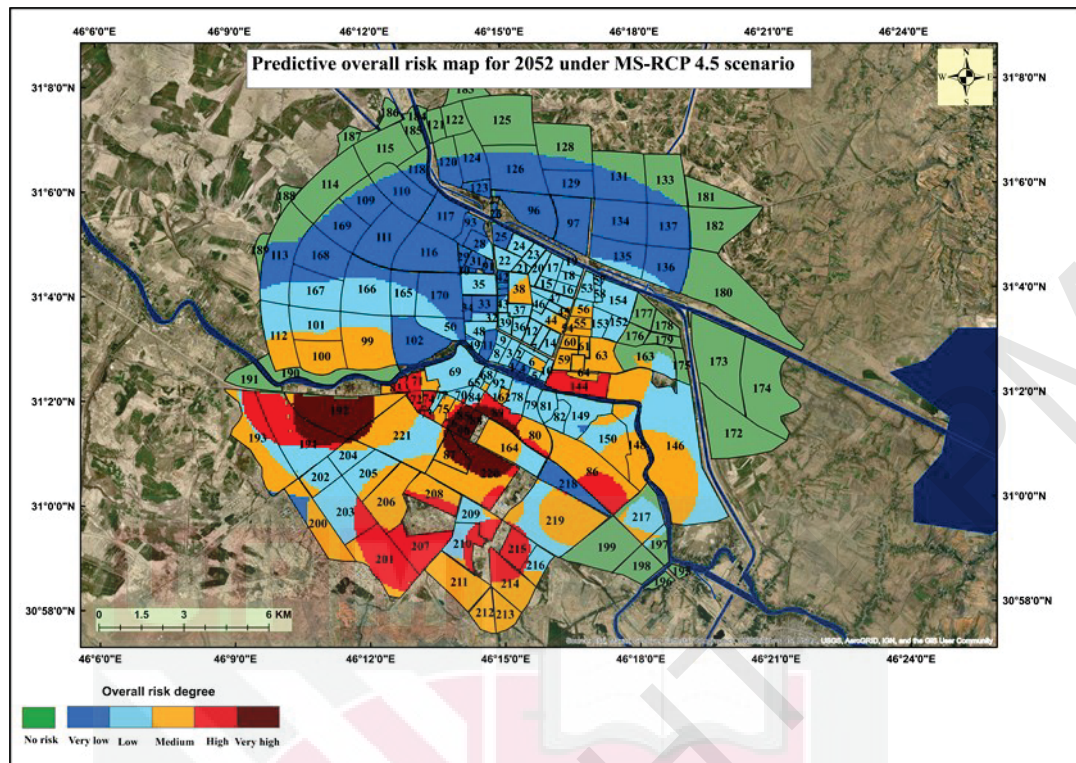


Figure 4.42 : The overall risks map for the year 2052 under the MS-RCP 4.5 scenario

4.4.7 Validation of Overall Risk Model

4.4.7.1 Calibration and Validation of the Hydraulic Model

Two gage stations belonging to the Gharraf River (i.e. gage 3 at 31°53'0.48" N, 46°3'27.14" E; gage 5 at 31°26'45.29" N, 46°10'34.07" E) were used to validate the hydraulic model, and the results are listed in Tables 4.8–4.9. In addition, Figures (4.43–4.44) show difference between observed and modelled streamflow for period of 2012–2021.

Table 4.8 : Calibration and validation result of the hydraulic model in gage 3

Gauge	NRMSE %	PBIAS %	NSE	R2	Period %	Type
Gage3	23	0.7	0.946	0.948	2012-01-01–2021-12-01 (120) months	All
Gage3	40.1	2	0.84	0.87	2012-01-01–2018-12-01 (84) months	Calibration (70%)
Gage3	32.2	–1.4	0.89	0.92	2019-01-01–2021-12-01 (36) months	Validation (30%)

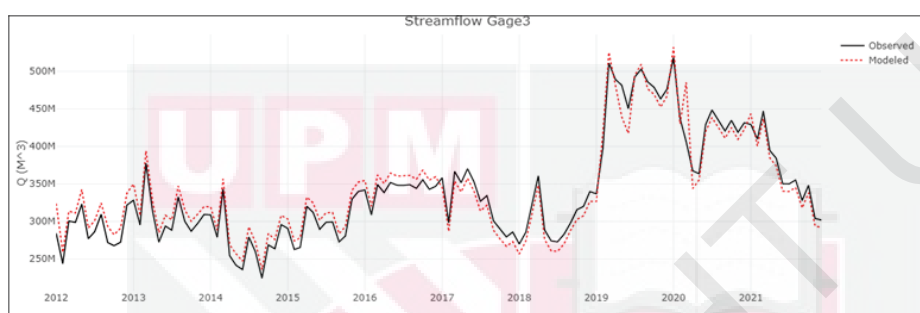


Figure 4.43 : Observed and modelled streamflow in gage3

Table 4.9 : Calibration and validation result of the hydraulic model in the gage 5

Gauge	NRMSE %	PBIAS %	NSE	d	R2	Period	Type
Gage5	38.7	4	0.849	0.954	0.865	2012-01-01 - 2021-12-01 (120) month	All
Gage5	51.3	5.8	0.73	0.94	0.87	2012-01-01 - 2018-12-01 (84) month	Calibration (70%)
Gage5	40.4	1.2	0.83	0.94	0.86	2019-01-01 - 2021-12-01 (36) month	Validation (30%)

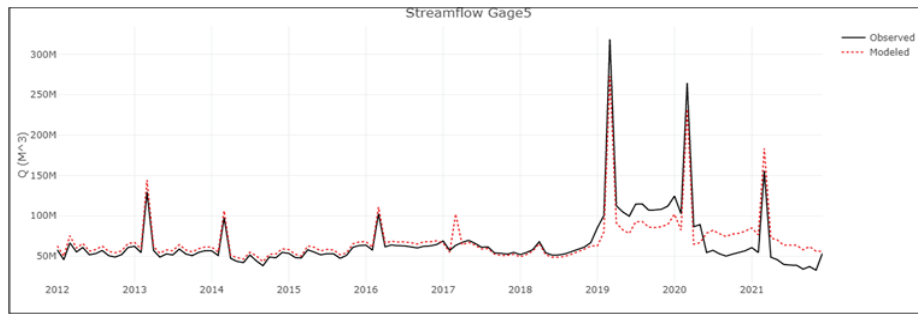


Figure 4.44 : Observed and modelled streamflow in the gage 5

4.4.7.2 Validation of Water Scarcity Risk for the Year 2052

Two kinds of ML algorithms, namely, RF and MPL, were selected to validate the prediction result of WSR for the year 2052 under two scenarios (HP-RCP 8.5 and MS-RCP 4.5), and the results are listed in Tables 4.10 and 4.11.

Table 4.10 : Validation result of WSR for the year 2052 under HP-RC 8.5

Algorithm types	TP Rate	FP Rate	Precision	Recall	F-Measure	Kappa statistic MCC	ROC Area	PRC Area
RF	0.973	0.031	0.973	0.973	0.973	0.944	0.996	0.996
MPL	0.984	0.015	0.984	0.984	0.984	0.967	0.999	0.999

Table 4.11 : Validation result of WSR for the year 2052 under MS-RC 4.5

Algorithm types	TP Rate	FP Rate	Precision	Recall	F-Measure	Kappa statistic MCC	ROC Area	PRC Area
RF	0.997	0.005	0.997	0.997	0.997	0.993	1	1
MPL	0.997	0.002	0.997	0.997	0.997	0.993	1	1

4.4.8 Discussion of Overall Risk Prediction

Future human and environmental security is complicated by the tension between sustainable development and urbanisation (Türk & Zwick, 2019a). Whilst urbanisation has led to wasteful use of natural resources (Dou Zhang et al., 2020b),

sustainable development is a crucial objective in the fight against the depletion of these finite supplies (Guiwen Liu et al., 2019). Additionally, with rapid urbanisation, increasing populations and climate change, water consumption has increased worldwide. Despite widespread water scarcity, dryness and extreme weather events, irresponsible water consumption is the dominant trait (Hunt & Shahab, 2021).

To improve the existing development strategies and fortify the integrated management of land and water resources, further research is needed to determine the effects of urbanisation and water consumption on sustainability (B. Gong & Liu, 2020; Dou Zhang et al., 2020a). Therefore, this study intends to develop a new approach called WSREV to predict WSR and EV together under high population growth and climate change scenarios up to the year 2052. In this approach, three techniques, i.e. CVA, WSRPP and UGFB, which were integrated and then coupled with WEAP, were used. The result of the model revealed that the proposed measures within the framework of the MS are effective. Whilst the water demand will be increased by 1493 mcm for the period of 2022–2052 under HP-RCP 8.5, it will be decreased by 1621 mcm under MS. Similarly, the unmet demand will be increased by 1723 mcm for the same period under HP-RCP 8.5, but it will be decreased by 3619 mcm under MS.

The results showed that the agricultural sector is the dominant sector of water. According to the overall scenario results, the agricultural water demand will be in the range of 95%–84% of total water demand for the period of 2022–2052, respectively, and the domestic water demand will be 5.2 %–15.9% for the rest of the industrial sector. Consequently, under HP-RCP8.5, the unmet water demand in Nasiriyah City will be 91% for most demand sites. Therefore, 185 of the 188 city neighbourhoods will be at drought risk; thus, about 3,305,358 persons will be under very high risk by

2052. By contrast, the effects of the proposed measures of water rationalisation with management scenario will be evident.

The unmet water demand will decrease from 91% to 9%–55%. Thus, in 2052, 74 of 188 city neighbourhoods will be able to access the water easily. Furthermore, the overall future risk based on the concept, $\text{Risk} = \text{threat WSR} \times \text{EV}$, showed that under HP-RCP 8.5, an intensive risk threat will affect the sustainability of the city. By the year 2052, 34% of the city's area will be under a very high and high degree of risk of pollution and water scarcity. This area will accommodate 920,000 persons, about 27% of the city population. It is located in the southern and southwestern parts of the city. By contrast, the situation under MS-RCP 4.5 will be better than HP-RCP 8.5. The prediction result of future risk showed that by the year 2052, only 9% of the city's area will be located under a very high and high degree of risk of pollution and water scarcity.

In contrast to most previous studies that adopted three alternative scenarios, such as 'business as usual' (BAU), climate change paths and rapid urban development, this study proposed nine scenarios to express all that could occur in the future (Li, Cheng and Han, 2020). In contrast to traditional approaches, this novel approach considered the two main pillars of the city's sustainability, the earth and the water (Zhang *et al.*, 2020b; Xiang *et al.*, 2021). In addition, it incorporated climate change scenarios and water scarcity mitigating measures into the future LULCC simulation to cover all future challenges.

Furthermore, it integrated driving factors that were neglected in most previous studies in a modelling process, such as population dynamics, LULCC, per capita income,

unmet demand, demand and supply patterns and environmental factors, to explore the future risk (Guo *et al.*, 2020). In contrast to most studies that have not considered the urban sprawl from the perspective of environmental security, this study evaluated environmental pollution coupled with water scarcity and urbanisation in the present and the future to enhance comprehensive understanding to guarantee sustainability (Pera, 2020; Zhang *et al.*, 2020b).

Consequently, this study presented a novel approach in which three types of simulation techniques were integrated: the LULCC prediction technique that was developed for this aim, the WSR prediction technique that was innovated using ML and PP and the WEAP model. In addition, the EV technique was used to produce the final risk. Additionally, the validation outcomes support the approach's effectiveness in terms of performance, as determined by the validation metrics that were assessed using ML algorithms. However, this method simulates urban expansion and water demand, offering decision-making possibilities for people who want sustainability and want to more sustainably direct urban development.

The study presented a package of measures to mitigate the effects of climate change, environmental pollution and water scarcity that were confirmed to be effective by the study results. However, given many data limitations and the complexity of land-use patterns, further spatial analyses are needed. In addition, other driving factors (land price, political and security factors and government budget for development) should be integrated to simulate the water situation and LULCC.

4.5 Summary

Chapter 4 provides a detailed examination of vulnerable areas in Nasiriyah city, projecting water security risk and urban sprawl trends up to 2052. The summary highlights the following key findings:

- Approximately 25% of the city's population, residing in 11 sectors, face significant vulnerability.
- 26% of the population lives in 17 sectors with very high-water scarcity risk (WSR).
- Urban area expansion is notable, increasing from 2.5% in 1992 to 12.2% in 2022, and projected to grow by 34%, 25%, and 19% by 2032, 2042, and 2052 respectively.
- By 2052, under high population growth and RCP 8.5 climate change scenario, 34% of the city's area will face very high to high risk. However, under the manage measure scenario and RCP 4.5 climate change path, this risk reduces significantly to only 9% of the city's area.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusion

Urbanisation has been driven mainly by high population growth, causing urban vulnerability and increasing pressure on the water demand. However, most of the previous methods that have analysed the effects of urbanisation have ignored the ecological issues that threatens the sustainability of urban communities. In addition, human perspectives are not included in machine learning decisions, despite the need of including the views of people who are affected by water management issues. Therefore, the main aim of the current study is to develop urban growth and water management models using GIS and machine learning. Four objectives were included to achieve the main goal.

In the first objective, a new technique, i.e. CVA, was developed. CVA uses comprehensive vulnerability indicators to assess metropolitan areas more accurately due to including environmental indicators that were integrated with social, urban and building indicators. This method integrates FAHP, FLM and FOG to form a new hybrid technique that eliminates ambiguity in vulnerability indicator categorisation and combination. The validation result confirms that the performance of the technique was 'almost perfect'. The findings showed, visually and statistically, that the city neighbourhoods experienced environmental pollution and regional marginalisation. Given rapid urbanisation and poor land use, a considerable portion of the city was affected by pollution, with residential land use overlapping with polluting industrial

usage. Additionally, the vulnerability maps showed that many communities were situated in zones with extremely high and high susceptibility.

In the second objective, a new method called WSRPP was developed. It uses ML and PP to forecast WSR. The performance of WSRPP was validated using ML algorithms; thus, high accuracy was obtained in both methods, i.e. direct ML model prediction and WLC function. However, the average weights of important criteria collected by five ML algorithms (MLP, SVM, RF, KNN and NBC) improved WSR prediction accuracy when using the WLC method. According to the WSRPP technique, 13% of the city's residents live in 18 neighbourhoods with high WSR, 26% live in 17 areas with very high WSR, and the remaining 61% lives in neighbourhoods with moderate to very low risk. Although an attendant uncertainty ratio exists, the WSRPP technique provided a clear interpretation of data; thus, it can assist decision-makers in the timely investigation processes of urban WSR.

In the third objective, a novel urban growth prediction technique called UGBF was developed. It integrates four ML algorithms to predict urban growth using the UGB tool. Four ML models, i.e. LR, RF, KNN and AdaBoost, were used. According to the validation metrics that were determined by the four ML algorithms, the performance of the UGBF technique was successful. The outcomes showed that the study area's (Nasiriyah City's) unregulated and haphazard growth has severe repercussions on urban and natural systems. Additionally, by the years 2032, 2042 and 2052, the city will have grown by 34%, 25% and 19%, respectively. UGBF is a useful tool in conjunction with optimisation land-use strategies to identify which locations will be covered by future city growth. In addition, it is a great strategy for making a long-term

choice on the best location because it includes a trained ML model that can predict UGBs with a simple step.

In the fourth objective, a hybrid technique was developed by integrating four types of techniques, i.e. the three techniques developed in the previous objectives in addition to the WEAP model. The hybrid technique predicts the overall risk by the year 2052. According to the validation metrics determined by the ML algorithms, the hybrid model's performance was effective. In addition, the findings expected that 34% of Nasiriyah City's area will be under a very high and high degree of risk of pollution and water scarcity under the PH-RCP 8.5 scenario by the year 2052. By contrast, 9% of the city's area will be under a very high and high degree of risk of pollution and water scarcity under the MS-RCP 4.5 scenario for the same year.

5.2 Contribution

The first contribution is a new technique called CVA. This technique can detect vulnerable urban areas and analyse environmentally degraded and spatially marginalised metropolitan regions. It can be applied effectively in the processes of allocating financial resources and mitigating vulnerability in the most susceptible metropolitan regions in Iraq and other developing nations.

The second contribution is a new approach called WSRPP. It ranks city districts by WSR level and determines the districts that are most affected by WSR. To my knowledge, the PP of local citizens was included for the first time in the water urban field to overcome subjectivity bias and ensure proactive mitigation assessment in vulnerable areas.

A new approach called UGBF, which can anticipate urban expansion over a long period and be simply linked with land use optimisation approaches, is the third contribution of the thesis. This approach provides a trained ML model to serve as a permanent decision support tool for any city anywhere in the globe. It is useful for urban planners, especially in selecting sites of pollution-causing projects.

The fourth contribution is a hybrid technique that considers the LULCC dynamic and PP to predict the future risks of environment pollution and WSR under different scenarios, including urbanisation and climate change scenarios, to increase the spatial-temporal prediction ability and improve land and water management by suggesting several alternatives and solutions.

5.3 Recommendations

While the proposed techniques exhibited commendable performance and surpassed numerous state-of-the-art methods, several limitations were identified. Firstly, due to data limitations and the complexity of land-use patterns, other important driving factors of water scarcity risk beyond those considered in this work were not incorporated. Secondly, there are no actual investigations to detect the effect of Depleted Uranium (DU) in the study area due to a lack of experience and tools, although international reports indicated to increase in the disease cases associated with using Depleted Uranium in the study area (Nasiriyah city). Additionally, the restricted study time frame and unavailability of data presented challenges in assessing the effects of industrial and other land uses on water pollution and human health. In light of these limitations in the current study, the following recommendations are proposed for future research:

- Future research should include other driving factors, such as land prices, political and security factors, the government budget for development to simulate the water situation, and urban growth.
- Future studies are required to examine the impacts of DU in-conflict zones generally and in Iraq specifically. In this context, PP can be integrated with ML as an efficient way to train models to obtain results.
- The current CVA technique should be improved to be able to detect the spatiotemporal effect of industrial activities on the health of people, including age categories.
- The WSRPP prediction model can be improved to detect WSR at a street scale in future research.
- Urban water pollution concerns could be detected by improving the WSRPP technique in future studies.

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